UNIVERSITY OF SOUTHAMPTON
FACULTY OF BUSINESS AND LAW

The Interdependence between the US and Emerging Markets' Industry Sectors: Time Varying, Linear and Nonlinear Assessments

By

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ABSTRACT

FACULTY OF BUSINESS AND LAW

Doctor of Philosophy

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By Bashir N.Osoble

The analysis of the interdependence between international equity markets has been a key issue in international finance as it has important practical implications for asset allocations, risk management, and economic policy. The objective of this thesis is to re-examine the interdependence amongst international equity markets at the industry sector level. In particular, the thesis investigates time varying, long run and short run dynamic relationships between industry sectors of the United States of America and three leading emerging markets/countries: Brazil, Malaysia, and South Africa between January, 2000 and December, 2009. The thesis advances previous studies on international industry sector relationships in three specific aspects. *Firstly*, it examines a large number of heterogeneous industry sectors from the global economy. *Secondly,* existing empirical studies in this area need to be updated to include the recent turbulent global economic and financial crisis period. *Thirdly,* the thesis offers a deeper analysis into the intra-industry sector interdependence than previously presented. Such analysis has important implications for international diversification strategies.

A crucial empirical contribution of the study is by applying liner and non liner econometric time series techniques for the evaluation for long run global relationships and causality linkages, including testing for asymmetric causality relations both in linear and nonlinear settings. This thesis also represents [to the best of my knowledge] the first study that extensively considers time-varying relationships amongst international industry sectors by examining time varying correlations and beta stability, as well as time varying cointegration and causality relationships. Another empirical motivation of this thesis is the need to extend existing empirical studies on industry sectors by examining the impact of the recent economic and financial crisis period. Specifically, the thesis investigates the shifts in cross correlations and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 economic and financial crisis.

The initial exploratory analysis of the return cross-correlations indicate that, though small or in a moderate range, the existence of co-movements amongst international industry sectors as all correlations coefficients are positive and significant at the one per cent level. The results for long run relationships provided by linear (without seasonal dummies) and nonlinear cointegration tests show no significant evidence of cointegration relations between the US and the emerging markets industrial sectors. Similarly, the results of the dynamic causality linkages, between the US and emerging markets industrial sectors indicate, there exist some significant short-run causal linkages (linear and nonlinear) between these markets' industry sectors, weak linkages. Overall, the results of time varying analysis indicate unstable relationships between the returns of US and the emerging economies' industry sectors over the sample period. The empirical results of crisis suggest increased cross correlations and causality relationships among the industry sectors of US and the emerging markets under study during the crisis of the sample period than pre-crisis period of the same sample. In summary, the empirical results of the research indicate relatively weak interdependence between the US and the emerging markets industry sectors, which suggest potential diversification benefits for US investors in diversifying their portfolio investment across industrial sectors of the emerging markets.

List of Contents

List of Contents	Page
Abstract	I
List of Contents:	II
List of figures	X
List of tables	XV
Declaration of Authorship	XVII
Acknowledgements	XVIII
Used Abbreviations	XX
Chapter 1: Introduction	1
1.1 Background and the problem	1
1.2 Research aims and questions	2
1.3 Why Industry Sector?	3
1.4 Sample, Data and Sources	4
1.5 Empirical Methodology	5
1.6 The Novelty of the Research	7
1.7 The structure of the Research work	8
Chapter 2: The Interdependence of International Equity Markets: Implications and Sources	10

List of Contents

2.1	Introduction	10
2.2	Background and the Implications of Equity Market Integration	11
2.3	Sources of Equity Market Co-movements	18
2.4	Empirical Measures of International Equity Market Integration	24
2.5	Conclusion	27

Chapter 3: Interdependence between International Equity markets: A review of empirical literature 29

3.1	Introduction	29
3.2	A Summary of Asset Pricing Models	20
3.3	A review of International Stock Markets Correlations	34
3.4	Long Run Co-movements of International Stock Markets: A review of cointegration literature	39
3.5	Dynamic Causality Links and Transmissions	51
3.6	Co-movement and Dynamic Linkages of International Industry and Firm Levels	59
3.7	Summary and research Strategy	68

Chapter 4: Sample, Data, and Preliminary Analysis 73

4.1	Introduction	73
4.2	Sample and the sources	73
4.3	Data and Graphical inspections	76

List of Contents

4.4 Descriptive Statistics for industry sector returns 82

4.5 Conclusion 86

Chapter 5: The Interdependence between US and Emerging Industry Sectors: Empirical Methodologies for Linear and Nonlinear analysis 88

5.1 Introduction 88

5.2 Co-movements between the US and the Emerging Markets' Industry Sector Returns 91

5.3 Empirical Methodologies for Long Run Linear Relations 92

5.3.1 Background 92

5.3.2 Testing for linear Unit Roots 93

5.3.3 Lag Length Selection for VAR/VEC Modelling 97

5.3.4 Cointegrating VAR Models: The Maximum Likelihood Estimation 99

5.3.5 Time variation in the cointegrating relationships between the US and emerging countries industry sectors: Recursive and Rolling Cointegration Analysis 103

5.4 Long Run Nonlinear Relations between US and Emerging Markets Industry Sectors 106

5.4.1 Nonlinearity behaviour in financial Assets: Background and Relevant Literature 106

5.4.2 Nonlinear Unit Roots and Cointegration Tests 109

5.4.2.1 Rank Tests for Nonlinear Unit Roots 109

5.4.2.2 Rank Tests for Cointegration Relations 112

5.4.2.3 The score test for neglected nonlinearity 116

5.5 Linear and Nonlinear Causality tests between US and emerging Markets industry sectors 120

List of Contents

5.5.1 Background 120

5.5.2 VAR model and linear Granger causality 122

5.5.2.1 Linear Granger Causality 123

5.5.2.2 Time-varying Granger causality relations: A Rolling Windows Analysis 126

5.5.3 Nonlinear Causality between the US and emerging countries' industry sector returns 127

5.5.3.1 Testing for nonlinear dependencies 127

5.5.3.2 The Mackey-Glass (M-G) model of nonlinear causality relationship 131

5.6 Asymmetric analysis for linear and nonlinear Granger causality relations 133

5.6.1 Background 133

5.6.1 Asymmetric Linear Granger Causality 134

5.6.2 Asymmetric Nonlinear Causality 136

5.7 The Linkages between the US and Emerging Markets' Industry Sectors before and during the 2007-2009 Financial Crisis: An application of Toda and Yamamoto Causality approach with bootstrap distributions 137

5.8 Conclusion 141

CHAPTER 6: Co-movements between the Returns of the US and the Emerging Markets' Industry Sectors 144

6.1: Introduction 144

6.2 Cross Correlation Analysis of US and emerging industry sector returns 146

List of Contents

6.3 Time Varying cross-correlations:
Rolling windows estimations 150

6.4 Time varying coefficient regressions:
An application of State-space and Kalman Filter 155

6.5 Conclusion 165

Chapter 7: Long-run relationships between US and Emerging Markets Industry Sectors: Evidence from Linear and Nonlinear Cointegration Tests 168

7.1 Introduction 168

7.2 Long-run Linear Tests 169

7.2.1 Testing Unit Roots for Industry Sector Indices:
Statistical results of ADF, DF-GLS, and KPSS tests 170

7.2.2 The Cointegrated VAR 173

7.2.2.1 Model Specification 173

7.2.2.2 Diagnostic Testing and Lag Length Determination 180

7.2.3 Cointegration tests and results 182

7.3 Time variation in the long run relationships between the US and emerging countries industry sectors: Evidence from Recursive and Rolling Cointegration Analysis 192

7.3.1 Recursive cointegration analysis 193

7.3.2 Rolling cointegration analysis 199

7.4 Rank Tests for Nonlinear Unit Roots and Cointegrations: Testing Procedures and Results 203

7.4.1 The Rank Test results for Nonlinear Unit Roots: 204

7.4.2 Empirical results of rank and score tests for
Cointegrations and Neglected nonlinearity 205

7.3.2.1 Rank Statistic tests for cointegrations 205

List of Contents

7.4.2.2 The score statistic tests for neglected nonlinearity cointegrations 213

7.5 Conclusion 217

Chapter 8: Empirical Results of Dynamic linkages between the US and emerging markets Industry Sectors 220

8.1 Introduction 220

8.2 Empirical results of linear Causality Relations between US and emerging industry sectors 222

8.2.1 Linear Granger Causality test relations 223

8.2.2 Time varying causality relations: Evidence from rolling Window analysis 227

8.3 Nonlinear Causality relations between the US and emerging sector returns: Testing procedures and empirical results 233

8.3.1 Tests results for nonlinear dependencies 233

8.3.2 Symmetric Nonlinear causality Relations: Evidence from the Mackey-Glass (M-G) model 237

8.4 Asymmetric effects on Linear and nonlinear causality relations between the US and emerging industry sector returns 240

8.4.1 Empirical results of Asymmetric effects on the linear Granger causality relations 241

8.4.2 Empirical results of Asymmetric effects on the nonlinear Granger causality relations 245

List of Contents

8.5: The Linkages between the US and Emerging Markets' Industry Sectors before and during the 2007-2009 Financial Crisis: Empirical Results 250

8.5.1: Cross correlations 250

8.5.2: Causalities linkages: Evidence from Toda and Yamamoto approach with bootstrap distributions 254

8.6: Conclusion 258

Chapter 9: Conclusions and recommendations for further areas of research 262

9.1 Review of Research objectives 262

9.2 Summary of the results and implications 263

9.3 Short comings of the thesis 268

9.4 Outlook for further Research 269

Appendices 273

Appendix A: Industry Super-sectors, their industry groups, and descriptions 273

A1: Super sectors and their industry group 273

A2: Super sectors and their descriptions 274

Appendix B: The results of unit root and stationarity tests: The ADF, DF-GLS, and KPSS statistics 275

B.1 Unit root and stationary tests of the US industry sector price levels and first differenced 275

B.2: Unit root and stationary tests of the Brazilian industry sector price levels and first differenced 275

List of Contents

B3: Unit root and stationary tests of the Malaysian industry sector price levels and first differenced 276

B4: Unit root and stationary tests of the South African industry sector price levels and first differenced: 276

Appendix C: The results of nonlinear unit root tests: The rank test statistics 277

C1: The rank test for nonlinear unit root of the US industry sector prices 277

C2: The rank test for nonlinear unit root of the Brazilian industry sector prices 277

C3: The rank test for nonlinear unit root of the Malaysian industry sector prices 278

C4: The rank test for nonlinear unit root of the South African industry Sector Prices 278

Appendix D: The results nonlinearity tests for the residuals of the linear models 279

D.1: Linear and nonlinear tests on residuals of AR(p) models for US Sector returns 279

D.2: Linear and nonlinear tests on residuals of AR(P) models for Brazilian Sector returns 279

D.3: Linear and nonlinear tests on residuals of AR(p) model for Malaysian Sector returns 280

D.4: Linear and nonlinear tests on residuals of AR(p) model for South African Sector returns 280

References 281

List of Contents

List of figures

Figures 4.1 - 4.4: Industry Sector Log Price Levels 79

4.1: Price levels of the US Industry Sectors 79

4.2: Price levels of the Brazilian Industry Sectors 80

4.3: Price levels of the Malaysian Industry Sectors 80

4.4: Price levels of the South African Industry Sectors 80

Figures 4.5 - 4.8: Industry Sector Returns 81

4.5: Returns of the US Industry Sectors 81

4.6: Returns of the Brazilian Industry Sectors 81

4.7: Returns of the Malaysian Industry Sectors 81

4.8: Returns of the South African Industry Sectors 82

Figures 6.1 to 6.10: Time varying correlations between industry sector returns: Rolling window estimations 151

6.1: Time varying correlations between Banking Sector returns 151

6.2: Time varying correlations between Basic Resources Sector returns 151

6.3: Time varying correlations between Chemicals Sector returns 151

6.4: Time varying correlations between Construction and Materials Sector returns 152

6.5: Time varying correlations between Financial Service Sector returns 152

6.6: Time varying correlations between Food and Beverage Sector returns 152

6.7: Time varying correlations between Industrial Goods sector returns 153

6.8: Time varying correlations between Personal and H/H Goods Sector returns 153

6.9: Time varying correlations between Retailing Sector returns 153

6.10: Time varying correlations between Telecommunications Sector returns 154

Figures 6.11 to 6.20: Time-varying bivariate regression coefficients: US industry sectors as the explanatory variables 158

6.11: Bivariate time varying coefficient of the Banking Sector returns 158

List of Contents

6.12: Bivariate time varying coefficients of the Basic Resources Sector returns 158
6.13: Bivariate time varying coefficients of the Chemical Sector returns 158
6.14: Bivariate time varying coefficients of the Construction Sector returns 159
6.15: Bivariate time varying coefficients of the Financial Services Sector return 159
6.16: Bivariate time varying coefficients of the Food and Beverage Sector returns 159
6.17: Bivariate time varying coefficients of the Industrial Goods Sector returns 160
6.18: Bivariate time varying coefficients of the Personal & H/H Goods Sector returns 160
6.19: Bivariate time varying coefficients of the Retail Sector returns 160
6.20: Bivariate time varying coefficients of the Telecommunications Sector returns 161

Figures 6.21 to 6.30: Time-varying coefficients of multivariate regressions: US sectors as the dependent variables 162

6.21: Multivariate time varying coefficients of the Banking Sector returns 162
6.22: Multivariate time varying coefficients of the Basic Resources Sector returns 162
6.23: Multivariate time varying coefficients of the Chemicals Sector returns 163
6.24: Multivariate time varying coefficients of the Construction and Material Sector returns 163
6.25: Multivariate time varying coefficients of the Financial Services Sector returns 163
6.26: Multivariate time varying coefficients of the Food and Beverage Sector returns 164
6.27: Multivariate time varying coefficients of the Industrial Goods Sector returns 164
6.28: Multivariate time varying coefficients of the Personal & H/H Goods Sector returns 164
6.29: Multivariate time varying coefficients of the Retail Sector returns 165
6.30: Multivariate time varying coefficients of the Telecommunications Sector returns 165

List of Contents

Figures 7.1-7.10: VAR residuals of the industry sector price indices 174

7.1: VAR Residuals of Banking Sectors 174

7.2: VAR Residuals of Basic Resources Sectors 174

7.3: VAR Residuals of Chemicals Sectors 175

7.4: VAR Residuals of Construction Materials Sectors 175

7.5: VAR Residuals of Financial Services Sectors 175

7.6: VAR Residuals of Food & Beverage Sectors 176

7.7: VAR Residuals of Industrial Goods Sectors 176

7.8 VAR Residuals of Personal Goods 176

7.9: VAR Residuals of Retailing Sectors 177

7.10: VAR Residuals of Telecommunications Sectors 177

Figures 7.11 to 7.20: Time varying cointegration relationships between industry sectors: Evidence from recursive estimations 194

7.11: Recursive tests for time varying cointegration relations between Banking Sectors 194

7.12: Recursive tests for time varying cointegration relations between Basic resources Sectors 195

7.13: Recursive tests for time varying cointegration relations between Chemicals Sectors 195

7.14: Recursive tests for time varying cointegration relations between Construction and Materials Sectors 195

7.15: Recursive tests for time varying cointegration relations between Financial Sectors 196

7.16: Recursive tests for time varying cointegration relations between Food and Beverage Sectors 196

7.17: Recursive tests for time varying cointegration relations between Industrial Goods Sectors 196

7.18: Recursive tests for time varying cointegration relations between Personal and H/H Goods Sectors 197

7.19: Recursive tests for time varying cointegration relations between Retailing Sectors 197

7.20: Recursive tests for time varying cointegration relations between Telecommunications Sectors 197

List of Contents

Figures 7.21 to 7.30: Time varying cointegration relationships between industry sectors: Evidence from rolling cointegration estimations 200

Figre 7.21: Rolling Window estimation for time varying cointegration relations between Banking Sectors 200

Figre 7.22: Rolling Window estimation for time varying cointegration relations between Basic Resources Sectors 200

Figre 7.23: Rolling Window estimation for time varying cointegration relations between Chemical Sectors 201

Figre 7.24: Rolling Window estimation for time varying cointegration relations between Construction and Materials Sectors 201

Figre 7.25: Rolling Window estimation for time varying cointegration relations between Financial Service Sectors 201

Figre 7.26: Rolling Window estimation for time varying cointegration relations between Food and beverage Sectors 202

Figre 7.27: Rolling Window estimation for time varying cointegration relations between Industrial Goods Sectors 202

Figre 7.28: Rolling Window estimation for time varying cointegration relations between Personal and H/H Goods Sectors 202

Figre 7.29: Rolling Window estimation for time varying cointegration relations between Retailing Sectors 203

Figre 7.30: Rolling Window estimation for time varying cointegration relations between Telecommunications Sectors 203

Figures 8.1 to 8.10: The rolling test results for time varying causality relationships between the intra-industry sectors of US and the emerging markets 229

8.1: Rolling Granger causality relationships between Banking sectors 229

8.2: Rolling Granger causality relationships between Basic Resources sectors 230

8.3: Rolling Granger causality relationships between Chemical sectors 230

8.4: Rolling Granger causality relationships between Construction sectors 230

8.5: Rolling Granger causality relationships between Finance sectors 231

8.6: Rolling Granger causality relationships between Food sectors 231

8.7: Rolling Granger causality relationships between Construction sectors 231

8.8: Rolling Granger causality relationships between Personal & H/H sectors 232

8.9: Rolling Granger causality relationships between Retail sectors 232

List of Contents

8.10: Rolling Granger causality relationships between Telecommunications sectors 232

List of Contents

List of tables

Table 4.1: Summary Statistics of US industry sector returns 84

Table 4.2: Summary Statistics of Brazilian industry sector returns 85

Table 4.3: Summary Statistics of Malaysian industry sector returns 85

Table 4.4: Summary Statistics of South African industry sector returns 86

Table 6.1: Cross Correlation Relations between the Industry sector returns 149

Table 7.1: The Trace test results for bivariate co-integration relations between the US and emerging countries' Industry Sectors 186

Table 7.2: The Trace test results for multivariate co-integration relations between the US and emerging countries' industry sectors 188

Table 7.3: The Trace test results for multivariate co-integration relations between the emerging countries' industry sectors 190

Table 7.4: The results of κ_T and ξ_T rank statistics for bivariate cointegration relationships between the US and emerging industry sectors 209

Table 7.5: The Rank test results for bivariate cointegration relationships between the industry sectors 210

Table 7.6: The rank test results for multivariate cointegration relationships between the US and emerging countries' industry sectors 212

Table 7.7: The rank test results for multivariate cointegration relationships between the emerging countries industry sectors 213

Table 7.8: The rank test results of bivariate cointegration relationships and the score statistic for neglected nonlinear cointegrations 215

Table 7.9: The rank test results of multivariate cointegration and the neglected nonlinear cointegrations 216

Table 7.10: The rank test results of multivariate cointegrations and the neglected nonlinear cointegrations for emerging countries 216

Table 8.1: VAR Granger Causality Results 226

Table 8.2: Symmetric nonlinear Granger causality relationships: Evidence from the Mackey-Glass (M-G) model 239

List of Contents

Table 8.3: The test results of positive asymmetric linear causality relationships 242

Table 8.4: The test results of negative asymmetric linear causality relationships 244

Table 8.5: The test results of positive asymmetric nonlinear causality relationships 247

Table 8.6: The test results of negative asymmetric nonlinear causality relationships 249

Table 8.7: Cross Correlations between the Industry sector returns of 2004-2006 252

Table 8.8: Cross Correlations between the Industry sector returns of 2007-2009 253

Table 8.9: Causality Tests Based on Toda and Yamamoto approach with bootstrap distributions: 2004-2006 255

Table 8.10: Causality Tests Based on Toda and Yamamoto approach with bootstrap distributions: 2007-2009 257

Declaration of Authorship

I, *Bashir Nur Osoble*…,declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

‘The Interdependence between the US and Emerging Markets’ Industry Sectors: Time Varying, Linear and Nonlinear Assessments’

…………………………………………………………………………………………

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;

2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;

3. Where I have consulted the published work of others, this is always clearly attributed;

4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;

5. I have acknowledged all main sources of help;

6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;

7. Either none of this work has been published before submission, or parts of this work have been published as: [please list references below]:

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Date: ………..…………………………………

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Beside these individuals, it is acknowledged that this dissertation uses extensively theoretical and empirical literature. However, any errors, misinterpretations and omissions are the author's responsibility, and are not attributed in anyway to the consulted literature.

List of Contents

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List of Contents

Used Abbreviations

BNK: Banking Sectors

BRS: Basic Resources Sectors

CHM: Chemical Sectors

CNM: Construction and Materials Sectors

FNS: Financial Services Sectors

FBV: Food and Beverage Sectors

ING: Industrial Goods Sectors

PHH: Personal and Household Goods Sectors

RTL: Retailing Sectors

TLC: Telecommunication Sectors

BR: Brazil

ML: Malaysia

SA: South Africa

US: United States of America

GICS: Global Industry Classification System

ICB: Industry Classification Benchmark

SD: Standard deviations

SK: Skewness test

KURT: kurtosis test

JB: The Jarque-Bera statistic

LB: The Ljung-Box portmanteau test

LB-Q^2: Squared Ljubg-Box Q test

LB(5): LB statistics with five lags

ACF: autocorrelation function

ADF: Augmented Dickey–Fuller unit root test

DF-GLS: lliott et al (1996) approach of modified DF unit root test

KPSS: Kwiatkowski, Phillips, Schmidt and Shin (1992) unit root test

Uni: Uuniform' version of the score statistics

Ins: inverse of normal scores statistics

AC: Akaike's information criterion

ARCH: Autoregressive conditional heteroscedastic

List of Contents

GARCH: Generalised autoregressive conditional heteroscedastic

AR(p): Autoregressive process with p terms,

AR(1): First order autoregressive process

SC: Schwarz’s information criterion

HQ: Hannan-Quinn’s information criterion

LM: Lagrange multiplier test

LM(5): Lagrange Multiplier test for Arch effect
LR: Te likelihood ratio test

VAR(p): VAR with k variables and p lagged terms process

VECM: Vector error correction model

BDS: Brock Dechert, Scheinkman and LeBaron (1996) test

M-G: Mackey-Glass Model

CHAPTER 1: Introduction

1.1 Background and the problem

The investigation of interdependence amongst international stock markets is a key issue in international finance as it has important practical implications for asset allocation, risk management, and economic policy. Although in recent years numerous studies in equity market relations have examined the relationships between international stock markets, several shortcomings remain in the literature. *Firstly*, numerous previous studies of international equity markets have used aggregate country level indices to examine the relationships between international stock markets. However, studies that address industry and firm level co-movements and dynamic linkages, or the comparison of the issues relating to which sectors co-move across industries at a global level, are relatively small compared to national level studies[1]. *Secondly*, the existing researches on industry or sector level interdependence have been done mainly focusing on particular geographical locations or certain markets, such as markets in developed countries or European markets'[2]. *Thirdly*, in the existing literature, most of empirical tests, like the unit root or stationary tests, cointegration analysis, and the tests for dynamic causality linkages are all built on the basis of a linear framework. However, since the mid 1980s, numerous studies [among others; Hinich and Patterson (1985), Scheinkman and LeBaron (1989), Hsieh (1991), Brock, Hsieh, and Le Baron (1991)] have documented that financial time series data can exhibit nonlinear dependencies.

[1] Recent studies on industry or sectoral level co-movements include, among others, Taing and Worthington (2002), Carrieri et al., (2004), Barben and Jansen, (2005), Kaltenhauser, (2002, 2003), Ratner and Leal (2005), and and Phylaktis and Xia (2006c), Bai and Green (2010, 211).

[2] See for example Beckers et al (1996), Taing and Worthington (2002), and Carrieri et al., (2004).

1.2 Research aims and questions

The aim of this thesis is to re-investigate the nature of the interdependence amongst international equity market relationships at a micro level, using price indices of equivalent industry intra -super sectors across markets. Specifically, the thesis investigates the long-run and short-run dynamic linkages between ten industrial sectors of the United States of America and three leading emerging markets/countries (Brazil, Malaysia, and South Africa) using various empirical techniques including linear and nonlinear tests. The industrial structure in emerging markets is generally different from that found in developed countries (Assaf and Cavalcante, 2005). USA is the world's largest economy, and has unrivalled influence on global stock markets, while the chosen emerging markets are the most developed countries in their prospective regions, and also have relatively large number of industry sectors. Furthemore, each market is from a different continent, allowing an interesting perspective on how the closeness of economic ties amongst them varies. Together, these markets can be considered as a reasonable representative for prospective (developed and emerging) equity markets respectively and therefore offer a reasonable portfolio diversification opportunity. Nevetheless, there are two limitations on the choice of the sample makets which need to be acknowledged. The first limitation is the exclusion of European and Japanese markets where there large industrial sector sectors. The second is the inclusion of Malaysian market, which is relatively small economy compared to some other emerging markets such as India and Russia, or even Indonesia. However, as to be explained in chapter four, currency denomination and the availability of industry sectors are main determinat or constrained factors.

Overall, this research aims to answer the following questions: What is the degree of long run relationships [linear or nonlinear] between developed and emerging markets? How stable are the long run relationships amongst industry sectors in the study? Are there any causal relations [linear or nonlinear] between the markets? How quickly is the industry price movements in one market transmitted to the other markets? What are the likely implications for international diversification? These questions will be important to international portfolio investors, and to economic and financial policymakers and regulators. In other words, as the sample of the research is well diversified in terms of market/country and industrial representation, the answers to these questions should provide reasonable empirical conclusions. If industry sector interdependencies are established, it can be seen as a key ingredient for stronger ties between the stock markets under study, which in turn may imply a reduction of international diversification benefits.

1.3 Why the Industrial Sector?

The effect of different industry mixes within national markets on the international equity market correlations has long drawn attention from researchers and market practitioners. For example, several early studies, such as Grubel and Fadner (1971), Lessard (1974) and Solnik (1974a), examined the influence of industry effects on country index returns, and found that country effects dominated industry effects. The dominance of country effects over industry effects has also been identified in recent studies including, amongst others, Heston and Rouwenhorst (1994), and Griffin and Karolyi (1998). Moreover, as Heston and Rouwenhorst (1994) note, imperfectly correlated industries might lead countries with different industry compositions to be imperfectly correlated and therefore the benefits of international diversification could stem from industrial diversification. However, as some other recent studies such as Baca et al. (2000), Cavaglia et al. (2000), Campbell et al. (2001), and Phylaktis and Xia, (2006a) have shown, the global industry factors are now becoming equally important as the country effects, or in some cases even more important than the country specific factors in driving the variation of international equity returns[3]. However, as some other studies (Serra, 2000 and Bai et al, 2006) indicate, the increasing importance of industry effects is not a phenomenon that is shared by emerging stock markets where country effects still largely appear to dominate returns.

[3] Such studies could be implying that, investors who diversify across industries within a particular country may find smaller benefits from international industry diversification.

Emphasising the importance of industry level analysis, Carrieri et al (2004, p.3) points out that 'the investigation of global integration at the industry level is important due to increasing economic integration, industrial reorganisation, and blurring of national boundaries (e.g., the European Union).' Nevertheless, as Meric et al (2005, p. 3377) explain 'although the portfolio diversification implication of the co-movements of the world's national equity markets has long been a popular topic in the financial literature, global sector analysis has not received sufficient attention'. Thus, re-examination of the relationship between the heterogeneity of industrial sectors is important for international diversification strategy.

1.4 Sample, Data and Sources

As mentioned earlier, this thesis investigates industry (super) sector linkages between the USA and three leading emerging markets (Brazil, Malaysia, and South Africa), representing the Asian, Latin American, and African continents. The US has virtually all industry sectors while the three emerging markets have the largest industry sectors in their respective continent, according to the Global Industry Classification Benchmark (GICB). The industry sectors used for this research are; Banking, Basic Resources, Chemicals, Construction and Materials, Financial Services, Food and Beverage, Personal and Household Goods, Retail, and Telecommunications. Although there are more industry sectors in each market, the data series of only the chosen sectors were available across the emerging markets over the sample period. The research sample covers a ten year period from January 4, 2000 to December 29, 2009, which corresponds to the time in which industry and firm level interests have been growing in international equity market studies. The sample period also includes the 2007 - 2009 economic and financial crisis and uses weekly data series of 10 industry sectors in which price indices were available for all markets of the study with a total of 40 sectors with 522 observations for each industry sector. The reason for employing weekly data series is twofold. First, is to get enough observations as opposed to monthly observations. Secondly, is to avoid issues relating to day of the week effects, commonly a problem when dealing with daily data, that is, the potential effects of noise characterising daily data. The use of weekly series is not uncommon in the literature (e.g. among other Carrier et al, 2004, and Berben and Jansen, 2005). According to Berben and Jansen (2005, p. 835) weekly data 'avoid spurious spillover effects due to non-synchronous trading hours'[4]. All the data series are obtained from DataStream International using Dow Jones industry indices and are denominated in the US dollar.

1.5 Empirical Methodology

To examine the interdependence between the industrial sectors under study, this thesis uses various time series econometric techniques including cointegration analysis causality relationships in linear and nonlinear frameworks, and dynamic transmission analysis. The first empirical analysis in the thesis employs several related empirical methods to study the co-movements between industry sector returns. Such methods include standard cross correlation analysis, time varying correlations and time varying return co-movements using the rolling correlation analysis, time varying coefficients or *beta* convergence applying state space framework, and Kalman filtering methods. For testing the long run linear equilibrium relationships between the industry sectors in the study, the thesis applies the conventional Johansen approach of cointegration (1988, 1991, and 1995). This thesis also examines the stability of long-run relationships between the US and the emerging markets' industry sectors by applying recursive cointegration analysis, as developed by Hansen and Johansen (1999) as well rolling cointegration estimtions.

An important shortcoming labelled on the linear Vector Autoregressive (VAR) or vector error correction model (VECM) techniques is that linear vector error correction models assume frictionless markets and the adjustment for premiums is linear and symmetrical. In this case, conventional linear models such as the unit root and cointegration tests can suffer from the failure to pass the normality tests.

[4] Chapter four presents more discussions on sample selection, data and sources, while chapter five discusses the econometric methodologies employed in the thesis.

In other words, ignoring the nonlinear nature of many financial time series, the conventional linear methods may lead to the misleading conclusion that no long-run relationship exist between stock markets series. To mitigate the shortcomings in the conventional models, an important recent development in the literature of time-series financial econometrics has been proposals of numerous nonlinear models that take nonlinearity in the dynamic relationships between variables of interest that cannot be adequately represented using a linear model. To examine nonlinear cointegrations between the emerging and the US stock markets, the thesis applies rank tests for a unit root and cointegration, as developed by Breitung (2001). Breitung's (2001) methodology can be used to first detect linear relationships amongst time series variables and then to test the nature of the nonlinearity or nonlinear cointegrations[5].

This thesis also examinines causality linkages between international industry sectors in linear and nonlinear settings. The linear causality tests are conducted through the standard Granger VAR model. For nonlinear causality analysis the thesis applies a recently proposed nonlinear causality method which is capable of capturing the affect of economic shocks, positive or negative, on the resulting causality amongst the variables. Specifically, the research applies the bivariate noisy Mackey-Glass (M-G) model, which was introduced to economic and financial studies by Kyrtsou and Terraza (2003, Kyrtsou and Labys (2006) and Hristu-Varsakelis and Kyrtsou (2008)[6]. In each case of linear and nonlinear causality tests, asymmetric causality relationships are also investigated. Testing the asymmetric effect of linear and nonlinear causality relationships for industry sector indices is an additional empirical novelty of this thesis. Furthermore, time varying causality tests which represent yet another empirical novelty of the thesis are conducted through a rolling window analysis.

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[5] To the best of my knowledge, no study has thus far considered nonlinear cointegration analysis to examine the long run relationships between industry sectors of developed and emerging stock markets.

[6] Prior to nonlinear causality analysis between industry sectors, univariate tests of nonlinear dependence were carried out. Such univariate tests present a first attempt for testing nonlinear dependence for sectoral level indices.

The sample period of the thesis coverers a period in which the interest of micro studies on international equity markets has been growing, and also includes more recent years of extreme economic and financial crisis. The crisis has resulted in the collapse of several large financial institutions, the rescue of banks by national governments, and downturns in stock markets around the world. In particular, between 2007 and 2009 the economic and financial headlines have reflected the failure of key businesses, plummeting stock markets around the world, and a severe global economic melt down[7]. The effect of financial or economical crisis is a topic that has attracted considerable amount of interests among academic researchers as it can have serious consequences for global financial linkages investors' portfolio gains. In other words, the co-movement between financial markets diminishes the diversification benefits and it is commonly known to be apparent especially in the equity markets durin the extreme condition. Therefore, another empirical task undertaken in the thesis is to investigate correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 economic and financial crisis using standard correlations tests and Toda and Yamamoto (1995) Causality approach with Bootstrap Distributions as proposed by Hacker and Hatemi (2006). Chapter five presents a detailed discussion of the econometric methods of the thesis.

1.6 The Novelty of the Research

Overalll, this thesis contributes to the existing literature in international industry sector relations in several ways. *Firstly*, this thesis extends previous studies by investigating sector level relations instead of national or general industry level. Specifically, the thesis takes a global approach by investigating the interdependence between industry sectors of different markets, in this case the US and the emerging countries, and taking different economic, legal, developmental, and trading characteristics, as well as different geographical locations into account. *Secondly*, as mentioned above and further detailed in later chapters, an

[7] See chapter seven for more discussion of the crisis.

important empirical contribution of this thesis is its extensive empirical analysis and employment of various techniques. *Finally*, as discussed above, this thesis investigates shifts in correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 economic and financial crisis. Specifically, for a comparative assessment, two period samples are examined using data series of 2004-2006 and 2007-2009 are conducted using standard correlations tests and Toda and Yamamoto (1995) Causality approach with bootstrap distributions as proposed by Hacker and Hatemi (2006). Is summary, given the limited existing empirical investigations on the international stock market relations at a sectoral level, the results from this research should be interesting for both global investors and empirical researchers.

1.7 The structure of the thesis

The thesis is structured as follows. Chapter two briefly discusses the theoretical aspects (implications and sources) of the integration, co-movement and dynamic linkages between the international equity markets. Chapter three presents a detailed review of the literature on the international equity market interdependence, both at a national and a micro (industry and firm) level. Chapter four discusses the sample selection strategy, sources and data, and the summary of basic statistics. Chapter five presents the main empirical methodologies of the research including procedures of linear and nonlinear cointegration relationships and time varying cointegration tests, linear and nonlinear causality linkages analysis. This chapter also discusses various market frictions such as transactions costs and information frictions, which can prevent the linear models converging to long run equilibrium in the assets of financial markets.

Chapter six to eight report the empirical findings of the thesis. Chapter six presents the results of several related empirical methods used to examine the co-movements between industry sector returns as discussed in section 1.5. Chapter seven reports the empirical results of linear and nonlinear cointegration relations, and presents graphical illustrations of time varying tests for long-run relationships using recursive and rolling cointegration. The same section also reports the results of linear and nonlinear unit root tests for the industry sectors in the study. Next, chapter eight reports the empirical results of the causality dynamic linkages between the US and the emerging markets' industry sectors including; linear and nonlinear tests, graphical presentations of rolling Granger causality analysis. The results of the univariate tests of nonlinear dependence behaviour of the industry sector return series are also reported in chapter eight. Chapter eight also reports the results of correlation correlation analysis and the dnamic causality linkages between the US and emerging markets' industry sectors for two sample period tests (2004-2006 and 2007-2009). Finally, chapter nine concludes the work of the thesis and outlines recommendations for extensions and further areas of research.

CHAPTER 2:
The Interdependence of International Equity Markets: Implications and Sources

2.1 Introduction

The amount of diversification provided by investing in international equity markets is dependent on the extent of integration or c-omovement between financial markets across the globe. Establishing the degree of integration or co-movement among different financial markets is crucial for the individual investors and corporations who wish to know for which countries stock market prices move together, in opposite directions or in altogether unrelated ways. Furthermore, the integration of capital markets has important implications for financial theories such as market efficiency and forecasting and when making various economic and financial market decisions. In summary, financial market integration has important implications for international investment decisions, financial market regulations, asset pricing models and market efficiency analysis, and financial polices of international corporations. It is also important for various economic issues such as monetary and economic growth and macroeconomic policies. Therefore, international investors need to understand the determinants behind the co-movement stock markets to evaluate the potential gains and risks in global diversifications. Similarly, policy-makers need to understand the driving forces behind global stock market co-movements.

This chapter briefly discusses the theoretical aspects (implications and sources) of the integration or co-movement and dynamic linkages between international equity markets. The work of the chapter is structured as follows. A brief background and implications of equity market integration are discussed in section two. Various sources of international stock market integration and short empirical reviews are also presented in section three. In the literature of international finance, several measuring methodologies of integration or co-movements between national equity markets have been presented. A short overview of various approaches (from correlation coefficients to long run models) of the integration between international stock markets is presented in the fourth section, whilst section five summarises the main points of the chapter.

2.2 Background and Implications of Equity Market Integration

In modern finance, the theories of portfolio and capital market are the two most important tools (Fabozzi and Modigliani, 2009). These theories can be traced back to the basic lessons drawn from both the mean-variance framework of Markowitz (1952) and the Capital Asset Pricing Model (CAPM) initially developed by Sharpe (1964), and further extended by Lintner (1965), Mossin (1966), Fama (1970), Merton (1973), and the arbitrage price theory of Ross (1976) [8]. From these theoretical underpinnings, investors, either individual or institutional, can reduce the volatility of their portfolios through allocating their investments into various classes of financial instruments, industries and other categories of assets that each move in different ways in response to the same event. Therefore, 'diversification benefits can be achieved because a portfolio's performance depends not only on the return and risk characteristics of the assets being held in the portfolio, but also on the correlation or co-movement of these assets', Arouri et al (2007).

Based on the same argument, portfolio theory advocates that investors diversify their assets across national borders (always provided that the expected returns from these assets are less than perfectly correlated with the domestic market). As Wang (2009, p. 83) points out 'seeking excess returns through international diversification is one of the strategies employed by large multinational financial institutions in an ever intensifying competitive financial environment, while national

[8] Portfolio theory deals with the selection of efficient portfolios (maximising expected returns with acceptable levels of risk), while capital market theory is concerned with investor decisions on security prices (Fabozzi and Modigliani, 2009).

markets, considered individually, appear to have been exploited to their full so that any non-trivial profitable opportunities do not remain in the context of semi-strong market efficiency'. The benefits of international diversification arise from the diversity of economic conditions in different countries and also the different distributions of industries in each country (McInish 2000). The argument for international asset diversification, particularly in terms of risk reduction, can be traced back to the 1960s and 1970s (i.e.Grubel, 1968, Levy and Sarnat, 1970, Grubel and Fadner (1971), Lessard (1974), Solnik (1974a), Errunza (1977), and Agmon and Lessard (1977)]. For example, as Grubel and Fadner (1971) have pointed out, there are gains from international diversification because returns in any one country are influenced by natural and man-made catastrophes, business cycles, and government policies whose effects are limited to, or felt most strongly, in the economy of that affected country.

Previously, most studies on equity markets merely focused on developed financial markets. However, in the last three decades, as a result of globalisation, financial innovations, and diversification strategies, financial market linkages around the world have been growing. International investors are now able to choose from assets denominated in different currencies. World financial markets in recent years have been characterised by trends toward integration, securitisation, and liberalisation. In addition, the economic reform process that started in many developing counties in the late 1980s, and the gradual opening of those countries' capital markets, has had major affects on global financial markets[9]. The reform process has allowed the financial markets of many developing economies to become viable alternate sources of capital for private and corporate investors. In other words, trading in emerging equity markets has become part of the reform and development process of many countries and has begun to be accepted in the global financial markets[10]. 'Equity flows have taken several forms: direct equity

[9] Although the reform process of developing economics can be traced back to the late 1970s and early 1980s, the major opening of the financial markets only really started in the 1990s. Taking a historical account of globalisation, Lothian (2002, p. 722) states 'a global financial marketplace …..has been around for centuries, if not in fact for more than a millennium'.

[10] Another historical account, Goetzmann and Jorion (1999, p. 1) states that 'in many countries, equity markets have grown rapidly from tiny, fledgling markets with little volume and limited

purchases by investors in host stock markets; investments through country funds; issues of right equities held by depository institutions in the form of American Depository Receipts (ADRs) and Global Depository Receipts (GDRs); and direct foreign equity offerings', Claessens (1995, p.3) . Furthermore, as Goetzmann et al (2005, p. 1) state, 'globalisation expands the opportunity set; but as a result, the benefits from the diversification rely increasingly on investment in emerging markets'[11].

As the result of globalisation and openness in the financial markets, central for many recent research activities in international finance is now the issue of integration versus segmentation between financial markets, in particular between advanced economies and the so-called emerging countries. Financial markets can be considered integrated if there are no barriers on free capital mobility and the same risk assets command the same return across the different markets. According to Bekaert and Harvey, (2002, p. 3) 'financial integration refers to free access of foreigners to local capital markets (and local investors to foreign capital markets)'. Alternatively, in segmented financial markets, barriers to arbitrage may allow assets traded in different markets to have different expected returns even when their risk characteristics are the same'. Segmentation arises when, for various reasons, international capital follows are restricted or even prohibited. In summary, 'if capital markets are integrated, then financial assets traded in different markets, but with identical risk characteristics, will have identical expected returns' Campbell and Hamao, (1992, p. 43)[12].

The interdepedence of international capital markets has a number of implications for various economic and financial issues. The Integration is an important concept

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international participation to important sources of capital with short but impressive track records of share price appreciation'.

[11] Bekaert and Harvey (2000) discuss various issues in which the presence of foreign investors in an emerging market can be assessed.

[12] Obstfeld and Taylor (2002), Prasad et al (2003), Kearney and Lucey (2004), and Kose et al (2006) survey various measures of financial market integration, while Lothian (2002), and Obstfeld and Taylor (2004) contain historical documentations of financial market integration.

because of its implication on possible gains from international diversification. The amount of diversification provided by investing in international equity markets is dependent on the extent to which the international equity markets are integrated or segmented. From an individual investor's perspective, in integrated capital markets where there are no restrictions on capital mobility or cross border portfolio investments, an investor can reduce investment risks by internationally diversifying his or her portfolio. In other words, as Korajczyk, (1996, p.267) points out ‘in financially integrated markets, capital should flow across borders in order to ensure that the price of risk - the compensation investors receive for bearing risk is equalised across assets.’ In contrast, if these assets are priced in segmented capital markets then their returns will be in accordance with the systematic risk of their domestic market.

From a corporate perspective, an obvious relevance of integration versus segmentation of international capital markets is the cost of capital for investing in a particular project. In integrated financial markets, all investors, irrespective of their country of residence, use similar or very close capital costs when they calculate the price of any given project (Sercu and Uppal, 1995). In contrast, if financial markets are segmented, one cannot simply value a cash flow from foreign investment the same as one would for the domestic country's investors. As Sercu and Uppal (1995, p.584), point out 'in the absence of free capital movements, there is no mechanism that equates prices and costs across the different markets’.

Capital integration of asset markets also has important implications for market efficiency and several other financial theory issues. A financial or capital market is said to be efficient if it fully and correctly reflects all relevant information in determining asset prices, and financial integration is expected to stimulate financial efficiency. As Laopodis (2004, p. 104) puts it, ‘the efficient market hypothesis postulates that as markets become more open and transparent to the public, the prices of assets should reflect the greater availability of information and be more efficiently valued’. Other issues in financial theory such as volatility, predictability, speculation and anomalies are also related to the integration issue. For example, financial integration is assumed to contribute to volatility spillovers between markets. These issues have been extensively discussed in the literature. Several other studies [Dwyer and Wallace, (1992), Engel, (1996), Yuhn, (1997), and Lence and Falk (2005)] have examined the efficiency and integration of asset markets while other studies have investigated volatility transmissions. Early studies on volatility transmissions include King and Wadhwani (1990), and King, et al (1994)[13].

On the other hand, policy makers are interested in the co-movements between equity markets because increased market integration, or reduced market segmentation, diminishes the ability of governments to achieve independent economic and financial market stability policies. For example, the preparation of monetary policy is often affected by the developments in international stock markets due to the international propagation of shocks via the equity markets, the wealth channel and the confidence effects. The global trend towards a greater role of the stock market in the economy has made this kind of spillover increasingly important. Generally this has led to improving the global allocation of capital and helping countries to better share risk by reducing consumption volatility (Kose et al, 2003). Indeed, according to Das (1993, p. 14) 'better integrated financial markets facilitate the reallocation of a broadening spectrum of risks, thus enhancing the scope and efficiency of international and inter temporal resource allocation'.

Another important implication of stock market integration is its effect on economic growth and development. As Claessens (1995), Singh, (1997), Levine and Zervos (1996, 1998), Arestis and Luintel (2001), and others have pointed out, stock markets perform various functions that are important for economic growth. As Kose et al (2006, p. 1) comments, 'for policymakers in developing countries, the topic [integration] is of enormous practical relevance, not least because countries such as China and India are still very much in the early stages of financial globalization, and face numerous ongoing decisions about the timing and pace of further integration'. Also, well developed stock markets are assumed to facilitate

[13] Poon and Granger (2003) surveyed the financial market volatility literature

direct financing which is an important factor for the rate of growth of a nation's economy. Arguing for the importance of equity market for economic growth Shachmurove (2005, p.2) states ' an emerging economy that wishes to attain high and sustainable rates of economic growth needs an active stock market to help fuel and finance this growth'[14].

To Summarize, the degree of integration in international stock markets has important implications for diversification strategies as individual investors and corporations try to diversify their portfolio risk by investing in different markets. In integrated financial markets, the diversification gains provided by investing in international equity markets are dependent on the extent of the co-movement of equity markets across the globe. As Shamsuddin and Kim (2003, p.2) comment, 'any potential gain from international diversification of a portfolio is inversely related to the extent of stock market integration'[15]. The integration or segmentation of international capital markets is also important for international corporations, as access to global capital markets can allow firms to reduce their cost of capital[16]. Also, the integration of international capital markets has implications for financial market regulations, asset pricing models and market efficiency, and the financial polices of international corporations. Furthermore, as discussed above, there are also important implications for various economic issues such as to economic growth policies, and monetary and macroeconomic policies that influence trade and fiscal policy amongst national economies. The interdependence of international financial markets has also an implication for open macroeconomics in terms of the Mundell-Fleming theories and international financial contagion risk (Hatemi *et al* 2006, p.65).

[14] As a result, the number of stock exchange markets in developing countries has been increasing in recent decades.

[15] In contrast, in completely segmented markets, excess returns depend only on the local price of risk.

[16] Companies seek a lower cost of capital through various global activities such as international borrowing, capital ventures, mergers and acquisitions, and foreign direct investment.

Chapter 2

Yet, another extensively debated (theoretical and empirical) in financial market literatue is the issue of interdependence and contagion. Accordint to Bonfiglioli and Favero, (2005, p. 1300), 'Interdependence accounts for the existence of cross market linkages, while contagion consists in modifications of such linkages during turbulent periods'. Moreover, Ssillover and contagion are (interchangeably) referred to when changes in prices, liquidity and/or volatility in one market are transmitted to others. A variety of definitions appear in the literature regarding spillover and contagion effects. For example, financial contagion can be defined as a shock in one country's asset market prices that induces changes in the asset prices of another country's financial market (Hassan and Malik, 2007). According to Bekaert et al (2003, p.1) contagion in equity markets refers to 'the notion that markets move more closely together during periods of crisis or level of correlation over and above what is expected'. Similarly, Forbes and Rigobon (2002, p. 2223) define contagion as 'a significant increase in cross-market linkages after a shock to one country (or group of countries)'. In another definition, Phylaktis and Xia (2006c, p. 2) state 'a striking feature during those crises is that markets tend to move more closely together compared to tranquil times, and such strong co-movement is frequently referred to as contagion'. Kodres and Prisker (2002) define contagion quite generally as a price movement in one market resulting from a shock to another market; while Kyle and Xiong (2001) refer to contagion when returns become more volatile and more strongly correlated. Positive and negative spillovers have also been mentioned in the literature. Ferreira and Gama (2007) refer to positive spillover as common information spillover and negative spillover as differential spillover effects or contrary to expected reactions.

Traditionally, correlation between stock markets has been used when measuring co-movements and defining contagion. In early studies, Bertero and Mayer (1990), examining a large sample of industrialised and developing countries, found also that the correlation coefficients increased appreciably following the equity market crash of 1987. Other studies have also considered the 1987 crash as evidence of stock markets overreacting to each other, and reported substantially increased co-movements among international stock markets after the crash. However, later studies have argued that focusing on correlations can be misleading. For instance, Forbes and Rigbon (2002) test for stock market contagion based on cross-market correlation coefficients in the light of the 1987 US market crash, the 1994 Mexican peso devaluation, and during the 1997 East Asian crisis. As Forbes and Rigbon (2002, p.2226) point out, 'high cross-market correlations during these periods are a continuation of strong linkages that exist in all states of the world (interdependence), rather than an increase in these linkages (contagion)'. A similar argument was made in Bekaert et al (2003) who state 'the increased correlation detected during the Asian crisis is not itself evidence of contagion'[17]. Several studies have examined the affect on the transmission of price volatility between markets in various crises since the 1987 crash. King and Wadhwani (1990) using hourly equity market data for the period September 1987to November 1987 examined cross-market correlations between the US, UK and Japan and found that these increased significantly after the US crash.

In recent decades, the gains from international diversification have been driven by the so called emerging capital markets. Emerging markets are relatively small markets on the margin of the world economy, and the costs and risks in investing them are potentially high, Goetzmann et al (2005, p). Therefore, 'given that the benefits of diversification depend on the degree of market integration or segmentation, the concern is that as emerging markets become increasingly integrated with world financial markets, return correlation will rise and hence the benefits from diversification will decline' Fifield *et al* (1998, p. 11). The next two sections will discuss various sources of integration or co-movement and the main empirical methodologies of measuring international equity market integration.

2.3 Sources of Equity Market Co-movements

As discussed in the last section, the integration of stock prices in different countries is crucial for individual investors and corporations engaging in international investment activities. It is also important for various economic and

17 Khalid and Kawai (2003) discuss several factors that can be attributed to the contagion in financial markets (foreign exchange rates, stock market prices and interest rates).

financial market policies. Thus, as Kim et al (2005, p. 2476) point out, 'the concept of financial market integration is central to the international finance literature'. As a result, international investors need to understand the determinants behind the integration stock markets to evaluate the potential gains and risks in global diversification. Similarly, policy-makers need to understand the driving forces behind global stock market integration. It is well accepted in the theoretical literature that integration of financial markets is fundamentally linked to economic relations through risk sharing benefits, improvements in allocation efficiency and reductions in macroeconomic volatility. Several other determinant factors of international stock market integration or co-movement, including industrial structure, country specifics, stock market development, investor herding, and contagion have also frequently been presented in the literature. Ripley (1973) considered these factors and others to be the source of the correlations and co-variations between national equity markets.

Industry Structure: Grubel and Fadner (1971) studied this issue at the industry level. They tested the hypothesis that correlation is an 'increasing function of the share of the industries' domestic consumption which is either imported or exported'. To address the underlying reason for international market correlations, Roll (1992) proposed a compelling Ricardian explanation based on country specialisation, and argued that increased industrial alignments between countries should increase their cross-market return correlations. Arshanapalli et al (1997) also suggested that industrial composition can explain substantial variations in national stock returns. However this view is not universal. For instance, after investigating the impact of macroeconomic variables, von Furstenberg and Jeon (1989) looked at industry effects and found little evidence that industry effects really help us understand these covariances better. Similarly, Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) reported that industrial structure actually accounts for only a very small proportion of variation in national stock market returns. However, in a more recent study, Recently, Carrieri et al (2008), after examining the industrial structure among large developed countries, found a positive and significant relation between changes in the alignment of the industrial mix and changes in their equity market correlations. They stated that 'this result is a unique empirical confirmation of Roll's (1992) argument that increased industrial alignment among countries should increase their cross-market return correlations' (p.6).

Economic linkages: Many analysts have linked the integration and interdependence of stock market prices to economic linkages across countries such as trade and direct foreign investment, real interest rates and dividend yields. In other words, the co-movements of the underlying macroeconomic variables across national economies may lead to co-movements in stock market prices in different economies[18]. This line of argument states that covariation in fundamental economic variables, especially stronger trade linkages and greater capital mobility, will lead to higher correlations of future dividend growth across countries and thus higher correlations of equity prices. The economic implications of financial market integration have been the subject of increased research interest in recent decades. Campbell and Hamao (1992) show how dividend-price ratio and interest rate variables drive co-movement between Japan and the United States. Bracker et al (1999) argue bilateral trade, macroeconomic variables, and linguistic determinants can all induce international stock market co-movements. Also, Forbes and Chinn (2004) find that cross-country trade is the most important determinant of stock market movements around the world.

Looking at the historical assessment of European stock market linkages, Choudhry (1996, p. 243) states 'the substantial economic and financial cooperation that took place in Europe after the First World War may explain the international link of these indices'. In another study, Darrat and Zhong (2005) suggest that the interdependent goods markets in the region were the primary reason behind the stronger equity market linkage observed in the post NAFTA period. Pretorius (2002) finds that bilateral trade and industrial production growth differentials are significant in influencing the correlations between 10 emerging markets. Similar conclusions were provided in Chen and Zhang (1997), Soydemir

[18] From a historical account, Goetzmann et al (2005, p.1) states, 'the correlation structure of the world equity markets varied considerably over the past 150 years and was high during periods of economic integration'.

(2000), and more recently in Tavares (2009). In summary, the underlying view of economic linkage theory is that trading activities link the cash flows of trading partners, thereby making their stock markets more correlated[19].

Country Specific: In addition to the above factors, there are other country specific factors that affect correlations involving certain countries. These factors may be due to particular characteristics in the structure of a nation's stock markets and special institutional factors. For example, in contrast to Roll's (1992) industry importance, Heston and Rouwenhorst (1994) show that industry differences and country specializations by industry cannot explain the degree to which country stock markets move in tandem. They argue that country effects, whether due to fiscal, monetary, legal, cultural, or language differences, dominate industrial explanations. Expected stock returns are also linked to the business cycle. In other words, coherence in their business cycles can also be considered a determinant factor that increases stock correlations between pairs of countries. Thus countries in the same cycle have similar expected returns and can be expected to have more correlated stock indices than countries which are in different phases of the business cycle. For instance, Kim et al (2005) examine the impact of the European Monetary Union (EMU) on the dynamic process of stock market integration from 1989 to 2003, and state 'the EMU has been necessary for stock market integration as unidirectional causality was found.' They continue to say that, 'stock market integration over this period was significantly driven in part by macroeconomic convergence associated with the introduction of the EMU and financial development levels.'

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19 Some studies have contradicted this widely held view of economic fundamentals. For example, Dumas et al (2003) argue that, the assumption of financial market integration might be more appropriate to explain observed stock market correlation. Ammer and Mei (1996) report that most of the covariance between national indices is explained by co-movements across countries in common stock risk premia rather then by co-movements in fundamental variables. A similar conclusion was reached by Karolyi and Stulz (1996) who argued that, 'the global component of national macroeconomic announcements or industry shocks on covariances is offset by their competitive effect' (p.952).

Moreover, stock market indices can be seen as indicators of economic developments in a country and hence the factors that increase economic links of similar economic conditions can be expected to contribute to increasing correlations of equity markets. That is, co-movements in stock prices among countries can arise due to similar national conditions such as personal income and the expectations of future economic developments which could affect the investors' abilities to purchase equities. There are no specific studies in the literature that examine the impact of globalisation and the development of equity markets on stock market linkages. Masih and Masih (2002) examine various dynamic linkages among national stock prices of six major stock markets, and suggest some degree of linkages between stock market developments and global market integration. In recent studies, Nor and Ergun (2009) made similar conclusions and state 'economic development stipulates the financial linkages'. Similarly, examining the long-term data set for a large sample of countries Tavares (2009, p.67) report 'strong evidence that analogous institutional development in two given economies leads to an increase in the co-movement of their stock returns'.

Investor Herding: In the last four decades, the trade in financial assets around the world has been growing. Wealth holders have expanded their horizons by abandoning their previous confinement to domestic capital markets and have turned increasingly to the international arena, diversifying their portfolio holdings and actively seeking foreign assets. In addition to the increased volume of international trade, the movement of financial capital has also been the result of various factors including communication technology improvements, deregulation of cross-border transactions, and increases in the international activities of multinational corporations. As Choudhry, et al, (2007, p. 244) point out, such changes 'have allowed investors to participate in international stock markets more freely, quickly, and informatively'. These changes also imply that investor behaviour can induce co-movements in national stock prices. As a large number of investors compete to earn high returns, stock prices in different countries should closely correlate regardless of the underlying economic fundamentals of investors' characteristics. The impact of such investor herding may be particularly relevant during times of financial market turbulence.

Moreover, multinational operations of companies also induce co-movements between international stock markets. When two countries' markets trade shares of the same group or similar groups of multi-national companies, expectations about the future of these companies would be similar and these experiences would be reflected in similar price movements (Ripley 1973). Although investor behaviour is a hot theoretical issue in the literature, no empirical studies have so far investigated the role of investor behaviour in international equity market relations[20]. Nevertheless, one can argue that, investor behaviour merely reflect market co-movements because investors incorporate into their trading decisions information about price changes in other markets.

In summary, an understanding of the sources of co-movement among international equity markets is important for several reasons. For investors, the design of a well-diversified portfolio crucially depends on a correct understanding of how closely international stock market returns are correlated. Changes in international correlation patterns call for an adjustment of the portfolio. Policy makers are interested in correlations among equity markets because of their implications for the stability of the global financial system. The preparation of monetary policy is also affected by international stock market developments due to the international propagation of shocks via equity markets, the wealth channel and confidence effects. The global trend towards a greater role of the stock market in the economy has made this kind of spill-over more important. Moreover, if contagion prevails in times of financial crises the benefits of international diversification can be adversely affected when they are most needed.

[20] Baker and Wurgler, (2007) present a good theoretical discussion of what they call 'Investor Sentiment in the Stock Market'. However, as the same authors (p. 135) state 'Investor sentiment is not straightforward to measure, but there is no fundamental reason why one cannot find imperfect proxies that remain useful over time'.

2.4 Empirical Measures of International Equity Market Integration

From a theoretical prospective, financial market integration has its roots in several postulates such as the law of one price (Cournot (1927) and Marshall (1930)), and, as discussed in section two, the portfolio diversification theory of Markowitz (1952), the capital asset price models of Sharpe (1964), Lintner (1965), and Mossin (1966), and arbitrage price theory Ross (1976). In the traditional financial models, integration of stocks and portfolios depends only on the market risk factor. In the last four decades, due to globalisation factors in international financial markets and investor diversification strategy, the theoretical postulates of the law of one price and the financial theory models have been extended to an international dimension and several empirical approaches have been proposed. In an attempt to measure the degree of integration between international equity markets several measuring criteria, including the correlation coefficient of different markets, various asset pricing models, and long run statistical models, have all been presented in the literature of international finance as possible measures for the degree of international financial markets integration. This section presents a brief overview of various empirical methodologies which have been used to measure the degree of integration between international stock markets[21].

Correlation Coefficient: Finance theory points out that the size and evolution of the correlations between international equity markets is crucial for appropriate diversification. In statistical terms, the correlation coefficient is defined as ‘a measure of association between variables’. In other words, as Fabozzi and Modigliani, (2009**,** p. 292) define it, ‘correlation is a statistical measurement of the similarity in the movement of two variables, such as rates of return on groups of stocks from two different countries’. A change in correlation would have an impact on the co-movements between any given two markets. Thus, the earliest methodology of stock market co-movements has been to compute the correlation

[21] A compmerhensive empirical review of the literature of international equity markets will be presented in the next chapter.

coefficients between the returns of market portfolios over two separate time periods. As will be discussed in the empirical review chapter, many early studies have reported stable or low correlations and argued for international diversification. However, recent empirical studies on cross-market correlation coefficients indicate statistically significant increases in cross-market correlation.

Asset Pricing Models: To model the degree of integration between national stock markets, numerous studies have tried to directly estimate international risk factors priced in the domestic asset returns using international versions of capital asset pricing models (ICAPM) and Arbitrage Pricing Theory (IAPT). Asset pricing models are often used to identify pricing or premium differences for similar asset classes across markets. As will be discussed in the empirical of the next chapter, numerous early studies [i.e. Solnik (1974, 1983), Stulz (1981a, 1981b), Adler, and Dumas, (1983), Errunza and Losq, E., (1985), and Korajczyk and Viallet, 1989)] have used the unconditional version of asset pricing and arbitrage models.

Time Varying ICAPM: A major shortcoming of the integrations based on the international versions of the CAPM and APT studies discussed above is that they focus on a comparatively static situation. However, as several previous studies, such as Harvey (1989, 1991) and Ferson and Harvey **(**1991, 1993) have indicated, the degree of segmentation changes only gradually over time. Other studies including, for example, Bekaert and Harvey (1995, 2000) and Stulz (1999), have also shown that financial liberalisation and market integration have changed the integration of emerging equity market returns with the 'global factor'. As a result, a recent approach of measuring equity market integration has been to focus on the time varying effect.

Non-Synchronous Trading: Another empirical analysis for integration which recently appeared in the literature is Non-Synchronous Trading. For example, Schotman and Zalewska (2006) argue that controlling time differences in the hours of stock market trading is important, and that time adjustments enhance the integration estimations. Schotman and Zalewska (2006), using daily data, examine co-movements between the stock markets returns of three main East

European countries' (the Czech Republic, Hungary, and Poland) and three developed stock markets (Germany, the UK and US) between 1994 and 2004, and report 'very dynamic integration' between these stock exchanges. Furthermore, they show that using a weekly frequency does not sidestep the consequences of the time-match problem but rather leads to a significant loss of information.

Long Run methodologies: In integrated financial markets, the prices of national stock indices are expected to have long-run relationships. As a result, since the late 1980s, a popular alternative approach for examining the integration among international equity markets has been the use of the cointegration methodology of Granger (1986), Engle and Granger (1987), Johansen (1988, 1991), and Johansen and Juselius (1990)[22]. There are now vast and expansive studies that have applied the cointegration methodology to international equity markets relations. Cointegration analysis can be used as an alternative to, or complementary with, correlation analysis under the common term of co-movements. Correlation assessments can be viewed as short-term investment decisions, while cointegration based analyses are necessary for long-term investment strategies. Cointegration analysis offers an effective method to test empirically the EMH in an international context. Empirical literature of correlation analysis and cointegration methodology is more fully reviewed in the next chapter.

Asymmetries and Nonlinearity: Another integration assessment approach for global stock markets that appeared in the literature recently is the utilisation of nonlinear econometric models such as Threshold Auto-regressive (TAR). Applying the 'Law of one price' (LOOP) Levy et al, (2006) argue that the TAR models capture the possible nonlinearities in the data and focus on the equivalence of the inter market equity premium outside the bands of no arbitrage caused traction costs and/or information frictions. According to them the cross-market premium (the ratio between the domestic and the international market

[22] The use of cointegration methodology is due to the recognition of the issue of non stationarity behaviour in economic and financial data.

price of cross-listed stocks) provides a valuable measure of international financial integration'.

2.5 Conclusion

This chapter briefly discussed the theoretical aspects of the integration or co-movement among international equity markets. Since the 1960s and 1970s the foremost argument for international investment is that it provides better diversification gains in terms of risk reduction as securities in different markets are assumed to move in opposite directions. Moreover, due to various globalisation factors, the flow of international investments has been rapidly increasing in the last four decades. Financial globalisation has resulted in extensive research interest from academic researchers, international investors, and policy makers. Central to these research interests has been the issue of integration or co-movement between global equity markets. The integration or co-movement among equity markets in different countries is crucial for the individual investors and corporations who wish to know which countries' stock prices move together, in opposite directions or in altogether unrelated ways. In other words, the amount of diversification provided by investing in international equity markets is dependent on the extent of integration between financial markets across the globe.

As will be reviewed in the next chapter, integration of capital markets and the argument for international diversification has been empirically examined extensively in the literature. The integration of capital markets has important implications for financial theories such as market efficiency and forecasting. The integration in international capital markets is also important for various economic and financial market decisions. Therefore, international investors and policy-makers are keen to understand the driving forces behind global stock market co-movement. In this chapter, various sources of international stock market integration and empirical methodologies, ranging from statistical asset pricing models to long run models, and short reviews of the empirical literatures of integration and interdependencies among international equity markets were discussed. An extensive empirical review of international equity markets will be presented in the following chapter.

CHAPTER 3:
Interdependence between International Equity markets: A review of empirical literature

3.1 Introduction

The co-movements of the world's national equity market indices have been investigated extensively in the last forty years. Due to various factors including increased volume of international trade, technological and telecommunications improvements and deregulation of cross border transactions the globalisation of capital markets has been growing. International investors have turned increasingly to the international arena, diversifying their portfolio holdings and seeking foreign assets. As Cheng (1998, p.1) states, 'financial market deregulation, liberalization of capital movements and securitization of national markets, together with significant increases in the cross listing of stocks of multinational companies, have been among the major trends in recent developments of financial markets all over the world'.

The globalisation and liberalisation in financial markets and international investing activities in recent decades has resulted in extensive interest from academic researchers, international investors, and policy makers. Investors need to plan their portfolio diversification and to know which world financial markets are either integrated or segmented. Academic researchers are interested in providing advice to investors and policy makers. Policy makers need to assess the impact of financial globalisation on economic policies and financial market decisions. Therefore, central in many empirical research activities has been to examine the mechanism through which the integration or co-movements among international equity markets are measured. To sum up, according to Masih and Masih, (2001, p. 3) 'the integration and interdependence of stock markets underlies a major cornerstone of modern portfolio theory that addresses the issue of diversifying assets'.

Chapter 3

In the literature of international financial markets (as noted in the last chapter), several measuring methodologies ranging from the correlation coefficient of different markets, through various versions of international asset pricing models (i.e. capital asset pricing and Arbitrage pricing theory), to long run models have all previously been presented in the literature as possible measures for establishing the degree of integration or co-movement between international stock markets Moreover, the issues of dynamics links and transmissions have both been studied extensively. This chapter presents an extensive review of the empirical literature of international equity market integration/co-movement and dynamic linkages. Throughout this review (and the rest of the thesis), the terms 'equity markets' and 'stock exchanges' will be used interchangeably.

In recent decades, many empirical studies on the integration of international equity markets were assessed through time varying correlations as well as econometric modelling for long run relations. Correlations and long run relationship analyses are often grouped under the common term of 'co-movements', see section three and four for more detail on this. In the literature of international stock markets the concept of integration covers not only the co-movement between different markets, but also the dynamic Causal Links and the transmission of stock prices or returns across equity markets. The empirical literature of dynamic causality linkages and price transmissions are separately discussed in section five. The aim of this research is to undertake disaggregated analysis to examine the long run relationships between equity markets using sector/industry level data. Therefore, the existing literature of industry and firm level studies are reviewed in section six. Finally, section seven summarises the main points of the literature review and describes the direction of the present research.

3.2 A Summary of Asset Pricing Models

As discussed in the last chapter, the extent of integration in international equity markets has significant implications for devising optimal portfolio allocation strategies. As a result, empirical analysis of financial market integration has been growing increasingly popular in the last thirty years. Several empirical approaches for investigating the integration and co-movements in international stock markets have been proposed. The early studies which include Solnik (1974, 1983), Stulz (1981a, 1981b), Adler, and Dumas, (1983), Errunza, and Losq, E. (1985), and Korajczyk and Viallet, (1989) who used the unconditional version of asset pricing and arbitrage models but could only provide inconclusive results (De Santis and Bruno Gerard, 1998). In mid 1990s, various studies including Harvey (1991), Campbell and Hamo (1992), Dumas and. Solnik, (1995), De Santis and Gerard (1997, 1998), and Korajczyk, (1996), and others, have tested the conditional version of those models. These later studies, with the exception of Korajczyk, (1996), focussed on matured equity markets and report results in favour of market integration. For example, Campbell and Hamo (1992), using data from the US and Japanese stock markets in the 1980s, applied the traditional capital asset pricing model (CAPM) and support the hypothesis of international market integration[23].

De Santis and Gerard (1997) test a conditional version of the capital asset pricing model (CAPM) in an international framework and its implications for international portfolio diversification. Using monthly data from the eight largest equity markets in the world (the G7 and Swiss markets), they test both the cross-sectional and time-series restrictions of the model, and examine ‘the effects of the increasing level of integration among financial markets on the expected gains from international diversification’. Their study supports the integration of international markets within the framework of international CAPM, and report a ‘world price of covariance risk equal across countries and changes over time in a predictable way whereas the price of country-specific risk is not different from zero’ (1881). However, as De Santis and Gerard (1997, p. 1882) state, ‘although the conditional version of the traditional CAPM provides useful information on the dynamics of market premia, a more adequate model of international asset pricing should probably include additional factors’. With this respect, Dumas and. Solnik, (1995), and De Santis and Gerard (1998) also incorporated the exchange risk premium. They showed

[23] Increased integration of financial markets is often interpreted as a decline in diversification benefits.

that the price of currency risk is significantly different from zero, and claimed that an international capital asset pricing model, which omits currency risk, might be missspecified. Other studies such as Chen and Knez (1995) and Korajczyk (1996) have tested a lack of integration, or deviations from integration, among international markets. As Goetzmann et al (2005, p. 6) states ‘ this approach is based on the presumption that the market price of systematic factors may differ across markets due to international barriers, transactions barriers and costs of trade, but it is silent on the root cause of risk- price differences and the determinants of market co-movement’[24]. Using monthly data drawn from a sample of 24 countries from developed and emerging markets, Korajczyk (1996) examines the lack of integration and reports smaller deviations from market integration for developed markets.

To examine the level of integration or segmentation between emerging and developed stock markets, several studies have also used international versions of asset pricing models such as the capital asset pricing model (ICAPM) and the arbitrage pricing theory (IAPT). According to Panchenko and Wub (2009, p.2) ‘international asset pricing models (IAPM) provide estimated return-based measures of market integration with implicit assumptions on what kind of risks are priced into emerging markets’. Using monthly stock market indexes of major industrial nations and a large number of emerging markets, Buckberg (1995) has reported increased integration of equity markets since the late 1980s within the framework of international (conditional) capital asset model (ICAPM). Buckberg (1995) attributes this integration to a rising of capital inflows from the developed countries to emerging markets. Furthermore, following Dumas and Solnik (1995) and De Santis and Gerard (1998), who examined the exchange rate risk for developed countries’ stock markets, several other studies have recently tested the currency risk for emerging markets. For example, as mentioned above, Phylaktis and Ravazzolo (2004) provide evidence within a dynamic integration framework

[24] Furthermore, as Harvey (1991) points out this could be due to incomplete market integration, the existence of more than one source of risk, or some other misspecification.

that a model with a local currency factor is superior to a model without exchange risk for a number of Pacific Basin markets[25].

In other recent studies, Carrieri and Majerbi (2006) estimate a partial integration model in an unconditional framework with global and local risk factors for the major emerging markets in Asia and Latin America. Their results, in contrast to the previous studies that conducted unconditional tests for major developed markets, support the hypothesis of a significant unconditional exchange risk premium in emerging stock markets. Carrieri at al (2006) use a conditional framework and conduct empirical tests of currency risk and local market risk. Using data from seven emerging markets that contain different regions and different exchange rate regimes, their study supports the hypothesis of a significant exchange risk premium related to the local currency risk, and suggests that exchange rate and domestic market risks are priced separately[26]. On the other hand, as mentioned above, Korajczyk, (1996), applying the International Arbitrage Pricing Theory (IAPT) to measure the deviations or segmentations from asset returns, found that market segmentations were much larger for emerging markets than developed markets[27].

Furthermore, as several previous studies, such as Harvey (1989, 1991), and Ferson and Harvey (1991, 1993), have indicated, the degree of segmentation changes only gradually over time. Other studies, including for example Bekaert and Harvey (1995, 2000), and Stulz (1999), have also shown that financial liberalisation and market integration have changed the integration of emerging equity market returns with the 'global factor'. As a result, the focus of many recent

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25. Nonetheless, integration tests based on the asset-pricing models are often hampered by the lack of a universal asset-pricing framework [i.e. Fifield et al (1998), Bekaert (1995)]. In addition, as Kearney and Lucey (2004, p. 5) state 'the degree of integration is closely related to the degree of currency risk and currency instability'.

26 Carrieri et al, (2006) contains an additional list of studies that have examined exchange risk within the conditional CAPM setting for developed stock markets.

27 As Bekaert (1995) points out, there are different categories of barriers to emerging market investment including direct barriers and indirect barriers, accounting standards and investor protection, and risks that are especially important in emerging markets such as liquidity risk, political risk, economic policy risk and currency risk.

studies on equity market integration has been on the time varying effect. For example, following Errunza and Losq's (1985) mild segmentation approach, De Jong and De Roon (2005) proposed 'Time-varying market integration' under the International asset pricing (ICAPM) framework and applied this to emerging markets. Jong and De Roon (2005) argue that, 'many emerging markets are partially segmented, that is, some assets can be traded freely, which they call 'investable assets', whereas some assets can only be held by domestic agents, which they call 'noninvestable' assets (p. 585). Using data from a large number of emerging markets across various regions, between January 1988 and May 2000, they conclude that emerging stock markets have become less segmented from world stock markets. Carrieri et al (2007) assess time varying integration for eight emerging markets between 1977 and 2000. Specifically, using GARCH-in- mean methodology they report that while none of the countries in the sample were completely segmented, substantial cross market differences were evident in the degree of integration. Other studies of international equity market elationships have extensively applied correlation analysis and cointegration methodology to address this issue. Cointegration analysis can be used as an alternative to or complementary with correlation analysis under the common term of co-movements[28]. Empirical literature in the area of correlation analysis of time varying data, and more recent globalisation and cointegration methodologies are reviewed in the following two sections.

3.3 A review of International Stock Market Correlations

The argument for international diversification goes back to the 1960s and 1970s. One of the important reasons for investing internationally is that, it provides better diversification gains in terms of risk reduction, as securities in different markets are assumed to move in opposite directions. As noted earlier, numerous early studies on international equity markets [i.e. Grubel (1968), Levy and Sarnat (1970),

[28] The use of cointegration methodology is due to the recognition of the issue of non stationarity behaviour in economic and financial time series data.

Lessard (1974), Solnik (1974a), Errunza (1977) and others] have argued that the potential benefits from international diversification. The correlation between national stock markets is very important for diversification strategy. A low correlation between returns on national stock indices allows investors to minimise portfolio risk by international diversification. Asset returns are assumed to be correlated much less across markets than within a given market. As Eun and Resnick (2004, p. 248) point out, ‘relatively low international correlations imply that investors should be able to reduce portfolio risk more if they diversify internationally rather than domestically’. Many other early studies have investigated the co-movements of the world’s national equity market indices by testing correlations between stock markets[29]. Those studies have reported low correlations between national stock markets which are often presented as evidence in support of the benefit of global portfolio diversification. The findings of little co-movement has been attributed to various barriers that prevented the flow of international capital, such as exchange controls, the lack of free trade, dissimilar government policies, the discriminate taxation on international investment, lack of information on foreign securities and investor bias against foreign securities (Grubel and Fadner, 1971). These barriers can imply that security returns are determined by domestic factors.

In the last four decades, due to the process of financial market globalisation and development and the opening of many developing countries’ equity markets, the argument for international diversification and the integration of global equity markets has resurfaced and become stronger. In particular, since emerging markets are now firmly part of global finance and accessible to foreign investors, as indicated by existing and expanding literature, it has been interesting to re-examine whether the diversification benefits documented by the earlier literature can still be gained from international equity markets. In addition, many recent research activities have been directed towards the correlations and co-variances among national equity markets in the context of time varying data. As Goetzmann et al (2005, p. 4) comments ‘the implication [of time varying

[29] These include; Grubel and Fadner (1971), Ripley (1973), Panton, et al. (1976), Hillard (1979), Maldonado and Saunders (1981), and Philippatos et al (1983).

correlations] is that evolution from a segmented to an integrated market fundamentally changes the co-movement with other markets as well[30].' Correlations and covariances are also related to the issue of volatility. King and Wadhwani (1990) were among the first to emphasise the importance of a correlated information channel in propagating price shocks across different national equity markets by examining changes in unconditional correlations between stock markets.

Numerous other studies, including Erb et al (1994), Longin and Solnik, (1995), Solnik et al (1996), Karolyi and Stulz, (1996), Cheng (1998), Stulz, (1999), Longin and Solnik, (2001), Ang and Bekaert, (2002), Bekaert and. Harvey (2002), Forbes and Rigobon (2002), and, Kearney and Poti (2005), have examined the international integration of equity markets from the perspective of time varying correlations and covariances. Many of these studies show that the correlations among international equity markets have been changing over time, and significantly increasing in recent years. Some studies, such as Longin and Solnik (1995), Karolyi and Stulz, (1996), Solnik et al (1996), and Forbes and Rigobon (2002), relate higher correlations to an increase in volatility in world markets at times of crisis[31]. For example, Longin and Solnik (1995), using a GARCH model specification and data from seven leading stock markets from 1960 to 1990, examine the hypothesis of a constant international conditional correlation. They report an increasing trend in the correlations among these equity markets in the 1980s. Karolyi and Stulz (1996), using daily returns for the US and Japanese stock markets, investigate the fundamental factors that affect cross-country stock return correlations. They distinguished between global and competitive shocks for asset returns (the first being associated with high return covariances while the latter are linked to low co-variances). They found evidence that the US and Japanese cross-country return covariance exhibits a number of predictable patterns.

[30] Ang and Bekaert (2002) examine its implications for international asset allocation.
[31] However, in another study, Longin and Solnik (2001), using extreme value theory, argue that high volatility does not necessary lead to an increase in conditional correlation.

Using canonical correlation analysis, Cheng (1998) reports a high co-movement between the US and UK stock markets[32]. Madura (2003) compared the correlations of two sub-periods in the 1990s (1992-1994 and 1995-19998), for several OECD countries (Canada, France, Germany, Japan, Australia and New Zealand) and Mexico and found that, although correlations of some pairs of markets declined, the average correlation among the stock markets increased over time. Madura (2003, p. 98) concludes 'although it is difficult to generalize how stock market correlations will change in the future, it is safe to say that some correlations will change over time, so the benefits of diversifying among stocks of different countries will change as well'. For example, he reported that the correlation coefficient between the Canadian and US stock market returns grew period from 0.47 in the 1992-1994 to 0.86 in the 1995-1998 periods. Similarly, Brooks and Del Negro (2004), in a firm and industry level study, report that the correlation coefficient of the US and other developed countries' stock returns has risen from a relatively stable level of around 0.4 in the mid-1980s to nearly 0.9 in the mid-1990s.

In recent studies, Kearney and Poti (2005) used daily data between 1993 and 2002 to study the correlation dynamics of the five largest Euro-zone stock market indices just before the official adoption of the Euro. They reported 'strong persistence of the correlation time series and its significant rise over the sample period' (p. 319). Carrieri et al (2008), after examining the industrial structure among large developed countries, reported a positive and significant relation between changes in the alignment of the industrial mix and changes in their equity market correlations. For emerging markets, Bekaert and Harvey (2002), using data from 20 emerging markets of various regions, have examined equity market correlations of these markets and the world. Their study shows that 17 of the 20 markets experienced an increased correlation with the world. Ratner and Leal (2005) examined the changes in the international equity sector as well as country indices correlations from 1981–2000. They used stock indices of 38 developed

[32] As Cheng (1998, p. 3) points out 'canonical correlation analysis estimates the factor loadings for two sets of data by examining only the inter-set correlation matrix'.

and emerging countries (18 developed countries and 20 emerging countries). The results of their study suggest that the market index integration has been rising over time.

Nevertheless, correlation literature varies substantially depending on the market and geographical proximity between countries, and some studies have reported a decrease in correlations. For example, King et al (1994) find little support for a trend increase in correlations among stock markets for the 1970-1990 periods. Solnik et al (1996), using monthly data between 1958 and 1995, studied stock market correlations between the US and five other leading countries and reported no increase in correlations among these markets. Similarly, Erb et al (1994) reported a decline in correlations among G-7 countries in the same period (from the 1980s to early 1990s). Furthermore, Stulz (1999) considered stock market correlations of a large range of countries, including emerging markets, with the word portfolio over two time periods and concludes ‘correlations have changed, but some increased and others decreased’, (p. 270). For emerging markets Stulz (1999, p. 272) reports ‘much lower correlations with the world market portfolio than matured markets’. Hearn and Piesse (2007) also report very low levels of correlations among a number of African stock markets and two major markets (UK and France).

A significant increase in the correlation coefficients is usually interpreted as a rise in stock market integration and a diminishing of diversification gains. However, from an empirical prospective, although the correlation coefficient is a measure of linear association between variables, ‘it does not necessarily imply any cause- and –effect relationship’, Gujarati and Porter (2009, p. 77). Specifically, as numerous studies in recent decades have indicated increased globalisation of international markets does not necessary imply increased correlation between equity markets. For instance, Longin and Solnik (1995, p. 5) state ‘looking at correlation alone one cannot reach conclusions with regard to market integration’, while Bekaert and Harvey (2002. p. 6) state ‘theoretically, it is not necessarily the case that market integration leads to higher correlations with the world’. In summary, as Taylor and Tonks (1989), Kasa (1992), and more recently Choudhry, et al (2007) have pointed out; a test of correlation coefficient is neither a necessary nor a sufficient condition for higher co-movements between the stock markets. Moreover, as Taylor and Tonks (1989, p. 333).comment, the 'test of correlation does not take into account any short run dynamics'. As a result, an alternative and more popular approach [to correlation analysis] for the investigation of long run linkages between international financial markets has been the use of cointegration methodology proposed by Granger (1986), Engle and Granger (1987), Johansen (1988, 1991), and Johansen and Juselius (1990). The cointegration literature is reviewed in the following section.

3.4 Long Run Co-movements of International Stock Markets: A review of cointegration literature

In the last twenty years, many empirical studies in stock market indices have applied either bivariate or multivariate cointegration methodology to examine linkages between international stock markets in either among developed countries or the relationships between emerging and more matured markets. In theory, as Narayan and Smyth (2004, p. 992) state "if stock markets are cointegrated this means that the potential for making supernormal profits through international diversification in the cointegrated is limited in the long run. On the other hand, a finding that markets are not co-integrated [segmented] implies that there is no arbitrage activity to bring the markets together in the long run'. In the later case, an investor can obtain long run gains through international portfolio diversification.

Nemerous early studies, including among others Taylor and Tonks, (1989), Arshanapalli and Doukas, (1993), Byers and Peel (1993), and Blackman et al. (1994), have examined the degree of linkages using the bivariate cointegration test of Engle and Granger, (1986, 1987). Under the Engle and Granger's (1987) approach of cointegration, the problem of testing the null hypothesis of no cointegration between a set of I(1) variables, is based on two-step estimation procedure (Boef, 2000, Boldin, 1995). In the first step, this method estimates the coefficients of a static relationship between these variables by ordinary least squares and then applies ADF unit root test statistics to the residuals. Rejecting the null hypothesis of a unit root is evidence in favour of cointegration. The above mentioned studies that applied Engel and Granger approach have reported mixed results. For example, Taylor and Tonks (1989) and Byers and Peel (1993) did not find cointegration, while Arshanapalli and Doukas (1993) found evidence of cointegration among major stock markets, with the exception of Japan, after the late 1980s. Similarly, Blackman et al. (1994), using the same approach, report that evidence of cointegration has increased in the 1980s, while no cointegration is found when compared to the behaviour of the markets in the 1970s, and concluded that the scope for diversification has decreased during their observation period.

The Engle and Granger's bivariate cointegration or residual based approach as also known has been criticised on the grounds that the cointegration considerations are confined to two-step estimation process as explained above[33]. As a result, most economic and financial analysts often use the maximum likelihood estimation procedure of Johansen (1988, 1991) and Johansen and Juselius (1990) within the multivariate vector Auto-regression (VAR) framework, which can be applied to bivariate and multivariate cointegration analysis. In addition, several studies have recently utilised cointegration techniques that allow for structural shifts in the long-run relationship[34]. The later approach, proposed by Gregory and Hansen (1996), is a residual-based test for cointegration with regime shifts. The literature on cointegration is extensive and covers almost every continent and region of the world. This section reviews selected literatures that have applied various multivariate cointegration tests such as the maximum likelihood procedure and regime shifts for long run co-movements among international stock markets both in developed and emerging markets[35].

[33] Nevertheless, Harasty and Roulet (2000) employing the E-G approach of co-integration and error correction modelling for stock markets of 17 countries argued that the error correction model has predictive power, which can be a useful tool in the investment decision making.

34 Other cointegration approaches that have recently been used for stock market data include the Auto-regressive Distributed Lag (ARDL) approach of cointegration proposed by Pesaran and Shin (1999b) and Pesaran et al (2001) and the recursive cointegration analysis of Hansen and Johansen (1999).

[35] Several other studies [i.e. Chan et al (1997), Masih and Masih (2002), and Lence and Falk (2005)] have examined the efficiency of the stock market within the cointegration framework.

Chapter 3

Many previous studies have investigated the long run relationships among major world equity markets within the multivariate cointegration framework. Kasa (1992), who was the first to apply this method to five well-established equity markets (the US, Japan, UK, Germany, and Canada) in order to estimate the permanent and transitory components of stock price series, found the existence of a single common stochastic trend as a driver of the cointegrated system. Similar results for major world markets are reported by Arshanapalli and Doukas (1993). However, the findings of an increased and strong integration have been not universal. For example, using daily closing prices from January 3, 1983 to November 29, 1996, the Johansen cointegration method and the Bierens nonparametric approach, Kanas (1998a) examines whether the US stock market is pair-wise cointegrated with six major European markets (Germany, France, Italy, the Netherlands, Switzerland, and the UK).

In contrast to previous studies, which reported linkages among the US and other major stock markets, this study [Kanas (1998a)] fails to support cointegratin among these markets; no pair-wise cointegration relationships between the European markets and the US market were found. However, in another study, Kanas (1999) examined the linkages between the UK and US equity markets in the pre- and post-October 1987 stock market crash periods, and found increased interrelationships during the after-crash period. In a recent study, Masih and Masih (2004) apply multivariate VAR analysis to examine the dynamic linkages and propagation of shocks among five European stock markets (France, Germany, Netherlands, Italy and the United Kingdom). Using monthly closing prices they study three sample periods for 'pre-crash' (January 1979 to September 1987), 'post-crash' (November 1987 to June 1994) and the 'full sample' (January 1979 to June 1994). Although they find non-cointegration among the five stock markets for the entire sample period including the crash, they report evidence of a single co-integrating vector in each of the pre- and post-crash models.

In other recent studies, Fraser and Oyefeso (2005) examine long-run convergences between the US, UK and seven European stock markets. Using monthly data that covers from January 1974 to January 2001, and the Johansen's multivariate cointegration tests, the results of their study suggest that the real stock prices among these markets ‘are linked by a common stochastic trend and therefore are perfectly correlated in the long-term.’ Similarly, Floros (2005), using daily data of closing prices for stock indices between September 9, 1988 to September 9, 2003, and the VECM Johansen cointegration approach, examines the long-term and short-term relationships among the US, Japan and UK stock prices. The result of later study suggests that these mature markets are cointegrated ‘indicating a stationary long-run relationship’. However, in another recent study, Psillaki and Margaritis (2008) using monthly indices and the structural error correction (SEC) formulation tested co-movements between the stock markets of France, Germany and the US between1980 to 2005. They found insufficient evidence to support the hypothesis of closer long-run interdependence between the three markets over the sample period. Furthermore, as they state (p.60) ‘there is insufficient evidence to show that the introduction of the euro has lead to closer market integration’[36].

A number of other studies have also considered whether one or more of the G7 stock markets are cointegrated with stock markets in a specific geographic region. Using daily prices from 3 January 1983 to 29 November 1996 and the maximum likelihood method of cointegration, Kanas (1998b), examines whether the Canadian stock market is pair-wise cointegrated with Japan, the USA and six major European markets (UK, Germany, France, Switzerland, Italy and the Netherlands). He reports no cointegration between the Canadian market and any of these markets either pre- or post the October 1987 crash. Alen and MacDonald (1995), using monthly data for the period 1970 to 1992, and both the Engle – Granger and the maximum likelihood approaches test pairwise cointegration between the stock markets of Australia and 15 other OECD countries and find no pairwise cointegrations, with the exceptions of Australia and Canada, Australia and the UK, and Australia and the Hong Kong markets. Their result suggests that for most of these pairwise studies there are long-run portfolio diversification gains

36 Other studies, for example, Pascual (2003) and Fratzscher (2003), also report partial and incomplete market integration amongst European stock markets.

to the Australian investors since there is no evidence of a cointegrating relationship.

Roca (1999) tests cointegration relationships between the Australian stock market and its major trading partners, including the US and UK. Using weekly data from 1974 to 1995, and the maximum likelihood procedure approach, this study also reports no evidence of cointegration between the Australian and other markets. Similarly, Narayan and Smyth (2004) examine the linkages between the Australian and the G7 stock markets. Using the maximum likelihood and regime shifting approaches of cointegration, they report pairwise cointegration only between the Australian equity market and the equity markets of Canada and the UK under the maximum likelihood tests. Under the regime shifting approach they find some evidence of a pairwise long-run relationship between the Australian stock market and the stock markets of Canada, Italy, Japan and the United Kingdom, while no pairwise cointegration is found between the Australian market and equity markets of France, Germany or the USA. However, in another study, Shamsuddin and Kim (2003) examine whether the Australian market is integrated with the Japanese and US markets. Using weekly stock market and exchange rate data from January 1991 to May 2001, they report stable long-run relationships among the Australian, US and Japanese markets prior to the Asian crisis, although this relationship disappeared in the post-Asian crisis period.

Several other studies including Atteberry and Swanson (1997), Ewing et al (1999), Gilmore and McManus (2004), Aggarwal and Kyaw (2005), Darrat and Zhang (2005), and Canarella et al (2008), have examined the existence of long-run co-movements and linkages among the stock markets of the three North American Free Trade Agreement (NAFTA) countries, Canada, Mexico, and the USA. Using daily data from the January 1, 198.5 through December 3 1, 1994, Atteberry and Swanson (1997, p. 36) concluded that ‘the potential benefits associated with diversification across equity markets within the North American system appear to be diminished during periods of economic uncertainty. Ewing et al (1999) examining the co-movement between the North American stock markets over the post-US stock market crash period, found no evidence of cointegration among these markets even after the NAFTA accord was passed.

However, applying the maximum likelihood cointegration procedure and vector error-correction (VEC) model, Gilmore and McManus (2004) reported a long-term relationship among these markets and long-run adjustment towards equilibrium, and argued that the implementation of NAFTA has promoted greater economic integration between the three North American countries. Similarly, Darrat and Zhong (2005) have examined the impact of NAFTA on the equity market linkage among the US, Canada and Mexico. Using daily, weekly, and monthly data series over the period of 1 June, 1989 through 10 April, 2002 (post 1987 crash), Darrat and Zhong (2005) state 'the evidence proves robust and consistently indicates intensified equity market linkage since the NAFTA accord'. Furthermore, Aggarwal and Kyaw (2005) examine the level of cointegration only for the post-NAFTA period, and state correlation coefficients are higher and that cointegration tests show evidence of cointegration among the three markets for the post-NAFTA period. Nevertheless, another recent study, Canarella et al (2008) found that the stock markets indexes of the three countries in North America share no long-run equilibrium relationships, conflicting with the results of other recent studies [Gilmore and McManus (2004), Darrat and Zhang (2005), and Aggarwal and Kyaw (2005)].

As discussed earlier, major developments in international financial markets in the last two decades has seen the development and liberalisation of many developing countries' capital markets. The development and liberalisation of developing countries' financial markets has attracted strong interest from investors, academics, the developing countries' policy makers, prompting extensive research activities. Numerous other studies on stock market interdependence in emerging markets have been undertaken on various geographical groups of markets, such as in the Asian, Latin American, African and MENA (Middle East and North African) markets. Moreover, from the mid-1990s onwards, cointegration methodology has widely been applied for the examination of long run relationships between the matured equity markets and the so called emerging markets, or even just between emerging markets, and the likely gains from diversification in these markets. Since the recent emerging market studies are so extensive and growing, selected studies from various regions are reviewed in the remainder of this section. Emerging stock markets may exhibit varying degrees of integration or segmentation according to regional economic and political conditions.

Asian Emerging markets: The Asian emerging markets are among the most actively researched equity markets. Many studies have assessed the level of integration between the stock markets of developed and Asian emerging markets in different regions[37]. For Example, Chung and Liu (1994) test the common stochastic trend among national stock prices of the US and five East Asian countries, Japan, Hong Kong, Singapore, Taiwan and Korea. Using weekly data over the period from January 1985 to May 1992, the result of their study shows that, with the exception of Taiwan, all the countries in the sample have a strong link with US market. The same is reported for the speed of adjustments from short-term disequilibrium toward the common trend. Masih and Masih (1997b) find cointegration in the pre-financial crisis period of October 1987 among the stock markets of Thailand, Malaysia, the US, the UK, Japan, Hong Kong and Singapore. However, there were no reported long-run relationships between these markets for the period after the global stock market crash of 1987.

Ghosh et al (1998) investigate the linkages between nine individual Asia-Pacific emerging markets, and the US and Japanese stock markets during the 1997 crisis. Using daily closing prices from March 6 to December 31 1997, they find no evidence that either the USA or Japanese stock market movements dominated these markets. Huan et al (2000) explored the cointegration and causality relationships among the US, Japan and several South East Asian countries, including two recently established markets in China (the Shenzhen and Shanghai exchanges). Using daily stock prices at market close from October 1, 1992, through to June 30, 1997 and the structural breaking cointegration technique, they reported no evidence of cointegration relationships between the South East Asian markets and either the US or Japan. Sheng and Tu (2000) apply cointegration

[37] Asian markets are often further divided into 'Far East Asia and South East Asia'.

analysis to examine the linkages among the stock markets of 12 Asia-Pacific countries, before and during the period of the Asian financial crisis. They use daily prices from July 1, 1996 to June 30, 1998, and multivariate cointegration and error-correction tests. Their results show no cointegration relationships before the period of the financial crisis (July 1, 1996 to June 30, 1997), and only one cointegration relationship among these stock market indices during the period of the financial crisis (July 1, 1997 to June 30, 1998).

In more recent studies, Phylaktis and Ravazzolo (2003) examine stock market linkages of a group of Asia-Pacific emerging countries (Hong Kong, South Korea, Malaysia, Singapore, Taiwan and Thailand) with the US and Japan by estimating the multivariate cointegration model in both the autoregressive and moving average forms over the period 1980-1998. Using monthly data from January 1980 to December 1998 and the multivariate cointegration model both in autoregressive and moving average formats, they found no linkages or dynamic interactions between the Asian emerging markets and the industrialized countries in the 1980s. However, their results suggested strengthened interrelations among these emerging and developed markets in the 1990s. Similarly, in a more recent study, Choudhry et al (2007), using stock price indices from 1 January, 1988 to 1 January, 2003, and several empirical methodologies including rolling correlation coefficients and the Johansen multivariate cointegration method, examined the long-run relationships between the stock prices of eight Far East countries during the 1997–98 Asian financial crisis. They reported ‘significant long-run relationship(s) and linkage between the Far East markets before, during, and after the crisis’, although the linkages were more significant during the crisis period. In addition, Yang et al (2004) examined the impact of the 1997-1998 crisis on large emerging stock markets, including Asian markets. Using recursive cointegration analysis, they reported no long-run relationships between the US and the emerging stock markets prior to 1997, but there was evidence of cointegration in response to the 1997–1998 global emerging market crisis. Similar results are reported in Ratanapakorn and Sharma (2002) for cross regional analysis[38].

Latin American markets: The issue of equity market co-movements in Latin America has been investigated many studies. For instance, Choudhry (1997), using weekly data from January 1989 to December 1993 and employing unit root tests, cointegration tests and error correction models, examines the long-run relationship between six Latin American markets and the US market. He finds evidence of cointegration relationships and significant causality among these markets. Fernandez-Sarrano and Sosvilla-Rivero (2003), using daily closing prices, examine the linkages between the US and six Latin American stock markets between January 1995 to 14 February 2002. They applied both conventional cointegration techniques and structural breaks and cointegration techniques that allow for structural shifts in the long-run relationship. Their results indicate strong evidence of long run relationships when the structural breaks model is applied. In contrast, when conventional cointegration tests are applied, a long-run relationship is found in only two cases (Brazil and Mexico). In a similar approach, Chen et al (2002) investigate the interdependencies among six equity markets in Latin America (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela) and report that diversification benefits are limited when investing in these markets particularly due to their high co-movements.

In another study, Johnson and Soenen (2003), using daily returns from 1988 to 1999 examine the degree of integration among America's equity markets (Nafta plus Latin America), and report 'a statistically significant high percentage of contemporaneous association' between these markets. Christofi and Pericli (1999) examine stock price relationships among five Latin American markets (Argentina, Brazil, Chile, Columbia and Mexico). Combining a vector autoregressive (VAR) model with a multivariate exponential GARCH process, they report evidence of significant cross-market linkages among these stock markets.

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38 Other studies which have investigated Asian emerging equity markets include Fernandez-Serrano and Sosvilla-Rivero (2001), Siklos and Ng (2001), Johnson and Soenen (2002), Manning (2002), Chelley-Steeley (2004), and Narayan et al (2004).

In addition, Yang et al (2004) examine the impact of 1997-1998 Asian Financial crisis on large emerging stock markets including Latin American markets. Using recursive cointegration analysis Yang et al (2004) report no long-run relationships between the US and emerging stock markets prior to 1997, while their results show evidence of cointegration in response to the 1997–1998 global emerging market crisis. Recently, Jawadi et al (2009) examine stock markets integration between six main emerging Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela) and the US market from January 1985 to August 2005 using threshold cointegration techniques (TVEC) of Hansen and Seo (2002). They reported a linear integration pattern between the Brazilian and US markets while no long-term relationships between the other Latin markets and the US market were found.

African markets: Although the studies that have investigated the dynamic interdependence between worldwide equity markets are so extensive, the emphasis has often been often on the developed economies and the emerging markets of the Asian and Latin American markets. Recently however, as the result of improvement in the continent's economic status and financial markets, and increasing globalisation of the financial market sector, interest in the African markets has increased significantly. The co-movements between African and developed countries' equity markets, and amongst African equity markets have been investigated by a number of studies including, among others Piesse and Hearn (2002), Wang et al (2003), and Hearn and Piesse (2007)[39]. For example, Hearn and Piesse (2007) examine the degree of price integration between major regional equity markets in Africa (Egypt, Kenya, Nigeria, and South Africa) as well as two European stock markets (the UK and France) in the context of the 'Law of Price' (LOOP). Using weekly data and Vector Autoregressive (VAR) as well as Autoregressive Distributed Lag (ARDL) models, Hearn and Piesse (2007) report generally weak market cointegration, with a few exceptions.

[39] Other recent studies on the African stock market include, among others, Appiah-Kusi and Menyah, (2003), Piesse and Hearn (2005) and Alagidede and Panagiotidis (2009).

A similar approach was also applied by the same authors (Piesse and Hearn, 2002) for three South African equity markets (South Africa, and two smaller markets, Botswana, and Namibia) which reported mixed results. Wang et al (2003) investigate long-run relationships as well as short-run dynamic causal linkages between five emerging African stock markets and the US market. Using weekly data (daily converted weekly) from January 1996 to May 2002 and VAR methodology of cointegration, they reported two co-integrating vectors before the crisis period of 1997 to 1998, while no cointegration was found in the post-crisis period . Their results suggest that the long-run relationships between the African and the world markets (represented by the US) were dented by the crisis. This result is in contrast with some other recent studies (i.e. Yang et al (2004) and Choudhry et al (2007)) which examine the impact of the emerging global market crisis in other regions during the same period.

Central and Eastern European markets: The equity market co-movements in central and eastern European markets have been investigated by several studies in recent years. Jochum et al (1999) found long run cointegration relationships among Eastern stock markets between 1995 and 1997 but that relationships disappeared after the 1997 stock market crisis. Syriopoulos (2004), using closing daily prices and the vector autoregressive error correction model, examines the linkages between three emerging Central European Stock Markets and two developed equity markets (the US and Germany). Syriopoulos' results show the presence of one cointegration vector, indicating a stationary long-run relationship. Again, in a more recent study, Syriopoulos (2007) investigates the short- and long-run relationships of four emerging Central European markets (Poland, the Czech Republic, Hungary, and Slovakia), and two developed markets (Germany, and the US), and assesses the impact of the EMU on stock market linkages. He finds strong linkages between these markets and their mature counterparts, with the US market being the most influential. In another paper, Chelley-Steeley (2004), using a variety of tests, reports 'a consistent increase in the co-movement of some Eastern European markets and developed markets'. In addition, Voronkova (2004) using regime shifting methodology (Gregory and Hansen, 1996) state that the 'central European markets have become more integrated with global markets'.

However, Gilmore and McManus (20002), applying Johansen's procedure of cointegration and weekly data over the period of 1995 to 2001, report no long-term relationships between the US stock market and three Central European markets. Similarly, Gilmore et al (2008), using daily data of closing prices between July 1995 and February 2005 and dynamic cointegration methods, report no long run relationships between three emerging Central European Stock Markets and two major European equity markets (the UK and Germany).

Middle East and North African (MENA) markets: Several studies have investigated the impact of global market integration on the Middle East and North African (MENA) stock markets. Using monthly data from October 1996 through to August 1999, and applying the Johansen-Juselius cointegration methodology, Darrat et al (2000) examine stock market integration of three MENA countries (Jordan, Egypt and Morocco). Their study suggests that although the Middle East emerging stock markets 'are highly integrated within the region', they are segmented globally. As they argue, 'the apparent segmentation of the markets in the Middle East from the global market implies that these emerging markets provide international investors with potential diversification gains'. In a more recent study, Shachmurove (2005) applied vector auto regression and Bayesian vector auto regression analyses to investigate how a shock in one market is transmitted to other markets. They used daily stock market price data of seven middle-eastern countries (Egypt, Israel, Jordan, Lebanon, Morocco, Oman and Turkey) from 22 October 1996 to 30 September 1999. Shachmurove (2005) results showed that no stock market was completely isolated and independent, but the dynamic linkage analysis indicated that these linkages are actually relatively small. In other words, as they conclude 'although markets are efficient, there are dynamic linkages that can be explored and exploited to benefit the diversified international investors.'

Maghyereh (2006), using a trivariate vector auto-regression model and daily equity market returns for an intra-regional study, investigates the interdependence among four major Middle East and North African emerging markets (Jordan, Egypt, Morocco and Turkey). The result indicates that, while none of the MENA markets is completely isolated and independent, 'the dynamic links indicate that the integration among these markets is still weak'. As Maghyereh (2006) concludes, the weak integration is perhaps due to 'the weakness of economic and financial ties between the MENA countries'. In another recent study, Yu and Hassan (2008), investigate the interdependence and transmission of equity returns and volatility between seven MENA stock markets (Bahrain, Oman, Saudi Arabia, Jordan, Egypt, Morocco, and Turkey) and three major equity markets namely the US, UK and France. Using Johansen's vector error-correction model (VECM) and daily time-series data that covers from 1 January 1999 through to 31 December 2005, they examine cointegration relationships between the stock market returns of the three major equity markets and the MENA regions. They report 'dynamic co-movement among countries and the adjustment process towards long-term equilibrium'.

3.5 Dynamic Causality Links and Transmissions

In the last section, an empirical review of studies that have used cointegration techniques to investigate the degree of integration or co-movements between international stock markets was presented. In integrated financial markets, the prices of national stock markets are expected to have dynamic causality and transmission relationships. In other words, the concept of integration covers not only the co-movement between different markets, but also the dynamic linkages and transmissions of stock prices or returns across equity markets. To put this differently, as Masih and Masih, (2001, p. 3**)** state, **'**the integration and interdependence [causality and transmissions] of stock markets underlies a major cornerstone of modern portfolio theory that addresses the issue of diversifying assets'. Previously, empirical strategies, such as Granger's (1969) causality analysis and Sims' (1980) vector autoregressive models, have often been employed to examine dynamic causality links just for economic data analysis. Similarly, in recent decades many researchers in international finance have investigated the dynamics and the transmission mechanism of stock market linkages. Granger's causality links within the vector error correction model (VECM) representation, VAR estimated in levels, forecast error variance decomposition, and impulse response function analyses are often complemented with the tests for cointegration or long run relationships.

The issue of dynamic linkages among national stock markets is ‘of particular significance to investors since they have implications for international capital flows, returns from diversification of assets across national boundaries and the existence of stock market leaders and followers’ (Masih and Masih, 2004, p.1). For example, causality provides useful information to forecasters and decision makers about the stock return dynamics. In other words, as Ozdemir et al (2009, p. 47) state ‘causal linkages among stock markets have important implications in security pricing, hedging and trading strategies, and financial market regulations’. On the other hand, dynamic transmission of stock market linkages is often considered as a joint study with the spill-over of prices and the volatility of prices. For instance, King and Wadhwani (1990) examine the importance of a correlated information channel where volatility is transmitted across markets by examining changes in unconditional correlations between stock markets. This section reviews empirical literature of dynamic casuality linkages and transmissions among international stock markets.

Many previous studies have attempted to investigate dynamic linkages and interdependence, or lead–lag relationships, between the prices of national stock markets following the 1987 stock market crash. Most of the previous studies emphasized the leading role of the US market in the world stock market. For example, Eun and Shim (1989) apply the vector auto-regression (VAR) methodology to investigate the dynamic transmission pattern of stock return movements of nine major markets (Australia, Canada, Germany, France, Hong Kong, Japan, Switzerland, the UK and US). Using daily closing prices from 1 December 1979 to 20 December 1985, Eun and Shim (1989) find a substantial amount of multi-lateral interaction among the markets, with the US stock market as the most influential. They also find that the UK market was influential on the Australian market, this is attributed to the so-called `commonwealth factor’. Dheeriya (1993), using Geweke's (1982) causality test and daily data from 1 January 1987 through 31 May 1988, examines the direction of causality and feedback of seventeen major stock markets[40]. Dheeriya finds that only a few stock markets (i.e. the UK and the US) influence other markets significantly, other major markets (Japan, France, and Canada for example) do not seem to be influential at all.

In another study, Espitia and Santamaria (1994), using the VAR methodology, examine the transmission mechanism of information between a sample of seven major stock markets (Germany, Japan, Spain, Italy, France, the US and UK), have also reported that the US market was the most influential equity market in the world. Espitia and Santamaria (1994, p. 5), state 'the responses observed in response to one unit of impulse generated on the New York stock market are reflected on the other markets on the following days and last up to four days'. Arshanapali and Doukas (1993) argued that the degree of international co-movements in stock price indices has changed significantly since the crash, with the UK, German and French stock markets relating with the US market only after the crisis. Masih and Masih (2004) apply multivariate VAR analysis to examine the dynamic linkages and propagation of shocks among five European stock markets (France, Germany, the Netherlands, Italy and the UK). Using monthly closing prices they study three sample periods: 'pre-crash' (January 1979 to September 1987), 'post-crash' (November 1987 to June 1994) and the 'full sample' (January 1979 to June 1994) which contains the crash period, their dynamic analysis shows that the lead–lag relationships changed quite significantly over the period of time following the crash. That is, they report that although 'each market was to some extent endogenous during the pre-crash era, results altered quite significantly for the post-crash period with the UK and Dutch stock markets being the leaders and the most exogenous of all.'

Masih and Masih (2002) assess the dynamic linkages, or lead-lag relationships, among national stock prices of six major international stock markets (Australia, Canada, Germany, Japan, US and UK). Using monthly closing prices, they define

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40 The seventeen markets are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the UK and the US.

two non-overlapping samples covering ‘pre-globalisation’ periods (January 1972 to December 1979) and ‘post-globalisation’ periods (January 1984–June 1996). They find that globalisation had a major effect on the Japanese market, which transformed from a strong endogenous (i.e. dependent) pre-globalization market to a strong exogenous (i.e. independent) market after the globalisation. Nevertheless, they find that both the US and the UK markets maintain their influence in the fluctuations of most of the other markets in both periods. Bessler and Yang (2003) examine the dynamic structure and the direction of causality between innovations across stock markets of nine major stock markets, applying an error correction model and directed acyclic graphs (DAG). They use daily closing prices of the stock markets indices of Australia, Japan, Hong Kong, the UK, Germany, France, Switzerland, the US and Canada, from 4 June 1997 to 15 June 1999. Bessler and Yang (2003) find that the Japanese market is among the most highly exogenous while the Canadian and French markets among the least exogenous. They also find that the US market is the only market that has a consistently strong impact on price movements in the other major stock markets in the long run.

Various other studies have also examined dynamic linkages between one or more developed markets and the stock markets of a specific geographic region. For instance, Alliaris and Urrutia (1992) examined causal relationships among six major stock markets (Australia, Hong Kong, Japan, Singapore, the UK and US). Using daily closing prices for the period of May 1, 1987, through March 31, 1988 they conducted unidirectional and bi-directional causality tests by means of the Granger methodology. They found no lead-lag relationships for the pre and post October crash period. However, they detected important feedback relationships and unidirectional causality during the month of the crash. Atteberry and Swanson (1997) investigate the lead- lag relations of the three North American Free Trade Association (NAFTA) countries (the United States, Canada, and Mexico). Using daily data covering from January 1, 1985 through to December 31, 1994 they find more causal relationships during periods of economic uncertainty than during periods of relative calm. The United States and Canadian markets are found to have significant bidirectional causality in the overall period.

Roca (1999), using weekly stock market data from 1974 to 1995, examines the price linkages between the equity market of Australia and those of the US, UK, Japan, Hong Kong, Singapore, Taiwan, and Korea. Although Roca's study did not find cointegration relationships between Australia and the other markets, the Granger causality and forecast variance decomposition analysis show that Australia is significantly linked with the US and the UK. Moreover, the impulse response analysis further shows that Australia responds to shocks from the US and the UK immediately during the first week, and this response is completed within a period of four weeks. However, in another study, Shamsuddin and Kim (2003) report that, following the Asian crisis, the US influence on the Australian market diminished while the influence of Japan remained at a modest level. In addition, their examination of the impulse response analysis indicates only a 'contemporaneous transmission of shocks from one market to other markets'.

In addition to co-movement studies, numerous studies have examined the presence of dynamic linkages between the equity markets of developed and emerging markets. For instance, Cheung and Mak (1992) investigate the causality relationship between the developed markets and the Asian emerging markets. They use weekly return series data of stock markets in Australia, the US, Japan, Hong Kong, South Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand, from January 1977 to June 1988. Cheung and Mak (1992) concluded that, the United States market is a 'global factor' which leads both the developed markets and most of the Asian emerging markets (with the exception of Korea, Taiwan and Thailand). Shachmurove (1996) examines dynamic linkages across the Latin American emerging markets, and among the Latin American markets and major world stock markets, within vector auto regression (VAR) models. Using daily returns of nine national stock market indices (Argentina, Brazil, Chile, Mexico, Canada, Germany, Japan, France and the UK) from December 31, 1987 to June 14, 1994, Shachmurove finds relatively weak dynamic linkages among the Latin American markets and among the Latin American and major world stock markets. He concludes (p.13) that 'although markets are efficient and cleared out in few trading days, there are dynamic linkages that can be explored and exploited to the benefits of the international investor'.

Masih and Masih (1997a) examine the patterns of dynamic linkages between stock market prices of four Asian NICs (Newly Industrialised Countries) and four developed countries. The four Asian NICs in this study were Hong Kong, South Korea, Singapore and Taiwan, while the four developed countries were Germany, Japan, the US and UK. Using monthly closing prices from January 1982 to June 1994, they tested for cointegration relations, causality relations within vector error-correction modelling (VECM), forecast error variance decomposition (VDC), and impulse response functions (IRFs). Masih and Masih (1997b) report a 'relatively established role of all leading markets in driving fluctuation in the NIC stock markets'[41]. Similarly, Masih and Masih (1999) examined the dynamic causal linkages among eight national daily stock price indices of four major established markets (Japan, Germany, the US and UK) and four Asian emerging markets (Hong Kong, Malaysia, Singapore and Thailand), and the dynamic interdependencies among the Asian markets. They used daily closing prices ranging from February 14, 1992 to June 19, 1997. At the global level, they found that both the US and the UK have significant relationships in the short- and long-term with most of the Asian markets, with the US being most influential. At the regional level, their results indicated a leading role from Hong Kong. Sheng and Tu (2000) applied the variance decomposition analysis to examine the dynamic linkages among the stock markets of twelve Asia-Pacific countries, before and during the period of the Asian financial crisis. Using daily prices from July 1, 1996 to June 30, 1998 their results show that, while there was cointegration relationships before the period of the financial crisis, Granger's causality test indicates that the US influenced most of the Asian countries during the period of crisis, thus confirming the US market's persisting dominant role.

Soydemir (2000) investigates the transmission patterns of stock market co-movements between four major developed markets (the US, Germany, Japan and the UK) and three emerging stock markets (Mexico, Brazil and Argentina) by estimating a VAR model. Using weekly data from the last week of December

[41] Chowdury (1994) also uses a VAR model to examine the transmission of shocks between these newly industrialised nations and developed markets and reports evidence in favour of stock market interdependence.

1988 to the second week of September 1994, Soydemir reports impulse response functions and variance decompositions that indicate significant links between the stock markets of the US and Mexico and weaker links between the US, Argentinian and Brazilian markets. He attributes these findings to ‘the underlying economic fundamentals rather than irrational contagion effects’. In another study, Masih and Masih (2001) investigate the dynamic causal linkages amongst nine international stock price indices, five leading markets (the US, UK, Germany, Japan and Australia) and four Asian markets (Hong Kong, Singapore, South Korea and Taiwan). Masih and Masih (2001) report significant interdependencies between the established OECD markets and the Asian markets, with the US and UK markets maintaining their leadership. For another region, Wang et al (2003) examine long-run relationships, as well as short-run dynamic causal linkages between five African emerging stock markets (South Africa, Egypt, Morocco, Nigeria and Zimbabwe) and the US market during the 1997–1998 international emerging market crisis. Using daily closing prices from January 1, 1996 to May 31, 2002, they report limited causal linkages between these markets, which were further weakened after the 1997–1998 crisis. Furthermore, applying generalized impulse response functions based on estimated VARs, their result show that none of the African markets, with the exception of South Africa, had any significant effect on the US market.

Recently, Fujii (2005) using the cross-correlation function (CCF) tests of Cheung and Ng (1996) investigates the causal linkages (both in the first and second moments of the stock returns) among the stock markets of several emerging economies in Asia and Latin America since 1990. Using US dollar-denominated of daily stock market indices of four Asian markets (Hong Kong, Malaysia, the Philippines and Thailand), and four Latin American markets (Argentina, Brazil, Chile and Mexico) from January 1, 1990 to November 14, 2001, Fujii reports significant causal linkages both within each region and across the two regions. Furthermore, as in a number of other recent studies [i.e. Yang et al (2004) and Choudhry et al (2007), Fujii (2005) also find that the linkages were particularly strong during the recent financial crisis. Another recent study of a multiregional dimension, Ozdemir et al (2009), examines the dynamic linkages between the equity market of the US and emerging markets by testing for bi-direction Granger-causality relations. Applying the US dollar-denominated of daily stock market indices of fifteen emerging markets (Argentina, Brazil, Chile, China Shanghai, Indonesia, Malaysia, Mexico, Peru, the Philippines, Singapore, South Korea, Taiwan, Thailand, Turkey and Venezuela) and the US, they find a bi-directional causality relationship that runs from the US market prices to the emerging markets 'but not vice versa'. As they conclude (p. 48), 'the results lend strong support to the view that large markets dominate the stock markets of the developing countries'.

In addition to linear causality tests, several studies have recently applied nonlinear causality to international stock market linkages. For example, Ozdemir and Cakan (2007) have examined the non-linear dynamic relationships between a group of the world's major stock markets (the US, Japan, France and the UK). Using daily closing stock price indices from August 3, 1990 to July 14, 2006 they conducted non-linear Granger-causality tests and report a strong bi-directional non-linear causal relationship between these stock markets[42]. Furthermore, as Ozdemir and Cakan (2007, p. 173) point out, 'while the US stock market Granger causes significantly the other considered stock markets, Japan and France do not linear Granger cause the US, but just the UK does'. Beinea et al (2008), using daily stock index returns from 1973 to 2003, test for linear and nonlinear Granger causality between the French, German, Japanese, UK and US stock markets. They report 'a strong contemporaneous linear dependence between European countries and a directional linear dependence from the US towards the other markets'. Furthermore, they find that linear causality increases after 1987. They attributed this finding to the financial liberalisations of recent decades.

For emerging markets, De Gooijer and Sivarajasingham (2008) examine long-term linear and non-linear causal linkages among eleven stock markets, six developed markets (Germany, Hong Kong, Japan, Singapore, the UK and US) and five South-East Asian emerging markets (India, Malaysia, South Korea, Sri Lanka and

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[42] The US index of this study was taken from the Dow Jones Industrial Average Index (DOW).

Taiwan). Using daily prices from 1987 to 2006, and a nonparametric test for Granger non-causality for filtered the VAR-residuals with GARCH-BEKK models, they examine two sample period data sets including the Asian financial crisis of 1997[43]. They first test for the presence of general nonlinearity in vector time series, and report substantial differences in terms of the total number of significant nonlinear relationships between the pre- and post-crisis period. Next, they run a new nonparametric test for Granger non causality and the conventional parametric Granger non causality test for both periods. Their findings suggest that, following the Asian financial crisis, the Asian stock markets have become more internationally integrated. Also, their result shows that 'nonlinear causality can, to a large extent, be explained by simple volatility effects[44].'

3.6 Co-movement and Dynamic Linkages of International Industry and Firm Level Equities

So far, as the review of literature indicates that most previous studies have used generic or country stock market indices to examine diversification gains and interdependencies among international equity markets. However, as the globalisation of financial markets increased in recent years, the pace at which companies have been diversifying internationally has also been growing. As Ratner and Leal (2005, p. 238) state, 'it is not just the major stock market indexes (i.e., Dow, Nikkei, FTSE, etc.) that are linked, but also industries and individual firms that are closely tied together'. In another study, Claessens and Schmukler (2007p. 1) point out, 'the increased integration of financial systems has involved greater cross-border capital flows, tighter links among financial markets, and

[43] The first data set covers from November 2, 1987 to June 30, 1997, which is the pre-crisis period. The second data set covers from June 1, 1998 to December 1, 2006, or post-crisis period.

[44] Several other studies have used nonlinear Granger causality analysis for to tests relationships between stock markets and other areas. For example, Hiemstra and Jones (1994) apply linear and nonlinear Granger causality tests to examine the dynamic relationship between daily Dow Jones stock returns and percentage changes in the New York Stock Exchange trading volume. Kanas (2005) examines the existence of nonlinearities in the stock price-dividend relationships for the UK, the US, Japan and Germany.

greater presence of foreign financial firms around the world'. For example, in the US market, firm level international cross-listings and American Depositary Receipts (ADRs) have become increasingly popular as an alternative vehicle for international diversification (Miller, 1999, Eun and Sabherwal, 2003, and Grammig at al, 2005). As a result, as noted in the introductory chapter, the interest in disaggregated (at industry or firm level) studies of international equity markets has been growing recently. This section presents a short literature review of the recent empirical studies on industry and firm level co-movements.

The effect of different industry mixes within national markets on international equity market correlations has long been of interest to both researchers and market practitioners. The industry level literature goes back to the 1970s (i.e. Grubel and Fadner, 1971, Lessard, 1974) and has been expanding rapidly in recent years, although relatively fewer empirical studies still exist compared to at a country level. The conclusion of earlier studies on sector indices is that, investors can obtain better a diversification for their portfolio by investing in the same industry in different countries rather than investing in different industries within the same country. In the recent globalisation period, many studies have investigated the integration and co-movements among international equity markets using industry level indices. For example, several studies such as Roll (1992) and Heston and Rouwenhorst (1994) have noted that imperfectly correlated industries might lead countries with different industry compositions to be imperfectly correlated, and that the benefits of international diversification could actually stem from industrial diversification.

Park and Woo (2002) examined the role of industrial structures on the co-movements and transmission of equity returns for the G7 countries. Using monthly stock price indices from January 1973 to May 2001, as well as ten industry groups from these countries, their results indicate a greater influence from the industry structures on the international co-movements of equity returns, which is largely driven by economic integration and recent technology spillovers. Specifically, they reported industry-specific transmissions in the telecom and media sectors. Kaltenhauser (2002) examines how innovations in European and US equity markets affect industry returns. Specifically, he estimates the time-varying spillover effects from European and US return innovations to ten industry sectors within the euro area, the US and the UK. Using daily data from January 1, 1988 to March 31, 2002, Kaltenhauser finds that sectors have become more heterogeneous over time, and the response to aggregate shocks has increasingly varied across sectors, which indicates that sector-specific effects have gained in importance. The results of this study also indicate that information technology and non-cyclical services, which are the most affected by the aggregate European and US shocks, are the most integrated sectors worldwide. On the other hand, basic industries, non-cyclical consumer goods, resources, and utilities are less affected by aggregate shocks.

In another study, Kaltenhauser (2003) distinguishes between three types of linkages: cross country linkages, cross-sector linkages within a given country**,** and the linkages among equivalent sectors across countries, and explores the spillover effects between equity returns of the same ten sectors in the euro area, the US and the Japanese markets. Using daily observations from January 1, 1986 to October 3, 2002, he estimates daily return spillover effects to examine the degree of equity market integration at the industry level within the GARCH framework. Kaltenhauser (2003) uses a two-step analysis to explore the linkages between equity returns of these sectors in the euro area, the US and Japan. The results indicate that the price innovations in European equities, stemming from both aggregate and sector returns, have substantially increased (either doubled or tripled) their impacts on other equity markets. At the same time, the response to aggregate shocks in the countries examined has increasingly varied across sectors. Overall, as the of Kaltenhauser's study indicates, the equity markets in the euro area and the US have become more integrated with each other during the late 1990s, and this higher integration is especially pronounced within individual sectors compared to the aggregate markets[45].

45 In the first step, Kaltenhauser estimates a trivariate GARCH model for European, US and Japanese market returns in order to identify the respective country specific shocks or cross-sector linkages within a given domestic aggregate market. In the second step, he estimates the trivariate GARCH model of European, US and Japanese equity returns of a given sector to identify the sector-specific shocks and the spillover mechanism or intra-sectoral linkages between equivalent industries in different countries.

Taing and Worthington (2002) examine long and short-run relationships among industry sectors across six European markets in the post-euro adoption period 1999-2002. Using value-weighted daily data of five sector indices from January 1, 1999 to February 29, 2002, they apply multivariate cointegration procedures, Granger-causality tests and variance decomposition analyses based on vector error-correction (VEC) and autoregressive models. Their results indicate fewer stationary long run relationships between sectors in different markets, but many significant short-run causal linkages between these sectors. Variance decomposition shows that the consumer discretionary, financial and materials sectors in the EU are relatively more integrated than the consumer staples and industrial sectors. Nevertheless, they also report that, regardless of the sector examined, the large markets such as France, Germany and Italy remain 'the most influential in terms of causality and the proportion of variance accounted for by innovations in these same markets'. Taing and Worthington (2004), using the same data set and the same industries, apply Generalised Autoregressive Conditional Heteroskedasticity in Mean (GARCH-M) models to examine the impact of returns in other European markets on the returns in each market across each sector. They reached similar conclusions to their 2002 study.

Carrieri et al. (2004) apply a conditional asset pricing framework to a sample of 458 weekly returns from 18 industries across the G-7 countries from 1991-1999. They find that the global industry risk is priced for some industries, and that the time variation in the prices of global industry risks has recently increased. Their evidence further shows that market level integration does not preclude industry level segmentation. That is, even if a market is integrated with world markets, some of its industries may still be segmented. Similarly, some of the industries may be integrated even though a market is segmented from the rest of the world. As Carrieri et al. (2004, p.1) point out, 'industries that are priced differently from either the world or domestic markets represent incremental opportunities for international diversification'. Berben and Jansen (2005) investigate shifts in correlation patterns among international equity returns at the market level as well as at the industry level. They propose a novel bivariate GARCH model with a smoothed time varying correlation to test for an increase in co-movements between equity returns at the market and industry level. Using weekly stock market indices from Germany, Japan, the UK and the US from 1980 to 2000, they find that conditional correlations among the German, UK and US equity markets have doubled and this correlation behaviour is broadly reflected at the industry level as well. However, their results indicate that the Japanese correlations have remained constant. Berben and Jansen (2005, p. 851) conclude 'the implications of our research for investors are that optimal portfolios have changed as a result of the correlation shifts'.

Ratner and Leal (2005) examine the changes in the international equity sector as well as in country indices correlations from 1981 to 2000. They use monthly stock indices of 38 developed and emerging countries (18 developed countries and 20 emerging countries), which they further subdivided into ten leading sector components for micro linkage analysis among these markets. The results of their study suggest that the sector correlation has been increasing over time among the total stock market indices of both developed and emerging markets. But they conclude, 'there is still substantial international diversification benefits' (p.237). In a similar approach, Meric et al (2005), using the principal components analysis methodology, examine the diversification implications of the co-movements of ten sector indices in nineteen developed countries in 'bull and bear markets'. They use dollar denominated daily national benchmark stock markets and ten sector equity indices between September 15, 1997 and March 24, 2000 for the bull market, and from March 24, 2000 to October 9, 2002 for the bear market. They conclude that 'geographical diversification can help investors maximize diversification benefit within the same sector'. Recently, Meric et al (2008) extended their 2005 study and applied principal components analysis and Granger causality tests to investigate the portfolio diversification implications of the co-movements of sector indices in the US, UK, German, French and Japanese stock markets. In their analysis they argue that investors can obtain more benefit with global diversification than with domestic diversification in a bull market, while in a bear market the diversification opportunity diminishes because the sectors of different countries tend to be more closely correlated.

In other recent studies, Phylaktis and Xia (2006b) apply the two-factor asset pricing model of Bekaert et al (2005) to investigate sector level market co-movement and contagion for a large number of sectors across countries in Europe, Asia and Latin America between 1990 and 2004. Using daily data from January 3, 1990 to June 30, 2004, they state in their conclusion (p.22) 'industries/sectors are found to have crossed the national boundaries and become integrated with the rest of the world'[46]. Ciner (2006) investigates the linkages among NAFTA stock markets by investigating whether the co-movement among the benchmark indexes in the late 1990s is driven by specific sectors. In addition to country benchmark indexes, Ciner uses daily industry level data from January 2, 1994 to November 17, 2004, and Johansen's cointegration methods. He reports a stable relationship between January 1994 and March 2000. Ciner attributes this relationship to an increased integration in the late 1990s which was mainly driven by the technology and telecommunications sectors. However, Ciner (2006) reports that, the period from March 1 2000 to November 17, 2004, saw the co-movement in the telecommunications and technology indexes disappear, with a lack of cointegration in the benchmark indexes[47].

In addition, due to financial globalisation and the rapid development of technology (i.e. internet), the number of firms engaging in international cross listing has been growing in recent decades. Various studies have also examined the relationships between the prices of cross listed firms, or American Depository Receipts (ADR) and General Depository Receipts (GDR) to their underlying foreign security prices. For example, Lau and Diltz (1994) examine the transmission of pricing information between the New York and Tokyo exchanges. They study daily opening and closing stock prices of seven Japanese corporations that are dually listed on the New York Stock Exchange (NYSE) and the Tokyo Stock Exchange (TSE) that cover the post-crash period from January 1, 1988 to December 31, 1989. In their study, Lau and Diltz (1994) conclude that the market imperfections that may inhibit

46 In the same study, Phylaktis and Xia (2006c) also examine sector/industry level contagion for Europe, Asia and Latin America and report sector heterogeneity of contagion.

47 In a firm-level study, Brooks and Del Negro (2004) also suggest that the increased importance of industry factors in international portfolio strategies in the late 1990s was mainly confined to stocks in telecommunications and technology.

information transfer between TSE and NYSE stock returns are not readily apparent and that international listings do not give rise to arbitrage opportunities. Bae et al (1999) extends Lau and Diltz's (1994) work by examining stocks which are listed on the London and Hong Kong Stock Exchanges. They have studied a sample of eighteen companies from January 4, 1993 to December 31, 1995, and report a transmission of information which runs in both directions and 'that most of the transmitted information continues to be processed throughout the following trading day.'

Lieberman et al. (1999) studied the importance of the location of trade on the pricing of stocks by examining the price dynamics of internationally dually listed stocks, investigating the relationship between prices of shares listed and traded both in the OTC in the US and in the Tel Aviv Stock Exchange (TASE) in Israel. Using daily closing prices of six firms based in Israel whose shares are listed and traded both in the US and in Israel, they estimated an error correction model (ECM) to explore the relationship between the price behaviour of dually listed stocks. Specifically, they attempted to answer the question of 'which market is the dominant one and which is a satellite by examining whether the adjustment of prices is asymmetric'. Among their findings was that 'arbitrage opportunities are generally not available and that the domestic market acts as the dominant market and the foreign market acts as a satellite market' (p. 294). Kim et al (2000) studied the dynamics of international transmissions between American Depository Receipts (ADRs) and their underlying foreign securities. In their study, they included the exchange rate and the US market index as well as the underlying securities when examining the price discovery process for European ADRs in the US market. Using daily firm data from January 4, 1988 to December 31, 1991, they apply vector autoregressive (VAR) model with a cointegration constraint to examine the relative importance and the speed adjustment of ADR prices to their underlying foreign securities[48]. They find a significant independent role for the US market index and the exchange rate in pricing ADRs, although the underlying shares appear to be the most influential factor.

[48] The composition of firms was: 21 Japanese, 21 British, 5 Dutch, 5 Swedish, and 4 Australian.

In other studies, Wang et al. (2002) examine the pricing information transmission for a group of Hong Kong stocks dually traded both on the Stock Exchange of Hong Kong and the London Stock Exchange (LSE). Taking daily opening and closing prices of seven stocks from October 22, 1996 to July 31, 2000, they find bidirectional return causality in the sense that ‘Hong Kong stocks are priced to reflect information from the London market as well as the Hong Kong market’. They also find that that the 1997-1998 financial crisis had a major negative impact on most of the dually-traded stocks. Eun and Sabherwal (2003) examine the extent to which the US stock exchanges contribute to the price discovery of non US securities cross-listed on these exchanges. Specifically, they look at the price discovery of Canadian stocks listed on several US exchanges and the Toronto Stock Exchange (TSE). Using high frequency data of a sample of sixty-two Canadian stocks listed in both countries' stock exchanges, they find that prices on the TSE and US exchanges are ‘co-integrated with equality of prices holding as an equilibrium relationship’. Kadapakkam et al (2003) studied the role of the London Global Depositary Receipts (GDR) market for Indian stocks. Using daily opening and closing prices of a sample of 23 Indian stocks with GDRs trading in London from January 3, 1995 to January 31, 2002, they find the existence of cointegration relationships between the London and the Mumbai prices ‘despite arbitrage restrictions imposed by Indian government regulations’. Furthermore, they state ‘the GDR market's contribution to price discovery increases with the foreign ownership of the firm and GDR issue size’.

In another study, Jeon and Jang (2004) examine the interrelationship between stock prices in the US and Korea through a vector auto-regression (VAR) model. They use daily stock prices of the national level index, the high-tech industry level and the semiconductor firm level from July 1, 1996 through to February 9, 2001. At the firm level, they find ‘the influence of Micron Technology on the leading semiconductor manufacturers in Korea to be strong and persistent by passing about 34 percent of its innovations to the Korean firms within the three-day period’. However, their results have indicated relatively small impacts from IBM and Intel on the Korean chip makers. Furthermore, as Jeon and Jang (2004) report, Korean stock market prices, at national level indices as well as individual high-tech stocks, have become much more responsive to innovations in the US stock prices during the post-1997 financial crisis period as compared to the pre-crisis period. Grammig et al (2005), using high-frequency data and Vector error correction models (VECM), investigate the issue of price discovery for three large German blue-chip firms that are traded on the Frankfurt and New York Stock Exchanges. They aimed to answer the question on how 'price discovery occurs for internationally traded firms and how do international stock prices adjust to an exchange rate shock'. Grammig et al (2005, p.163) conclude 'the evidence suggests a structure of the international equity market that has the home market largely determining the random walk component of the international value of a firm along with an independent role for exchange rate shocks to affect prices in the derivative markets.'

Similarly, Phylaktis and Manalis (2005) examine whether the location of trade matters in the pricing of internationally listed securities by examining the price dynamics of stocks listed on the Greek (Athens) Stock Exchange and two German stock exchanges (Frankfurt and Berlin). Using daily closing prices of a sample of seven Greek companies from mid-1998 to March 2001, Phylaktis and Manalis (2005) examine short run and long run arbitrage profit possibilities. Specifically, they applied cointegration analysis to capture the possibility of long-run arbitrage profits, and ECM and innovation accounting, such as forecast variance error decomposition and impulse response analysis, to investigate the possibility of short-run arbitrage profits and uncover the price discovery process. They find that the prices of stocks in the German markets are priced with reference to the Greek market; a result that they argue implies irrelevance of trading location and a certain degree of market integration. In addition, their impulse response analysis shows that the Berlin and Frankfurt prices adjust less and faster than the Athens prices, implying that the price discovery process takes place in the German markets. Furthermore, the results from the forecast error variance decomposition confirm that the Berlin and Frankfurt market prices are more exogenous than those of the Athens market. Other studies, such as Miller (1999) and Korczak and Bohl (2005), have investigated the implications of cross-listing for companies.

3.7 Summary and Research Strategy

In recent decades, due to various globalisation factors, the flow of international investments has been rapidly increasing. Financial globalisation has resulted in extensive research interest from academic researchers, international investors and policy makers. Central to these research interests has been the issue of interdependence among global equity markets. The empirical objective of this thesis is to investigate the degree of interdependence between international industry sectors of developed and emerging countries using time varying, linear and nonlinear econometric models. The disaggregation approach is likely to capture the main differences across national markets. In this chapter, a detailed review of the existing empirical literature in the field of interdependence among international equity markets, raging from statistical asset pricing models and correlation analysis to long run models and dynamic linkages, has been presented.

To examine empirically the degree of integration and co-movement in global equity markets, many of the previous studies were based on various versions of international asset pricing models which have provided statistical evidence of integration or segmentation at the country level. In addition, numerous other studies on equity market integration or co-movements have often focused on correlation analysis. Correlation has been used as the main indicator for diversification in short term opportunities within asset classes and on an international basis within countries. Correlations or co-variances are of interest to investors who wish to profit from international portfolio diversification. The early studies investigating relationships among world stock markets only found evidence of low or stable co-movements among the world stock markets. However, many of the empirical studies on cross-market correlation coefficients in recent decades have indicated time varying and statistically significant increases in cross-market correlations.

Nevertheless, correlation is a short term analysis and therefore not really sufficient for integration assessment. As a result, many of the long run co-movement studies have been conducted within the framework of cointegration techniques. Evidence of cointegration indicates that the stock markets follow the same long-run stochastic trend, implying that any diversification gains across international markets only occur at short-run horizons when markets can temporarily diverge from their long-run path. Lack of cointegration on the other hand, is interpreted as evidence of no long-run linkages among national indices and hence there is potential for long-run portfolio benefits in risk reduction. Thus, the bulk of the empirical review in this chapter has been on the studies of co-movements among international stock market indices through correlation analysis and cointegration methodologies.

In the last twenty years, many studies have used the cointegration measure to analyse the long-term relationships between developed markets, between developed and emerging markets, and on a regional basis. Evidence of cointegration among major equity market indices suggests that many of these markets move together in the long run, which implies a reduction of long-term benefits from international diversification. For example, Kasa (1992, p.122) states, ‘these results imply that to investors with long holding periods the gains from international diversification have probably been overstated in the literature’. On the hand, various other studies have reported a lack of cointegration relationships. Lack of cointegration has been interpreted as evidence of no long-run linkages among national indices and hence as potential for long-run portfolio benefits in risk reduction (Kanas, 1998a, p. 607).

To sum up, according to many of empirical studies, one can argue that the dynamic interdependence of major financial markets has increased markedly in recent decades with the elimination of barriers to capital movements. However, it is also worth noting the following conclusion that Bessler and Yang (2003, p. 285) have reached.

> 'International stock markets are neither fully integrated nor completely segmented, which immediately suggests the potential for international diversification. The partial segmentation pattern among major stock markets (as specifically revealed in the innovation accounting results) may be particularly helpful for international investors to make diversification decisions. For example, the Japanese market is found to be relatively isolated from other markets in this study, which might suggest Japan to be a good candidate for the purpose of international diversification'.

In addition, a number of studies have indicated evidence of cointegration relationships between individual markets in developed and emerging markets, which may suggest that the long run diversification gains from emerging equity markets are limited. In practice there are a number of reasons which could allow for international investors to benefit from diversification in emerging equity markets. Firstly, the growth of capital flow to emerging markets in general has been continuing in recent years. This, in itself, is a sign that investing in these markets offers diversification benefits for international investors. Secondly, different securities will have varying degrees of financial risk and, as a result, their cash flows will be varied across national markets. To put this in another way, the statistical characteristics of returns for emerging and developed markets arise from the underlying real and financial nature of these economies. This means that although the benefits of portfolio diversification in cointegrated markets might be restricted in the long run, in practice they are unlikely to ever be eliminated. Thirdly, investing in international markets is constrained by a number of additional considerations. For example, barriers imposed by taxation, exchange rates between different currencies or investor tradition [home bias] may further segment national markets sufficiently so that assets are priced in domestic conditions rather than as an international environment. Fourthly, different countries are at different stages of development which leads to the argument that there may be potential gains from diversification across countries because of these differences in development. Finally, as Fifield et al (1998, p. 12) points out [international] 'investors in emerging stock markets may gain access to shares in industries that do not exist or are inaccessible in the domestic market'.

Furthermore, as a number of recent industry level studies (i.e. Meric et al (2005, 2008) and Ratner and Leal (2005)) indicate, although the benefit of global diversification with national equity indexes has been decreasing because of increased correlation between countries, there are still substantial global diversification opportunities with sector investments. For example, as Ratner and Leal (2005, p.248) state 'the rising correlations indicate a potential loss in international diversification benefits on a total market basis, but sector investing still may offer effective benefits due to consistent or low correlations'. This thesis aims to extend the existing literature on the co-movements and dynamic transmissions of international equity markets by re-examining industrial level prices in a global perspective approach. The focus on industry or sector level relations in a global context is important as the extent to which industries in different markets co-move is likely to be related to the differing nature of national economies, the extent of multilateral and bilateral trade liberalisation, and capital flows and control.

As noted in the introduction chapter this thesis advances the existing literature of international equity markets by addressing a number of short comings. Firstly, although there already exists a large amount of industry level literature [old and new], the existing studies that address industry level linkages and interdependencies, or the comparison of the issues of which sectors co-move across industries at a global level, are relatively small compared to national level studies. Secondly, the existing studies on industry level equity relations, with the exception of few studies [i.e.Ratner and Leal (2005) and Phylaktis and Xia (2006c)], generally concentrate on either developed countries such as the US, UK and Japan, the euro zone or the G-7 countries. Thirdly, only a small number of studies (i.e. Taing and Worthington (2002), and Ciner (2006)) have so far used time series econometric techniques based on linear framework such as cointegration procedures and Granger-causality tests to examine long and short-run relationships between equity markets at the aggregate industry level.

Thus, this research aims to fill the gap and extend recent studies (i.e. Ratner and Leal (2005), Phylaktis and Xia (2006c), and Meric et al (2005, 2008)) that have looked at the implications of industry integration for portfolio management at a global level, and Taing and Worthington (2002), and Ciner (2006) which have applied time series econometric techniques on particular markets[49]. Specifically, the aim is to assess the degree of interdependence among international industry sector prices of developed and emerging countries using industry sectors of US and three leading emerging countries [Brazil, Malaysia, and South Africa]. In addition, to the usual statistical summaries and correlation relationships, the thesis uses various time varying analysis, linear and nonlinear econometric methodologies. As motioned in chapter one, another empirical objective of this thesis is to investigate correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 economic and financial crisis. If industry integration or dynamic co-movements between the selected equity markets are established, then it can be seen as a key marker for stronger ties between global equity markets, which in theory may imply a reduction in international diversification benefits.

[49] Few very recent studies on industry level studies on emerging markets include; Bai and Green (2010, 2011), and Bai et al (2012).

CHAPTER 4:
Sample, Data and Preliminary Analysis

4.1 Introduction

Previously, many studies on international equity markets have used aggregate or country level indices to examine the interdependence between international stock markets. The empirical objective of this thesis is to re-investigate the co-movements and dynamic linkages among international equity markets at the industry level by examining the heterogeneity of industry sector prices from the developed and emerging stock markets. Specifically, as mentioned in the introductory chapter, the thesis examines the price indices of ten industry sectors from the US and three emerging markets (Brazil, Malaysia, and South Africa) employing both linear and nonlinear econometric methodologies. As argued in the introductory chapter, the use of aggregated industry sector data is more appropriate for micro analysis of international stock market relations instead of individual stock indices. For specific empirical analysis, the thesis uses time varying analysis, linear and nonlinear cointegration tests, linear and nonlinear causality tests and dynamic transmission analysis. Testing the possibility of time varying relationships between the international industry sectors of the study is another empirical objective of the thesis. Prior to the econometric techniques, this chapter discusses the sample selection strategy and the sources, the data, and presents the summary statistics of the returns. The chapter is organised as follows: Section two discusses the sample selection strategy and the sources, and explains the choice of industry sectors in the research. Section three discusses the data and return and presents a graphical inspection of sector prices and returns based on natural logarithms. Next, section four presents the results of the univarite statistical summaries for the sector returns and tests nonlinear dependencies. Finally, section five summarises the work of the chapter and the basic statistical analysis.

Chapter 4

4.2 Sample and sources

The thesis investigates industry (super) sector linkages between the US and three leading emerging markets (Brazil, Malaysia, and South Africa). The US is the world's largest economy and has unrivalled influence on global stock markets with a substantial number of firms in virtually all sectors. On the other hand, the three selected emerging markets have relatively large industry sectors according to the Industry Classification Benchmark (ICC), and a long history of stock price data. Also, regionally speaking, they represent three different continents, Asia (Malaysia) Latin America (Brazil), and Africa (South Africa)[50]. However, the industrial structure in the emerging markets is often found to be quite different from that found in the developed countries (Assaf and Cavalcante, 2005). Furthermore, many emerging markets including Brazil, Malaysia, and South Africa often rely on some particular industrial sectors such as financial service, natural resources, telelcommunication and tourism. As a result, one might argue for cautioning emnpirical results of those markets industrial sectors. Nevertheless, the selected stock markets (US Brazil, Malaysia, and South Africa) represent different continents and the closeness of the economic ties among them varies. Therefore, they can be considered as reasonable representatives for international financial markets, and therefore be appropriate economies of portfolio diversification. Furthermore, since all industry sector data were not readily available cross markets for emerging markets, the choice of the sample sectors and these countries is constrained in mainly by data availability.

In an economy where equity trading takes place, there is at least one domestic index which measures general price movements. In addition, to meet the increased activities in international equity investing, there exist several respected international equity market indexes that are used to benchmark the performance of a given market. Stock market benchmarks allow an investor to measure the

[50] The other matured markets which have well established industry sectors are the UK and Japan, while a number of emerging countries, including Mexico, Indonesia, Thailand, and Taiwan, have sizeable industry sectors.

average performance of a national stock market. One approach to industry classification enjoying widespread use among investment practitioners is the Global Industry Classification System (GICS). The Global Industry Classification Standard (GICS) has become an industry model widely recognised by market participants' worldwide (Chan et al (2007)). There are several other global industry index providers, such as the Dow Jones and the FTSE according to the Industry Classification Benchmark (ICB). In this thesis the Dow Jones Global Industry Indices are used. The Dow Jones industry classification is categorised into 10 Industries (Level 1), 19 Super sectors (Level 2), 41 Sectors (Level 3), and 114 Sub-sectors (Level 4). The super sectors (Level 2) on which this thesis is based include: Banking, Basic Resources, Chemicals, Construction and Materials, Financial Services, Food and Beverage, Health Care, Industrial Goods and Services, Insurance, Media, Oil and Gas, Personal and Household Goods, Retail, Technology, Telecommunications, Travel and Leisure, Utilities, and Real Estate[51]. Table A1 of appendix A presents the 19 Industry Super-sectors and their industry groups, while table A2 of the same appendix contains the descriptions of the Super-sectors according to the Industry Classification Benchmark (ICB).

The Dow Jones Industry Indices, which provide benchmarks for international investors with more industry classifications than any other index provider, have been widely used in the literature on equity market relations. As Hassan and Malik, (2007, p. 374) point out, 'the Dow Jones' indexes are especially important to examine because financial market participants use these indexes more than any others to follow movements of industry groups and [they] are widely used for measuring sector performance'. A similar expression was also made by Phylaktis and Xia (2006c). Although the US and the emerging countries in the sample contain most of the industry super sectors, the emerging countries have fewer industry sectors, which data were available over the sample period. As a result, the sample size chosen in this study was determined by the maximum number of similar industry sectors that were available in all markets in the study. In total, ten super sector price series were available across all markets in the sample period

[51] At the time of writing this chapter, the Dow Jones and FTSE contain identical industry super sectors according to the Industry Classification Benchmark (ICB).

(excluding fixed price series). The ten industry sectors for this study are; Banks, Basic Resources, Chemicals, Construction and Materials, Financial Services, Food and Beverage, Industrial Goods and Services, Personal and Household Goods, Retail, and Telecommunications.

Throughout the empirical analysis in the thesis, the following industry sector codes or abbreviations are used where necessary. Banks (BNK), Basic Resources (BRS), Chemicals (CHM), Construction and Materials (CNM), Food and Beverage (FBV), Financial Services (FNS), Industrial Goods and Services (ING), Personal and Household Goods (PHH), Retail (RTL) and Telecommunications (TLC). In addition, a combination of these codes and country abbreviations; United States (US), Brazil (BR), Malaysia (ML), South Africa (SA), will also be used when necessary[52]. The sample of the research covers a ten year period from January 4, 2000 to December 29, 2009, which yields 522 weekly observations and corresponds to a very recent period in which industry and firm level interests have been growing in international equity market studies. As the sample of the thesis is well diversified across countries and industries, empirical estimations based on such a dataset should be less biased and can reflect more accurately on the global industry effects of stock market relationships. Therefore, from a portfolio diversification perspective, the disaggregation analysis into the ten sectors from these leading markets is sufficient to adequately capture the major differences among industries sectors. The next section explains further the data series and returns, and presents graphical inspections of price levels and returns in natural logarithms.

4.3 Data and Graphical Inspections

This thesis uses weekly data (from January 4, 2000 to December 29, 2009) of industry super sector price indices from the US and the three emerging stock markets. The reason for employing weekly data as opposed to monthly observations or weekly is to get enough observations, and at the same time to

[52] e.g. USBNK, BRBNK, MLBNK, SABNK for banking industry, and so on.

mitigate the potential effects of noise characterising daily data and the day-of-the-week affect problem (Roca, 1999). Some researchers, including Elyasiani et al (1998), and Karolyi and Stulz (1996), have argued that daily returns are preferred to the lower frequency data such as weekly and monthly returns because longer horizon returns can obscure transient responses to innovations which may last for only a few days. Other analysts such as Eun and Shim (1989), Hamao et al. (1990), and De Santis and Gerard (1997) also suggest that, weekly observation might not fully capture the short-lived co-movements between the equity markets. However, as Karolyi and Stulz (1996, p. 954) point out 'the major problem with the use of daily returns across countries is the non-synchronous trading periods for different markets around the globe'. As some analysts (Eun and Shim, 1989, Hamao et al., 1990) argue, the non-synchronous trading issue can be solved by 'carefully examining the structure of time difference' and using lagged values. Nevertheless, as Serra (2000, p. 136) points out 'high frequency data could introduce a downward bias in contemporaneous correlation because of time differences between markets and lags in information transmission'. Furthermore, according to Roca (1999, p. 505), 'daily data are deemed to contain ''too much noise'' and is affected by the day-of-the-week effect while monthly data are also affected by the month of the year effect'[53]. Weekly data series can also be considered as high frequency (Berben and Jansen, 2005).

As explained before, the data series consists of 10 (super) sector price indices for each of the four markets/countries in the sample, with a total of 40 sectors and 522 observations for each industry sector. Although the four national stock markets in this study represent different continents and time zones, these are assumed to adjust to a weekly calendar time. Furthermore, the industry sector price indices are not adjusted for dividend payments or market price developments as perceived by policy investors or reported in the financial press. All data series are obtained from DataStream International using Dow Jones industry indices and are denominated in US dollars. Investing internationally confronts investors with the decision of how to deal with the foreign currency exposure implied by their foreign investments, and the use of US dollar denominated (or another currency)

[53] See also Berben and Jansen (2005, p. 835).

is equivalent to a full hedge on exchange rate. However, as some analysts argue, from an investor point of view, hedging decision on exchange rate might not be a desirable choice as it 'is neither complete hedging back to an investor's base currency nor total avoidance of currency hedging' (Gastineau,1995, p.16), hence, one might use exchange rate risk to hedge equity risk (Campbell et al., 2010). However, in a recent study, Schmittmann (2010, p.23) concludes, 'Hedging currency risk reduces the risk of international investments in almost all cases significantly statistically as well as economically'. Moreover, as Ratner and Leal, 2005, p. 241) comments, 'using U.S. dollar returns instead of local returns has the added benefit of accounting for disparate levels of inflation, particularly in some of the emerging countries'.

In this study, following the standard practice in empirical studies, a logarithmic transformation is applied to each industry sector indice prior to empirical analysis. In financial research, returns are often used instead of price indices (levels and logs). Campbell et al (1997, p.9) cited two reasons for this theoretical justification. First, 'for the average investor, the return is a complete and scale-free summary of the investment opportunity'. Second, 'returns have more attractive statistical properties than prices, when examining as stationarity and ergodicity'. Therefore, the weekly returns of each industry sector indices are computed as the natural logarithm of the price relatives, as follows

$$r_{it} = \log(p_t / p_{t-1}) \qquad (4.1)$$ [54]

where r_t is the return at period t, p_t is the market price index at period t, and p_{t-1} is the market price index of the previous week. The return values also represent the first differences in logarithmic transformation. An important assumption in the finance literature is that the log of returns r_t are normally distributed by random variables with mean (μ) and variance (σ^2), or $r_t \sim N(\mu, \sigma^2)$. Financial markets are often characterised by sudden deviations from normal operation caused by crashes and other global events.

[54] Return calculations can also be expressed in percentage format multiplying by 100.

Chapter 4

In empirical studies, it is a customary to complement any formal statistical tests with visual or graphical inspections of the series under consideration. Thus, to get a visual impression of the trend behaviour of the industry returns, figures 4.1 to 4.4 and 4.5 to 4.8 respectively plot the price levels in logarithm and log-returns of weekly industry sector indices. The graphical visualising provides several indications of the characteristics of international sector indices in the study. The examined industry sector indices, though, are not parallel despite seem to share the same characteristics or features. In other words, the visualisation indicates that the price indices are not mean reverting in levels and, therefore, they are not stationary. On the other hand, the differences of the examined indices seem to be mean reverting and therefore stationary. Also, the return figures show the existence of periods of high volatility and outliers. The next section presents the usual statistical summaries of the international industry sector returns including statistics testing for normality and serial independence, while formal tests of non-stationarity through various unit root tests will be examined in chapter seven. From a US investor point of view, although many industry sectors in the study seem to share the same characteristics across markets, they form a geographically diverse mix of developing countries. Therefore, as correlation is a key factor in determining the benefits of portfolio diversification, the potential benefit (in terms of lower correlation) of the emerging countries industry sectors will be investigated in chapter six.

Figures 4.1 - 4.4: Industry Sector Log Price Levels

Figure 4.1: Price levels of US Industry Sectors

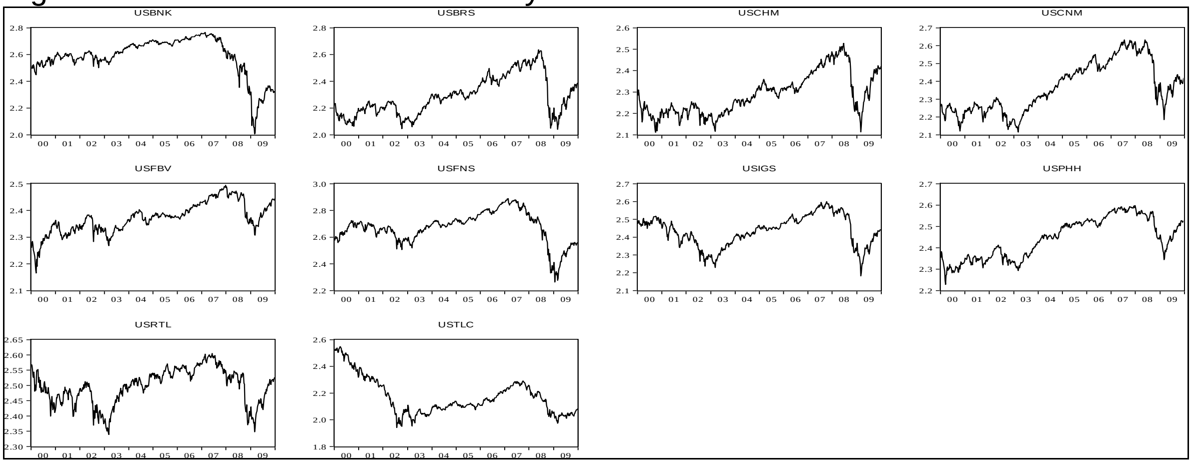


Figure 4.2: Price levels of Brazilian Industry Sectors

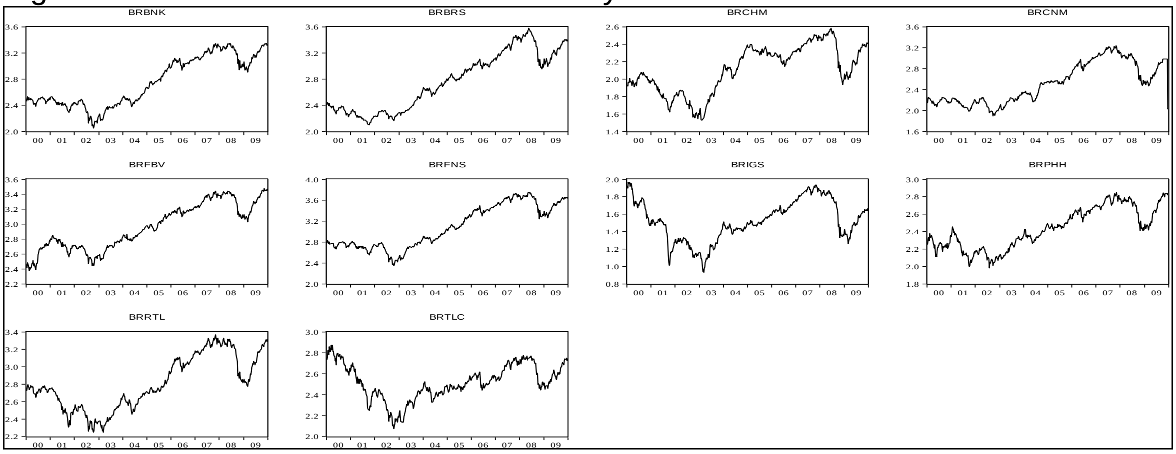


Figure 4.3: Price levels of Malaysian Industry Sectors

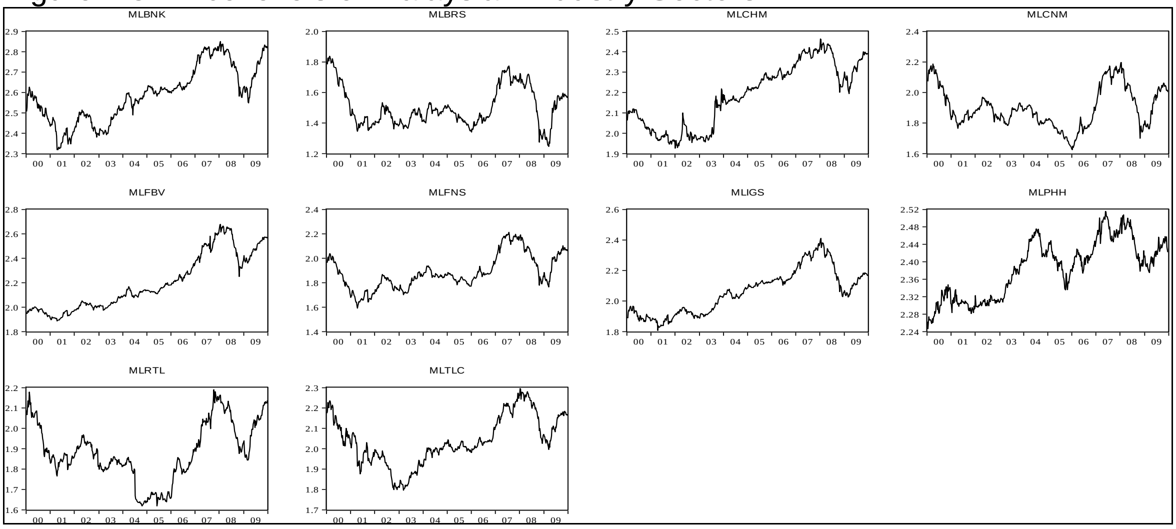
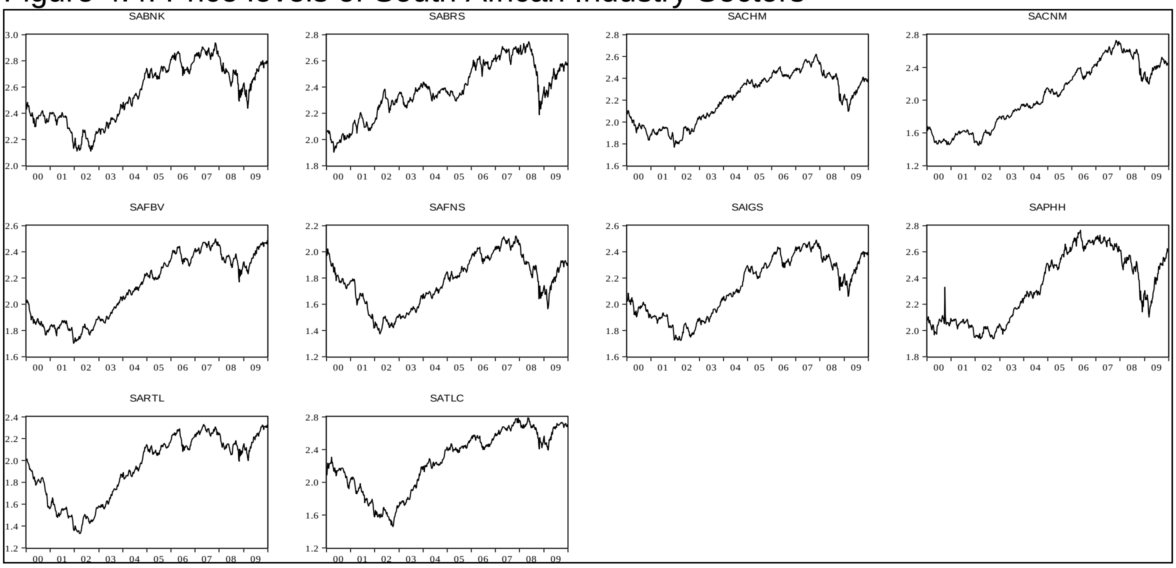


Figure 4.4: Price levels of South African Industry Sectors



Chapter 4

Figures 4.5 - 4.8: Industry Sector Returns

Figure 4.5: Returns of US Industry Sectors

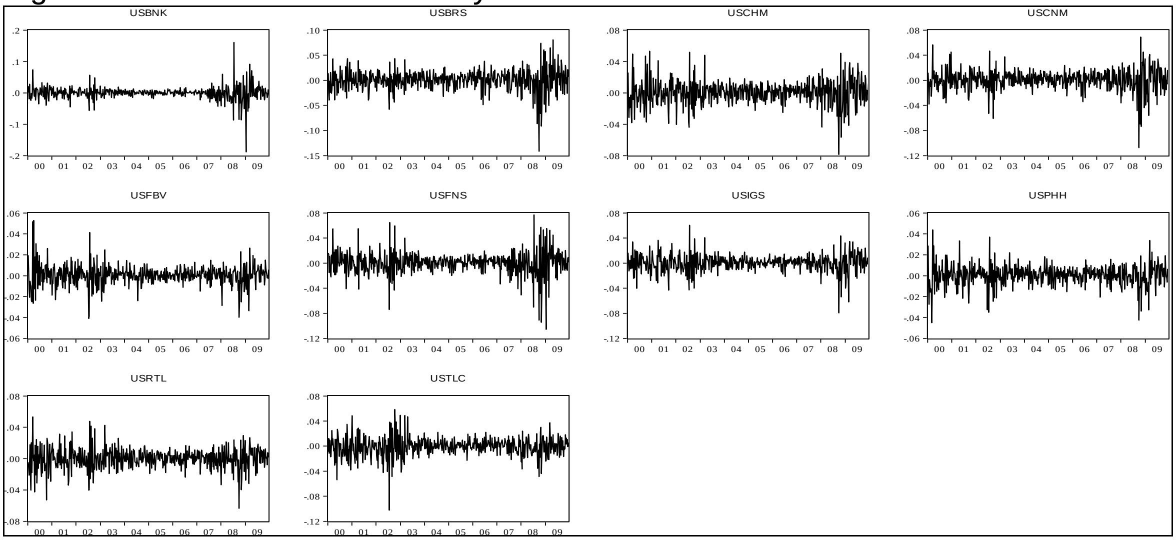


Figure 4.6: Returns of Brazilian Industry Sectors

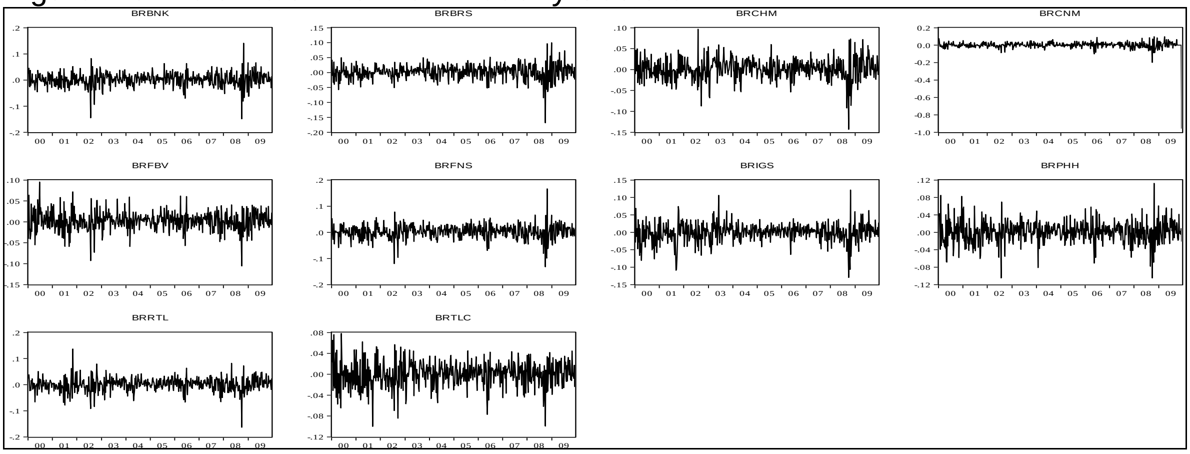


Figure 4.7: Returns of Malaysian Industry Sectors

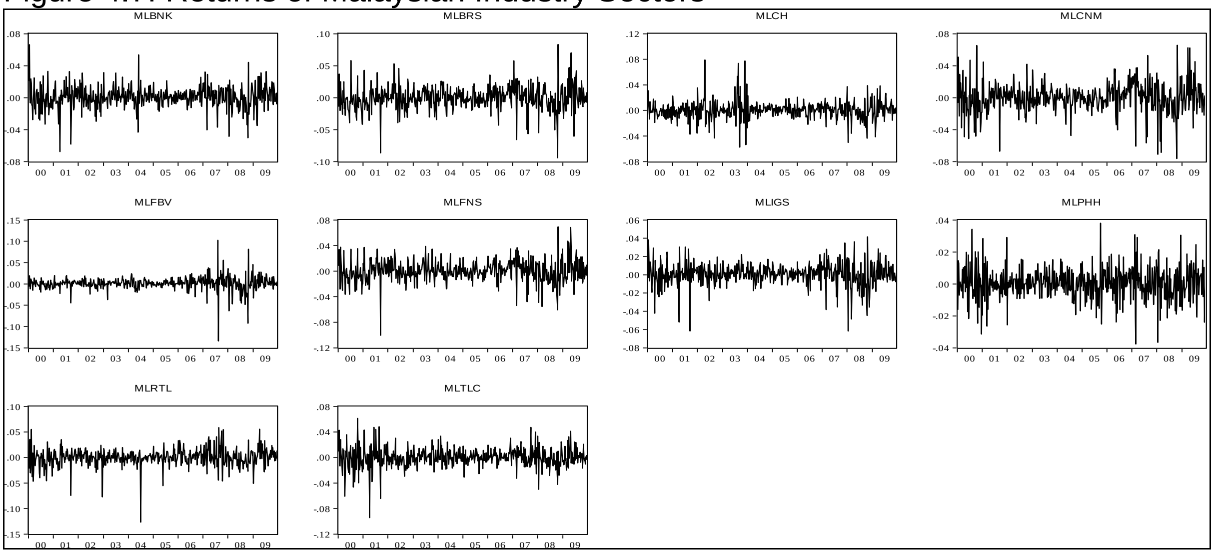
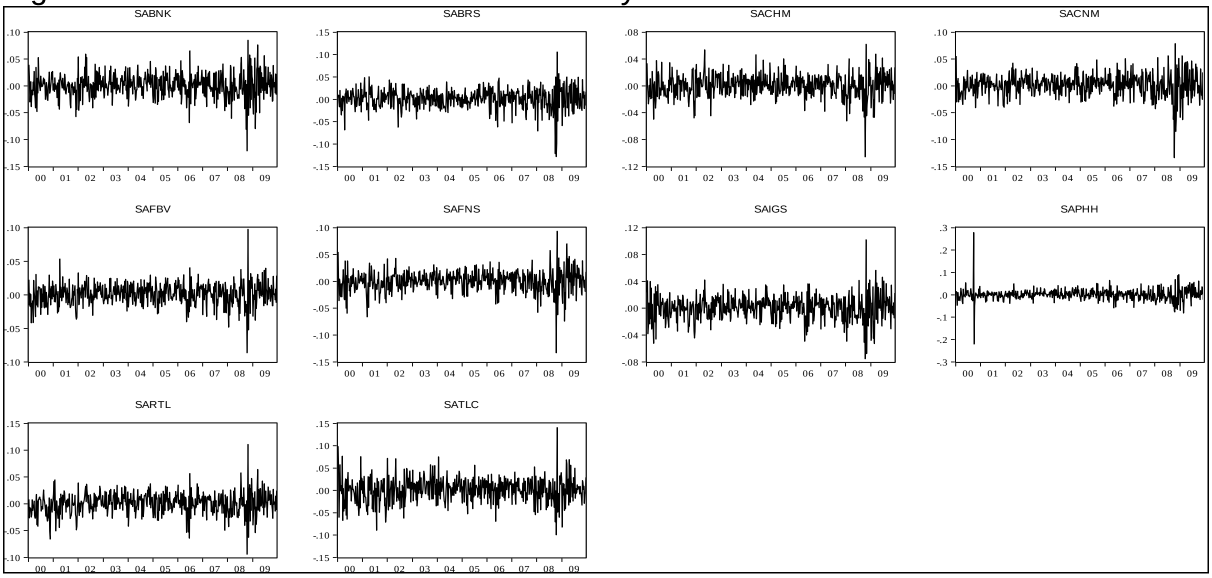


Figure 4.8: Returns of South African Industry Sectors



4.4 Descriptive Statistics for Industry Sector Returns

This section presents the summary statistics of the returns and including the autocorrelation function (ACF) using the Ljung-Box portmanteau test. To exammine the nature of the volatility and normal distribution of the sector returns, the measures of standard deviations, skewness and kurtosis are used. The skewness measure whether the sample distribution is symmetrical or not, while the kurtosis gives an indication on the tail characteristics of the sample distribution (e.g. how fat they are). For normal distribution, the skewness and kurtosis parameters are equal to zero and three respectively. The Jarque-Bera (1980) normality test is used for joint normality tests. The Jarque-Bera (JB) test is a joint test for the skewness and kurtosis of the disturbances, asymptotically distributed as a chi-squared random variable with two degrees of freedom under the null of normality[55].

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[55] $JB = \left(\sqrt{\frac{n}{6}}S\right)^2 + \left(\sqrt{\frac{n}{24}}(K-3)\right)^2 = n\left(\frac{1}{6}S^2 + \frac{1}{24}(K-3)^2\right) \approx \chi^2(2).$ The null hypothesis of normality is rejected for large values of JB.

Another issue that plays an important role in time series analysis is the series autocorrelation, or autocorrelation function. The autocorrelation function captures the linear dynamics of the time series variable. Therefore, the autocorrelation function (ACF) test is used to identify the degree of autocorrelation for sector returns. Also, the dependence behaviour of returns and squared returns is examined. In other words, to test jointly for serial correlations of industry sector returns, the Ljung-Box (1978) statistic is applied to each return series. The LB statistic is a variant of the Box-Pierce (1970) Q statistic, and for large samples takes Q and follows a chi square distribution with *n* degrees of freedom. The Ljung-Box statistic tests the hypothesis that autocorrelations up to the nth lag are jointly statistically significant. In this analysis, the LB statistics of five lags, LB(5), is used to test serial or linear dependencies of industry returns series.

Tables 4.1-4.4 report descriptive statistics for each market/country's industry return series for the sample period. The sample means, standard deviations, skewness, kurtosis, Jarque–Bera statistic and p-value are reported in columns 2-6 of the table for the weekly dollar returns series of the industry indices. The summary statistics offer several preliminary insights into the data. The sample means of all industry sectors in all markets are not statistically different from zero[56]. The standard deviations seem to be more volatile over time, and volatility varies substantially across sectors and countries. In general, the US industry sectors show the smallest standard deviations, followed by the Malaysian sectors. The results of standard are consistent with the general impression that emerging stock markets are more volatile than their counterparts in the developed markets. The measure for skewness (though very small) shows that many return series are negatively skewed with respect to the normal distribution. In addition, the kurtosis statistics of all industry sector returns indicates excess values in all markets. The high values of the kurtosis coefficient indicate the distributions of returns for all sectors in all markets are characterised by a peakness and fat tail relative to a normal distribution. Furthermore, given the non-zero skewness levels and that the

[56] Expressing the return calculations as a percentage by multiplying by 100 would not have made any difference.

kurtosis demonstrates excess values of all the return series; the Jarque-Bera (JB) tests strongly reject the null of normality for all the industry sector returns. In summary, the statistics provide a strong indication of non normality for the unconditional distribution of all industry sector return series due to multiple outliers[57].

Next, the autocorrelation coefficient for individual lags are then examined for each sector returns. The results, which are not reported here due to space considerations, indicate no systematic patterns in many cases, although statistically significant autocorrelation is detected in a small number of cases. Testing for joint lack of serial auto-correlation in returns is also carried out using the Ljung-Box portmanteau statistic. The result of the joint test serial correlations, or dependency behaviours of returns, are reported in the last column of the tables, using the Ljung-Box statistics with five lags, LB(5). The results of the LB tests indicate insignificant serial correlations on the returns series of many sectors in most markets at the one per cent significance level. The lack of evidence for serial dependence on the sector return series is particularly evident in the emerging market industry sectors.

Table 4.1: Summary Statistics of US industry sector returns

Industry code	Mean	SD	Skew	Kurt	JB	JB Pro	LB-Q(5)
BNK	-0.0003	0.021	-0.679	24.850	10402.62	0.000	9.6729
BRS	0.0003	0.021	-0.946	8.733	791.165	0.000	12.858
CHM	0.0003	0.016	-0.219	5.264	115.490	0.000	3.6936
CNM.	0.0003	0.016	-0.865	8.273	668.650	0.000	10.064
FNS	-3.2E-05	0.018	-0.750	9.205	884.914	0.000	**27.328**
FBV	0.0003	0.009	0.081	8.182	583.500	0.000	13.286
IGS	-6.1E-05	0.014	-0.589	7.095	394.214	0.000	13.348
PHH	0.0003	0.002	-0.315	6.070	213.213	0.000	7.5175
RTL	-8.1E-05	0.013	-0.289	5.428	135.285	0.000	**17.188**
TLC	-0.0008	0.015	-0.528	7.713	506.377	0.000	4.5314

[57] A rejection of univariate normality, however, does not always preclude multivariate normality of the joint distribution of returns.

Table 4.2: Summary Statistics of Brazilian industry sector returns

Industry Sector	Mean	SD	Skew	Kurt	JB	JB Pro	LB-Q(5)
BNK	0.0016	0.026	-0.560	7.936	556.240	0.000	**20.247**
BRS	0.0019	0.024	-0.702	8.220	633.958	0.000	10.356
CHM	0.0009	0.025	-0.425	5.821	188.510	0.000	**20.941**
CNM.	-0.0001	0.051	-12.55	233.47	1166773.	0.000	1.8834
FNS	0.0017	0.027	-0.314	7.542	456.433	0.000	**20.144**
FBV	0.0019	0.023	-0.190	5.055	94.902	0.000	10.592
IGS	-0.0005	0.027	-0.479	6.186	240.368	0.000	**18.361**
PHH	0.0011	0.025	-0.177	5.047	93.723	0.000	10.428
RTL	0.0011	0.026	-0.424	7.400	434.751	0.000	4.5991
TLC	5.1E-06	0.025	-0.354	4.132	38.720	0.000	**17.950**

Table 4.3: Summary Statistics of Malaysian industry sector returns

Industry Code	Mean	SD	Skew	Kurt	JB	JB Pro	LB-Q(5)
BNK	0.0006	0.013	-0.304	6.65	297.8	0.000	4.0699
BRS	-0.0004	0.019	-0.145	6.52	271.4	0.000	12.691
CHM	0.0006	0.014	0.648	9.63	991.54	0.000	4.0440
CNM.	-0.0001	0.018	-0.282	5.79	176.42	0.000	7.8324
FNS	0.0002	0.017	-0.301	6.51	275.45	0.000	14.582
FBV	0.0011	0.015	-1.162	22.03	7982.37	0.000	**16.377**
IGS	0.0005	0.012	-0.882	7.48	503.04	0.000	6.7801
PHH	0.0003	0.010	-0.040	4.59	55.17	0.000	**21.610**
RTL	9.5E-05	0.017	-0.992	10.90	1443.60	0.000	5.5715
TLC	1.2E-05	0.015	-0.406	7.85	525.95	0.000	1.7141

Table 4.4: Summary Statistics of South African industry sector returns

Industry Code	Mean	SD	Skew	Kurt	JB	JB Pro	LB-Q(5)
BNK	0.0007	0.023	-0.288	6.06	99.19	0.000	10.107
BRS	0.0010	0.023	-0.760	7.24	440.45	0.000	**15.452**
CHM	0.0009	0.025	-0.425	5.82	188.51	0.000	**20.941**
CNM.	0.0016	0.021	-0.615	6.67	325.60	0.000	6.2741
FNS	-0.0001	0.020	-0.604	7.72	516.02	0.000	6.2737
FBV	0.0009	0.016	-0.121	6.32	240.60	0.000	7.4859
IGS	0.0007	0.018	-0.091	5.32	117.37	0.000	**17.023**
PHH	0.0010	0.027	0.992	31.51	17734.77	0.000	**26.396**
RTL	-0.0001	0.020	-0.603	7.72	516.02	0.000	6.3727
TLC	5.1E-06	0.025	-0.354	4.132	38.72	0.000	**17.950**

Table Notes:
Industry codes (abbreviations): As explained in section 4.2
Mean: Means of industry sectors returns. SD: Standard Deviation. Skew: Skewness coefficient. Kurt: Kurtosis coefficient. JB: the Jarque–Bera test for normality at 2 degrees of freedom and 5% significance level. JB Pro: Probability value of the Jarque–Bera test for normality.
LB(5): The Ljung–Box test statistic for return autocorrelations at lag 5, and distributed as χ^2 with 5 degrees of freedom. The critical value of 1% significance level for 5 degrees of freedom is 15.0863.
The bolded figures denote statistical significance for return autocorrelations and insignificance for squared return series at 1% significance level.
The econometric application of EViews was used for all above tests.

4.5 Conclusion

This chapter discusses the sample selection strategy, the sources and the data, and presents graphical visualisations of price levels in logs and returns for the industry sectors in the study. The chapter also presents the results of the summary statistics for the return series of the industry sectors in the research. Graphical inspections and the results of the summary statistics reveal several characteristics of industry sector indices. For example, the price levels are nonstationary, while the returns or the differences seem to be mean reverting and therefore stationary. The sample period of this study covers a somewhat volatile time period for the international stock markets, and the extreme volatility is confirmed by graphical inspections of the returns series which show the existence of periods of high and low volatility. The standard deviation indicates that there is a greater variance of industry sector returns in all markets. The measure for skewness (positive or negative) is very small for many return series, and therefore not a major problem in this study. However, the kurtosis measure indicates that all series are highly leptokurtic relative to the normal distribution in all cases in the data. This result is confirmed by the Jarque-Bera normality test, which strongly rejects the normality distribution for all the return series at the 1 per cent significance level.

In addition, serial autocorrelations or the dependencies of returns series are examined using the Ljung-Box test statistic of up to five (5) lags. The Ljung-Box (LB) test results indicate that there are insignificant linear dependencies in many return series of industry sector indices, especially in the emerging markets. As mentioned in the introductory chapter, numerous studies have shown that financial data series often exhibit nonlinear dependencies. The nonlinear dependencies could be due to autoregressive conditional heteroskedasticity effects, as documented by several previous studies in stock markets (i.e. Booth et al (1992), Ramchand and Susmel, 1998)). The nonlinear dependency behaviour of the industry sector returns are further investigated in chapter 8 using several statistical tests. In particular, the McLeod and Li (1983) test for squared residuals, the Engel (1982) test for the ARCH effect and the BDS test for randomness independence or nonlinear dependence are applied using the residuals of autoregressive AR (p) modelling or the residuals of the GARCH filtering procedure. Prior to that, as the initial step of evaluating the degree of integration or co-movements between industry sectors in the research, chapter six examines the return relations between the industry sectors of the emerging countries and the US by applying time varying correlations and beta coefficients.

CHAPTER 5:
The Interdependence between US and Emerging Industry Sectors: Empirical Methodologies for Linear and Nonlinear analysis

5.1 Introduction

As noted in the introductory chapter, the studies that address industry (or firm) level co-movements and dynamic linkages at a global level are relatively small compared to those that look at the national level. The empirical objective of this thesis is to investigate the co-movement and dynamic linkages amongst the US and three leading emerging markets by examining the heterogeneity of industry sectors. Previously, many empirical researchers in economic and financial time series data have often used linear econometric methodologies such as co-integration tests and dynamic analysis in a linear framework. However, empirical modelling of nonlinearity in economic and financial time series data has been gaining in importance in recent decades. This thesis extends the literature of international financial markets by investigating the co-movements and dynamic linkages between stock markets at the industry sector level both in linear and nonlinear empirical settings. Specifically, the thesis investigates the dynamic of long run and short run relationships between the industry sector indices of three leading emerging countries (Brazil, Malaysia, and South Africa) and the United States of America. This chapter discusses in detail empirical methodologies used in the thesis; including linear and nonlinear cointegration procedures, linear and nonlinear causality linkage tests, and various time variation testing techniques including time varying correlations, time varying beta convergence, time varying cointegration and cuausality analysis.

Empirical strategy for long run linear tests is based on the Johensen's (1988, 1991, 1995) maximum likelihood estimation of cointegration for long run relations. Another empirical objective of this thesis is to examine time variation long-run relationships between industry sectors by applying recursive cointegration analysis developed by Hansen and Johansen (1999) and rolling window cointegration analysis. Empirical investigations for long run nonlinear cointegration relationships between the industry sectors of the US and the emerging markets/countries in the study are conducted using the rank test techniques proposed by Breitung (2001).

The concept of interdependence covers not only the integration or co-movement between different markets, but also the dynamic causality linkages and transmissions. Hence, in addition to the analysis of linear and nonlinear cointegration relationships, the short run dynamic linkages between the international industry sectors in the study are also examined and their empirical tests formulated in this chapter. Specifically, Granger causality analysis between industry sector indices is investigated using both linear and nonlinear modelling. For linear Granger causalities, the thesis firstly examines linear causality relationship tests based on conventional vector auto-regressive (VAR) or vector error-correction (VECM) models where long run or co-integration relationships are found. In the conventional Granger causality ((GC), Granger (1969, 1988)) approach, no assumption is being made between the possible effect of a positive and a negative shock in absolute terms on causality relations. Thus, following Hetemi (2012a), this thsis extends further the linear Granger causality by investigating the possiblity of asymmetric causality relationships between the industry sectors of the emerging countries and US markets. Testing for time varying causality linkages is also another task undertaken in this thesis.

To determine the nonlinear causal relationships between industry sector returns, I apply the bivariate noisy Mackey-Glass (M-G) model proposed by Kyrtsou and Terraza (2003) and Kyrtsou and Labys (2006) and further extended by Varsakelis and Kyrtsou (2008). The (M-G) model assumes that a small change in one variable can produce a multiplicative and disproportionate impact on the other variables in the presence of nonlinearity. As noted in the introductory chapter, this research also tests asymmetric versions of the M-G model for nonlinear Granger causality relationships, as proposed by Varsakelis and Kyrtsou (2008). Prior to investigating the nonlinear causality relationships, the nonlinear dependence of the univariate industry sector returns are examined using McLeod and Li (1983) for an ARCH alternative, Engle LM (1982) for GARCH, and Brock et al (1996) for a randomness or general linearity test.

In addition, in order to provide robustness analysis to the interdependece between the industry sectors of US and the emerging countries/markets in the study, this thesis examines the co-movemnets among the industry sector returns of US and the emerging countries by applying the standard cross correlation analysis, time varying correlations and time varying beta convergence analysis. Such analysis can be considered as the first step for evaluating the degree of interdependence amongst the international industry sectors in this study. Furthermore, as earlier mentined earlier and to be explained further in later chapters, the sample period of this study covers a somewhat volatile time period for the international stock markets. The crisis in the sample period, which originated from the banking crisis in America, had a major impact on global business and financial markets. In particular, between 2007 and 2009 the economic and financial headlines have reflected the failure of key businesses, plummeting stock markets around the world, and a severe global economic meltdown. Hence, another empirical advancement of this thesis is to investigate separately shifts in correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 financial crisis. Specifically, for a comparative assessment, two period sample tests are conducted using data series of 2004-2006 and 2007-2009[58]. The work of the chapter is structured as follows.

Before discussing the econometric methodologies for linear and nonlinear relationship assessments, section two of the chapter presents short discussions of several methods for examining co-movements between the returns of US and the emerging markets' industry sectors including; cross correlation analysis, time varying correlation and time-varying estimation. Section three explains the testing

[58] While the 2007-2009 economic and financial crisis is well known, the 2004-2006 can generally be considered a stable period as no major crisis in global financial markets occurred.

strategies for long run linear relations; including several test statistics for linear unit roots and lag length selection procedures that proceede testing for linear relations, and the Johensen's (1988, 1995) maximum likelihood estimation of cointegrations for long run relationships. This section also discusses time varying cointegration relationships through recursive and rolling cointegration analysis. Section four of the chapter deals with nonlinearity issues in long run equilibrium. The first part of this section presents a brief discussion of some of the important shortcomings levied against the assumptions of the linear methodologies, and the need for nonlinearity empirical techniques in financial asset modelling. The second part of the same section presents the testing methodologies for nonlinear unit roots and cointegration relationships based on rank tests. Next, sections five and six respectively present the methodology tests for linear and nonlinear Granger causality, and the tests for asymmetric [linear and nonlinear] causality relationships. Section seven explains briefly the testing proceedure for causality relations between the US and emerging markets' industry sectors before and during the 2007-2009 Financial Crisis. Finally, section eight summarises the chapter.

5.2 Co-movements between the US and the Emerging Markets' Industry Sector Returns

Prior to the extensive econometric methodologies for linear and nonlinear assessments, this thesis employs several related empirical techniques to study the co-movements between the industry sector returns of US and the three emerging in the study. Specifically, in addition to the standard cross correlations, the dynamic nature of the return co-movements between the US and the emerging industry sector returns is examined by conduction two of measures of time-varying rutrun co-movements. Firstly, a rolling correlation analysis technique, a popular method of examining the time variation of correlations among stock markets is applied. Secondly, to investigate further the time varying co-moment behaviour for the returns of industrial sectors in the study, this thesis also employs time series regressions to model the time-varying coefficients or *beta* convergence, by employing a state space framework and the Kalman filter. A special contribution of this thesis is the combination that investigates time varying coefficients and time varying correlations for industry sector level indices, which have been separately applied by few recent studies (i.e. Meric et al, 2007, Park and Kim, 2009, and Mergner 2009). Chapter six of the thesis presents more detailed discussions of these testing techniques and the results of their empirical applications to the returns of the industry sectors in this study.

5.3 Empirical Methodologies for Long Run Linear Relationships

5.3.1 Background

As detailed earlier in the literature review chapter, most economic and financial studies have recently been using the standard VAR cointegration methods. Cointegration methodology has gained significant interest since the so-called Granger representation theorem (Engle and Granger, 1987), which states that cointegrated variables have a vector error correction model (VECM) representation, which can be thought of as a VAR model including a variable to represent the deviations from the long-run equilibrium[59]. To investigate the long run (linear) relationships for industry sectors, this thesis applies Johensen's maximum likelihood co-integration estimation within VECM methodology, which can be applied to both bivariate and multivariate cointegration tests. According Gonzalo (1994), and Hargreaves (1994), the maximum likelihood approach performs better for larger sample sizes than a range of other estimators for long run relationships. Indeed, as Hargreaves (1994, p. 102) states 'a major advantage of the maximum likelihood procedure is that it leads to a whole battery of hypothesis tests'[60]. The maximum likelihood uses estimators of the cointegrating vectors for a vector autoregressive process with Gaussian errors, and

[59] The VECM representation provides a basis for analysing the dynamics of the movement from short term to long-term equilibrium among the equity markets' prices and testing for Granger-causality as well as to determine the impacts of shocks to the variables using impulse response functions.

[60] Nevertheless, as Hargreaves (1994, p. 103) points out 'one practical problem with the Johansen estimator is the difficulty of expressing what is going on inside the 'black box' which it probably is to most users'.

incorporates the whole error structure of the underlying multivariate process, including different short-run and long-run dynamics, for a system of economic variables.

Although the cointegration methodologies are well known and have been applied widely for international stock markets, very few studies have so far used these techniques to examine the long run relationships between industry sectors between US and emerging markets. Many economic and financial time series data, including asset prices, exchange rates and the levels of macroeconomic aggregates like real GDP, exhibit nonstationarity behaviour. Thus, in testing for cointegration or causality relationships, it is a customary to test for the stationary and nonstationarity properties of each variable before modelling the long relationships using one or more unit root tests. Furthermore, the estimation of the VAR or VEC model requires the specification of a common lag length. The remainder of this section presents the discussions and testing statistics of linear unit roots for the industry indices in this study, the mathematical expositions of the familiar maximum likelihood procedure (which has been used by many empirical studies on stock market cointegration relationships including the often cited papers of Kasa (1992) and Richards (1995)) and the statistical procedures for multivariate lag order selections.

5.3.2 Testing for Linear Unit Roots

This subsection discusses the testing procedures of linear unit roots for the price indices (log levels and first differences) of the international industry sector in the research. Several statistical techniques for testing nonstationarity or stationarity [I(1), I(0)] of time series variables have been presented in the empirical literature of economics and finance . These include, among others, the Augmented Dickey–Fuller test (ADF), the Phillips–Perron test (PP), the Elliot, Richardson and Stock (ERS) DF-GLS, and Ng and Perron (NP), which have often been used for conventional linear studies. In particular, the ADF and PP tests have been widely applied in the literature to test whether the unit roots of the series under consideration are non-stationary or stationary in their levels or differences. The

ADF test attempts to account for temporally dependent and heterogeneously distributed errors by including the lagged sequences of the first differences of the variable in its set of regressors. The Phillips-Perron (PP) procedure non-parametrically transforms the test statistics generated by Dickey-Fuller unit root tests. This modification permits the presence of serial correlation and autoregressive heteroscedasticity in the residuals of the Dickey- Fuller regression models[61].

Although the ADF and the PP tests have been the standard applications for unit root tests in applied time series econometrics, their power is known to be very low against the alternative hypothesis of (trend) stationarity (DeJong et al, 1992, Toda, and Yamamoto, 1995). As a result, in empirical literature these conventional tests have been largely complemented with improved alternatives. For example, in an attempt to address the low power problem of the unit ADF root test, Elliott et al (1996) introduced the generalised least squares (GLS) approach. This is the so-called DFGLS unit root test that is a DF test applied to the regression residual, which arises from the GLS estimators employed in the original regression. Stationarity tests, on the other hand, are for the null hypothesis that y_t is I(0). The most commonly used stationarity test is the KPSS test, named after Kwiatkowski, Phillips, Schmidt and Shin (1992). Under the KPSS test, the null hypothesis of stationary series is tested against the alternative hypothesis of non-stationary series. The KPSS test is also used to investigate the possibility that a series is fractionally integrated, i.e. neither I(1) nor I(0) (see Lee and Schmidt, 1996). In this thesis, for the sake of comparative analysis the test statistics of the Augmented Dickey–Fuller tests (ADF), 1979, 1981), the DF-GLS test (Elliott, Rothenberg and Stock 1996), and the Kwiatkowski et al. (1992) test are used for the linear stationarity (or unit roots) test for the returns of international industry sectors in the study. The remainder of this sub-section presents short discussions of the testing methodologies of ADF, KPSS and DFGLS statistics as follows.

[61] The PP test statistic has an asymptotic distribution similar to the ADF test statistic, and has been tabulated in Davidson and MacKinnon (1996).

Chapter 5

The ADF Test**:** Testing for the presence of unit roots for price indices of industry sectors in the study, an ADF test is performed on the auxiliary regressions of the levels and the first difference or returns for each series. A test with intercept and time trend stationary is performed for each sector index as in the following equations:

Levels

$$p_t = \alpha + \vartheta t + \rho p_{t-1} + \sum_{i=1}^{m} (\Delta p_{t-I}) + \zeta_t \quad (5.1)$$

First differences

$$\Delta p_t = \alpha + \Phi t + \phi p_{t-1} + \sum_{i=1}^{m} (\Delta p_{t-i}) + \zeta_t \quad (5.2)$$

for i = 1, 2, n, the lagged first difference (Δp_t) is added to ensure that ζ_t is white noise. The ADF test statistic is the ratio of ρ to its standard error obtained from OLS regression. The null hypothesis of a unit root is rejected for a value of ρ, which is negative and significantly different from zero using the significance levels calculated by ADF (1979, 1981). The criterion of selecting lag orders is based on the significance value of the lag orders and the requirement that there should be no evidence of serial auto correlation. To purge possible serial auto-correlations in the residuals, unit root tests are often augmented with sufficient lags.

The DF-GLS test: This study extends the traditional ADF statistic for testing the presence of unit roots using the Elliott, Rothenberg and Stock (1996) ADF-GLS test. The ADF-GLS, or ERS test, named after the pioneering authors; Elliott, Rothenberg and Stock (1996), is similar to the (augmented) Dickey-Fuller test, but has better overall performance when there is a small-sample size. According to Elliott et al (1996, p. 813), the DFGLS 'has substantially improved power when an unknown mean or trend is present'. Assuming that, the data observations (y_1 ..., y_t) were generated in terms of the following format

$$y_t = d_t + e_t \text{, for t=1, …, T} \quad (5.3)$$

where $e_t = \gamma e_{t-1} + v_t$ and {d_t} is a deterministic component and {v_t} is an unobserved stationary zero-mean error process whose spectral density function is positive at zero frequency. Next, ERS (1996) proposed conducting the usual augmented Dickey-Fuller t test using the residual series of a de-trending (without deterministic) generalized least squares (GLS) as

$$y_t^d = y_t - \hat{B}' v_t \qquad (5.4)$$

where $\hat{B}$ is the OLS estimator of Equation (5.3). As in the case of the ADF test, to address serial correlation the ERS test also added the lags of Δy_t, as follows

$$\Delta y_t^d = \alpha + \delta_t + \gamma y_{t-1}^d + \sum_{i=1}^{m} \vartheta \Delta y_{t-i}^d + \varsigma_t \qquad (5.5)$$

where *m* is the maximum lag. The DFGS test is more efficient than ADF test under the hypothesis of normal residuals. For lag selection criterion, the DFGS test uses the Schwarz information criterion, or the modified AIC' (MAIC) criterion. Approximate critical values for the GLS de-trended test are given in Table 1 (p.825) of ERS (1996)[62].

The KPSS Test: The ADF (and PP) unit root tests are used for the null hypothesis that a time series y_t is I(1). An alternative test, which is for stationarity or the null hypothesis that y_t is I(0), is the KPSS test named after Kwiatkowski, Phillips, Schmidt and Shin (1992). The KPSS Test differs from the previously described unit root tests in the sense that the series is assumed to be trend stationary under the null. The KPSS test for stationarity of a time series can be conducted under the null of either level or trend stationarity. Thus, assuming {y_t}, t = 1, 2, …, N, be the observation series for testing stationarity, the KPSS statistic is based on the residuals,{e_t}, from the OLS regression of the y_t on the exogenous variables z'_t as follows

[62] Two excellent recent discussions on DF-GLS Unit Root Tests are Vougas (2007) and Wu (2010).

$$y_t = \delta z'_t + \varepsilon_t \tag{5.6}$$

where εt is a stationary error. Under the null hypothesis: in the case of trend stationarity, the residuals $\{e_t\}$ (t = 1, 2, …, N) are from the regression of y_t on an intercept and time trend, $e_t = \varepsilon_t$; whereas in the case of level stationarity, the residuals $\{e_t\}$are from a regression of y_t on intercept only, that is $e_t = y_t - \hat{y}$.

Letting the partial sum process of the residuals, (e_t) be S_t, the KPSS (1992) test statistic can be formulated as

$$\Re(e) = N^{-2} \sum_{n=1}^{N} S_t^2 / N^{-1} \sum_{n=1}^{N} e_t^2 \tag{5.7}$$

where N represents the sample size. For maximum lag order, the consistent estimator of σ^2 can be constructed from the residuals e_t (Newey and West, 1987). The KPSS statistic, $\Re(e)$, has a non-standard distribution and approximate critical values taken from KPSS (1992). If the calculated value of $\Re(e)$ is large, then the null of stationarity for the KPSS test is rejected. The optimal number of lags for this test is chosen using a number of lag selection criteria, including the Newey-West truncation.

5.3.3 Lag Length Selection for VAR/VEC Modelling

A crucial aspect of empirical research based on the linearity test of vector autoregressive modelling (VAR) is the determination of the lag order, as all inference in the VAR model is based on the specification of chosen model. To determine an appropriate lag order for a vector autoregressive model subject to restrictions of cointegration, a number of lag order selection strategies have been presented in the literature. These selection strategies include, among others, the sequential modified likelihood ratio (LR) test, and the multivariate versions of information criteria procedures such as the Akaike information criteria (AIC), the Schwarz criteria (SC), the Hannan-Quinn (HQ), and the Forecast Prediction Error (FPE). In this research, the lag order is determined by using both the likelihood ratio (LR) test and thre**e** classical informational criteria: Akaike (AIC), Schwarz (SC), and Hannan-Quinn (HQ), and then taking the lag length with the minimum value. This subsection briefly presents the testing methodologies of these lag selection strategies. The optimum number of lags in the VAR models can be determined using the likelihood ratio test statistic defined as

$$LR= (T-C)[\log|\Pi r|/ \log|\Pi u|] \qquad (5.8)$$

where Πr and Πu are the estimated variance-covariance matrices of the error terms from the restricted (p-1 lags) and unrestricted (p lags) models, and c is a correction factor for improving small sample properties (Sims, 1980) which is equal to the number of variables in each unrestricted equation in the system. The test is asymptotically distributed as χ^2 with degrees of freedom equal to the number of restrictions.

Information criteria tests are based on the maximal value of the likelihood function, with an additional penalising factor related to the number of estimated parameters, defined as:

$$AIC(P) = \ln|\Pi(p)|+ (P^2 k)\frac{2}{N} \qquad (5.9)$$

$$SIC(P) = \ln|\Pi(p)|+ (P^2 k)\frac{\ln N}{N} \qquad (5.10)$$

$$HIQ(P) = \ln|\Pi(p)|+ (P^2 k)\frac{2\ln\ln N}{N} \qquad (5.11)$$

The idea is to calculate the test criterion for different values of *k* and then choose the value of k that minimizes the information criteria. The AIC criterion asymptotically overestimates the order with positive probability, whereas the SIC and HQ criteria estimate the order consistently under fairly general conditions if the true order p is less than or equal to p_{max}. When using these information criteria for the choice of optimum lag length, it is important that the tested empirical model is specified correctly. It is also the case that the above information criterions differ according to the associated penalty. In addition, after an appropriate VAR/VEC model has been specified and tested, various checks of model adequacy or diagnostic testing should also be carried out.

5.3.4 Cointegrating VAR Models: The Maximum Likelihood Estimation

Assuming a set of non-stationary k-variable time series, $y_{it} = (y_{1t}, y_{2t}, \ldots y_{kt})$, a test for a linear multivariate model can be formulated as follows

$$y_{it} = y_{1,t} + y_{2t} + \ldots\ldots + y_{pt} + \varepsilon_{it}\text{ , with } i,t = 1, ., ., n \qquad (5.12)$$

where the lower case represents the logs of the variables (price), and the y_{it} are (nx1) vectors of endogenous or dependent variables. In this linear setting, parameters are assumed to be linear and constant. All variables are assumed be integrated by a degree of 1 and the disturbance terms (ε_t) are normally distributed and serially uncorrelated but can be contemporaneously correlated. In equation (5.12), the error term ε_t is referred to as the disequilibrium error or the cointegrating residual. For a long-run equilibrium, the disequilibrium error u_t is zero and the long-run equilibrium relationship becomes

$$y_{it} = y_{1,t} + y_{2t} + \ldots\ldots + y_{pt} \qquad (5.13)$$

In a multivariate setting, a vector auto-regression model (VAR), where changes in a particular variable are related to its own changes (lags) and to changes in other variables (or in other sector indices), provides a useful tool for analysing multivariate relationships between variables (Sims, 1980). Furthermore, in time series data, co-movements among non-stationary variables are generally evidence of the presence of cointegration relationships. Therefore, the dynamics between the variables (y_{it}) of the multivariate linear model can be described using a vector auto-regression (VAR) of the following

$$y_{it} = \alpha + \Pi y_{t-1} + \Gamma_1 y_{t-1} + y_{t-2} + \ldots\ldots + y_{t-p} + \omega z_t + u_t \qquad (5.14)$$

where y_{it} (i =1, ….n) are a kx1vector of dependent variables, α is an intercept, z_t is a n x1 vector of exogenous variables containing deterministic terms (i.e. trend, seasonal dummies etc), and $u_t \approx iid\ (0, \sigma)$ is a kx1 dimension vector. The normality distribution or multivariate Gaussian process is imposed since Johansen's approach uses maximum likelihood procedure. When a VAR model has cointegration restrictions it can be represented as a VECM. The VECM representation, which is referred in the literature as 'Granger Representation Theorem' due to Engle and Granger (1987), is argued to be more appropriate than the VAR model in modelling asset prices since it takes into account both the short-run dynamics and the long-run relationships between the variables. In other words, in the case of *n* variables, y_{it}, equation (5.14) can also be rewritten in a first difference format or a vector error correction model (VECM) with p-1 lags as follows

$$\Delta y_t = \alpha + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-1} \ldots + \Gamma_{p-1} \Delta y_{t-1+1} + \omega z_t + u_t \qquad (5.15)$$

where Δ is the first difference operator, $\Pi = -(I - \Pi_1 - \ldots - \Pi_p)$, and $\Gamma_{i+1} \ldots + \Gamma_p)$[63]. The matrix coefficient Π provides information about the long run relationships among the variables. Depending on a rank of Π matrix there may be three possible outcomes (Johansen and Juselius, 1990). First, Rank Π = *n*, indicating that Π is a full-rank matrix, and the vector process y_t is stationary. Second, Rank Π = 0, indicating that Π is a null matrix, and equation (5.15) is a traditional differenced VAR model. Third, Rank Π = r, 0 < r < n, indicating that there are *n x r* matrices α and β. The presence of *r* linearly independent cointegrating vectors implies that the long-run impact matrix Π can be represented as $\Pi = \gamma\beta'$ where α

[63] The Johansen's ML test can be affected by the lag length used in VECM, and therefore it is important to select the lag length carefully (Hall, 1991).

and β are both p x r matrices of full column rank. Thus, assuming the existence of cointegration relationships, to model the short-term dynamics and long run relationships, the VECM in equation (5.15) can be re-modelled as follows

$$y_t = \alpha + \gamma\beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-1} \; .. + \Gamma_{p-1} \Delta y_{t-p+1} + \omega z_t + u_t \qquad (5.16)$$

where γ and β are dimensions (n x r), β denotes the matrix of co-integrating vectors, while γ represents the matrix of speed with which each co-integrating vector enters each of the Δy_t equations. The short-term dynamics of the model are captured by the matrix coefficients of Γ_1 through Γ_{p-1}.

The Johansen's maximum likelihood approach of cointegration is based on estimating equation (5.15) while imposing the restriction $\Pi = \gamma\beta'$ as in (5.16) for a given value of *r*. Thus, the first step of the maximum likelihood estimation involves identifying the rank for the long run matrix Π. In other words, presenting the cointegration hypothesis as a reduced rank condition on the matrix $\Pi = \alpha\beta'$ implies that the processes Δy_t and $\beta' y_t$ are stationary, while the levels of the y_t variables are nonstationary. Since the rank of the long-run impact matrix Π gives the number of cointegrating relationships in the variables, Johansen formulates the likelihood ratio (LR) statistics for the number of cointegrating relationships as LR statistics for determining the rank of Π, or the number of columns β. Furthermore, as Hamilton (1994, Ch. 20) shows, for a given r, the ML estimate for β equals the matrix containing the r eigenvectors corresponding to the r largest estimated eigenvalue of a nxn matrix of long run multipliers.

Therefore, one can use the estimated eigenvalues denoted, say $\lambda_1 > \lambda_2 > ...\lambda_n$, to test hypotheses about the rank of Π. Johansen (1988, 19915) proposes two tests to determine the number of co-integrating vectors. The first is the likelihood ratio test based on the *trace test* and the second is the likelihood ratio test based on the *maximal eigenvalues*. The *trace test* statistics of the maximum likelihood procedure evaluates the null hypothesis, H_0: $r \leq r_0$ versus the alternative H_1: $r_0 < r$

≤ n. The trace statistic for the null hypothesis of r cointegrating relationships is expressed as

$$\lambda trace(r) = -T.\sum_{i=r+1}^{p} \ln(1-\hat{\lambda}_i) \qquad (5.17)$$

The trace test checks whether the smallest n - r_0 eigenvalues are significantly different from zero. The *maximum* eigenvalue statistic tests the null hypothesis of r cointegrating relationships against the alternative of r+1 cointegrating relationships. That is, it evaluates the null hypothesis of H_0: $r \leq r_0$ versus the alternative H_1: $r = r_0 +1$ and is presented as

$$\lambda_{\max}(r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \qquad (518).$$

Since these tests are based on ML estimates, they are in effect likelihood ratio tests and so do not have the usual Chi-squared distribution. As Johansen (1991) shows, the presence of a linear trend in the ECM alters the asymptotic distributions of the Browman motion. Johansen and Juselius (1990) tabulated the critical values of suitable distributions for these tests[64]. Also, as Brooks (2002, p. 408) points out 'the Johansen method allows a researcher to test a hypothesis about one or more coefficients in the cointegrating relationship by viewing the hypothesis as a restriction on the Π matrix'. For example, the hypothesis for the presence of an intercept in the cointegrating relationships can be tested using the following likelihood ratio test:

$$LR = \varpi_{(n-r)} = -T\sum_{i=1}^{r} \ln\left(\frac{1-\lambda i^{*}}{1-\lambda i}\right) \approx \chi^2(n-r) \qquad (5.19)$$

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[64] As will be discussed in chapter seven, other critical values for the rank tests include Osterwald-lenum (1992) which were updated by Johansen (1995), and MacKinnon et al's (1999) p-values. In this thesis as to be xplanied in chapter seven the Gamma approximation of Doornik (1998) is applied.

where λ_i^* and λ_i are the eigenvalues or characteristic roots of the estimated restricted and unrestricted Π matrices, respectively, and the restriction implies the presence of the intercept in the cointegrating relationship. Test statistic, ϖ, follows a chi-square distribution with (*n-r*) degrees of freedom. As mentioned earlier, in the analysis of non-stationary economic and financial time series, it is a customary to precede the empirical tests for co-integration with unit-root tests of the variable under consideration using one or more of a number of tests. The testing procedures for liner unit roots and their results, and the estimation results of cointegration tests for the industry sector indices are reported in the empirical chapter.

5.3.5 Time variation in the cointegrating relationships between the US and emerging countries industry sectors: Recursive and Rolling Cointegration Analysis

The conventional cointegration tests assume that the long-run equilibrium relationships between the economic variables in question are stable over the entire sample period. However, as mentioned earlier, due to global events, the sample period of this study covers a somewhat volatile time period for the international stock markets. These events suggest that finding stable long-run relationships between the industry sectors of the US and the emerging markets in the study may prove unlikely. In other words, there may be a period of time in which long-run relationships did exist, whilst there may also be a period where no long run relationships exist. Therefore, to provide a robustness analysis to the cointegration results between the industry sectors of the US and the emerging countries/markets, this thesis examines the dynamic convergence between the indices of industry sectors under study through time varying multivariate cointegration tests. Specifically, recursive cointegration tests proposed by Hansen and Johansen (1999), as well as rolling window cointegration tests are implemented. The use of recursive and rolling estimations can be justified for a number of reasons. First, recursive and rolling estimations allow the relationship between the variables evolve through time. Second, the recursive and rolling estimations can capture instability across different subsamples which might attribute to the presence of structural changes in data series over the sample period.

Comparing the two time-varying methods, the recursive cointegration analysis is applied to examine the stability of the cointegration relationships over each data point during the sample period. The rolling tests on the other hand, are 'used to investigate the degree of convergence during different sub-samples of the full sample' (Rangvid and Sørensen 2002, p. 185). In other words, the recursive estimation with a growing window of data assumes that the system is evolving to the final outcome form, while the rolling estimation with a fixed-length window can ensure that the effects of regime shifts are isolated and can be used to track possible structural breaks. 'Both methods have the advantage of tracing the stability of long-run cointegrating relationship', Sheu and Liao (2011, p. 3677). By conducting such analysis, this thesis presents another empirical novelty in the literature of international industry equities. That is, (to the best of my knowledge) recursive and rolling window cointegration analysis has so far not been used to investigate the dynamic of long-run relationships between the price indices of international industry sectors.

Generally, when estimating a model recursively an initial sample is kept fixed and the sample length is increased by adding additional observations to subsequent recursive estimations. In other words, tests statistics are computed choosing an initial sample 1, …, T_1 where $T_1 < T$, and then extending the sample by one period (T_1+1), and so on until the full sample (T) is reached. Two representations or models of recursive cointegration analysis are used under the estimation of a VAR/VEC model. The first is the X-representation, in which all the parameters of the VEC model are re-estimated during the sequence of recursive tests. The second is the R-representation, in which the short-term parameters Γ_i are fixed to their full sample values and only the long-run parameters in the model are re-estimated (Juselius, 2006, Canarella et al, 2008). In the recursive tests, the statistics obtained from the cointegration tests are scaled using the critical values of the chosen level of significance. Under the R-representation, rejections of stability reflect changes in the long-run structure, that is, a structural break in the cointegrating ranks. On the other hand, rejections of stability under the X-representation reflect either shifts in the short-run dynamics or changes in the long-run structure (Canarella et al, 2008). Several studies that have previously applied the recursive cointegration analysis to international stock markets include, are among others, Yang et al (2004) for US and emerging markets, and Canarella et al (2008) for the North American Free Trade Association (NAFTA) stock markets, and Sheu and Liao (2011) for US and BRIC (Brazil, Russia, India, and China) markets.

Furthermore, following the lead of several empirical studies (Rangvid and Sørensen (2002), Breda et al (2005), MCMillan (2006), Awokuse et al (2009), Mylonidis and Kollias (2010), and Sheu and Liao (2011), who applied rolling cointegration analysis to other fields in financial markets, this thesis also uses rolling window tests to examine for time varying coinegration relationships amongst price indices of the industry sectors under study. The rolling cointegration analysis can be considered to more appropriate than the alternative recursive analysis (Mylonidis and Kollias, 2010). When conducting rolling window tests the size of subsamples is kept constant, and both the first and the last observation in the subsamples roll through until the full sample is reached. That is, the test statistics are calculated for a rolling n observations time window by adding one observation to the end and removing the first observation and so on. As Mylonidis and Kollias (2010, p. 2060) state ‘continuous plots of trace test statistics for a rolling, fixed length, window provides essential information about the time varying pattern of the number of cointegrating vectors’. As in the case of recursive tests, the statistics obtained from the rolling cointegration tests are scaled by the adjusted critical values of the chosen significance level are plotted. Similarly, a value of the scaled test statistic above one means that, the corresponding null hypothesis can be rejected for the specified sub-sample period at a given level of significance. Testing procedures and graphical presentations of recursive and rolling window cointegration estimations for the industry sectors in the study will be presented in chapter seven.

Chapter 5

5.4 Long Run Nonlinear Relationships between the US and Emerging Markets Industry Sectors

5.4.1 Nonlinearity Behaviour in Financial Assets: Background and Relevant Literature

The behaviour and relationships of financial market indices have been, and continue to be, of interest to academics, practitioners and market regulators. In theoretical financial models, such as the traditional capital asset pricing models and option pricing models, empirical estimations are based on the assumptions of linearity and normal distribution, or independent and identically distributed (IID). Moreover, many previous empirical studies in financial time series have often been conducted using a linear framework. For example, time series linear vector autoregressive (VAR) models or vector error correction models (VECM) have often been applied to financial data to jointly model multiple time series. The linear models implicitly assume the possibility that the relationships between non stationary variables move towards the long-run equilibrium in every time period. Furthermore, the assumption of linear relationships also underpins the mechanics for testing market efficiency. However, in empirical finance the linear conditional expectation functions implicit in the linear specification do not always follow the same pattern. Indeed, the distribution of many asset returns is often found to be highly leptokurtic. Studies that have used nonlinear modelling have also cast doubt on this weak form of efficient market hypothesis. For instance, according to Antoniou et al (1997), if these assumptions are not valid, or the return generating process is nonlinear, and a linear model is used to test efficiency, then the hypothesis of independence of successive price changes may be wrongly accepted. Moreover, as Alagidede and Panagiotidis (2009, p.4) point out 'the presence of nonlinearities in the series could imply evidence of return predictability'. Therefore, ignoring the problem of nonlinearity in market returns may invalidate the test results concerning the individual and collective efficiency hypothesis.

Chapter 5

Several market frictions, such as transactions costs and information frictions, which can prevent the linear models converging to long run equilibrium in financial markets, require nonlinear and asymmetric adjustments have been in the literature. As Anderson (1997, p. 465) states, 'transaction costs are often ignored in studies of asset markets, in part because they complicate the analysis of such markets, but mainly because they are known to be small, and their effects are therefore assumed to be negligible'. In practice, transactions costs could be substantial and persistent and may prevent the adjustment of disequilibrium errors as long as the benefits from the adjustment remain smaller than their costs (Anderson, 1997) [65]. Thus, transaction costs imply discontinuous prices adjustments and persistent deviations of stock prices from their fundamental levels. Market frictions give rise to asymmetric adjustments to equilibrium. Other suggested potential sources of nonlinearities include: 'diversity in agents' beliefs' (Brock and LeBaron, 1996), 'heterogeneity in investors' objectives arising from varying investment horizons and risk profiles' (Peters, 1994), and 'herd behaviour' (Lux, 1995). In other words, investors have often different degrees of information understanding and are heterogeneous anticipations (i.e. noise traders, chartists, fundamentalists, aware investors, professional investors). Therefore, the interactions between the different categories of agents can induce delays in the adjustment process of stock price dynamics. In summary, as Campbell et al (1997, p. 467) state 'the strategic interactions among market participants, the process by which information is incorporated into security prices, and the dynamics of economy wide fluctuations are inherently nonlinear'.

As a result, testing for non-linearity of financial market data has been gaining particular emphasis in the literature of financial econometrics in the last three decades. Numerous studies, including Hinich and Patterson (1985), Scheinkman and LeBaron (1989), Hsieh (1991), Brock, Hsieh, and Le Baron (1991), Abhyankar et al (1995), Brooks et al (1999), Opong et al (1999), and more recently, among

[65] The theoretical evidence of nonlinear price adjustment with transactions costs can be traced back to Dumas (1992) who examined the dynamic process of the real exchange rate in spatially separated markets under proportional transactions costs. Also, Mishkin (1995) has argued for the importance of transaction costs in analysing financial markets.

others, Ammermann and Patterson (2003), and Lim and Hinich (2005), have documented that stock data can exhibit nonlinear dependence. For example, Hinich and Patterson (1985) were among the first in reporting evidence of nonlinearity in stock returns using daily data of the NYSE. Scheinkman and LeBaron (1989) showed that a substantial part of the variation of US weekly stock returns is actually coming from nonlinearities as opposed to randomness. Opong et al (1999) examine the behaviour of several equity indices on the London Financial Times Stock Exchange (FTSE) All Share Index (FTSE100 Index, and the 250 and 350 series), and report that the FTSE Index series examined are not IID. In another study, examining nonlinearity for high frequency returns and volumes of companies traded on the London Stock Exchange (LSE) Brooks et al (1999, p. 176) state ‘an important message stemming from analysis is that researchers should be cautious about estimating models over long time series for financial data, since the implicit assumption of parameter constancy is most unlikely to be valid’. Other studies (e.g. Brooks, 1996) have also shown that nonlinearity is a fundamental feature of foreign exchange data. In the present study, the behaviour of nonlinear dependencies in the industry sector returns in all markets will be tested in chapter eight.

The observed asymmetry or nonlinearity behaviour in asset prices suggests that linear models, such as the standard vector autoregressive model (VAR) or the vector error correction model (VECM), may not be the most appropriate tools of choice to examine long run relationships between asset prices as these models imply symmetric adjustments. As a result, nonlinear time series models have been receiving a growing interest in recent decades both from the theoretical and the empirical point of view, and many of these models have been used for examining the nonlinearity dynamic relationships between financial time series. Although the presence of nonlinear dependencies may suggest the inadequacy of linear models, it does not provide any insight into the appropriate functional form for the non-linear model. Several nonlinear methodologies have been presented in the time series literature, and a large number of studies have recently applied various versions of nonlinear models to look at cointegration relationships of economic and financial data. Some of the most frequently used nonlinear cointegration models include: nonparametric tests (Bierens, 1997, and Breitung, 2002), cointegration rank tests (Breitung 2001), threshold vector equilibrium correction models (TVECM) introduced by Balke and Fomby (1997) and further advanced by Hansen and Seo (2002), and Switching Transition Error Correction Models (STVECM) advanced by Rothman et al (2001) and Van Dijk, et al (2002).

Despite recent increasing interest in nonlinear studies in financial market co-movements, to the best of my knowledge the possibility of nonlinear relationships between industry or firm level prices has not been examined previously. Therefore, in addition to linear analysis, this thesis presents the first attempt to examine nonlinearity relationships between international industry sector indices. In this thesis, to examine nonlinear cointegration relationships between the US and the emerging countries (Brazil, Malaysia and South Africa) industry indices the rank test for nonlinear cointegration relationships, proposed by Breitung (2001), is used. The rank test for nonlinear cointegration relationships is based on the difference between the sequences of ranks, and the main advantage of it is that there is no requirement to be explicit with regard to the exact functional form of the nonlinearity. As in the case of linear analysis, the rank tests for nonlinear cointegration also follow the unit root tests. Therefore, as mentioned before, the rank test procedures for the nonlinear unit root, proposed by Breitung and Gourieroux (1997), are also applied for this study. The following section presents the testing methodologies of rank tests for nonlinear unit roots and cointegration relationships (rank tests), while the empirical results for the international industry sectors under study are reported in chapter seven.

5.4.2 Testing Nonlinear Unit Roots and Cointegration Relationships

5.4.2.1 Rank Tests for Nonlinear Unit Roots

As discussed earlier, most conventional (linear) tests, including unit-root tests, are based on the assumption of normally distributed errors. However, it is well known that the distributions of financial data exhibit much fatter tails than assumed normality. Moreover, several recent studies of nonlinearity, including Pippenger and Goering (1993), Balke and Fomby (1997), and Enders and Granger (1998), have casted doubt about the conventional tests for unit-roots and cointegration by showing they all have low power in the presence of asymmetric adjustment. In addition, other studies of nonlinear (STAR) models [i.e. Sollis, (2002), and Kapetanious et al. (2003)] have also shown that the adoption of linear stationarity tests is inappropriate for detecting mean reversion if the true data generating process (DGP) is in fact a stationary non-linear process. As mentioned above, to test nonlinear unit roots for international industry sectors, Breitung and Gourieroux's (1997) rank tests are employed in this thesis. The remainder of this subsection discusses the testing methodology of the rank tests.

Following Sehmidt and Phillips' (1992) score statistic, Breitung and Gourieroux (1997) proposed procedures for tests based on the ranks of the observations for testing the null hypothesis of the unit root. According to Breitung and Gourieroux (1997, p.8) the 'rank tests are robust against a wide class of outlier'. In their rank tests, Breitung and Gourieroux (1997) use the Sehmidt and Phillips (1992) score statistic for testing the null hypothesis of the unit root, which involves the following models

$$y_t + \beta_0 + \beta_1 y_{t-1} + \xi_t \qquad \text{with } \beta_1=0 \tag{5.20}$$

without trend stationary model, against the trend stationary model

$$y_t + \beta_o + \mu t + \beta_1 y_{t-1} + \xi_t \qquad \text{with } |\beta_1|=0 \tag{5.21}$$

Breitung and Gourieroux (1997) relax this assumption by allowing heteroskedastic or serially correlated errors, with the loss of the possibility of obtaining the exact null distribution. Schmidt and Phillips' (1992) score principal gives rise to the following statistic

$$\Phi_T = \frac{\sum_{t=2}^{T} x_t S_{t-1}}{\sum_{t=2}^{T} (S_{t-1}^2)} \tag{5.22}$$

To modify (and use) the score statistic defined in equation (5.22), Breitung and Gourieroux (1997) introduce a variable denoting a change of ranks in place of the observations of the variable y_t as

$r_{1,T} =$ *Rank* [of Δy_t *among* $\Delta y_1, \ldots\ldots \Delta y_T$] $- \frac{T+1}{2}$.

They then defined a rank counterpart of the score statistic as

$$\Phi_T^R = \frac{\sum_{t=2}^{T} r_{t,T} S_{t-1,T}^R}{\sum_{t=2}^{T} (S_{t-1,T}^R)^2} \tag{5.23}$$

Using the rank counterpart of the score statistic in equation (4.28) Breitung and Gourieroux proposed two testing procedures based on the ranks of the observed differences. First is the ‘uniform’ version of the score-type rank test statistic. Letting R_t be the uniform rank of the differenced observations, the uniform rank test statistic is presented as

$$\pi_t(Uni) = T^{-2} \sum_{t=1}^{T} \sum_{s=1}^{t} (\sqrt{12 \wp_{s,} T^{-1}})^2 \tag{5.24}$$

Where $\wp_{s,T} = R_{t,T} T^{-1}$ is the normalised rank. Another version suggested by Breitung and Gourieroux (1997) is based on the ‘inverse normal scores’ (INS) transformation of the ranks as follows

$$R_t^* = \Phi^{-1}(T^{-1} R_t + 0.5)$$

where $\Phi^{-1}(.)$ is the inverse of the standard normal cumulative distribution function. In the present analysis, following Li (2006), the INS version of the rank test statistic is modified as

$$\pi_t(\text{Ins}) = \sum_{t=1}^{T}{}^{-2}\left(\sum_{s=1}^{t} R_s^*\right)^2 \qquad (5.25)$$

Since the problems of non-normality, outliers, heteroscedasticity etc in financial data are well-known, an important property of the rank tests is that these tests are invariant with respect to these problems (Li, 2006, p.184) [66]. The critical values of $\pi_T(Uni)$ and $\pi_T(Ins)$ are given in Appendix B of Breitung and Gourieroux (1997).

5.4.2.2 The Rank Tests for Cointegration Relationships

In recent years, studies for nonlinear dynamic relationships in financial assets have been receiving increasing interest, and many empirical models have been proposed in the literature. In this thesis, to test nonlinear cointegration relationships among international industry sectors, rank test methodology developed by Breitung (2001) is adopted, and discussed in this sub-section. Several studies, including Li (2006), Onour (2008), and Haug and Basher (2009), have recently applied the rank tests technique to various financial fields in financial markets to test for non-linear cointegration relationships[67]. This approach takes the problems of unit-root tests into account, and as such can be considered more appropriate for financial data studies than most of other nonlinear models which require data series to be stationary. For a nonlinear relationship between ‘two real-valued time series’ Breitung (2001) proposes a bivariate model of the following format

[66] The inverse normal scores equation is adopted from Li (2006). However, Li’s presentation does not contain the negative square of the first summation.

[67] However, to the best of my knowledge no study has thus far employed this technique for sectoral or firm level co-movement tests. This thesis closely follows Li (2006) who employs this methodology for cross-market cointegrations between Australia, Japan, New Zealand, the UK and the US.

$y_t = h(z_t) + u_t$ (5.26)

where $y_t \sim I(1)$, and $h(z_t) \sim I(1)$. Under the null hypothesis of cointegration, u_t is assumed to be I(1), and under the alternative hypothesis of a cointegration relationship, u_t I(0). To mitigate the problems of unit-root tests detecting nonlinear cointegration, Breitung transformed the series by applying a rank transformation, formulated as

$f(y_t) - h(z_t) = u_t$ (5.27)

where, as before, the $f(y_t)$ and $h(z_t)$ are both I(1) series, but u_t is I(0), and the functions f() and h() are monotonically increasing.

In the above formulation, the zero integration of u_t, implies the existence of a nonlinear cointegration relationship between the y_t and z_t variables. However, since the sequence of ranks is invariant to a monotonic transformation of the original data, the behaviour of the f() and h() functions are unknown, that is, monotonically increasing or decreasing. In that case, one can construct the rank statistic by replacing the $f(y_t)$ and $h(z_t)$ with the rank transformation series $R_T()$, so that $R[f(y_t)] = R(y_t)$ and $R[h(z_t)] = R(z_t)$. It is assumed that, since y_t and z_t are I(1) series, then $R(y_t)$ and $R(z_t)$ will also be I(1) series. According to Breitung (2001) a bivariate nonlinear cointegration relationship can be tested by using a k-type and/or ξ-type statistic, which their testing procedures formulated as follows.

$$\kappa_T = T^{-1} \sup |d_t| \quad (5.28)$$

$$\xi_T = T^{-3} \sum_{t=1}^{T} d_t^2 \quad (5.29)$$

where d_t is the difference between R(y_{1t}) and R($y_{2\,t}$), and sup$|d_t|$ is the maximum value of $|d_t|$ for t = 1,2, …T. The tested null hypothesis of linear cointegration between y_t and z_t, is rejected when the results of the statistics are smaller than the critical values at the chosen level of significance, as tabulated in Breitung (2001, table 1)[68].

The test statistics in equations (5.28) and (5.29) are based on the assumption that the variables are independent, that is, uncorrelated. In many cases, however, it is possible that the y_t and z_t series are correlated. To mitigate the possibility of correlation between the variables, Breitung (2001) also proposes modified versions of the above test statistics. The modified test statistics are based on the size of the correlation and involve two cases. If the absolute value of the correlation coefficient is small but not near to zero, the test statistic is corrected as follows

$$\kappa_T^* = \frac{\kappa_T}{\sigma_{\Delta d}} \tag{5.30}$$

$$\xi_T^* = \frac{\xi_T}{\sigma^2{}_{\Delta d}{}^2} \tag{5.31}$$

where $\sigma_{\Delta d}^2 = T^{-2}\sum_{t=2}^{T}(d_t - d_{t-1})^2$.

On the other hand, if the absolute value of the correlation coefficient is high (close to 1) the test statistics are modified as follows

[68] Breitung (2001, p.333) provides further explanations of the κ and ξ statistics.

$$\kappa_T^{**} = \frac{\kappa_T^{*}}{\lambda_\kappa^\alpha\left(E\rho_T^R\right)} \quad (5.32)$$

$$\xi_T^{**} = \frac{\xi_T^{*}}{\lambda_\xi^\alpha\left(E\rho_T^R\right)} \quad (5.33)$$

where $E(\rho_T)$ is the expected correlation coefficient of the rank differences and is formulated as follows

$$\rho_T^R = \frac{\sum_{t=2}^{T}\Delta R_T(y_t)\Delta R_T(z_t)}{\sqrt{\left(\sum_{t=2}^{T}\Delta R_T(y_t)^2\left(\sum_{t=2}^{T}\Delta R_T(z_t)^2\right)\right.}} \quad (5.34).$$

However, as Breitung (2001, p. 335) states 'the test statistics κ^{**} and ξ^{**} have the same limiting distributions (and hence the same critical values) as κ^{*} and ξ^{*} respectively'. Breitung (2001, table 1) tabulates the critical values of equations (5.28) to (5.33).

In addition to the above test statistics, which are only for a bivariate model, Breitung (2001) also proposes multivariate rank test statistics for testing nonlinear cointegration relationships. A general nonlinear multivariate time series model, testing for nonlinear cointegration relationships, can be rewritten as $f_i(y_t) = h_i(z_{i,t})$, for i=1, 2,.k. As before, the series are assumed to be all I(1) series, and the functions () are monotonically increasing functions. If cointegration relationships exists then the difference between the series should be I(0). That is,

$$f_i(y_t) - h_i(z_{i,t}) = u_t, \text{ with } u_t \approx I(0) \quad (5.35).$$

As before, the sequence of ranks is invariant to a monotonic transformation of the original data series. Thus, replacing $h_i(y_{i,t})$ with $R_T[h_i(y_{i,t})]$ where $R_T[]$ is a kx1vector, Breitung (2001) proposed a multivariate rank statistic which is obtained from running a regression of $R_T(y_t)$ on $R_T[z_{i,t}]$ and then using the residuals to compute the following test statistic

$$\Xi[k] = T^{-3} \sum_{t=1}^{T} \left(\hat{u}_t^R\right)^2 \qquad (5.36)$$

where $\hat{u}_t$ = $R_T(y_t) - \beta R_T[z_{i,t}]$, and β is the least squares estimate from the regression, and *k* is the number of long-run relationships to be tested. To account for a possible correlation between the series, the above test statistic is adjusted and rewritten as

$$\Xi^*[k] = \frac{T^{-3} \sum_{t=1}^{T} \left(\hat{u}_t^R\right)^2}{\sigma_{\Delta\hat{u}}^2} \qquad (5.37)$$

Where $\sigma_{\Delta\hat{u}}^2 = T^{-2} \sum_{t=2}^{T} \left(\hat{u}_t^R - \hat{u}_{t-1}^R\right)^2$.

Table 1 of Breitung (2001) provides the critical values of equation (5.37) with a sample size of 500, which is close to the sample size of the present study. The null hypothesis of linear cointegration between the variables is rejected if the test statistic is smaller than their respective critical values. The empirical analysis of this research will be utilising both versions of Breitung's statistics for bivariate and multivariate tests of nonlinear cointegration relationships between the US and the emerging countries industry sector prices.

5.4.2.3 The score test for neglected nonlinearity

Although the rank tests of the last subsection can be used to detect the presence of long-run or cointegration relationships, it is less straightforward to detect the nonlinearity of such cointegration relations. Therefore, it is important to know if the detected relationships between the variables under study (industry sector prices in this case) are indeed nonlinear. As a result, this thesis applies Breitung's (2001) rank procedure to test for the presence of neglected non-linearity in linear cointegration equations. This subsection presents the testing methodologies for the presence of neglected non-linearity. Assuming a linear relationship model, Breitung (2001) suggests a bivarate neglected nonlinearity of the following format

$$y_t = \alpha + \beta z_t + f^*(z_t) + u_t \qquad (5.38)$$

where $\alpha + \beta_1 z_t$ is the linear part of the relationship, $f^*()$ describes the non-linear part of the model, and u_t is an error term. Under the null hypothesis of only a linear relationship, the $f^*()$ is assumed to be zero for all t. Assuming z_t to be exogenous and white noise to be u_t, and using the rank transformation, $[R_T(z_t)]$, Breitung then proposes a score test statistic ($T \times R^2$) computed from the following estimation`

$$\breve{u}_t = c_0 + c_1 z_t + c_2 R_T(z_t) + \varepsilon_t \qquad (5.39)$$

where $\breve{u}_t$ is from the least squares estimate of regressing y_t on z_t. Since the variables z_t and $R_T(z_t)$ are nonstationary, applying the usual asymptotic theory to derive the limiting null distribution of the test statistic is a problem. However, as Breitung (2001, theorem 3) shows, under the null hypothesis of $c_2 = 0$ the score statistic is asymptotically Chi-square distributed. To accommodate the endogeniety of regressors and the serial correlation of errors, Breitung proposes estimating the DOLS regressions of Stock and Watson (1993) and the modified null hypothesis of the linear relationship as follows

$$y_t = \eta_0^* + \sum_{j=1}^{\infty} \gamma_j y_{t-j} + \eta_1^* z_t + \sum_{j=-\infty}^{\infty} \lambda_j^* \Delta z_{t-j} + \upsilon^* \qquad (5.40).$$

Next, we regress the residuals, υ^{*}, of equation (5.40), on the regressors of the same equation as well as on the $R_T(z_t)$ as follows

$$\upsilon^{*} = \eta_0^{*} + \sum_{j=1}^{\infty} \gamma_j y_{t-j} + \eta_1^{*} z_t + \sum_{j=-\infty}^{\infty} \lambda_j^{*} \Delta z_{t-j} + R_T(z_t) + \tau_t \qquad (5.41).$$

The lagged and differenced parts are added to accommodate the endogeniety of the regressors and the serial correlation of the residuals, (v_t). Finally, a nonlinear cointegration relationship is tested by choosing appropriate lag parameters, and forming the score statistic (TxR^2). Once again, Breitung (theorem 3) indicates that under the null hypothesis of a non linear cointegration relationship, this score statistic is also asymptotically Chi-square distributed.

The above approach for testing neglected nonlinearity cointegration is only for bivariate relationships. However, as Chang et al (2001, p.4) state, 'in nonlinear regressions with integrated time series, the asymptotic theory for multiple regressions turns out to be different from that of simple regression in a nontrivial way'. In this thesis, following the lead of Li (2006), the investigation for neglected nonlinearity cointegration is extended to a multivariate framework. Assuming a set of non-stationary k-variables time series, $y_{it} = (y_{1t}, y_{2t}, \ldots y_{kt})$, with t = 1, 2, ……n, a general nonlinear multivariate model of *k* variables can be formulated as

$$y_{i,t} = f_i^{*}\left(y_{t-p}, z_{t-q}, \theta_t\right) + u_t \qquad (5.42)$$

where y_t is a (kx1) random vector, $f^{*}(\cdot)$ are unknown real-valued functions that can be measured and which depend on the (ψx1) parameter vector θ_t. The term u_t is $_t$ is also a (kx1) vector of random disturbances, which is serially uncorrelated but can be cross-correlated at lag zero and identically distributed randomly. Following Blake and Kapetanios (2008), a generalisation of Breitung's bivariate neglected nonlinear model in (5.38) is presented as

$$y_t = \mu + \sum_{j=1}^{n} \alpha_j z_t + f_j^*(\beta, z_t) + u_t \qquad (5.43)$$

where z_t is a kx1 vector of integrated regressors generated by $z_t = z_{t-1} + \xi_t$, and $f(\cdot)$ is the nonlinear elements of the model, which is an unknown function. Different approaches (e.g. Lee et al, 1993) are used in the literature to approximate the unknown function, f(.). Thus, using the generic form of a neural network approximation to nonlinear functions, as in Blake and Kapetanios (2008), the nonlinearity framework of equation (5.43) is written as

$$y_{i,t} = \mu + \sum_{j=1}^{n} \alpha_j z_t + \sum_{j=1}^{n} h_j [f_j^*(\beta, z_t)] + u_t \,. \qquad (5.44)$$

Next, following the lead of Li (2006) and substituting the summation of the f_j^* function with the rank transformation, R_T, the above generalisation is re-written as

$$y_{i,t} = \mu + \sum_{j=1}^{n} \alpha_j z_{j,t} + \sum_{j=1}^{n} h_j [R_T(\beta, z_t)] + u_t \qquad (5.45)$$

To test for nonlinearity within the rank transformation framework, Li (2006) first proposes the following dynamic expansion for the linear part of relationship

$$y_{i,t} = \mu_0 + \sum_{j=1}^{q} \mu_j y_{t-j} \sum_{j=1}^{n} \alpha_j z_{j,t} + \sum_{j=1}^{n} \sum_{j=-q}^{q} \pi_j \Delta z_{j,t-j} + \nu_t \,, \quad j = 1, 2, \ldots k \qquad (5.46)$$

As before, a test for nonlinear cointegration involves estimating the score test statistic (*TxR*^{2}) after regressing the residuals (ν_t) of equation (5.46) on the regressors of the same equation, and the summation of rank transformations as follows

$$\nu_t = \vartheta_0 + \sum_{j=1}^{q} \vartheta_j y_{t-j} \sum_{j=1}^{n} \theta_j z_{j,t} + \sum_{j=1}^{n} \sum_{j=-q}^{q} \lambda_j \Delta_{j,t-j} + \sum_{j=1}^{n} [\beta_j R_T(z_{j,t})] + \pi_t \qquad (5.47)$$

A null test of $\beta_1 = \beta_2 = \beta_j = 0$ provides a test of no nonlinearity in the cointegrating relationship. To put this differently, a significant ($T \times R^2$) formed from the above regression indicates that at least one is non-zero, which can be taken as evidence of nonlinearity in the cointegration relationship. As in the bivariate case, the score statistic is still asymptotically Chi-square distributed under the null of a joint hypothesis with degrees of freedom equal to the number of elements in β_j.

5.5 Linear and Nonlinear Causality test between the US and Emerging Markets industry sectors

5.5.1 Background

To investigate the causality nature between a set of economic variables, or to examine whether past information of one series could contribute to the prediction of another series, numerous empirical approaches have been used in the conventional linear vector auto-regression (VAR) frameworks. These include: standard Granger causality (Granger, 1969), Sims' version of Granger causality test (Sims, 1972, 1980), the Error Correction Model (ECM) of Engle and Granger, 1987), the VECM (Johansen, 1995), and the long-run causality test suggested by Toda and Yamamoto (1995). As a result, most studies on international stock markets have previously focused on the linear causality relationships between national markets. Specifically, if the time series are non-stationary and co-integrated, the Granger Causality tests are based on the vector error correction model (VECM) within the maximum likelihood approach of cointegration. For example, as has been pointed out by King, Plosser, Stock and Watson (1991), and Toda and Phillips, (1993), the maximum likelihood approach provides an efficient method of testing causality.

Although traditional linear Granger causality tests are effective in uncovering linear causal relations, their ability can be low for nonlinear causal relationships (Hiemstra and Jones, 1994). In other words, there may be (hidden) nonlinearity causality relationships which conventional linear tests might not be able to account for. As a result, there has been growing interest in testing nonlinearity relationships between financial variables in recent decades. Several nonlinear causality methodologies have been suggested in the literature of applied econometrics. The most commonly used nonlinear causality method for financial markets is the nonparametric statistical method, or 'modified approach', introduced by Baek and Brock (1992). Baek and Brock generalizes the BDS (1992) approach of testing general nonlinearity dependence. Hiemstra and Jones (1994) further advanced the modified approach by relaxing the *IID* assumption, and used their model to find bi-directional causality between changes in trading volume on the New York Stock Exchange and returns from the Dow Jones Industrial Average Index[69]. Under the modified approach, testing for non-linear Granger causality is implemented using the residual series from a vector auto regression VAR model rather than the initial returns. An alternative technique for modelling nonlinear causality which has been active recently especially in medical research, is the bivariate noisy Mackey-Glass (M-G) model proposed by Kyrtsou and Terraza (2003, Kyrtsou and Labys (2006) and further extended by Varsakelis and Kyrtsou (2008). The (M-G) model assumes that a small change in one variable can produce a multiplicative and disproportionate impact on the other variables in the presence of nonlinearity[70].

[69] Some of the many studies that have used the Baek and Brock (1992), and Hiemstra and Jones (1994) methodology for non-linear causality analysis for international stock markets include: Brooks and Henry (2000) Chen and Lin (2004), Kanas (2005), Ozdemir and Cakan (2007), Beinea et al (2008), and Chiang et al (2010).

[70] Many other nonlinear causality methodologies have been suggested in the literature. Bell et al (1996) proposed a procedure for causality testing between two univariate time series using non-parametric regression. Skalin and Teräsvirta (1999) have developed a nonlinear Granger causality test based on the STAR model. Rothman et al (2001) extended this approach to the 'Switching

In this thesis, both linear and non-linear causality linkages are tested for in the international industry sectors. Testing nonlinear causality relationships for industry sector indices is an empirical novelty of this thesis. First, the traditional Granger causality tests based on the bivaraite VAR setting are conducted. The traditional Granger causality test is designed to detect only linear causality, and therefore is very poor in detecting nonlinear causal relationships (Hiemstra and Jones, 1994). However, testing for nonlinear Granger causalities is much more difficult and the statistical functions are still underdeveloped in econometric applications. To determine the nonlinear causal relationship between the international industry sector returns, this thesis applies the bivariate noisy Mackey-Glass (M-G) model in its symmetric and asymmetric versions[71]. The following two subsections present respectively the linear and nonlinear Granger causality methodologies (in their symmetric approaches), while their empirical results are reported in chapter eight (the empirical results of dynamic linkages).

5.5.2 VAR model and linear Granger causality

An important empirical undertaking of this thesis is to examine the causality and dynamic transmissions. For a set of time series variables, a vector auto-regression model of lag order p , VAR(p), can be formulated as of the following

$$y_t = \mathrm{A}_{i0} + \sum_{k=1}^{p} \mathrm{A}_{ip} x_{t-p} + \varepsilon_t \qquad (5.48)$$

where $A_{i\mathbf{0}}$ are the intercept parameters and nx1 dimentional, and A_{ip} (A_1 through A_p) are the *(n×n)* coefficient matrices, which are given respectively by

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Transition Vector Error Correction Models (STVECM) methodology. Chen et al (2004) extended Granger's idea to nonlinear situations by proposing a procedure based on a local linear approximation of the nonlinear function. Bell et al (1996) proposed a procedure for causality testing between two univariate time series using non-parametric regression. Peguin-Feissolle and Terasvirta (1999) proposed a statistical method based on a Taylor expansion of the nonlinear model. Peguin-Feissolle et al (2007) further extended this approach. Kernel Method adopted for nonlinear Granger Causality by Marinazzo et al (2008), while Ancona et al (2004) proposed nonlinear Granger causality based on the kernel auto-regression scheme, instead of a linear auto-regression.

[71] See next section for discussion of the asymmetric causality tests.

$$A_{i0} = \begin{bmatrix} a_{10} \\ a_{20} \\ \vdots \\ a_{k0} \end{bmatrix} \quad A_{ip} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} \end{bmatrix}$$

and ε_t is also an *(n×1)* unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix, Ω, given by

$$\begin{bmatrix} \sigma_{11}^2 & \sigma_{12}^2 & \cdots & \sigma_{1k}^2 \\ \sigma_{21}^2 & \sigma_{22}^2 & \cdots & \sigma_{2k}^2 \\ \vdots & \vdots & & \vdots \\ \sigma_{k1}^2 & \sigma_{k2}^2 & \cdots & \sigma_{kk}^2 \end{bmatrix},$$

Furthermore, the series of [y_t] and [x_t] are assumed to be weakly stationary. The test of x_t is not Granger causing y_t, and vice versa, is thus a test of linear hypothesis in the linear model. An alternative method of obtaining further information regarding the relationships among the variables in the model is via the dynamics transitions of impulse response functions and variance decomposition analysis. The remainder of this subsection presents the testing methodology of the conventional linear Granger causality.

5.5.2.1 Linear Granger Causality

A linear causality test between two stationary series was first proposed by Granger (1969). The identification of the direction of Granger causality for a given series (x_t) and y_t), is based on the predictions of future values of the series using information from a collection of p past values of the same series. To put it differently, Granger causality tests 'the prediction ability of time series models, an index causes another index in the Granger sense if past values of the first index explain the second, but past values of the second index do not explain the first' Worthington and Higgs (2004, p.5). This subsection presents an overview of the conventional linear Granger causality test which will be implemented in the thesis. Causality tests for two price or return series [y_t and x_t] from similar sectors of two given markets can be written in terms of the following bivariate VAR representation

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \varepsilon_t \quad (5.49a)$$

$$x_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \varepsilon_t \quad (5.49b)$$

where y_t and x_t are stationary variables and *p* and *q* are the lag lengths of y_t and x_t respectively obtained by using one of information criteria procedures, and ε_t and ε_t are the vectors of error terms.

In a stationary time series, tests for the causality linkages between variables can be accomplished with the above standard Granger causality formulation of VAR. However, as Engle and Granger (1987) show, if variables are non-stationary and are cointegrated, a VAR in first differences will be miss-specified. In that case, the VAR model is augmented with a one-period lagged error- correction term, obtained from the cointegrated model. That is, the VAR model is augmented with a one-period lagged error- correction term which is obtained from the cointegrated model which accounts for any long-term information essentially lost through differencing (King, Plosser, Stock, and Watson (1991) and Toda and Phillips (1993))[72]. As a result, a popular method for testing the causality relationships between economic and financial time series has been to use the vector auto regression error-correction model (VECM) with cointegration methodology

[72] An alternative approach for testing causality which will be discussed later is the integrated variables approach proposed by Toda and Yamamoto (1995).

(Johansen, 1988, 1991, and Johansen and Juselius, 1990). In other words, if cointegration relationships between the variables exist, the above Granger causality tests are examined within the framework of an error correction model (ECM) as follows

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \Theta e_{t-1} + v_t \quad (5.50a)$$

$$x_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \Theta^* e_{t-1} + v_t^* \quad (5.50b)$$

where the terms (e_{t-1}) are the lagged residuals from equations (5.49a) and (5.49b), and the Θ and Θ^* are the error correction terms derived from the long-run cointegrating relationships. The error correction term can be estimated using the residuals from a cointegrating regression. In either case, the null hypothesis in the Granger causality test is that y_t does not cause x_t, which represented by $H_0 : \beta_1 = \cdots \beta_j = 0,$ and the alternative hypothesis is $H_1 : \beta_j \neq 0$ for at least one j. The linear Granger causality test has been constructed in the context of an *n* dimensional of the VAR (*p*) model.[73]

There are several approaches used for testing the significance of the elements of matrices A_k. For instance, , given assumptions of covariance stationarity on y and x, the computation of F statistics can be performed by considering the ratio of the residual variances, described in Geweke (1982). An alternative approach for performing multivariate Granger-causality tests for VAR cointegrating systems is to apply the methodology proposed by Dolado and Lutkepohl (1996). Dolado and Lutkepohl (1996) suggest a method which leads to Wald tests with standard

[73] Tjøstheim (1981) gave a formulation of the concept of Granger causality in general multivariate framework and developed a test procedure for causality in multivariate autoregressive series. In a more general context, measures of linear dependence and feedback between multivariate time series were defined by Geweke (1982). Other recent papers in multivariate causality methodology include Östermark, (1998), Gourévitch et al (2006), and Bai et al (2010).

asymptotic χ^2 distributions with degrees of freedom equal to the number of restrictions, without the need for the usual procedure of estimating a first order differenced VAR if variables are known to be I(1) with no cointegration, and an error correction model if they are known to be cointegrated[74]. The Wald test statistics correspond to the standard F test. Also, to identify multivariate Granger causality relationships among the variables, one could use the likelihood ratio (LR) test suggested by Sims (1980) and discussed in section two, or the Lagrange multiplier (LM) test. To determine an appropriate lag order for the vector autoregressive model, numerous lag selection strategies, including information criteria procedures such as Akaike (AIC), Schwarz (SC), Hannan-Quinn (HQ), the Forecast Prediction Error (FPE), and the Wald test, or the likelihood ratio (LR) test, have been discussed in the literature[75]. In the conventional linear Granger causality test, no distinction is made between the positive and negative shocks on the causality relationships. In this thesis, following Hatemi (2012a), asymmetric causality tests (positive and negative) are conducted. Hatemi's testing procedures for linear Granger causality are discussed in the next section while empirical results will be reported in chapter eight.

5.5.2.2 Time-varying Granger causality relationships: A Rolling Window Analysis

Another way to examine the causality relationships between the industry sector returns is to test whether the causal linkages have been changing over time. To do this in this study conducts rolling Granger causality analysis. By applying the rolling regression method, it might be possible to detect changes in the Granger causality, which indicates structural breaks in the causality linkages. . Previously, very few studies, namely Aaltonen and Östermark (1997), Hill (2007), and Hernandez and Torero (2010), have applied rolling tests of Granger causality relationships to other fields of empirical studies. However, to my awareness no study has so far applied this for micro analysis of stock market relationships. The

[74] In the VAR framework, the Wald test for testing the Granger causality will have non-standard asymptotic properties if the variables considered in the VAR are integrated or cointegrated.

[75] Another approach for choosing optimal lag orders, which will be presented in the next section, was proposed by Hatemi (2003).

testing procedures and graphical presentations of the rolling Granger causality relationships between US and emerging countries industry sectors will be presented in chapter eight.

5.5.3 Nonlinear Causality between the US and the emerging countries industry sector returns

As mentioned before, numerous studies have previously employed the conventional Granger causality test, which is based on the assumption that relationships between variables are linear. However, as noted earlier, the nonlinear behaviour of financial time series is well documented in the literature. For example, among others Hinich and Patterson (1985), Scheinkman and LeBaron (1989), Brock et al (1991), and Hsieh (1991) have all documented evidence of significant nonlinear dependence in stock returns. In addition, as noted by Granger (1988), univariate and multivariate nonlinear models represent the proper way to model a real world that is almost certainly nonlinear. Therefore, the linear Granger causality test results should be viewed as merely preliminary analysis. This thesis extends previous studies that have examined nonlinear causality for international stock markets by investigating nonlinearity causality relationships among global industry sectors, and applies the bivariate noisy Mackey-Glass (M-G) model for nonlinear Granger causality. Before testing the M-G model for nonlinear causality relationships between industry sectors in the study, the dependence behaviour of the individual series are tested. The following subsection discusses several test statistics for the nonlinearity behaviour which will be applied to the international industry sector returns.

5.5.3.1 Testing for nonlinear dependencies

Several statistical tests for non-linear dependence have been proposed in the literature including, among others, the McLeod & Li (1983) Q test, Engle's1982) LM ARCH effect, the BDS test, named after Brock, Dechert, Scheinkman and LeBaron (1996), Tsay (1986), Hinich & Patterson (bicovariance) (1985), Ramsey's (1969) Reset tests, and the Windows test of (Hinich and Patterson, 1995), and more recently model selection criterion (Pena and Rodriguez, 2005)[76]. As Tsay (2005, p.183) states, 'because nonlinearity may occur in many ways, there exists no single test that dominates the others in detecting nonlinearity'. A common assumption of many nonlinear tests is that once any linear dependence is removed from the data series, any remaining dependence should be due to a non-linear data generating mechanism. Although these tests have been extensively applied in the literature of financial markets, there appears to be less action in firm or industry studies. To check nonlinear dependencies for industry sector returns, this thesis first employs the McLeod and Li (1983) test for squared residuals, the test for ARCH effect (Engel,1982) and the BDS test for randomness independence or nonlinear dependence (Brock et al, 1996) using the residuals of autoregressive AR (p) modelling.

The McLeod and Li (1983) test: The McLeod and Li (1983) test is similar to the Ljung -Box (1978) Q test in the sense that it is a test based on the autocorrelation of the residuals, or the squared residuals of the AR or ARMA model, to check for model adequacy and nonlinear dependencies. In other words, the Ljung-Box modified Q^2 test for the squares of the residuals provides a convenient way for performing the McLeod and Li (1983) test for nonlinearity. As several recent studies on stock return markets, such as Booth et al (1992), Ramchand and Susmel, 1998), and others have indicated, non-linear dependencies may be due to autoregressive conditional heteroskedasticity. Furthermore, according to Brooks (1996, p. 310), the McLeod and Li (1983) test is 'relatively powerful in detecting departures from linearity which may be attributed to the presence of ARCH effects'[77]. The Ljung-Box Q-statistic of the McLeod-Li test is given by

$$Q(m) = \frac{N(N+2)}{N-k}\sum_{k=1}^{m}\hat{r}_k^2(e^2) \qquad (5.51)$$

[76] See, among others, Brooks (1996), Tsay (2005), and more recently Kyrtsou and Serletis (2006) for many other univariate nonlinear tests.

[77] Tsay (2005) makes a similar argument

where N is the sample size and *m* is an appropriately chosen number of autocorrelations used to the test.

The term $\hat{r}_k^2(e^2)$ is the autocorrelation of the squared residuals obtained fitting the AR (ARMA or GARCH) model to the return series. As Brooks (1996) notes, the McLeod and Li (1983) test (represented here by the Ljung-Box modified Q^2 test) has limited power compared to other nonlinear alternatives. Thus, to check the robustness of the McLeod and Li (1983) test results on the squared residuals, the Arch effect test for conditional heteroscedasticity and the BDS test for randomness or nonlinearity are also implemented. For further analysis, the Engel (1982) test for ARCH effect and the BDS test are then applied to the same statistical tests with the residuals of the GARCH (1:1)-AR(p) filtering procedure. The testing methodology of the ARCH effect and the BDS test statistics are summarised as follows.

The ARCH Effect test: A nonlinear test which several studies (among others, Brooks, 1996, and Rodrıguez and Ruiz 2005) have used is the ARCH effect, originally proposed by Engle (1982) and also known as 'conditional heteroscedastic'. The heteroscedasticity specification was motivated by the observation that in many economic financial time series, the magnitude of residuals appeared to be connected to the magnitude of recent previous residuals. The ARCH test is computed from running a regression of the squared residuals of a fitted model (i.e. AR) on constant plus lagged squared residuals as follows

$$u_t^2 = \alpha_0 + \sum_{t=1}^{p} \alpha_k u_{t-1}^2 + \varepsilon_t \qquad (5.52)$$

The ARCH test is a Lagrange multiplier (LM) test which can be defined as $LM = TR^2$ for autoregressive conditional heteroscedasticity (ARCH) in the squared residuals of the fitted model (4.3). Under the null hypothesis that there is no ARCH effect: $a_1 = a_2 = a_k = 0$, the test statistic is given by

$$LM = T.R^2 \approx \chi^2(p) \qquad (5.53)$$

where T is the sample size and R^2 is computed from the regression (5.52) using estimated residuals, and the null hypothesis is rejected if the computed valued of TR^2 is large. The LM test for ARCH effect can also be used as a general test for possible nonlinear dependences in the data series.

The BDS Test: The BDS statistic is a portmanteau which is derived from the correlation integral and has its origins in previous work on deterministic nonlinear dynamics and chaos theory in financial series by Scheinkman and LeBaron, (1989), Hsieh, (1991), Willey (1992), and Sewell et al (1993). It can be used for testing against a variety of possible deviations from linear independence or non-linear dependencies. The BDS test is often applied to a series of estimated residuals to check if the residuals are independent and identically distributed (*iid*). The BDS test can be applied either to the raw returns or directly to the residuals of any time series model (AR, ARMA or GARCH)[78]. According to Brock et al (1996), the BDS test is not just a test of nonlinearity, but can also be a good test of model specification. The formulation of the BDS test statistic involves several steps. First, assuming a scalar time series $\{x_i\}$, i=1; 2; . . . ;N, an *m*-dimensional or historical space of the series is presented as

$$x_i^m = (x_i, x_{i+t}, ..., x_{i(m-1)t}) \qquad (5.54)$$

where i=1; 2; . . . ;N-*m,* and *t* is the index lag or time delay. Second, the correlation integral at the embedding dimension *m* is defined as

$$C_m(\delta) = \frac{2}{N_m(N_{m-1})} \sum_{i<j} \lambda_\delta(x_i^m, x_j^m) \qquad (5.55).$$

[78] Alternatively, one can apply it to the logarithms of squared standardized residuals

where *N* is the size of the data sets, λ_{δ} is an indicator function that equals one if $\| x_i^m - x_j^m \| < \delta$, and zero otherwise. In descriptive terms, as Tsay (2005, p. 185) points out, 'the correlation integral measures the fraction of data pairs of $\{X_t\}$ that are within a distance of δ from each other'. Next, under the assumption of *IID*, the BDS test statistic is computed as follows

$$C_m(\delta) = \frac{\sqrt{N\left\{C_m(\delta) - C_1(\delta)^m)\right\}}}{\sigma_m(\delta)} \qquad (5.56)$$ [79]

where $C_m(\delta) = 4\left(N^m + 2\sum_{i=1}^{m-1} N^{m-i}C^{2i} + (m-1)^2)*C^{2m} - m^2NC^{2m-2}\right)$.

An important advantage of the BDS test is that it is a statistic which requires no distributional assumption on the data to be tested. Similar to other nonlinear tests, the data are also usually bleached through linear filtering to obtain new series whilst conducting the BDS test.

5.5.3.2 The Mackey-Glass (M-G) model of nonlinear causality relationships

As mentioned before, this research investigates the nonlinear causal bivarite noisy Mackey-Glass (M-G) model proposed by Kyrtsou and Labys (2006) and Varsakelis and Kyrtsou (2006), and further extended by Hristu-Varsakelis and Kyrtsou (2008). According to the authors, the main advantage of the M-G approach for nonlinear causality over the conventional VAR model is that it is better able to capture more complex dependent dynamics in a time series[80]. In

[79] Brooks (1996) and Tsay (2005) contain more details on these steps.

[80] The Mackey-Glass model, which is based on mathematical studies of delay-differential equations, can be traced back to Mackey and Glass (1977) and Glass and Mackey (1979). In its earlier applications, the Mackey and Glass model was used to illustrate the appearance of complex dynamics in physiological control systems.

addition, the M-G nonlinear causality model allows the separation of the effects to either negative or positive values of the independent variable on the dependent variable. In its symmetric version, it assumes an underlying process with a special type of nonlinear structure, known as the bivariate noisy Mackey-Glass (MG), which can modelled as follows

$$y_t = \alpha_{11}\frac{x_{t-\tau_1}}{1+x_{t-\tau_1}^{c_1}} - \delta_{11}x_{t-1} + \alpha_{12}\frac{y_{t-\tau_2}}{1+y_{t-\tau_2}^{c_2}} - \delta_{12}y_{t-1} + \eta_1; \eta \approx N(0,1) \quad (5.57)$$

$$x_t = \alpha_{21}\frac{x_{t-\tau_1}}{1+x_{1,t-\tau_1}^{c_1}} - \delta_{21}x_{t-1} + \alpha_{22}\frac{y_{t-\tau_2}}{1+y_{t-\tau_2}^{c_2}} - \delta_{22}y_{t-1} + \eta_t; \eta \approx N(0,1) \quad (5.58)$$

Where y_t and x_t are a pair of related time series variables, α and δ in models (5.57) and (5.58) are the parameters to be estimated, τ_i represent the delay parameter, and c is a constant. The parameters τ_1, τ_2, c_1, and c_2 are selected before implementing the M-G model. The maximum log likelihood and/or the Schwarz information criterion (SIC) is used to determine the optimal delay integers (τ_1, τ_2).

The M-G nonlinear causality test attempts to test whether the past values of a variable such as y_t have predictive non-linear effect (of the type $\frac{y_{t-\tau_2}}{1+y_{t-\tau_2}}$) on the current value of another variable, x_t, and vice versa. Statistically significant M-G terms in a pair of series suggest nonlinear feedback as the generating mechanism of the interdependences between y_t and x_t.

Essentially, 'the M-G test is similar to the linear Granger causality test, except that the models fitted to the series are MG processes based on variable transformations', (Hristu-Varsakelis and Kyrtsou, 2008, p.2). As in the linear case, one applies ordinary least squares to estimate the parameters of an M-G model 'that best fits the given series'. Next, given assumptions of covariance stationarity on y and x, one can apply the conventional F- statistic (as in the case of linear Granger causality test) of the following format.

$$S_f = \frac{(S_c - S_u)/k}{S_u/(N-m-1)} \approx F_{k,N-m-1} \quad (5.59)$$

The null hypothesis that y does not M-G cause x is α_{12} =0. To test the reverse causality relationship (from x to y), a second M-G model is estimated, under the constraint α_{22} =0. The null hypothesis is rejected when the F-statistic exceeds the critical value at the conventional critical levels. Kyrtsou and Labys (2006) and Varsakelis and Kyrtsou (2008) provide more details and neater expositions of the M-G Model. As Hristu-Varsakelis and Kyrtsou (2008) pointed out, the M-G model allows separation of the effects of either negative or positive values of the independent variable on the dependent variable. Therefore, to examine the impact of a positive or negative shock, the asymmetric version of the M-G model of nonlinear causality will also be implemented. Asymmetric nonlinear causality is discussed in the next section, while the testing procedure of the M-G model and the empirical results will be reported in chapter eight.

5.6 Asymmetric tests for linear and nonlinear Granger causality relations

5.6.1 Background

As mentioned before, a major of objective of this thesis is linear and nonlinear causality analysis of the interdependence among the US and the emerging countries industry sectors. The causality analyses are implemented using symmetric and asymmetric tests. The testing methodology of symmetric causality, based on the conventional VAR model and the bivariate noisy Mackey-Glass (M-G) model for nonlinear causality, has been discussed in the previous section. To examine further the causality linkages between the industry sector indices and the diversification implications, linear and nonlinear Granger causality tests are extended through investigations of asymmetric causality analysis[81]. In the real world, whether through information phenomenon or from another reason, the potential for asymmetry exists which can induce asymmetric causal effects. In the theory of economics, Akerlof (1970), Spence (1973), and Stiglitz (1974) have presented arguments for asymmetric effects. To the best of my knowledge, asymmetric linear and nonlinear Granger causality analysis in industry sector indices has not been reported in the literature. Following Hatemi (2012a) and Hristu-Varsakelis and Kyrtsou (2008), this section presents a discussion of testing for asymmetric linear and nonlinear Granger causality analysis.

5.6.2 Asymmetric Linear Granger Causality

The conventional Granger-causality (GC), Granger (1969, 1988), has been an important tool that has been much used in empirical macroeconomics and empirical finance studies. The Granger causality test examines the existence of lead-lag relationships between sectors, and whether one market's sectors index helps another's sector index forecasting. Nevertheless, as mentioned earlier, there is no distinction possible between the causal impact of positive and negative shocks in the conventional Granger causality. As discussed in the subsection 5.4.1, various arguments, including the asymmetric information phenomenon, have been presented in the literature for the possibility of asymmetric causal effects. Hatemi (2012a) proposed asymmetric (linear) Granger causality 'in the sense that positive and negative shocks may have different causal impacts'. As Hatemi (2012a, p. 274) states 'separating the impact of positive shocks from negative ones is important, especially in the financial markets, because people tend to react more to negative shocks than to positive ones even in cases when the size of the shock is the same in absolute terms'. Therefore, following Hatemi (2012a), the possibility of asymmetric (positive or negative) causal relationships between the industry sectors under study is also investigated. Assuming a causal

[81] The asymmetric character of returns and the underlying correlations in financial markets have previously been examined in the literature (see Hatemi, 2012a, for citations). Also, see Hatemi-J for further discussions of theoretical citations.

relationship between two integrated variables, y_t and x_t, Hatemi proposed a random walk process of the following format

$$y_t = y_{t-1} + \xi_{1t} = y_{1,0} + \sum_{i=1}^{t} \xi_{1i} \tag{5.60}$$

$$x_t = x_{t-1} + \xi_{1t} = x_{1,0} + \sum_{i=1}^{t} \xi_{2i} \tag{5.61}$$

Where $y_{1,0}$ and $x_{2,0}$ represent initial values, t =1, 2,---,T is the sample series, and the denotations ε_{1i} and ε_{2i} stand for the error terms. Hatemi then defined positive and negative shocks respectively as $\xi_{1i}^{+} = \max(\xi_{1i}, 0), \xi_{1i}^{-} = \min(\xi_{1i}, 0)$, and $\xi_{2i}^{+} = \max(\xi_{2i}, 0), \xi_{2i}^{-} = \min(\xi_{2i}, 0)$. These shocks can then be expressed as $\xi_{1i} = \xi_{1i}^{+} + \xi_{1i}^{-}$ and $\xi_{2i} = \xi_{2i}^{+} + \xi_{2i}^{-}$, and equations (5.60) and (5.61) as

$$y_t = y_{t-1} + \xi_{1t} = y_{1,0} + \sum_{i=1}^{t} \xi_{1i}^{+} + \sum_{i=1}^{t} \xi_{1i}^{-} \tag{5.62}$$

$$x_t = x_{t-1} + \xi_{1t} = x_{1,0} + \sum_{i=1}^{t} \xi_{2i}^{+} + \sum_{i=1}^{t} \xi_{2i}^{-} \tag{5.63}$$

Hatemi then defined the positive and negative shocks in a cumulative format $y_t^{+} := \sum_{i=1}^{t} \xi_{1i}^{+}, y_t^{-} := \sum_{i=1}^{t} \xi_{1i}^{-}$ and $x_t^{+} := \sum_{i=1}^{t} \xi_{2i}^{+}, x_t^{-} := \sum_{i=1}^{t} \xi_{2i}^{-}$.

As Hatemi (2012a, p. 3) states out, ‘each positive as well as negative shock has a permanent impact on the underlying variable’. To apply positive and negative shocks for asymmetric (positive and negative) causal relationships between the two vector series (y_t, x_t), the VAR model in equation (5.48) can be re-written as

$$y_t^+ = A_0 + \sum_{k=1}^{p} \mathrm{A}_{i\,p} x_{t-p}^+ + v_{1t}^+ \qquad (5.64)$$

$$y_t^- = A_0 + \sum_{k=1}^{p} \mathrm{A}_{i\,p} x_{t-p}^- + v_{2t}^- \qquad (5.65)$$

A similar representation holds for the other variables. To determine the optimal lag order, following Hatemi-J (2003), Hatemi-J.(2012a) adopted the following information criterion

$$HJC = \ln(/\,\hat{\Omega}_i\,/) + i\left(\frac{n^2 \ln T + 2n^2 \ln(\ln\ T)}{2T}\right), \text{ for } i = 0,1,\ldots p \qquad (5.66)$$

where $/\hat{\Omega}_i/$ is the estimated variance-covariance matrix of the VAR model error terms and based on lag order i, ln is the natural logarithm, *n* is the number of variables in the model, and *T* is the number of observations used to estimate the VAR model.

To deal with the problem of non-normality Hatemi (20012a) employs a bootstrapping simulation test instead of the standard Wald test statistic, which has asymptotic distribution of a chi-square with degrees of freedom equal to the number of restrictions and corresponds to an F test. As Hatemi (p.2) states, 'the advantage of the bootstrap simulation technique is that it relies on the empirical distribution of the underlying data set, which does not necessarily have to follow a normal distribution'. Hatemi (2012a) presents more details and testing procedure of asymmetric Granger causality. Empirical results of the asymmetric Granger causality will be reported in chapter eight.

5.6.3 Asymmetric Nonlinear Causality

It is worth mentioning that although nonlinear tests can have more power to detect nonlinear causal relationships they do not take into account the likelihood asymmetric effects on causality relations. As explained in the last section (subsection 5.4.3.2), to determine the nonlinear causal relationship between the industry sectors of the US and the emerging stock market returns, this thesis applies the bivariate noisy Mackey-Glass (M-G) model . In the symmetric version of M-G model, there is no separation between the causal impact of positive and negative shocks. However, the M-G model for nonlinear causality tests is capable of conditioning when the samples of the causing variable are either positive or negative, Varsakelis and Kyrtsou (2008). Hence, irrespective of the causality relationships identified under the symmetric version of the bivaraite Mackey-Glass model, it is interesting to test 'whether those relationships hold when conditioning for positive or negative returns', Hristu-Varsakelis and Kyrtsou (2008, p.3). Following Varsakelis and Kyrtsou (2008), asymmetric nonlinear Granger causalities are investigated for the return series under study using the M-G. 'Asymmetric causality testing can reveal interesting information about the inherent dynamics of the processes studied', Hristu-Varsakelis and Kyrtsou (2008, p.1). As shown by Varsakelis and Kyrtsou the extension of the M-G model to asymmetric nonlinear causality tests is quite straightforward (although it may be difficult to implement). Empirical results of the nonlinear asymmetric causality will be reported in chapter eight.

5.7 The Linkages between the US and Emerging Markets' Industry Sectors before and during the 2007-2009 Financial Crisis: An application of Toda and Yamamoto Causality approach with bootstrap distributions

As mentioned earlier, an important empirical analysis under taken in this thesis has been to examine industry sector relationships between the United States of America and the three emerging markets of the study (Brazil, Malaysia, and South Africa) over a sample period that includes 2007- 2009 economic and financial crisis. As Mollah and Hartman (2012, p. 166) state, 'the staggering crisis contributed to the failure of key businesses, decline in consumer wealth estimated at trillions of US dollar, substantial financial commitments incurred by governments bundled with a significant decline in economic activity'. Since international diversification benefits depend on the correlation between markets or between across country sectors as in the present study, international investors will be more interested to have some empirical understanding on the increased uncertainty resulting from recent financial crisis. As mentioned in the introductory section of this chapter, this thesis conducts separate tests to investigate shifts in correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 Financial Crisis. Specifically, for comparative assessments, in addition to the standard cross correlation tests, tests for two period (2004-2006 and 2007-2009) causality relations are undertaken in this thesis using Toda and Yamamoto (1995) approach for testing non causality with bootstrap distributions as proposed by Hacker and Hatemi (2006). This section discusses briefly this testing approch for the two period causality testing.

It is a common practice in the empiricaliterature to test the Granger-causality within a linear Vector Autoregressive (VAR) ramework using standard F test or (Wald) F-test which are considered to be asymptotically chi-squared, as they are in stationary or trend stationary systems. However, as Toda and Yamamoto (1995, p. 226) point out, 'conventional asymptotic theory is, in general, not applicable to hypothesis testing in levels VAR's if the variables are integrated or cointegrated'. Toda and Yamamoto (1995) propose a testing procedure which is robust to the integration and cointegration properties of the process, often referred to as the modified Wald (MWALD) statistic for causality test. The Toda and Yamamoto approach is based on Wald test statistic which has a chi-square asymptotic distribution irrespective of the order of integration or cointegration properties of the variables in the model. In this study, to examine dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009, this study employs the modified Wald (MWALD) test statistic with bootstrap distributions and leveraged adjustment as proposed by Hacker and Hatemi (2006)[82]. Hatemi et al (2006) applied this approach to

[82] Toda and Yamamoto (1995), Hacker and Hatemi (2006), and Hatemi et al (2006) present more details of these techniques.

examine causality relationships between the equity markets of the US and other Developed Countries before and after September 11 (the attack on world trade centre). However, to the best of my knowledge, no study has so far employed them applied to the context of international sector linkages**.**

The starting point of the Toda-Yamamoto procedure is to reconsider a *p* lag(s) augmentation of the conventional VAR (p) model of equation (5.48) which for convience is represented in here as follows

$$y_t = \mathrm{A}_{i0} + \sum_{k=1}^{p} \mathrm{A}_{ip} x_{t-p} + \varepsilon_t \qquad (5.67)$$

where as explained before y_t is a nx1 vector dimension of dependent variables, A_{i0} a vector dimension of intercepts, A_{ip} is a *nxn* matrix of parameters for lag *r* *(r=1,…, p)*, and ε_t is a nx1-dimensional vector of error terms. Toda and Yamamoto (1995) proposed estimating a level VAR through an augmented VAR (*p+d*) model as of the following, and the use of the conventional ordinary least squares (OLS)

$$y_t = \hat{\mathrm{A}}_{i0} + \sum_{k=1}^{p} \hat{\mathrm{A}}_{ip} x_{t-p} + \hat{\mathrm{A}}_{p+d} dy_{t-p-d} + \hat{\varepsilon}_t \qquad (5.68).$$

Technically, this procedure is based on VAR for the level of variables with the lag order *p* in the VAR model given by $p=k+d_{max}$, where *k* is the true lag length and d_{max} is the possible maximum integration order of variables, which cannot exceed the true lag length *k.* From the model in (5.68), the null hypothesis of no Granger causality can be expressed as follows

H_0: the row *m*, column *n* element in $\hat{\mathrm{A}}_{ip}$ equals zero for *i* = 1,…, *p* (5.69).

Toda and Yamamoto (1995) suggested applying modified Wald (MWALD) test statistic for testing the null hypothesis of non-Granger causality between integrated variables as follows

$$MWALD = (Q\hat{B})\left[Q\left((\Omega'\Omega)^{-1}\Phi\Psi_u\right)Q'\right]^{-1}\left(Q\hat{B}\right) \tag{5.70}$$

where Φ is an element of matrix multiplication operator or the Kronecker product, Q = a px$n(1+n(p+d))$ and is a matrix used to identify restrictions implied by the null hypothesis. The elements in each row of Q get the value of one if the related parameter in $\hat{\mathrm{B}}$ is zero under the null hypothesis, and they get the value of zero if there is no such restriction under the null. Ψ_u is the estimated variance-covariance matrix of residuals in equation (5.70).

The modified Wald (MWALD) test guarantees the asymptotic distribution of the Wald statistic (χ^2 distribution) and is robust to the integration and cointegration properties of the properties. The MWALD test statistic which follows a χ^2 distribution can also be applied to the error terms provided that the erroes are normally distributed. However, as shown by Hacker and Hatemi (2006), when the error terms are non-normal and autoregressive conditional heteroscedasticity (ARCH) exists, the MWALD statistic tends to reject easily the null hypothesis of causality. Hacker and Hatemi (2006) proposed a test based on leveraged bootstrap simulations. Also, as stated in Hatemi et al (2006, p. 70) 'the bootstrap-derived distribution provides more precise critical values and thus, leads to less bias in statistical inference'[83]. Empirical results of the standard cross correlations as well as the Toda and Yamamoto causality approach with bootstrap distributions will be reported in chapter eight.

[83] See Hacker and Hatemi (2006), and Hatemi et al (2006) for details of their representation, additional explaination of the modified Wald (MWALD) test statistic, and the discussions of the leveraged bootstrap simulations.

5.8 Conclusion

The interdependence between international stock markets has important practical implications in asset allocations, risk management, and economic policy. As a result, vast studies have been conducted in recent years to examine international equity market relationships using long run and short run dynamic econometric analysis. However, two shortcomings are noticed in the existing literature. Firstly, most existing studies on interdependence among international markets are built on the basis of linear modelling framework. However, as various studies in recent decades have documented, financial time series can exhibit nonlinear dependences. Secondly, although there is a large volume of industry level literature, empirical studies that address industry or company level co-movements and dynamic linkages, or the comparison of the issues of which sectors co-move across industries at a global level, are relatively small compared to national level studies. The empirical objective of this thesis is to re-investigate the degree of interdependence among international industry sector indices of developed and emerging countries using multivariate linear and nonlinear econometric models. Specifically, the thesis examines the industry relationships between the US and three leading emerging countries; Brazil, Malaysia and South Africa. In addition to the usual return correlation relationships and time varying analysis, this thesis investigates the long run co-movements, dynamic causality and transmissions among industry sectors using linear and nonlinear econometric methodologies including linear and nonlinear cointegration relationships, time varying co-movements, and linear and nonlinear dynamic causality linkge analysis.

This chapter presented the main metric methodologies of the thesis while empirical results will be reported in chapters six, seven and eight. To test long run industry sector relations, the thesis applies linear and nonlinear cointegration methods. For long run linear relationships, the thesis first applies Johensen's maximum likelihood approach of cointegration, based on the conventional vector error correction (VEC) model. The vector autoregressive (VAR) or vector error correction model (VECM) techniques assume frictionless markets that are linear and symmetrical. However, due to various frictions such as transactions costs and information frictions, and external factors, the distributions of many asset price changes are often found to be highly leptokurtic which is an indication of nonlinearity. Recently, empirical modelling of nonlinearity among economic and financial time series data has been gaining special importance recently. To examine nonlinear cointegration relationships, this study uses nonparametric procedures proposed for nonlinear cointegration by Breitung (2001), based on the difference between the sequences of rank. In addition to the investigations of long run analysis for price relationships (an initial indicator of co-movements), this thesis examines co-movements between weekly returns of US and emerging industry sectors in the form of standard cross correlations, time varying correlations and time varying regression coefficient estimations.

The term ‘interdependence’ also covers the short run dynamic linkages such as causality relationships and shock transmissions. Therefore, in addition to the investigations of long run relationships, the causality linkages between international industry sector indices are also investigated using linear and nonlinear analysis. The linear and nonlinear causality tests are conducted using the standard Granger VAR. For nonlinear causality analysis this thesis applies a more recent nonlinear causality methodology which is also capable of capturing the effect of economic shocks on the variable being either positive or negative. Specifically, the research applies the bivarite noisy Mackey-Glass (M-G) model, which is introduced in economic and financial studies by Kyrtsou and Terraza (2003, Kyrtsou and Labys (2006) and Varsakelis and Kyrtsou (2008)[84]. In a real world situation, the potential for asymmetric (i.e. information) exists that can induce asymmetric causal effects. Therefore, in each case of the linear and nonlinear causality tests, asymmetric causality relationships are also investigated. Testing the asymmetric effect on linear and nonlinear causality relationships for industry sector indices is an additional empirical novelty of this thesis.

[84] Prior to nonlinear causality analysis between industry sectors, univaraite tests of nonlinear dependence have been carried out. Such univaraite tests represent a first attempt to testing nonlinear dependence for sectoral level indices.

Furthermore, time varying Granger causality tests are conducted through a rolling window analysis.

The research in this thesis uses data series of a sample period which includes 2007-2009 economic and financial crisis. Therefore, another empirical advancement of this thesis is to conduct separate tests for the shifts in cross correlation patterns and causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 financial crisis. In particular, for a comparative assessment, in addition to the standard cross correlation tests, Toda and Yamamoto's (1995) causality approach with bootstrap distributions and leveraged adjustment as proposed by Hacker and Hatemi (2006) is applied to examine causality linkages between the US and emerging markets' sectors using data series of 2004-2006 and 2007-2009. A short discussion of this approach has been presented in section seven of the chapter, while empirical results of all the testing techniques discussed in this chapter will be reported in the next three chapters.

CHAPTER 6:
Co-movements between the Returns of the US and the Emerging Markets' Industry Sectors

6.1: Introduction

The empirical objective of this thesis is to assess the degree of interdependence between international equity markets using industry sector indices of the US and three emerging countries. From an investor's point of view, when national stock markets have a high level of dependence, the sector diversification strategy should dominate the asset allocation decisions giving a better opportunity for risk reduction than the country diversification strategy. In particular, it is interesting to note that empirical studies in this area are often extended using the intra-industry sector returns to include the recent global financial turbulences. To investigate the interdependence between industry sectors from different national equity markets, this thesis considers several steps of empirical tests including linear and nonlinear econometric analysis. Prior to the econometric linear and nonlinear assessments in the next two chapters, this chapter employs several related empirical techniques to study the co-movements between the industry sector returns of the four stock markets in this study over the sample period, 4th January 2000 to 29th December 2009. The first of these techniques is the standard cross correlation analysis, which can be considered as the first step for evaluating the degree of international equity market integration or co-movement. Since international diversification benefits depend on the correlation between assets across markets, the results of this study would be useful to international investors. A significant increase in the correlation coefficients is usually interpreted as a rise in stock market integration and a diminishing of the diversification gains[85].

[85] Similarly, Carrieri, Errunza and Hogan (2007) argue that correlation is not a satisfying measure for financial market integration, as it tends to underestimate the degree of integration

Chapter 6

As mentioned in the literature review chapter, numerous empirical studies on the integration of international equity markets have assessed time varying correlations in recent decades. Such studies include Erb et al (1994), Longin and Solnik (1995), Solnik et al (1996), Karolyi and Stulz (1996), Cheng (1998), Stulz (1999), Longin and Solnik (2001), Ang and Bekaert (2002), Bekaert and Harvey (2002), Forbes and Rigobon (2002), and, more recently, Kearney and Poti (2005) and Goetzmann et al (2005), have examined the international integration of equity markets from the perspective of time varying correlations and covariance. Many of these studies show that the correlations among international equity markets have been changing overtime, and significantly increasing in periods of higher economic and financial integration. Nevertheless, those studies are based on national market level indices. Thus, in addition to the standard cross correlations, the dynamic nature of the correlations between the US and the emerging industry sector returns is also examined in this thesis by conducting time varying return co-movements. The two time varying measures employed are time-varying correlation and time-varying coefficient methods.

First, following the lead of Meric et al (2007), the rolling correlation analysis technique is applied, a popular method of examining the time variation of correlations among stock markets. Second, to investigate further the time varying co-moment behaviour for the returns of industrial sectors in the study, this thesis also employs time series regressions to model the time-varying coefficients, or the concept of *beta* convergence, by employing a state space framework and the Kalman filter. Although few studies have recently applied such analysis, a special feature of this thesis is the combination that investigates time varying coefficients and time varying correlations for industry sector level indices. The work of this chapter is organised as follows. Section two presents the cross correlation analysis of international industry sectors, which can be regarded as the first step for evaluating the degree of international market co-movement integration at an industry level, followed by graphical presentations of rolling correlation analysis in section three for time varying correlatios as discussed in chapter five. Next, section four presents a brief introduction of the general structure of state-space and the Kalman filter techniques followed by graphical presentations of the time-varying estimation coeffiecient results. Finally, some concluding remarks are presented in section five.

6.2 Cross Correlations between the US and the emerging market industry sector returns

In statistical terms, correlation is a statistical measurement of the similarity in the movement of two variables, such as rates of return for groups of stocks from two different countries (Fabozzi and Modigliani, 2009)). The analysis of the (unconditional) correlation coefficients of returns provides a simple indicator of the co-movements of international stock indices, or a rough measure of market interdependence, and as such is fundamental in the context of global portfolio diversification. That is, as Tsay (2005, p.339), points out 'for an investor or financial institution holding multiple assets, the dynamic relationships between returns of the assets plays an important role in decision making'. Therefore, as the first step to evaluating the degree of international industry integration or co-movement, this section re-examines the cross-correlation relationships of industry sector returns for the US and the emerging markets in the study.

The correlations can provide a preliminary understanding or a rough indication of market integration and co-movements between the industry sectors of the study over the sample period. A time series is strictly stationary if all moments are independent of time, that is, they do not change over time. Hence,

$$r_t = (r_{1t,}\dots,r_{kt})' \qquad (6.1)$$

Mean vector: μ_t $[\mu_1, \dots. \mu_k]$

Covariance matrix:
$$\Omega_0 = \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_{1k} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma_n^2 \end{bmatrix}$$

Correlation matrix: $p(0) \equiv [\rho_{ij}(0)] = D^{-1}\Gamma_0 D^{-1}$ (6.2)

$$\rho_{i,j} = Cov(r_{i,t}, r_{j,t}) = \frac{Cov(r_{i,t}, r_{j,t})}{std(r_{i,t})std(r_{j,t})} \quad (6.3)$$

where ρ_{ij} is the correlation coefficient between r_{it} and r_{jt}. In the literature of time series, such a correlation coefficient is referred to as a 'concurrent or contemporaneous correlation coefficient because it is the correlation of the two series at time t', (Tsay, 2005, p. 340).

Table 6.1 presents the results of contemporaneous cross-country correlations of each industry sector returns of the ten global stock markets. For brievety, only correlations between the US and the emerging are discussed. Initial exploratory analysis of the sample's cross-correlation matrix or contemporaneous correlation indicates the existence of interdependence among international industry sectors in the sense that almost all series are positively correlated. The correlation of the emerging markets' industry returns shows varying degrees of correlation with the Unites States industry returns .The highest correlation coefficient occurs between the US and Brazilian basic resources industry, followed by South Africa for the same industry sector, 0.69 and 0.60 respectively, while the lowest correlation occurs between the US and Malaysian telecommunications industry, 0.077. For further analysis of the correlation relations, t-tests for the cross-correlation relations were conducted. As can be seen from the table, the coefficients for the international sector returns are significantly different from zero in all cases except in the case of US and Malaysian telecommunications. In summary, the correlation results indicate the existence of co-movements among the US and emerging countries industry sectors in the sense that almost all series are positively correlated.

Nevertheless, though all are positive, and high in some cases, the correlations between the US and the emerging sectors are mostly low. This indicates a weak linear association between the sectors of the markets considered in the study over the sample period. Although the correlation coefficients presented in this section provide some preliminary insight into the interdependence of the international industry sectors in the study, it must be pointed out that, since these results are from static measures they should not be considered to reflect the dynamic relationships between the sectors under study. In other words, simple correlation is not necessarily sufficient to imply the existence of long run co-movements. Therefore, for long-run relationship assessments, which are the main empirical objectives of this thesis, dynamic econometric modelling is necessary, which is to be discussed in the next two chapters. Prior to these formal tests for long run and dynamic relationships, the next two sections of this chapter investigate whether a structural change has occurred in the cross correlations between the international industry sectors under study[86]. A simple investigation of the cross correlation between sector return series can provide important information for the subsequent Granger causality tests, which will be taken in chapter eight. It is often stated that the pattern of correlations changes during the period of economic and financial turbulence. Therefore, a seperate analys on cross correlations before and during the recent financial crisis will also presented in chapter eight.

[86] Another important exploratory tool for modelling multivariate time series could have been the cross correlation function (CCF), which generalizes the univariate autocorrelation function (ACF) to the multivariate case. For a univariate time series y_t the autocorrelations ρk and auto-covariances γ_k summarize the linear time dependence in the data. With a multivariate time series Y_t each component has autocorrelations and auto-covariances but there are also cross lead-lag covariances and correlations between all possible pairs of components.

Chapter 6

Table 6.1: Cross Correlations between the Industry sector returns

	Market				
Industry Sector	Market	Brazil	Malaysia	South Africa	USA
Banking	Brazil	1.000 - -			
	Malaysia	0.253(5.95)**	1.000 - -		
	S. Africa	0.**435**(11.01)**	0.264(6.24)**	1.000 - -	
	USA	0.365(8.93)**	0.183(6.124)**	0.368(9.03)**	1.000 - -
Basic Resources	Brazil	1.000 --			
	Malaysia	0.356 (8.69)**	1.000 --		
	S. Africa	**0.607** (17.40)**	0.366 (8.96)**	1.000 - -	
	USA	**0.699** (22.29)**	0.330 (7.96)**	**0.600(17.07)**	1.000 - -
Chemicals	Brazil	1.000 - -			
	Malaysia	0.282 (6.71)**	1.000 - -		
	S. Africa	0.332 (8.03)**	0.300 (7.18)**	1.000 - -	
	USA	0.**418** (10.50)**	0.212(6.195)**	0.**424** (10.31)**	1.000 - -
Construction and Materials	Brazil	1.000 - -			
	Malaysia	0.191 (6.144)**	1.000 - -		
	S. Africa	0.215 (5.01)**	0.326 (7.85)**	1.000 - -	
	USA	0.243 (5.70)**	0.284 (6.75)**	0.**424** (10.67)**	1.000 - -
Financial Services	Brazil	1.000 - -			
	Malaysia	0.340 (8.24)**	1.000 - -		
	S. Africa	0.**445** (11.31)**	0.354 (8.62)**	1.000 - -	
	USA	0.**477** (12.35)**	0.255 (6.00)**	0.**451** (11.52)**	1.000 - -
Food and Beverages	Brazil	1.000 - -			
	Malaysia	0.255 (6.00)**	1.000 - -		
	S. Africa	0.330 (7.96)**	0.304 (7.27)**	1.000 - -	
	USA	0.259 (6.10)**	0.134 (3.08)**	0.239 (5.61)**	1.000 - -
Industrial Goods and Services	Brazil	1.000 - -			
	Malaysia	0.348 (8.46)**	1.000 - -		
	S. Africa	0.**406** (10.11)**	0.300 (7.17)**	1.000 - -	
	USA	0.**458** (11.75)**	0.248 (5.84)**	0.**504** (13.29)**	1.000 - -
Personal and Household Goods	Brazil	1.000 - -			
	Malaysia	0.131(3.01)**	1.000 - -		
	S. Africa	0.239 (5.61)**	0.182(6.122)**	1.000 - -	
	USA	0.287 (6.82)**	0.101 (2.32)*	0.221 (5.17)**	1.000 - -
Retailing	Brazil	1.000 - -			
	Malaysia	0.225 (5.26)**	1.000 - -		
	S. Africa	0.379 (9.34)**	0.249 (5.85)**	1.000	
	USA	0.374 (9.19)**	0.183(6.123)**	0.357 (8.71)**	1.000 - -
Telecommuni -cations	Brazil	1.000 - -			
	Malaysia	0.132 (3.04)**	1.000 - -		
	S. Africa	0.356 (8.68)**	0.177 (6.110)**	1.000	
	USA	0.**434** (10.99)**	0.077 (1.76)*	0.316 (7.58)**	1.000 - -

Table notes: Bolded text indicates strong and significant correlation coefficients (40% or more), while* and ** denote significance at the 5% and 1% significant levels respectively.

Chapter 6

6.3 Time Varying Cross-Correlations: Rolling Window estimations

One measure to assess the degree of changes in correlations between equity markets is to look at the correlation of returns between financial markets over time. Correlation between the assets of different markets plays an important role in financial markets. However, the size and signs of the correlations depend on the chosen sample period and investment horizon. As mentioned earlier, numerous recent studies have shown that the correlation between global stock markets tends to be quite volatile over time, especially in a period of high financial turbulence. In the present study, given the empirical characteristics of the data series as reported in chapter four, it is reasonable to assume that the true coefficient of the correlations is not constant but rather is changing over time. Using traditional cross correlation it is also difficult to observe changes in the degree of integration. In the literature, a technique that has been used to measure such changes is to estimate the rolling correlations.

In this section, calculations of time varying correlations based on yearly rolling window estimations are computed to assess the varying behaviour of correlation coefficients between the weekly industry sector returns of each pair of industry sectors across markets in the study. The yearly rolling coefficients between weekly returns are estimated by rolling the sample period forward one week at a time starting with first year. In other words, adding the latest weekly observation and deleting the earliest weekly return observation. An upward slope indicates rising co-movements between the US and an industry sector price, while a downward slope reveals declining co-movements. In other words, for a given time period, if the cross coefficient reaches point one, then there is strong cross correlation in that sub-period, regardless of the sub-period for which it has been estimated. Figures 6.1-6.10 present the results of time varying correlations between intra-industry sectors of US and the emerging countries over the sample period, and based on yearly rolling window estimations. The vertical axes of the graphs indicate correlation coefficients between US and the emerging countries industry sectors.

Chapter 6

Figures 6.1 to 6.10: Rolling window estimations for time varying correlations

Figure 6.1: Time varying correlations between Banking Sector returns

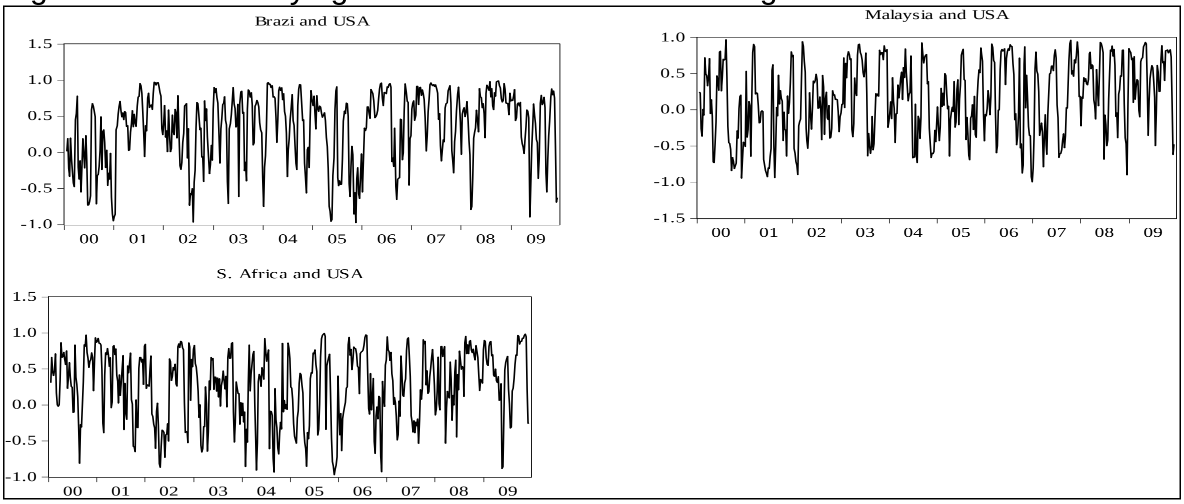


Figure 6.2: Time varying correlations between Basic Resources Sector returns

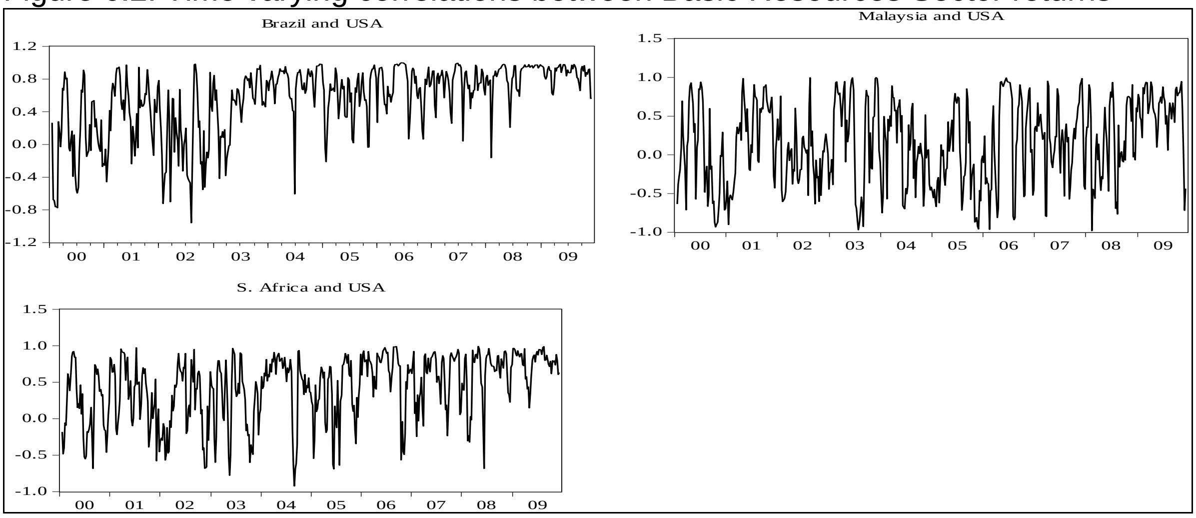


Figure 6.3: Time varying correlations between Chemicals Sector returns

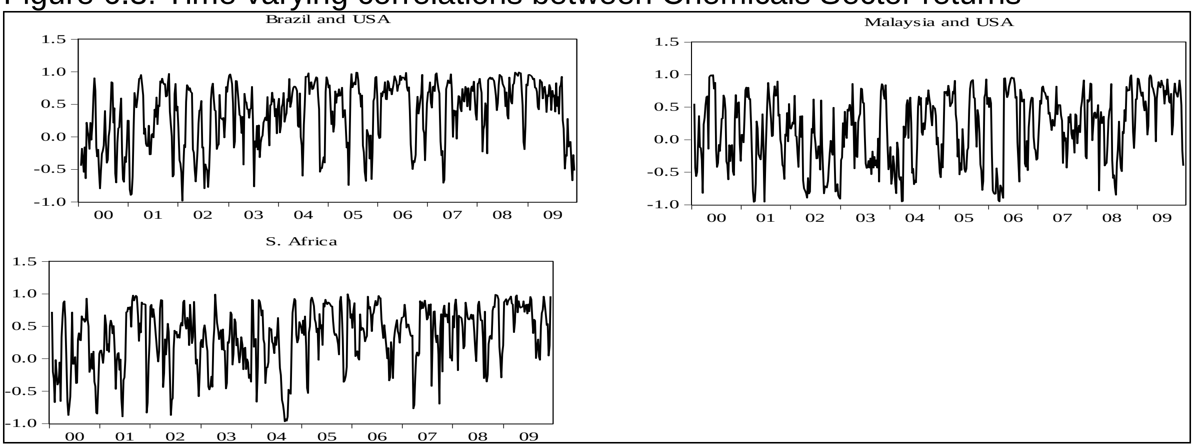


Figure 6.4: Time varying correlations between Construction and Materials Sector returns

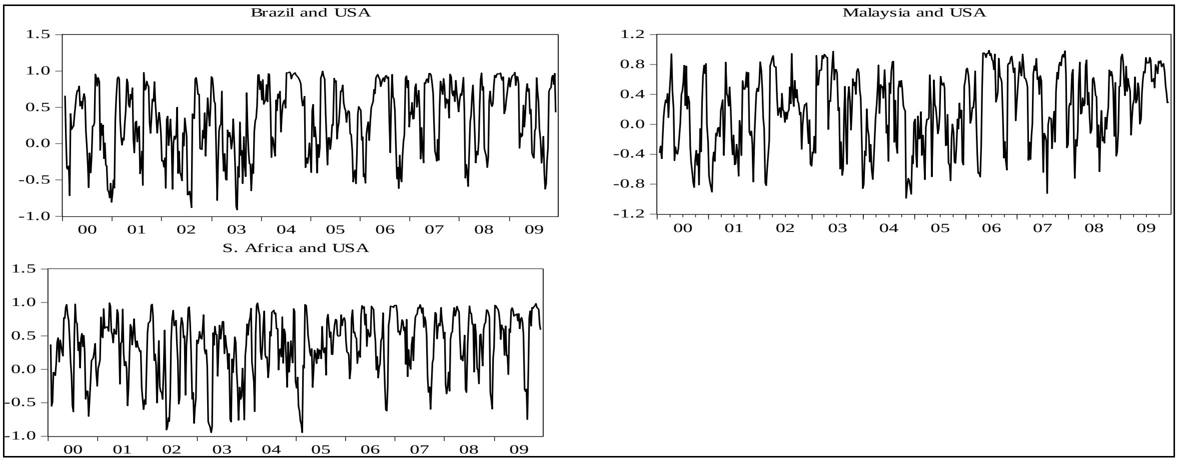


Figure 6.5: Time varying correlations between Financial Service Sector returns

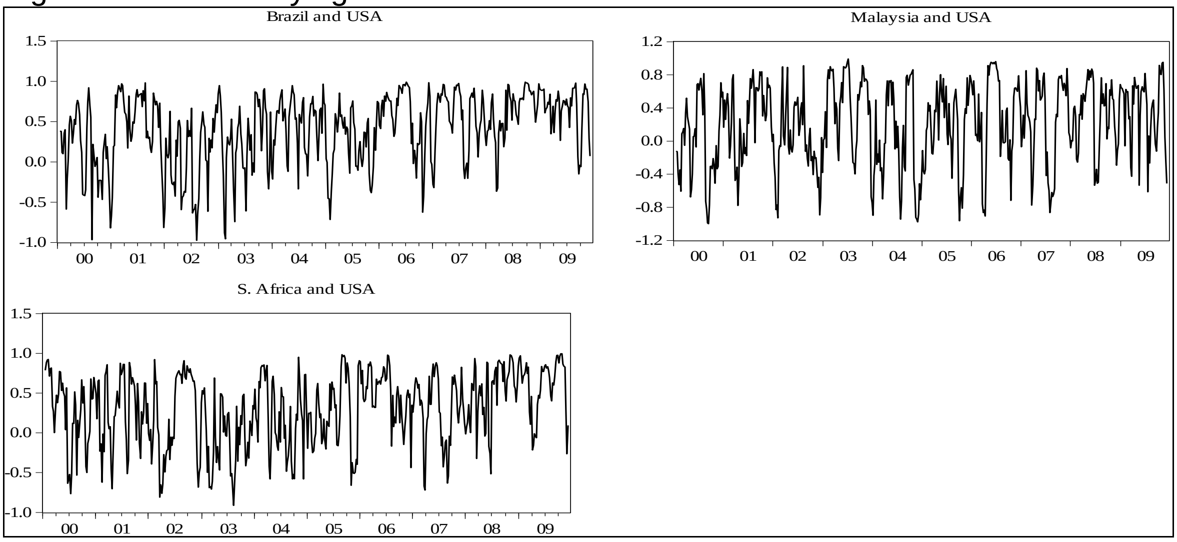


Figure 6.6: Time varying correlations between Food and Beverage Sector returns

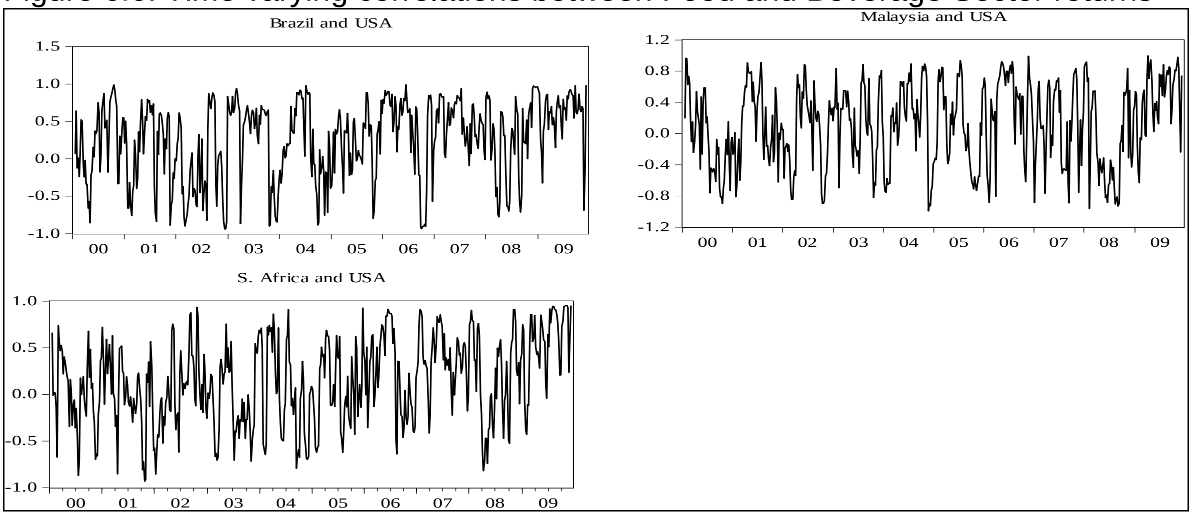


Figure 6.7: Time varying correlations between industrial Goods sector returns

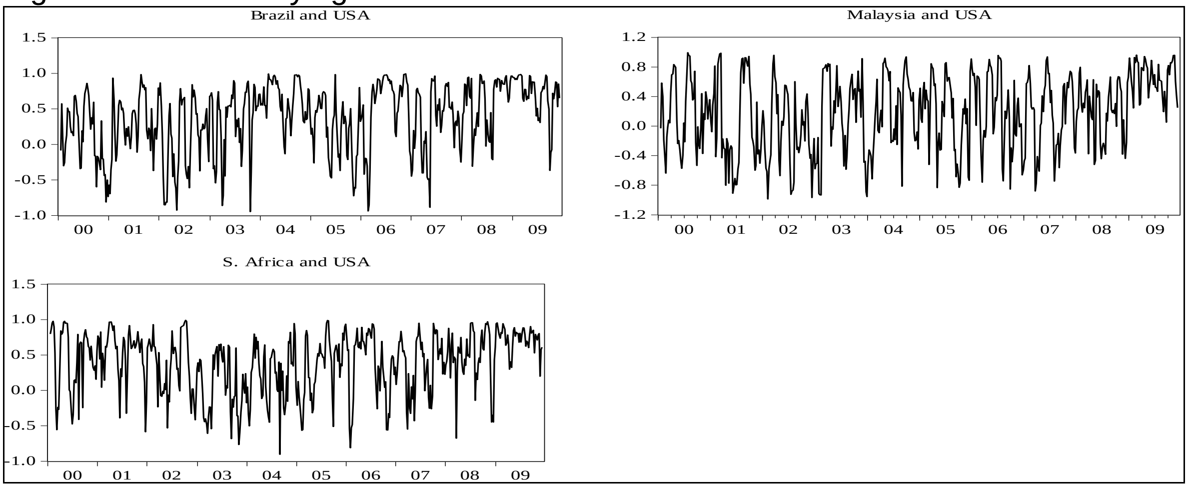


Figure 6.8: Time varying correlations between Personal and H/H Goods Sector returns

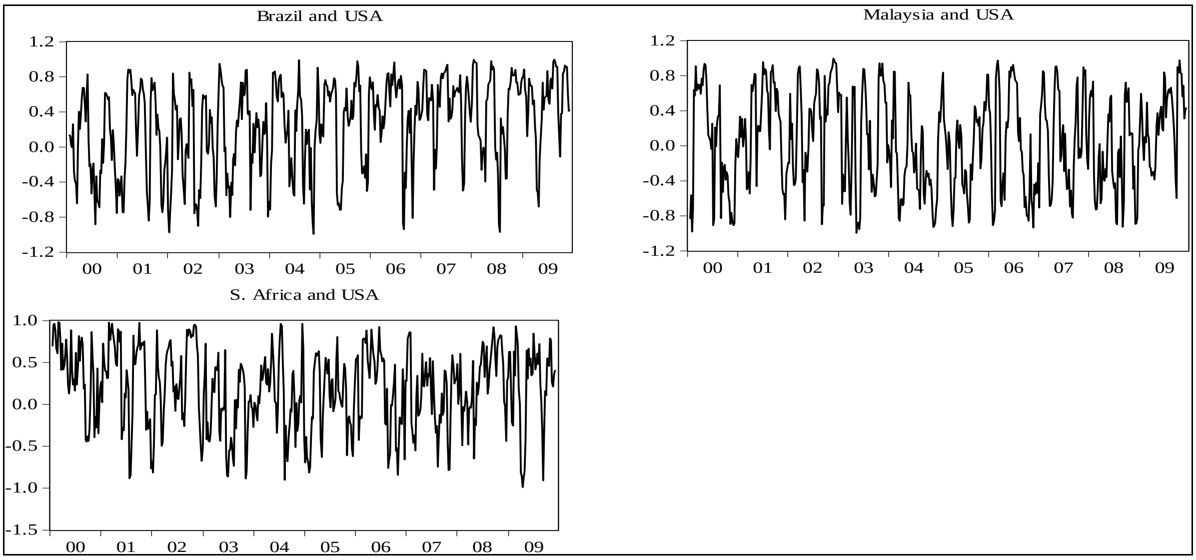


Figure 6.9: Time varying correlations between Retailing Sector returns

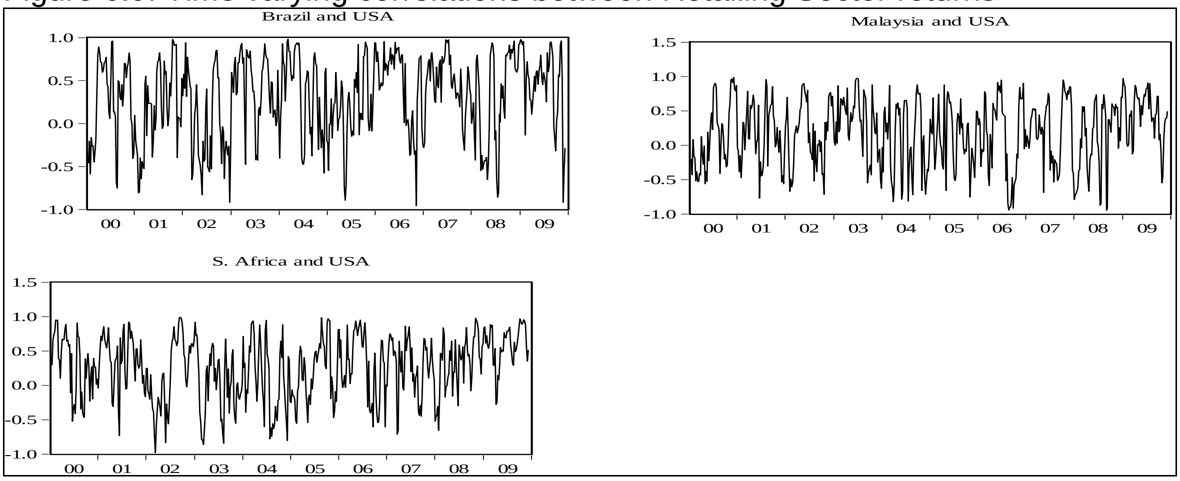
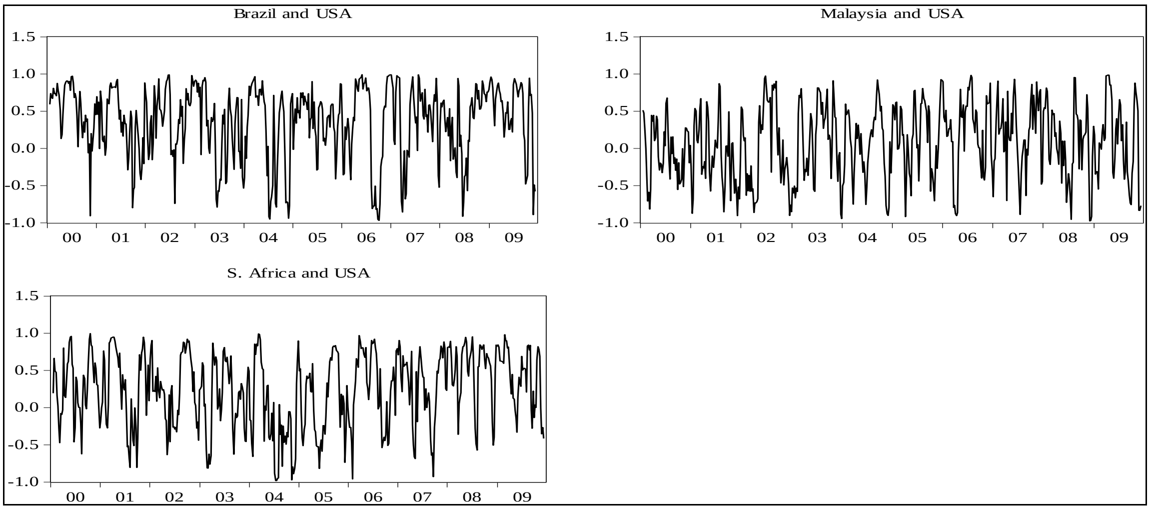


Figure 6.10: Time varying correlations between Telecommunications Sector returns



To conserve space only the rolling correlations between the US and the three emerging markets are reported. The analysis of the rolling correlations exhibits richer dynamics than standard cross correlations. Overall, the graphs of the rolling window estimations indicate instability in the correlations between the industry sectors of the US and the emerging countries under study over the sample period. That is, as can be seen from the figures, the rolling correlation analysis results indicate, without exception, considerable variability in the correlations between the industry sectors of the US and the emerging countries over time. The most volatile correlations occur between the banking, financial services, retailing, and telecommunications sectors of the Brazilian and US markets. Furthermore, as the figures show, the highest correlations occurred in 2009 for most industry sectors. Overall, the result of the time variation correlation reaffirms the view that the correlation between global stock markets tends to be quite volatile over time, and particularly high in a time of high financial turbulence. As an alternative procedure to time variation co-movements amongst the international industry sectors under study, the next section presents time-varying regressions to model the time-varying coefficients by employing a state space framework and the Kalman filter.

Chapter 6

6.4 Time varying coefficient regressions: An application of State-space and Kalman Filter

As revealed by the rolling correlation analysis presented in the last section, there have been significant structural changes in the co-movements between the returns of the US and emerging industry sectors under study in the sample period. To further examine such structural changes, this section applies time-varying coefficient regressions using state space and kalman filtering techniques. The industry sector returns of each market are considered in turn as the dependent variable, with a constant intercept and time-varying coefficient. This section first outlines a brief discussion of the state-space models and the Kalman filter technique, which can be applied to a wide range of estimates, and then presents the graphical display of the results of time-varying regression coefficients obtained by the use of the Kalman filter estimations. Although the interest in using state space models and the Kalman filter for financial markets has grown in recent years, only a few studies (i.e. Park and Kim, 2009, and Mergner 2009) have so far applied this for industry sector analysis[87].

In a typical time series regression model, the price or return series of one market can be considered as the dependent variable while the series of other markets are the explanatory variables**,** and used to estimate the following regression model

$$y_t = \alpha + x_t\beta + \varepsilon_t, \ \ \varepsilon_t \approx N(0, \mathrm{H}_t) \qquad (6.4a)$$

where y_t is a vector of the dependent variable (or return at time t) of n×1 dimension, α is a stochastic constant, β is a kx1 vector of unknown coefficients, and x_t is the vector of explanatory variables at time *t*. The size of β is a direct measure of the speed of convergence in the overall markets.

[87] Dunis and Shannon (2005), and Chow et al (2011) have also applied the state space models and Kalman filtering techniques to the analysis of equity market return relationships between developed and emerging markets at national level.

The above model assumes that the coefficients, β, is fixed, but as a number of previous studies (e.g. Bakaert and Harvey, 1995) indicate, financial time series data are often time-dependent and parameters are more likely to change over time instead of remaining constant. Therefore, assuming that the parameter β can vary in each time period instead of being fixed over time, denoted as β_t, the time series model with the time-varying coefficient can be fitted into a state-space framework as

$$y_t = \alpha + x_t \beta_t + \varepsilon_t \qquad (6.4b)$$

where β_t is now the time-varying coefficient or state vector. A state space model is in principle any model that includes an observation process X_t and a state process β_t. The equations may be nonlinear, or non-Gaussian

In a state space analysis the time series observations are assumed to depend linearly on a state vector that is unobserved and is generated by a stochastically time-varying process (Commandeur et al, 2011, p.2). Thus, assuming that β_t follows according to some linear process, the state vector with an autoregressive process of order 1 is then re-written as:

$$\beta_t = \delta + Z\beta_{t-1} + \nu_t \qquad \nu_t \approx N(0, \varpi) \qquad (6.5)$$ [88]

where β_t is unobserved state process or , δ is a constant, and β_{t-1} is a matrix of (lagged) coefficients. The disturbance terms, ε_t and v_t (equations 6.4 and 6.5) are assumed to be uncorrelated with each other in all time periods and uncorrelated with the initial state. Equations (6.4b) and (6.5) are the general linear Gaussian state space model for the *n*-dimensional observation sequence, and are referred to respectively as the observation or measurement equation and the state or transition equation. The state space approach to time series analysis can be used for bivariate and multivariate time series.

[88] In this study, no lagged dependent is included in the estimations, and a zero lag based on the Schwarz information criterion is determined as the optimal lag length for all tests.

Next, having specified a state space model, the Kalman filtering procedure can be applied to compute the time-varying coefficient, β_t. The Kalman (1960) Filtering procedure is a particular algorithm that is used to solve state space models in the linear case, and can be applied for various estimations (i.e. forward and backward, or filter and smooth). A key property of the Kalman filtering is that if the measurement equation (6.4b) is appropriately augmented, the estimated β_t can be made to satisfy linear constraints. In other words, assuming that the elements δ, Z, H and ϖ in equations 6.4a and 6.5 are known, optimal estimates of β_t can be obtained using the Kalman filter which satisfies the linear time-varying constraints. In practice, these elements will not be known and will have to be estimated prior to obtaining β_t. However, as shown in the literature (i.e. Harvey, 1989, Durbin and Koopman, 2001, and Commandeur and Koopman, 2007), under the assumption of linear Gaussian it is possible to determine the unknown parameters and make inference about the time varying coefficient β_t using an unknown vector parameter through maximum likelihood estimation. Although few recent studies have applied the state space models and Kalman filtering to examine time variation co-movements among industry equity returns; Park and Kim (2009) for US and South Korea and Mergner (2009) for Eurpean industry sectors; to the best of my awareness, no study has thus far employed these techniques for a large study of industry sectors of developed and the emerging markets as in the present thesis.

In this thesis, estimations of time-varying betas based on Kalman filtering approach are conducted. To reflect possible asymmetric effects between industry sectors of these markets, estimations in both directions are implemented. Smoothed estimates of the coefficients βt are displayed graphically. Optimal lag lengths were determined using the Schwarz information criterion (SIC). Figures 6.11 to 6.20 display the Kalman model estimation for time-varying bivariate regression coefficients. Emerging industry sectors are taken as the dependent variables and the US industry sectors as the explanatory variable. As the figures show, the beta (β_t) coefficients shown in the vertical exes, are clearly non-stationary for most industry sectors.

Chapter 6

Figures 6.11 to 6.20: Time-varying bivariate regression coefficients of Sector returns: US industry sectors as the explanatory variables

Figure 6.11: Banking Sectors

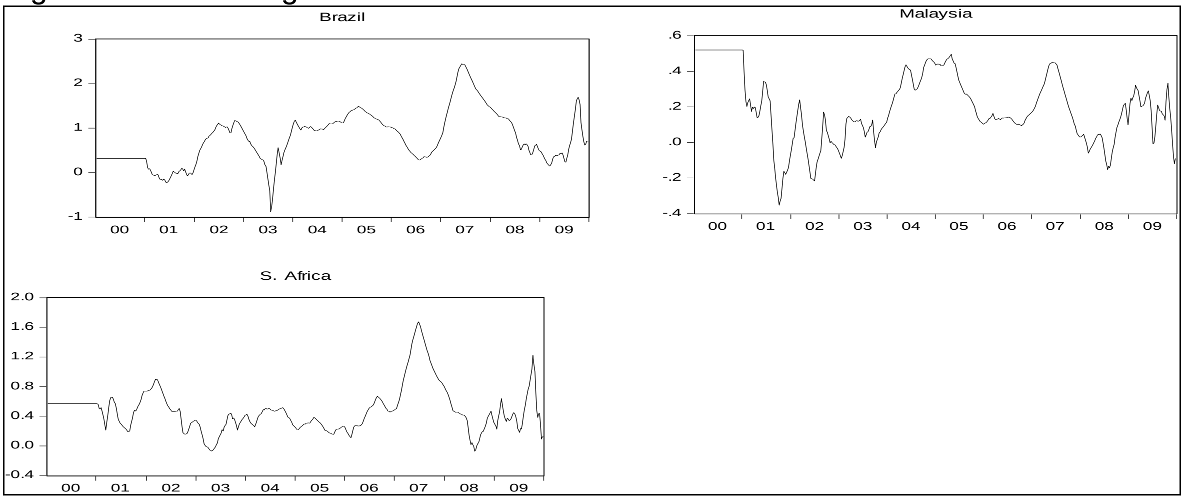


Figure 6.12: Basic Resources Sectors

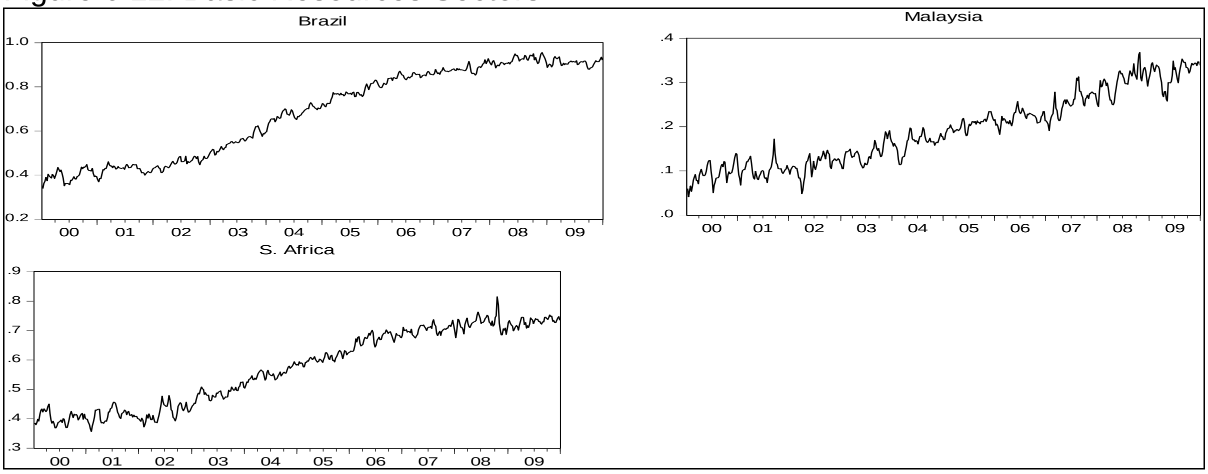


Figure 6.13: Chemical Sectors

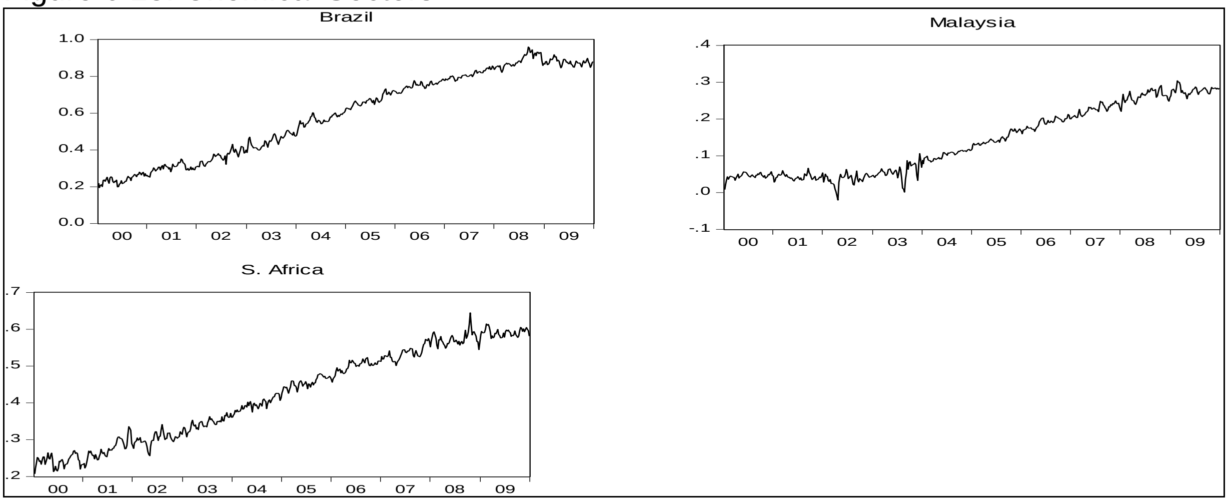


Figure 6.14: Construction and Materials Sectors

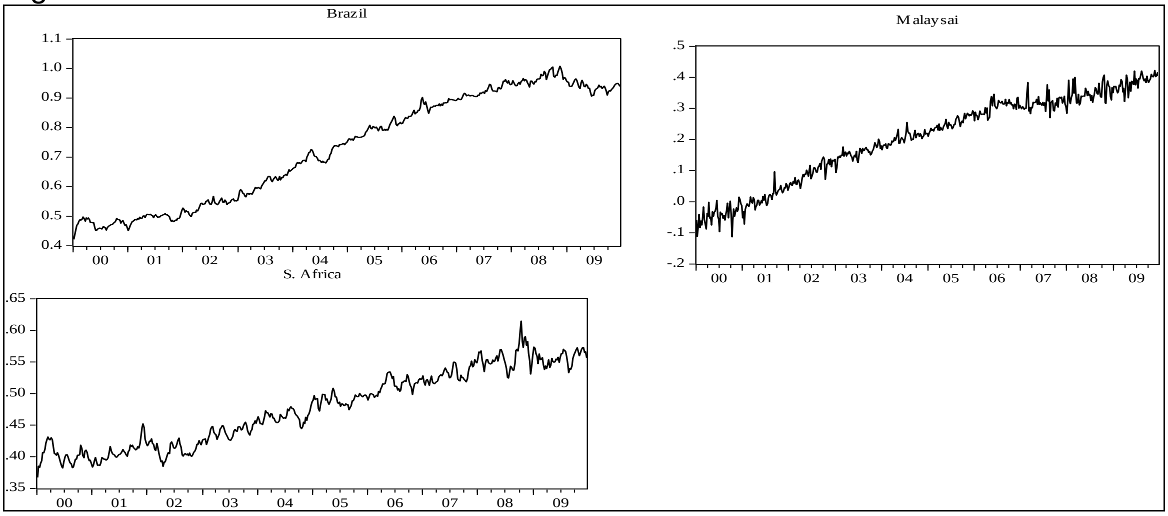


Figure 6.15: Financial Services Sectors

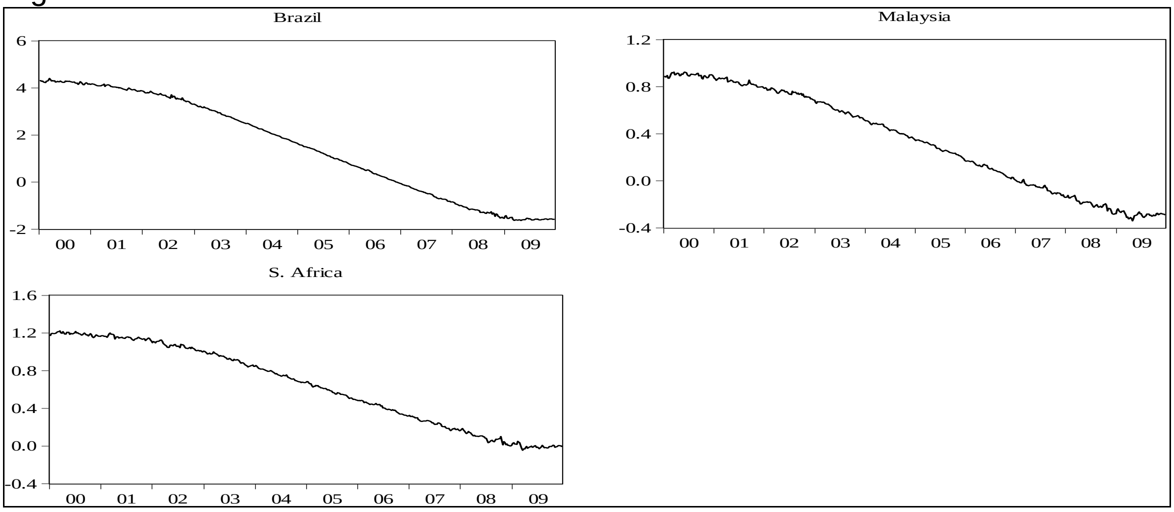


Figure 6.16: Food and Beverage Sectors

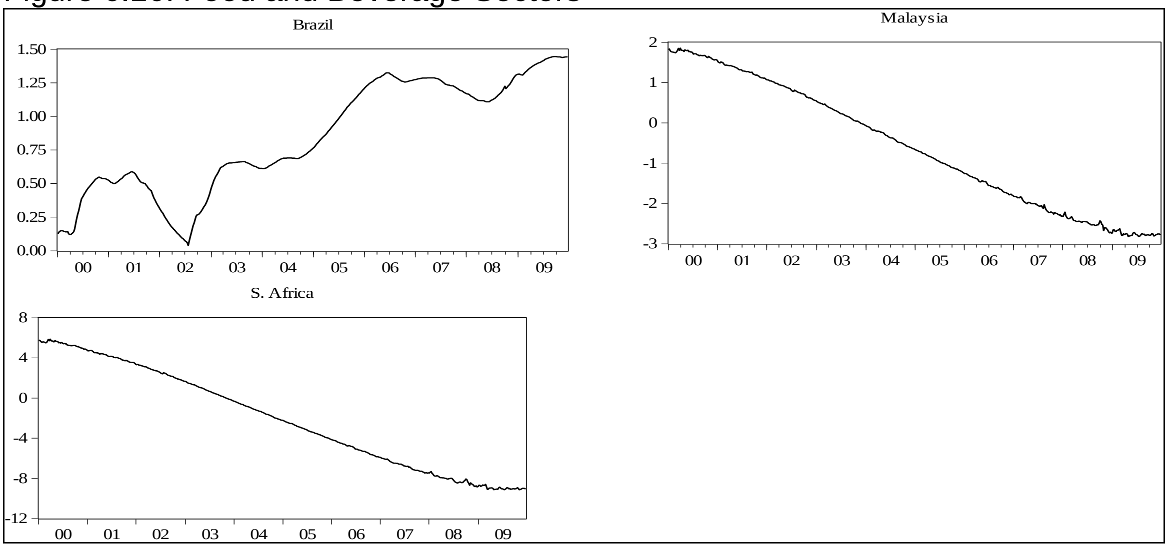


Figure 6.17: Industrial Goods Sectors

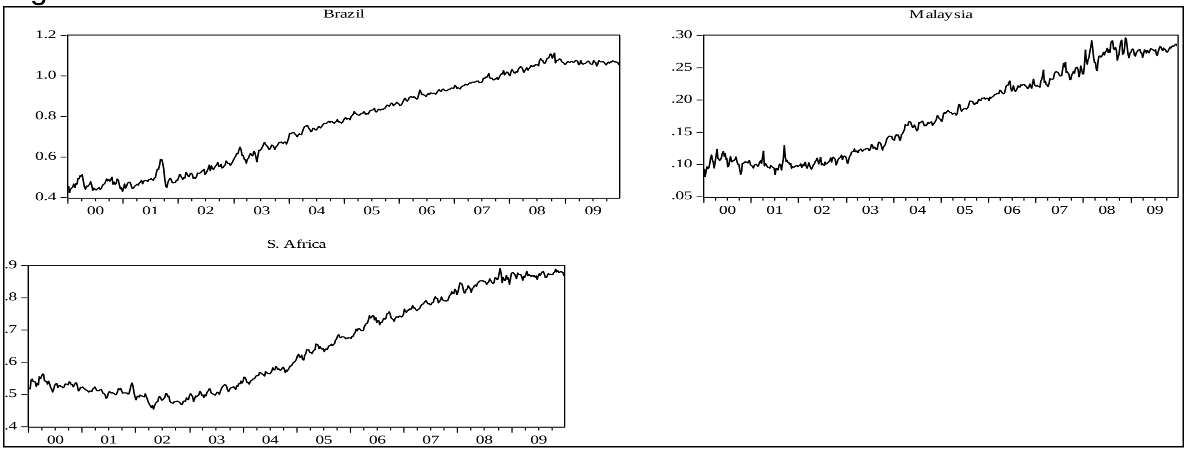


Figure 6.18: Personal & H/H Goods Sectors

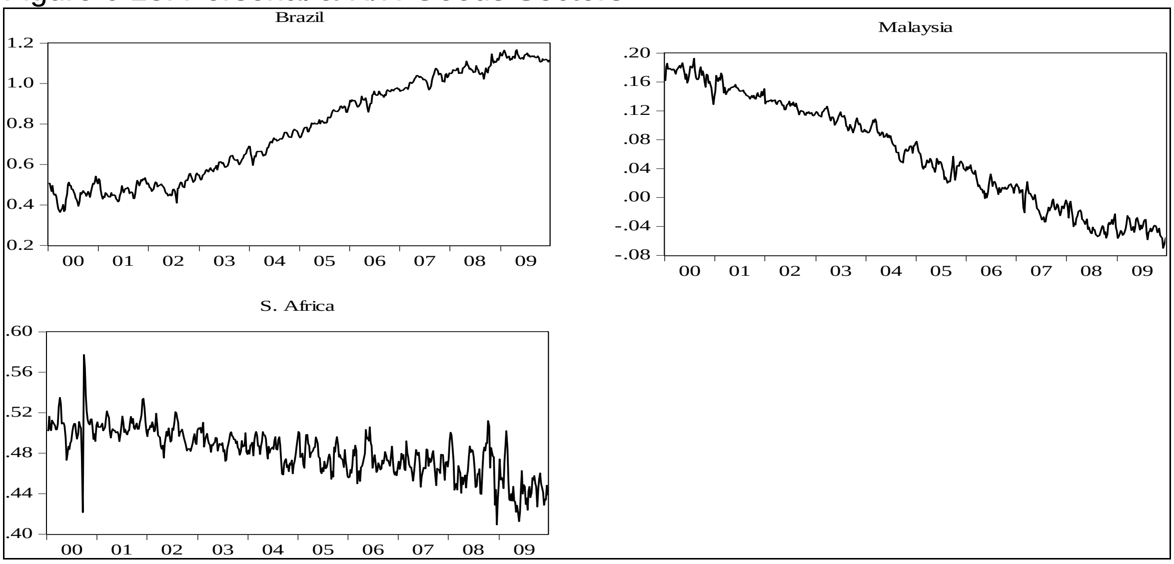


Figure 6.19: Retail Sectors

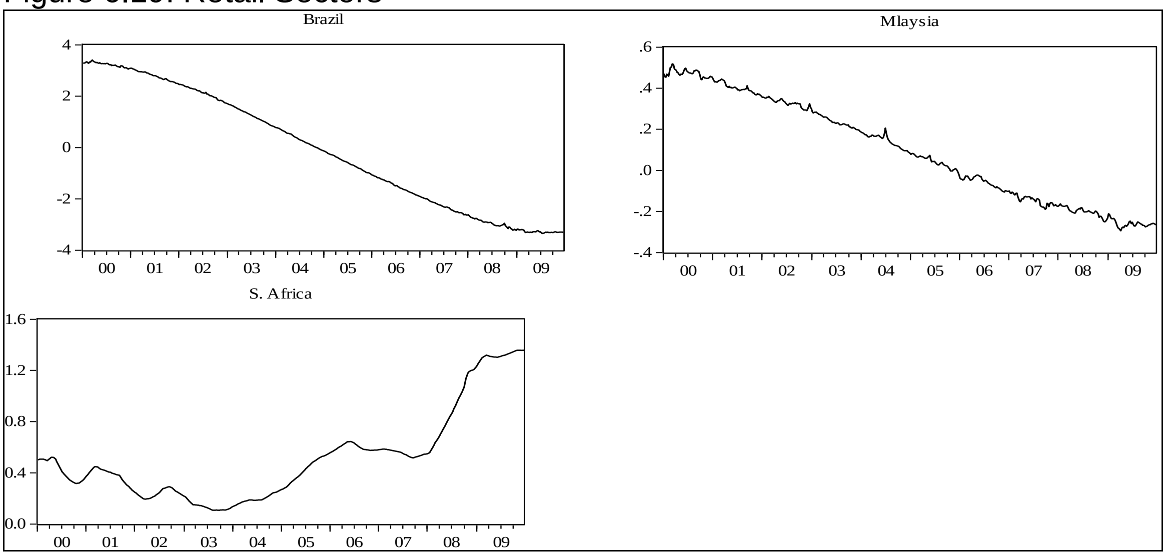
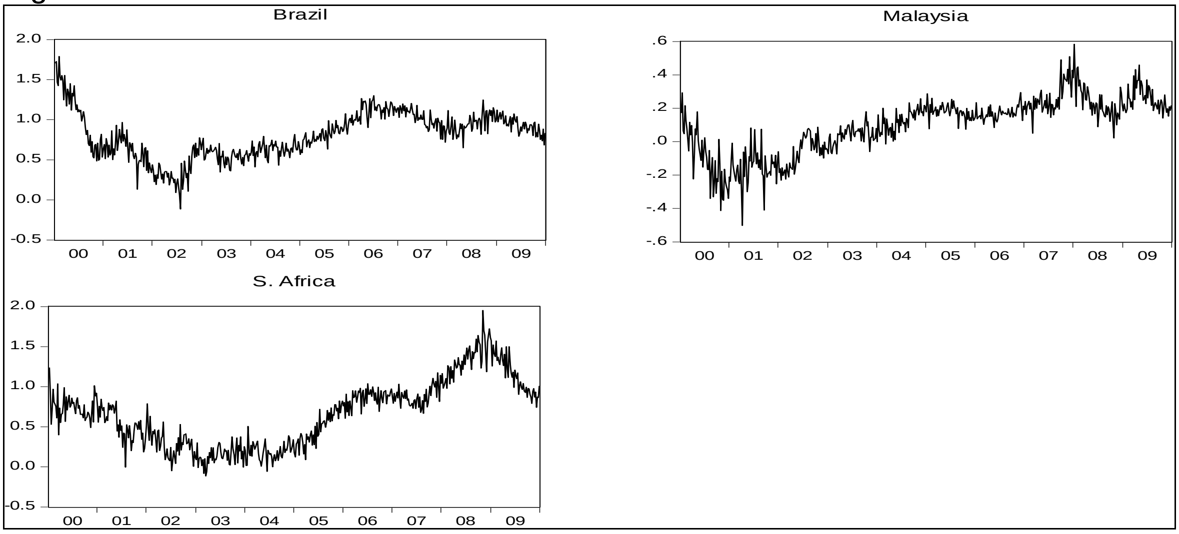


Figure 6.20 of Telecommunications Sectors



In summary, the results of our time-varying estimations for the industry sector of the US and emerging countries of the study show mixed results. For example, there is no convergence among the Banking, while time-varying co-movement among the telecommunications sectors is stationary and also the most volatile as the figure 6.20 suggests. As can be seen from the figures, there is rising and stable convergence in the case of the Basic resources, Chemicals, and Construction and materials, and Industrial goods sectors for all markets over the sample period. As the figures 6.5 and 6.6 show, the time varying coefficient estimates indicate smooth but declining beta convergences in the case of Financial Services in all cases, and Food and Beverage sectors in the case of the Malaysian and South African markets with the US, and rising and occasional fluctuating (e.g. mid 2000) convergence of similar sectors between the Brazilian and US markets. Also, there exist mixed results in Persnal and Retailing sectors, while there is also volatile convergence in the telecommunications sectors as mentioned above.

Next, figures 6.21 to 6.30 present the time-varying coefficients of multivariate regressions, taking each of the US sectors as the dependent variables and the emerging industry sectors as the explanatory variables. Once again, it is clear from the figures that, the co-movements between the emerging and US industry sector returns are not stable over the sample, especially in the global financial market turmoil of late 2009. The Banking and Telecommunications sectors show the most volatile beta convergence. Only few sectors, such as the Chemicals, Constructions, and the Industrial Goods indicate some (positive or negative) beta convergence. Overall, the results of the time varying estimations which complement those of the time varying correlations indicate volatile co-movements between the industry sectors of the US and the emerging markets in the study.

Figures 6.21 to 6.30: Time-varying coefficients of multivariate regressions: US sectors as the dependent variables

Figure 6.21: Multivariate time varying coefficients of Banking Sectors

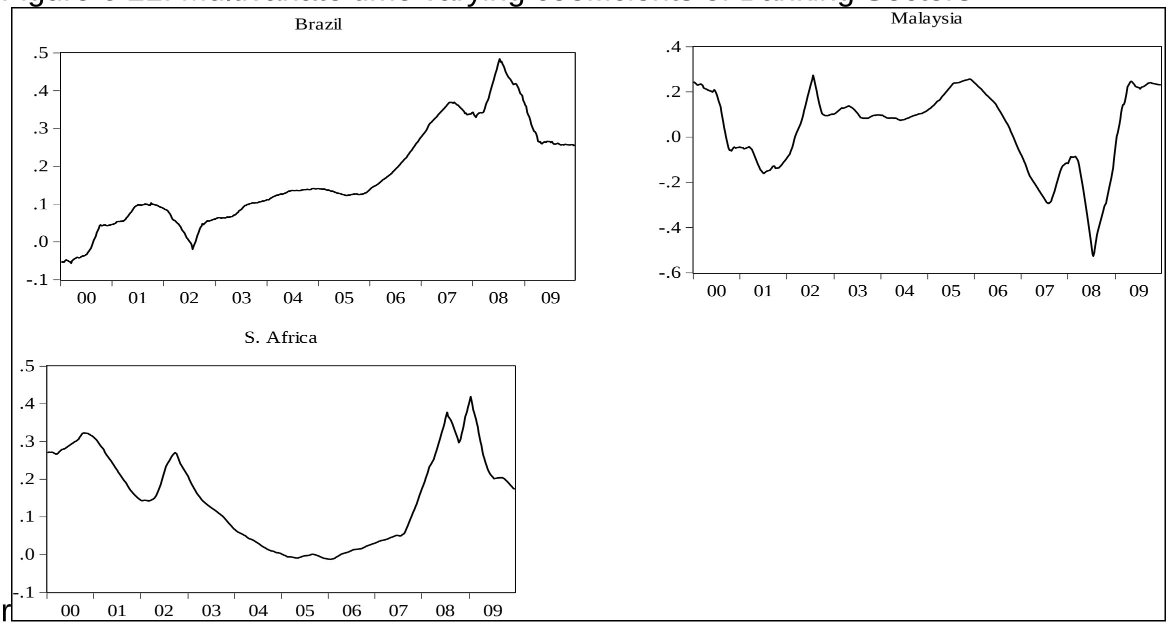


Figure 6.22: Multivariate time varying coefficients of Basic Resources Sectors

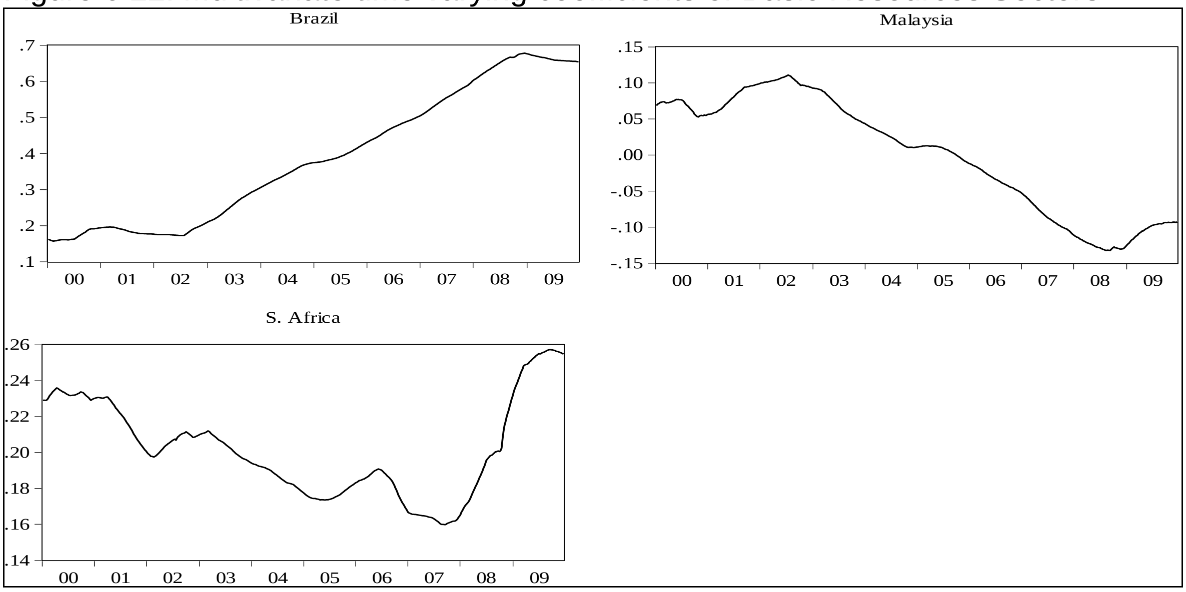


Figure 6.23: Multivariate time varying coefficients of Chemicals Sectors

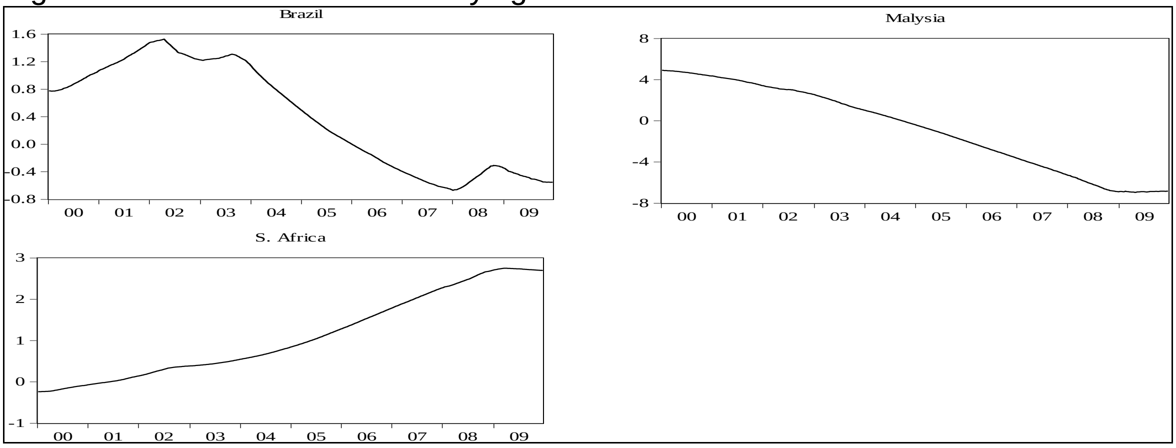


Figure 6.24: Multivariate time varying coefficients of Construction and Materials Sectors

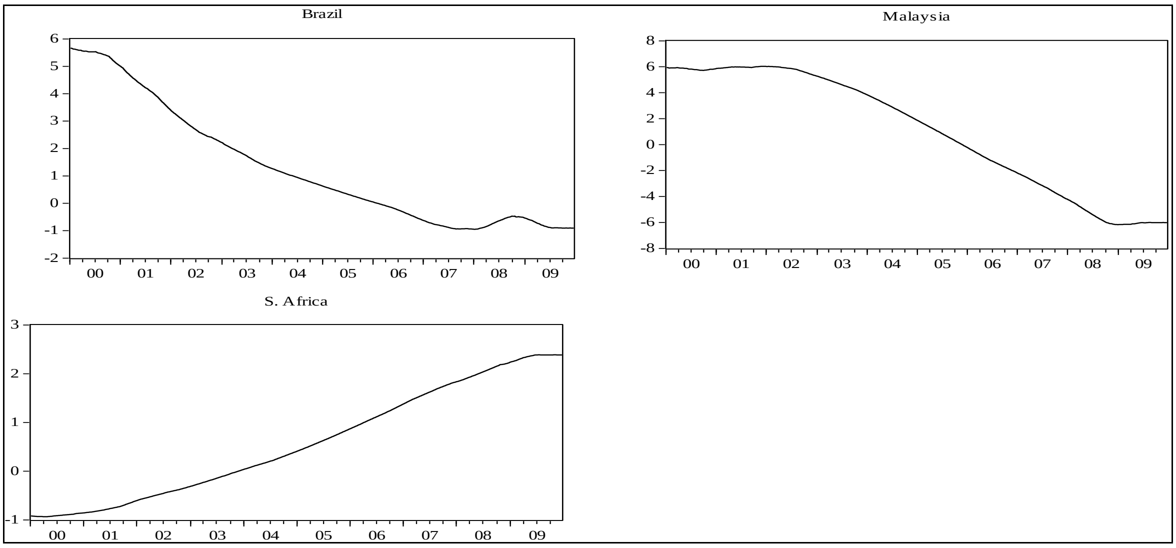


Figure 6.25: Multivariate time varying coefficients of Financial Services Sectors

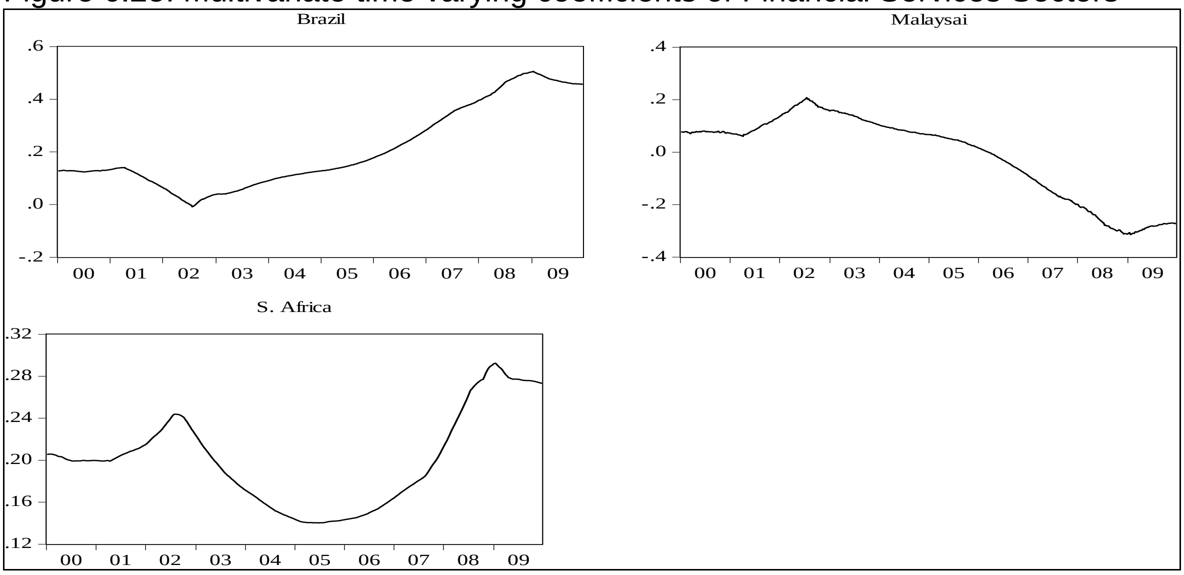


Figure 6.26: Multivariate time varying coefficients of Food and Beverage Sectors

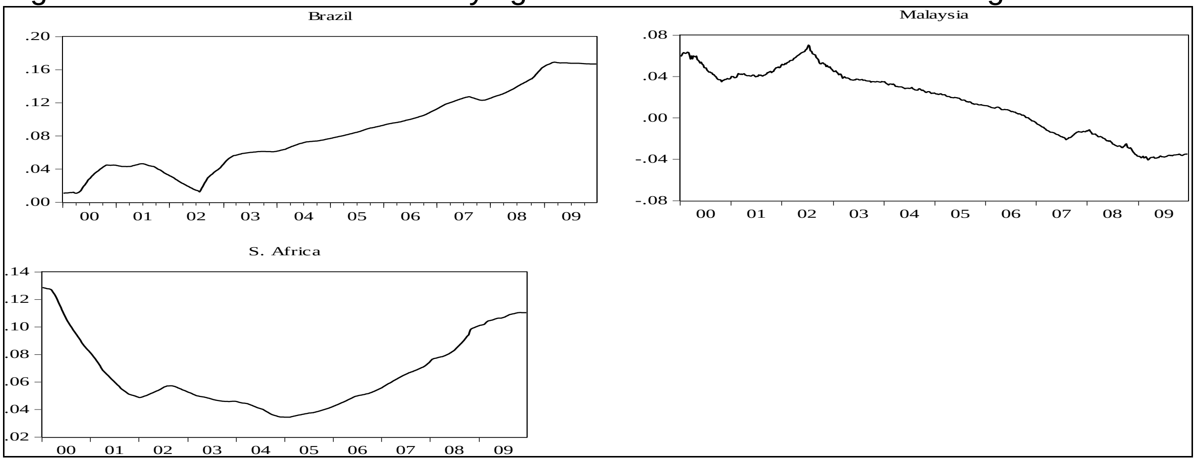


Figure 6.27: Multivariate time varying coefficients of Industrial Goods Sectors

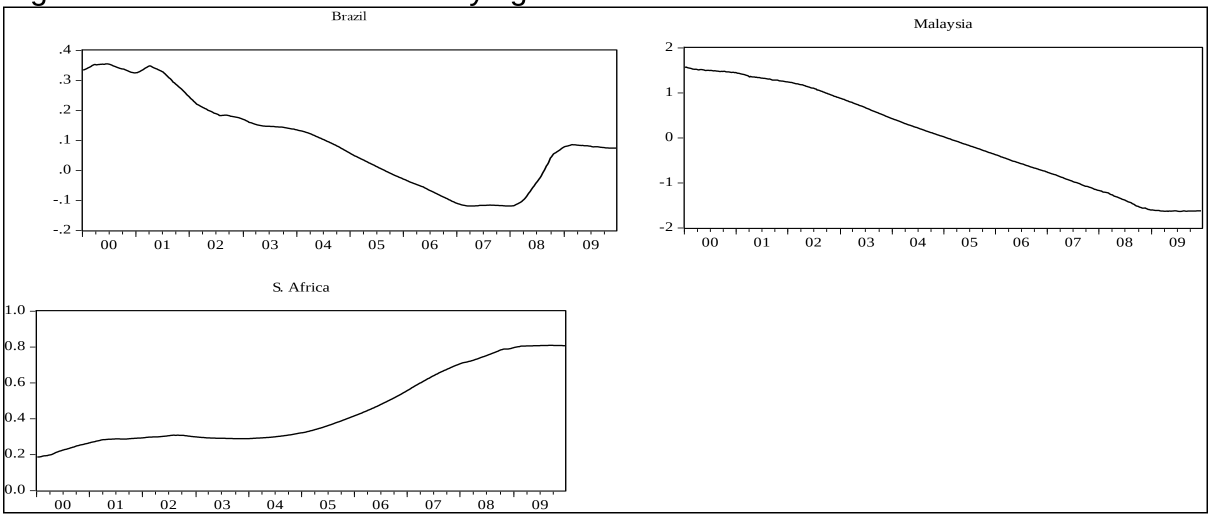


Figure 6.28: Multivariate time varying coefficients of Personal & H/H Goods Sectors

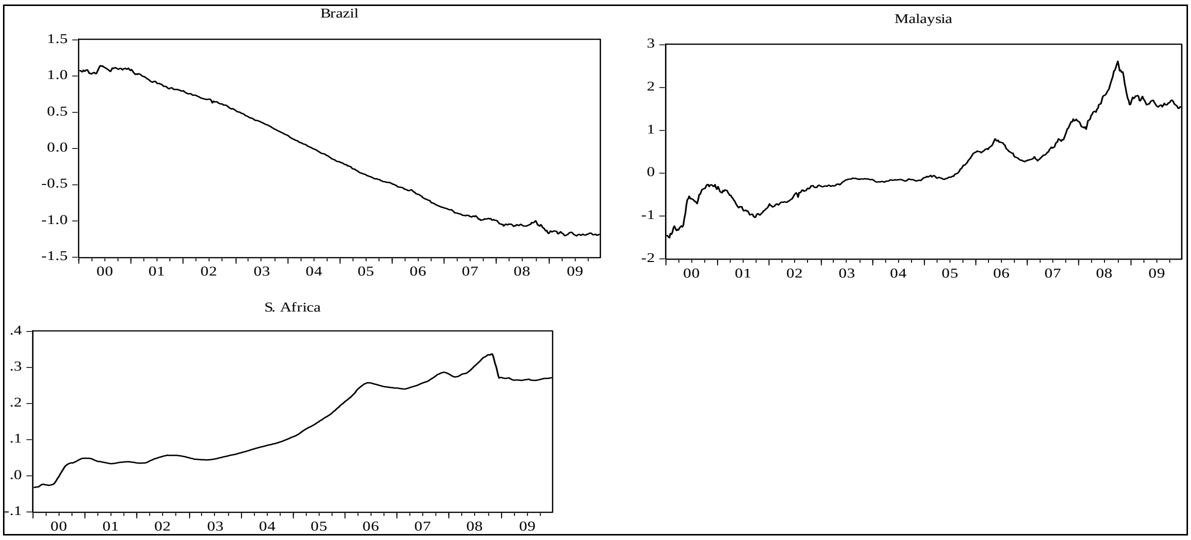


Figure 6.29: Multivariate time varying coefficients of Retail Sectors

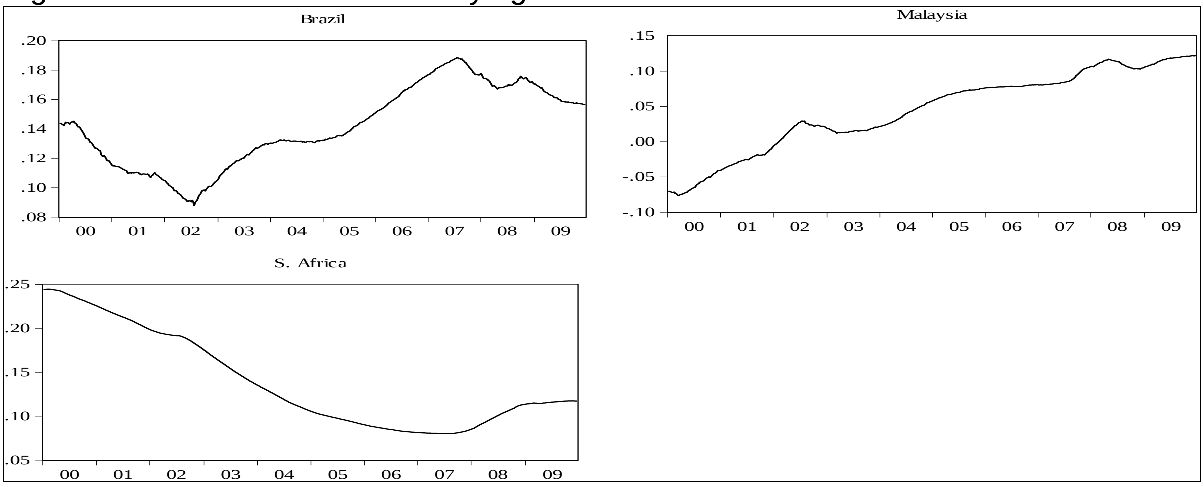
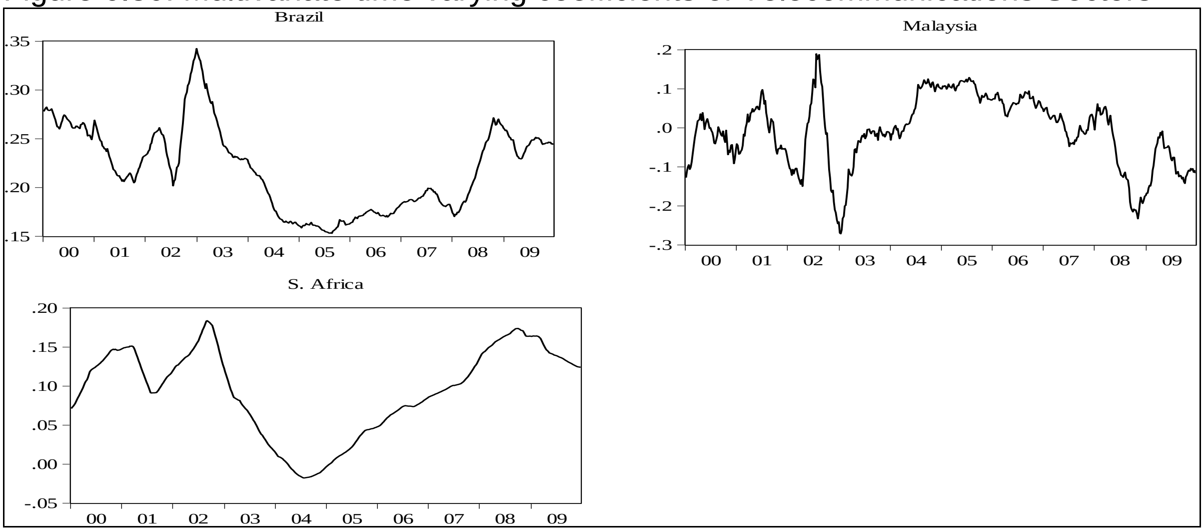


Figure 6.30: Multivariate time varying coefficients of Telecommunications Sectors



6.5 Conclusion

To investigate the interdependence between the industry sectors in this study, several empirical assessments are considered. In this chapter, as the initial step for co-movement analysis, the returns co-movements between weekly returns of the US and emerging industry sectors in the form of standard cross correlations, time varying correlations and time varying regression coefficient estimations are assessed. Correlations between the assets of different markets play an important role in financial markets as they are widely used in portfolio diversification and risk management strategies. The initial exploratory analysis of the sample's cross-correlations indicates, though in a moderate range, the existence of interdependency among international industry sectors as all correlations are positive and prove significant (at the one per cent level). Most estimated values of correlation coefficients are lower than 50 percent, while only a few industry sectors indicate about 60 percent or more. To summarise, the cross correlation results indicate a weak linear association between the sectors of the markets considered in the study over the sample period. However, the analysis of cross correlations in the returns is a short-run phenomenon; studies of long-run relationships are needed to investigate the possibility of co-movements between asset prices. Long-run equilibrium among price indices and the dynamic relations between returns will be investigated and represented in chapters seven and eight respectively.

Given the empirical characteristics of the data series of the study as discussed in chapter four, it is reasonable to assume that the true relations between the sector returns in the study are not constant but rather are changing over time. Therefore, prior to undertaking long run analysis for price relationships, this chapter conducts time varying correlations and time varying coefficient regressions to examine the time variation co-movements between weekly returns of the US and emerging industry sectors. Time varying analysis of cross correlation relationships based on yearly window estimates are conducted and graphs presented in section three. Overall, as the plots (6.1 to 6.10) of the rolling window estimations indicate, there is high instability in the correlations between the industry sectors of the US and the emerging countries under study over the sample period.

The finding of unstable correlations over the sample period motivates further analysis to examine the time-varying sensitivities. Therefore, a distinctive feature of this thesis is the combination of a time varying correlations analysis and time varying coefficient methods for industry sector level indices. In other words, as an alternative procedure, section four presents the time series regressions to model the time-varying betas by employing a state space framework via Kalman filtering. In summary, as can be seen from the bivariate and multivariate time varying estimations as presented by the graphs 6.11 to 6.20 and 6.21 to 6.30, there is generally unstable beta convergence among the returns of the US and the emerging countries' industry sectors over the sample period. Overall, the results of time varying analysis indicate unstable relationships between the returns of US and the emerging economies' industry sectors over the sample period. Another way to examine time varying interdependence between the industry sector returns is to test whether the causal linkages have been changing over time. Time varying causality relationships between the returns of the US and the emerging markets of the study will be discussed in chapter eight.

CHAPTER 7:
Long-run Relationships between the US and Emerging Markets' Industry Sectors: Evidence from Linear and Nonlinear Cointegration Tests

7.1 Introduction

As mentioned before, the aim of this thesis is to examine the interdependence among international stock markets through the use of industry sector price indices and linear nonlinear econometric methodologies. This chapter examines the long-run relationships between the ten industry sector indices of the US and the emerging countries applying linear and nonlinear cointegration techniques. The long run linear relationships are examined through the application of the maximum likelihood approach of cointegration analysis (Johansen 1988, 1991, and 1995), which suggests testing cointegration relationships through the building of a Vector Error Correction (VEC) model. As will be discussed later in this chapter, the sample period of this study covers a time in which severe financial crisis and high volatility in the international stock markets has been persistent. Crisis events can change the degree of long run relationships between variables, or international industry sectors in this case, and need to be taken into account. Therefore, to further examine the dynamic of long run relationships between international industries or long-run convergence, this study also examines the stability or time varying characteristics of long-run relationships between the industry sectors under study using recursive cointegration analysis, as proposed by Hansen and Johansen (1999). In addition, rolling cointegration tests are also used to investigate the degree of dynamic convergence between the US and emerging countries industry sectors during different sub-sample periods of the full sample using the cointegration rank tests of Johansen (1988, 1995) tests[89].

[89] Recursive and rolling estimations can capture structural changes in data series without testing for structural breaks.

Chapter 7

Linear models are regarded as a restricted form of more general nonlinear models. A number of market frictions, such as transactions costs, and information frictions can prevent the linear models converging to long run equilibrium in financial markets and may necessitate nonlinearity modelling for long relationships among asset prices. As a result, the possibility of cointegration relationships among financial asset prices being nonlinear has been receiving some attention in recent years from academic researchers and practitioners. To test for nonlinear cointegration relationships in the industry sectors in the study, the rank tests for nonlinear unit roots and cointegration relationships proposed by Breitung and Gourieroux (1997) and Breitung (2001) are employed. Breitung's (2001) rank statistic is first applied to detect relationships among time series variables in linear, and then the nature of nonlinearity or nonlinear cointegrations is assessed using score statistics. This chapter also presents the testing procedures and empirical results of nonlinear relationships for the international industry sectors in the study.

The work of the chapter is organised as follows. Section two of the chapter explains the testing procedures of linear relationships including unit roots, model specification and the selection of lag orders, cointegration and, and presents the empirical results of Johansen's trace test statistics. Section three presents the results (graphical displays) of recursive and rolling cointegration analysis for the time-varying nature of long-run relationships between the industry sectors of US and emerging coutries (Brazil, Malaysia, and South Africa) in the study. Next, section four presents the testing procedures and empirical results for nonlinear unit roots and cointegration relationships (the rank tests). Finally, section five presents the summaries of the linear and nonlinear empirical results and offers some explanations of the likelihood implications of the empirical results.

7.2 Long-run Linear Test Results

Econometric analysis for long run linear price linkages in this study proceeds in three steps. Firstly, as a test for linear cointegration relationships is often based on the notion that all variables in the system are nonstationary, it is a customary procedure in empirical studies, before the empirical analysis of cointegration is conducted, to transform all the series into natural logs and investigate their integrated properties using various unit root statistics. The next subsection presents the unit root test results. To see the general characteristics of the multivariate residuals, the second sub-section first estimates a general VAR model for the price indices of the industry sectors under study and presents graphical representations of the VAR residuals. Next, diagnostic tests of the VEC model specification residuals, as well as a discussion of lag length selection procedures, are reported. A set of multivariate lag order tests, including the sequential modified likelihood ratio (LR) statistic and various information criterion (IC) procedures are conducted to determine the appropriate lag lengths. The results of the linear cointegration tests or long run relations for the international industry sectors are presented in the third subsection. Finally, testing procedures and graphical illustrations of time varying cointegrating test results, using recursive cointegration analysis, are presented in the fourth subsection.

7.2.1 Testing Unit Roots for Industry Sector Indices: Statistical results of ADF, DF-GLS, and KPSS tests

In economic and financial time series data, the equilibrium relationships between the levels of time series variables are often described as being I(1). To examine time series for cointegration or long run and causality relationships, it is important to be able to determine the presence of a unit root in that time series, or to say whether the series may be considered stationary. In terms of testing methodology, this means whether the series exhibits I(1) (unit root) or I(0) (stationary) behaviour. As explained in the methodology chapter, this study applies three unit root test statistics (ADF, DF-GLS, and KPSS) for nonstationarity and stationarity tests. In addition, a nonparametric statistical test, the RANK tests for nonlinear unit root tests, is also implemented. This section presents testing procedures and the results of (linear) nonstationarity using the augmented Dickey-Fuller (ADF) test and the Elliott, Rothenberg, and Stock (ERS, 1996) DF-GLS unit root test for both price levels and the first differences of the industry sectors in natural logarithms. The null hypothesis to be tested is that each price indices in the logs is I(1), and the alternative is that each price series is I(0) about a deterministic time trend. The study also applies the Kwiatkowski et al (KPSS, 1992) statistics to the US and emerging countries' industry indices. The null hypothesis of the KPSS statistics is that the series exhibit stationarity, I(0). The results of these tests are then compared and contrasted with the results of the RANK test for the presence of nonlinear unit roots.

The implementations of the unit root tests often necessitate the selection of an appropriate lag length. Traditionally, several selection models or information criteria procedures such as the Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC), the Hannan-Quinn (HQ), and the Forecast Prediction Error (FPE) have been the standard techniques in applied time series econometrics for the lag order determination of the ADF test for unit roots. Recently, an alternative method has been proposed for the lag order determination of the ADF and DFGLS tests, and the sequential t-test of Ng and Perron (1995). Ng and Perron compared these two approaches in the context of the ADF test and found that the general to specific approach performed better than information criteria. Moreover, Ng and Perron (2001) argue that the relatively poor performance of traditional information criteria is due to the fact that they are not designed for nonstationary data, and proposed modified information criteria (MIC) to address this problem. In this study the information criteria approach is adopted to determine an appropriate lag length using Schwarz Information Criterion (SIC). To determine the lag orders of the ADF and DF-GLS statistics, a regression of an autoregressive model with lags from 0 to 10 is tested for each log price level and first differenced series, and then selected as the most optimal (minimum) lag according to the Schwarz Information Criterion (SIC). For the KPSS test for stationarity, the optimal number of lags was chosen using the Newey-West (1994) truncation of automatic bandwidth selection procedure of the Quadratic Spectral kernel. All the ADF, DF-GLS and KPSS tests are applied with a constant and a linear deterministic trend included in each test equation.

Appendix B presents the results of the ADF, DF-GLS, and KPSS statistics of unit root and stationarity tests for the industry sector price levels in logarithms and first differenced. All tests are included both an intercept and a deterministic trend term. As can be seen from the tables in the appendix, none of the computed results of the ADF test are significant for price levels in logarithm, and hence all the original industry sector indices are non-stationary. On the other hand, all the difference series are significant which means that, in the first-differenced form at least, all the series are stationary. Like most prior work on financial time series, all the data series are integrated in order one, I(1) according to the ADF test statistic. Some econometric theorists (i.e. Greene (2008) and Hamilton (1994)) argue that the ADF test can fail to distinguish between a unit root and a near unit root process and will too often indicate that a series contains a unit root. Hence, Elliott et al (1996) propose a de-trending approach using generalised least squares (GLS) as a means of improving the power of the DF test, which I also used in this thesis.

The DF-GLS test also indicates insignificant results for price levels in logarithm for all indices in the study, while the first difference series are all significant according to the DF-GLS test[90]. On the other hand, the results of the KPSS statistics support stationarity properties for all tests of the same series. The results of the employed unit root test statistics are very much consistent with prior work on stock index values and support figures 4.1 and 4.8 of chapter four. Having establishing that all sector indices in the study are integrated with I(1), the next step is to test the existence of long run relationships using the maximum likelihood approach (Johansen-Juselius) of cointegration through error-correction models (ECMs).

[90] The EViews econometric application has been used for the empirical analysis of all the unit root tests.

7.2.2 The Cointegrated VAR

7.2.2.1 Model Specification

Empirical implementation of cointegration tests requires the specification of a VAR (p) or VEC (p) model for the series under study (y_t). In this study, to investigate the long relationships among industry sectors, let y_t be a (nx1) = (USy_t; BRy_t; MLy_t; SAy_t;)' be a vector of time series of natural logs of industry sector indices for the US and emerging markets (Brazil, Malaysia and South Africa) at time t. The possibility of dynamic relationships between a set of variables (y_t) and a multivariate linear model with *n* variables and p lags can be described using a VAR model of the following format

$$y_{it} = \mathrm{A}_i \sum_{i=1}^{p} y_{t-p} + \varepsilon_t \text{ , } \varepsilon_t \sim IND(0,\Sigma) \qquad (7.1)$$

As a starting point for model specification for vector autoregressive (VAR) cointegration tests, a basic VAR model, as in (7.1), with up to 4 lags is first estimated for each industry price series in natural logarithm. The fitted estimations are then inspected graphically using the generic plot method. Figures 7.1-7.10 present the visual inspections of the estimated VAR residuals for the prices levels in logarithm of the industry sectors in the study. The conventional assumption is that stock markets behave according to a random Gaussian or normal distribution properties. However, as graphical inspections of the multivariate residuals indicate, there are several periods in which the price index series of many industry sectors has large volatilities. Therefore, it appears that the underlying multivariate normality assumption is unlikely to be satisfied. The graphs also show the heterogeneity of the residuals as there are several large volatility periods and multiple outliers. Various events in the sample period may have induced observations that are inconsistent with the normality assumption. These events include: the attack on the world trade centre in September 2001, the sharp drop of stock prices in stock exchanges across the United States and Europe, in July, September and December of the year 2002, and the economic and financial crisis in the late 2000s. It is difficult to pinpoint a particular crisis period which has had a common effect on all markets/countries' industry sectors. However, the late 2000s (2007 -2009) are visible in all sector graphs. The vertical axes of the figures report the volatility level of VAR residuals.

Figures 7.1-7.10: VAR residuals of the industry sector price indices

Figure 7.1: VAR Residuals of Banking Sectors

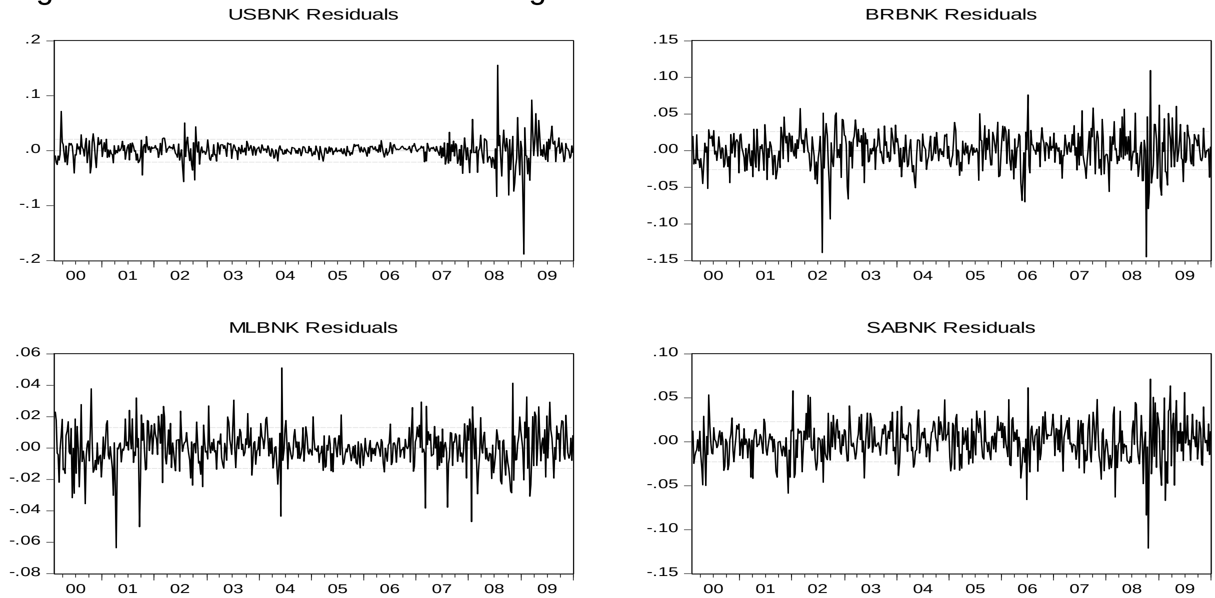
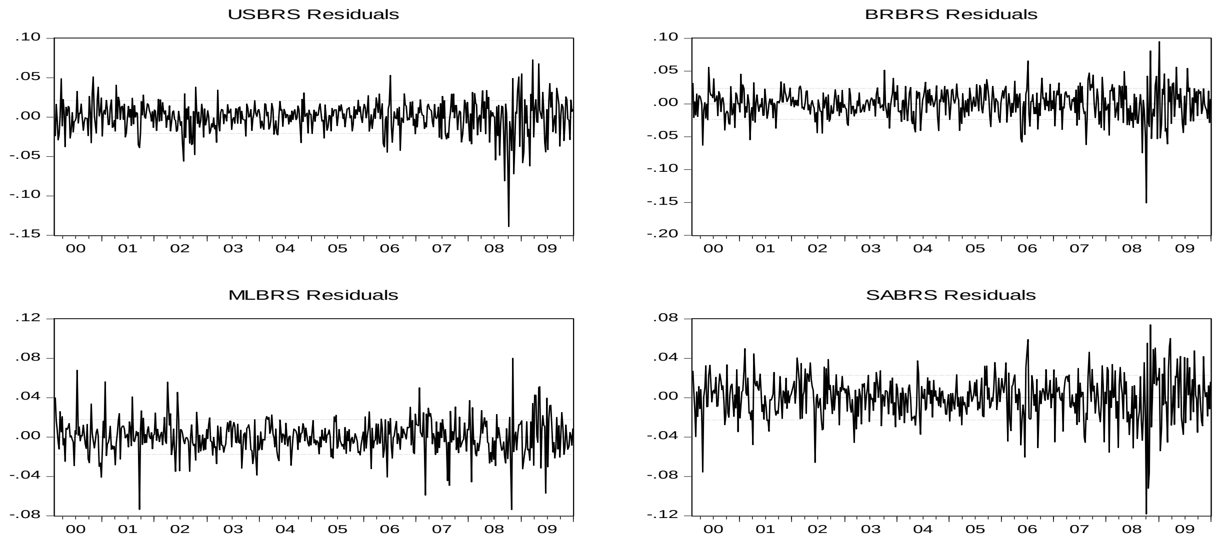


Figure 7.2: VAR Residuals of Basic Resources Sectors



Chapter 7

Figure 7.3: VAR Residuals of Chemicals Sectors

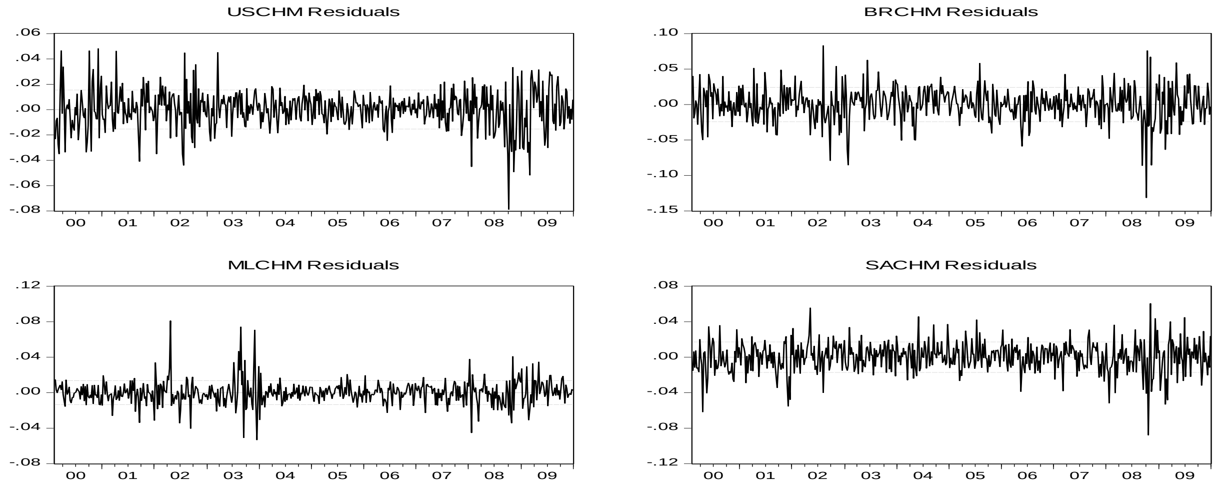


Figure 7.4: VAR Residuals of Construction Materials Sectors

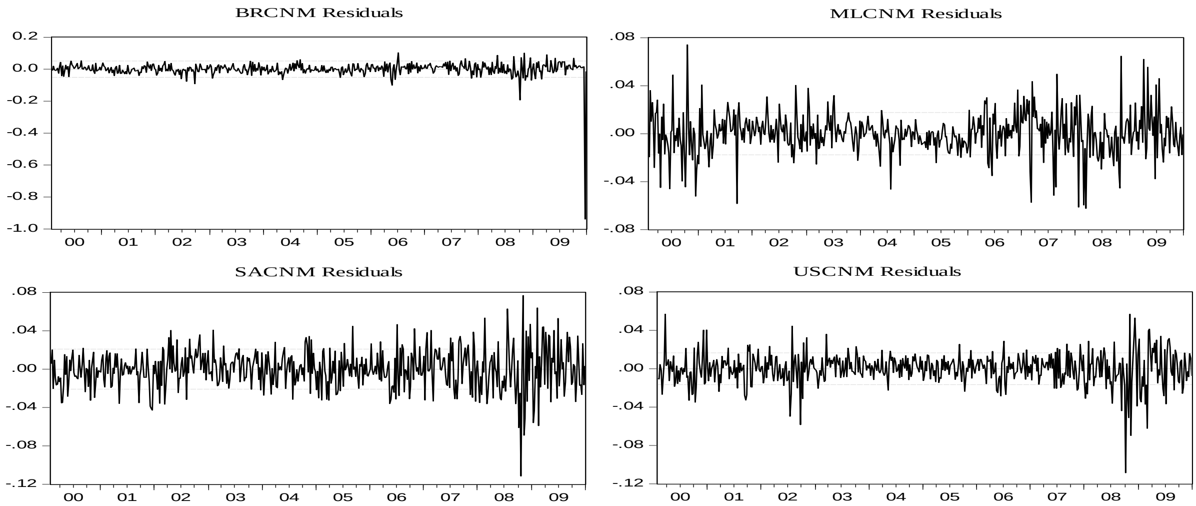


Figure 7.5: VAR Residuals of Financial Services Sectors

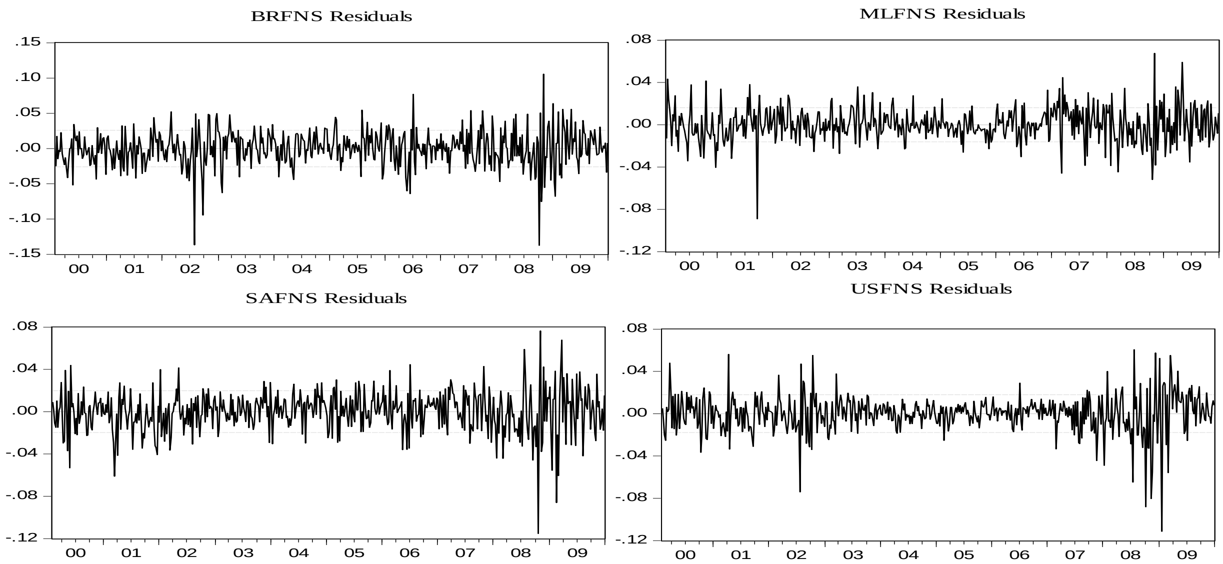


Figure 7.6: VAR Residuals of Food & Beverage Sectors

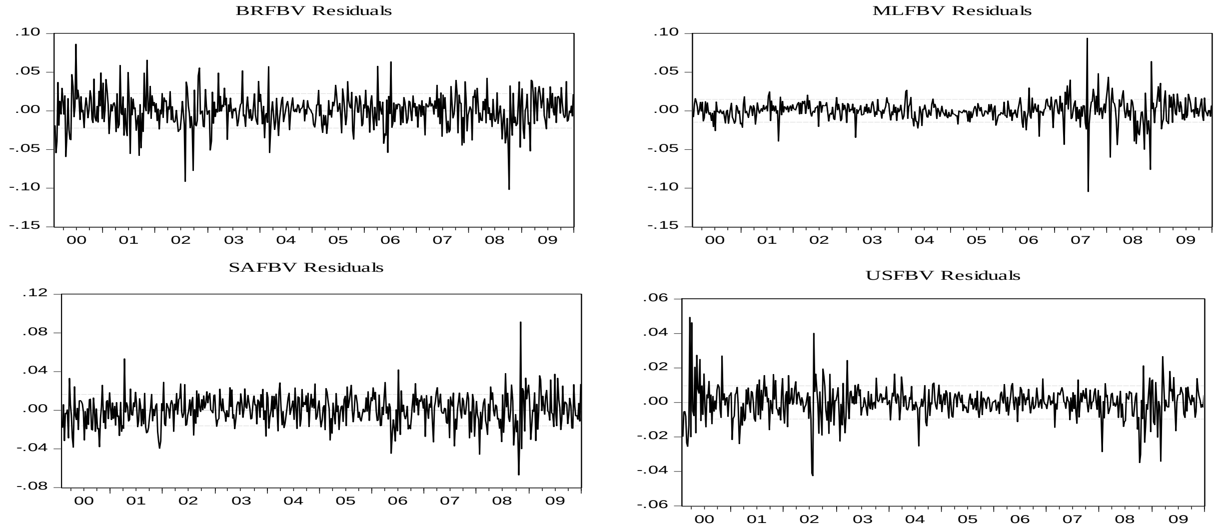


Figure7.7: VAR Residuals of Industrial Goods Sectors

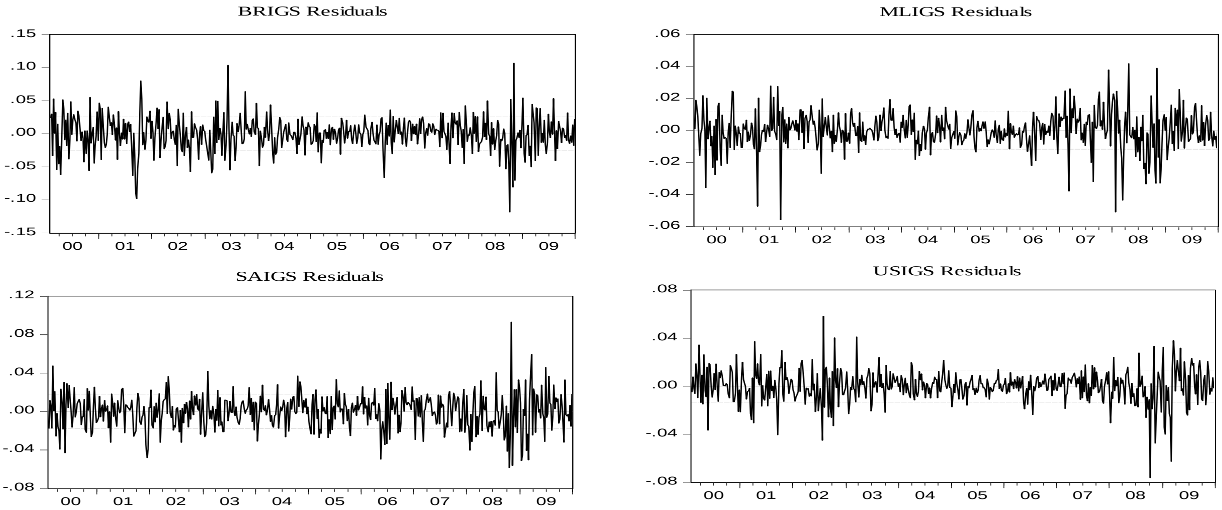


Figure 7.8 VAR Residuals of Personal Goods

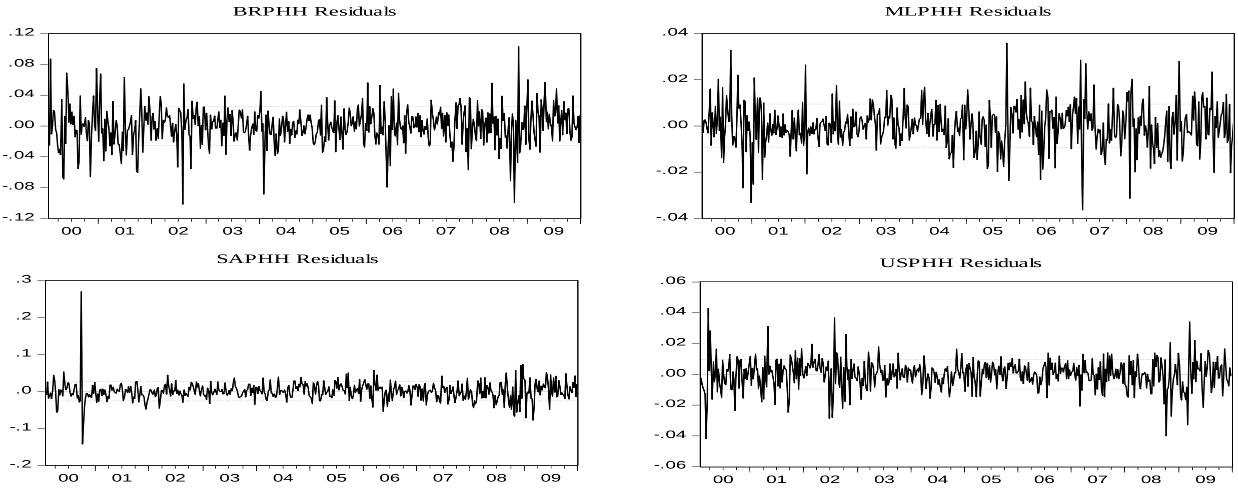
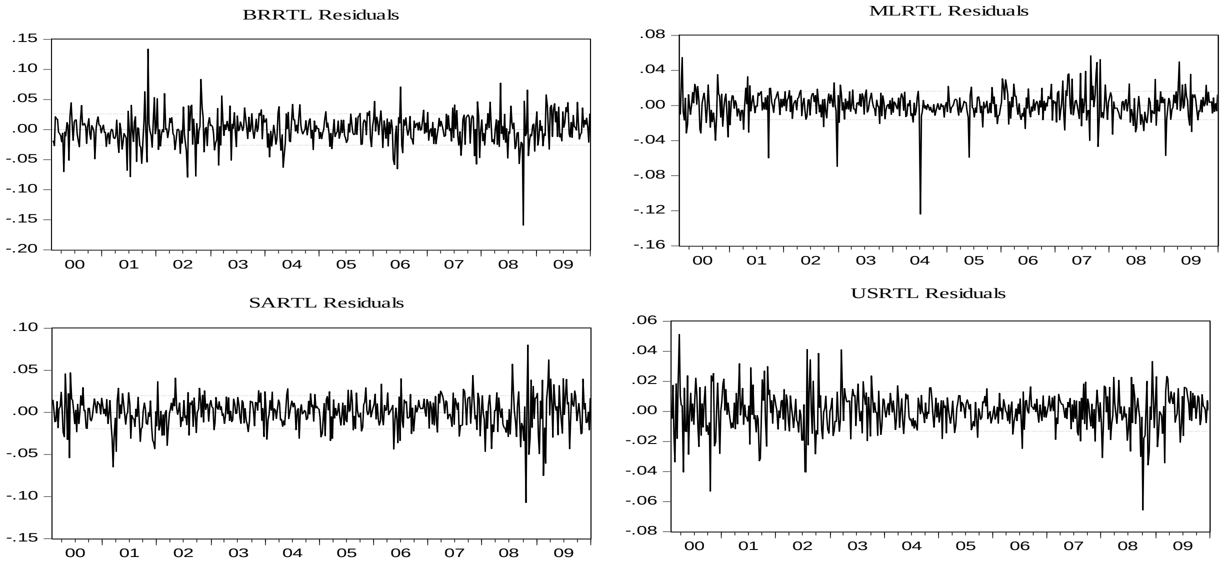
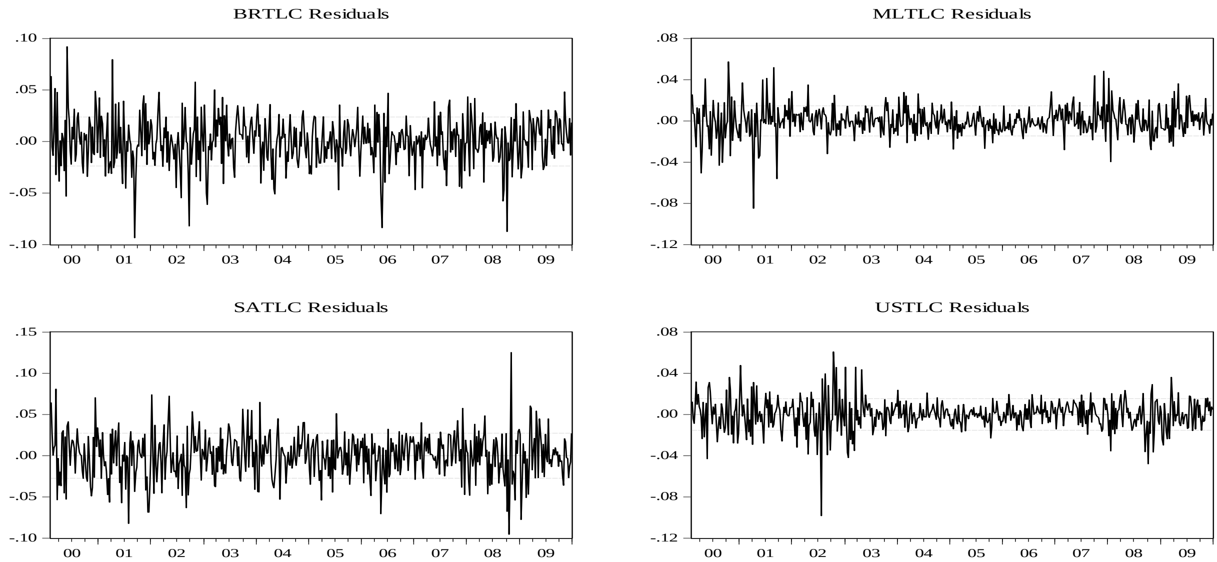


Figure 7.9: VAR Residuals of Retailing Sectors



7.10: VAR Residuals of Telecommunications Sectors



The economic and financial crisis of the late 2000s has resulted in the collapse of several large financial institutions, the rescue of banks by national governments, and downturns in stock markets around the world. In that period, according to Baily and Elliott at Brookings' business and public policy (2009), 'declines in the real economy exacerbated the problems of financial institutions, which then created a credit crunch hurting the real economy and so it went on'. By the beginning of 2009, most advanced economies were already in recession, with job losses and home repositions intensifying across the board. Emerging market economies and currencies also came under extreme pressure. Investors were pulling money out of countries in Eastern Europe, Latin America and Asia acting on fears that the vulnerable countries will not only be hit hard by the financial crisis but may also default on debt. 'The equity market reaction to the financial crisis of 2008-2009 is one in which equity markets worldwide have suffered a serious decline', Bartram and Bodnar (2009. p. 1250)[91]. Indeed, the economic and financial crisis of late 2000, so often called the Credit Crunch or the Global Financial Crisis, has been labelled by many economists and commentators (i.e. Roubini 2009) as the worst financial and economic crisis since the 1929 stock market collapse and the Great Depression in the 1930s. Many industries, including automobiles, aircraft, building materials, consumer goods, steel, services such as transport services, and a number of manufacturing industries were severely affected (UNCTAD 2009).

In the present study, as the residuals of the VAR graphs indicate, nearly every industry sector of the considered economies, from banking to telecommunications, is affected by the late 2000s economic and financial crisis. The crisis can change the degree of the long run relationships between the variables under study and therefore it is appropriate to control the most volatile dates or periods with seasonal and impulse dummies (Juselius, 2006). Therefore, using the weekly data as explained before, a seasonal dummies term, D_t, is included in the unrestricted part of the VAR model specification, which represents a complete two year period from January 2008 to December 2009. As can be seen from the graphs, the series in this period have been observed to contain relatively larger volatilities,. As in the basic VAR model discussed above, a modified VAR model with up to 5 lag orders is estimated for all the industry sector price indices. To avoid duplications and save space, the graphical inspections of the modified VAR model are not reported here. However, all graphical inspections of the residuals show no qualitative differences as they all indicate large volatilities and heterogeneity.
For nonstationary or I(1) integrated variables, as in the present study, the level VAR representation is not the most suitable representation for analysing the

[91] Among others, Bartram and Bodnar (2009) and Mollah and Hartman (2012) present broader discussions of the impact of the recent crisis on global equity markets.

cointegrating relationships as such relationships might not be explicitly apparent in a VAR model. Therefore, a VECM is considered to be more applicable[92]. The following general format of the vector error correction (VEC) model with dummy terms is used to construct the Johansen's maximum likelihood cointegration tests for the long run relationships between industry sectors of the US and emerging markets as follows[93].

$$\Delta y_{it} = \alpha_t + \Pi y_{t-1} + \Gamma_i \sum_{i=1}^{p-1} y_{t-p} + \Phi D_t + \varepsilon_t, \ \varepsilon_t \sim \text{IND}(0,\Sigma) \qquad (7.2)$$

where, as explained before, each y_t is a *n x1* vector of the variables observed series at t and are I(1) series with an nx1 vector constant vectors (α), and Δ denotes the first difference operator. The VECM specification contains information on the long-run relationships and short- run adjustments to changes in y_t, via the estimates of Π and Γ_i respectively. ε_t is also a nx1 vector of residuals and Σ the variance/covariance matrix of the ε_t. In the present study, each y_t is a 4x1 vector, and Γ_i and Π are (4x4) coefficient matrices. The unrestricted seasonal dummies, D_t, is also an nx1 and represents the late 2000s economic and financial crisis, taking the value 1 in the crisis period and zero elsewhere. The number of cointegrating relationships is given by the rank of Π = αβ' and will be determined after specifying the model. The VEC model specification in equation (7.2) is used as a benchmark model to investigate the linear cointegration relationships between price indices of the industry sectors of the US and the three emerging countries in the study. Equation (7.2) corresponds to the equation of the methodology chapter but the deterministic components are now specified as separate terms. The results of the diagnostic testing of the specified VEC model

[92] Juselius (2006) discusses a number of advantages in reformulating the VAR model in a vector error correction (VEC) format.

[93] In cointegrated VAR applications, the usual practice of dealing with the large residuals has often been to include unrestricted dummies in the cointegrating space (i.e. Hendry and Juselius 2001). However, Nielsen (2004) questions this approach and advocates distinguishing between additive outliers and innovational outliers.

and the lag length selection strategy based on the underlying un-differenced VAR models are reported below.

7.2.2.2 Diagnostic Testing and Lag Length Determination

To support the model specifications of the study, a series of diagnostic testing, including serial correlation, normality and Heteroscedasticity tests, are implemented for the residuals of the estimated VEC models. Serial autocorrelation tests are based on the Ljung–Box Q (portmanteau) test statistics with up to 10 lag orders [94]. Multivariate Heteroscedasticity test effects in the residuals are also tested using the no cross terms test. The normality of the residuals is tested using the Lütkepohl (2005) approach. Lütkepohl suggests using the multivariate generalization of the Jarque-Bera test (Jarque and Bera, 1987) to test the multivariate normality of the residuals, which compares or tests the skewness and kurtosis properties of the residuals against those of a multivariate normal distribution of the appropriate dimension. To conserve space, the diagnostics results of the residuals from the estimated VEC estimations are not reported here. However, the results show that each test of the VEC systems passes the test of Residual Portmanteau Tests for Autocorrelations based on the Ljung–Box Q statistics. On the other hand, the no cross terms tests for multivariate ARCH effects strongly rejects the null hypothesis of no heteroskedasticity. The results correspond to the univarite results for ARCH effects as reported in the data analysis chapter. Nevertheless, according to Rahbek et al (2002) the cointegration tests prove robust against ARCH affects. The model misspecification tests also indicate rejection of multivariate normality due to non-normality in the univaraite variables, as has been reported in the data analysis chapter. However, since non-normality of residuals does not bias the results for the Johansen's cointegration tests, the test results still prove valid (Gonzalo, 1994).

[94] Hosking (1980) derives the multivariate analogue to the LB portmanteau test statistic for autocorrelation.

Chapter 7

Another important issue for the Johansen's cointegration test is to choose appropriate lag lengths. Hence, the next task in the specification process is to choose an optimal lag order for each test of the multivariate system of equations, and to test for serial auto correlations from the estimated unrestricted VAR model with dummies. As Hall (1991) points out, too few lags may lead to a serial correlation problem, whereas too many lags specified in the VECM system will consume more degrees of freedom and thus lead to the small sample problem. As discussed in the methodology chapter, the lag lengths of the VAR/VEC model is determined by the use of the multivariate versions likelihood ratio (LR) test and/or the information criterion (the final prediction error (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HIQ)) of the underlying unrestricted or VAR model. Other suggested criteria include the Lagrange Multiplier (LM) test and a small-sample correction (Ivanov and Kilian, 2005). Information criteria normally choose shorter lag lengths but may not always be sufficient to remove serial correlation from the VAR residuals.

For a comparative assessment and a wider choice of lag order selection methods, the test likelihood ratio (LR) statistic and information criterion (IC) tests are conducted in this thesis, and then the most optimal lag order is chosen, applying residuals of the unrestricted VAR models. In addition, as for additional lag selection criterion, residual autocorrelation tests are estimated for all un-differenced VAR models using the Lagrange Multiplier (LM) test. The lag length selection tests of the un-differenced VAR model are performed using up to 10 lags for each industry model. When two or more selection criterions indicate different optimal lag lengths, the lag length which passes the tests for serial correlation with the most insignificant result (based on the LM test) is adopted. The results of this study, which are not reported, show that all the chosen lag lengths are appropriate since they all passed the autocorrelation tests based on the Langrange multiplier (LM) tests. The cointegration results tables indicate the adopted lags for the corresponding VEC models (or cointegration tests). The adopted length orders for the cointegration tests correspond to the unrestricted VAR whose optimal order is one greater than the VEC model (VAR-1).

7.2.3 Cointegration tests and results

In cointegration testing, the trend terms in the y_t time series can be classified into five cases of unrestricted and restricted versions (Johansen 1995). The unrestricted versions may exhibit quadratic trends, and there may be a linear trend term in the cointegrating relationships. The restricted versions, on the other hand, may show the trending nature of the series in y_t. Since the asymptotic distribution of the test statistics for cointegration depends upon the specification of the deterministic components, extra care is required to appropriately specify the VAR/VEC the model[95]. In this study, a model of unrestricted constant and restricted linear trend with dummies is first considered for each of the industry price indices. Thus, the VEC model in equation (7.2) is rewritten as

$$\Delta y_{it} = \mu + \alpha(\beta^{'} y_{t-1} + \rho_t) + \Gamma_i \sum_{i=1}^{p-1} y_{t-i} + \Phi D_t + \varepsilon_t \text{ , } \varepsilon_t \qquad (7.3)$$

where α and β are the nxr matrix of coefficients, β defines the r cointegrating ranks ($\beta' y_t$), and Γi, i = 1, , k, are sequences of nxn matrices which define the lag structure of the VECM. The term (ρ_t), represents the linear deterministic trends in the cointegrating vectors**.** This approach 'allows for a linear trend both in the stationary and nonstationary combinations of the data and is often favoured in empirical applications', (Nielsen, 2004). In addition, for a comparative assessment, the proposed model is first tested without dummies for cointegration relationships among endogenous variables only. Next, the proposed model is also tested with seasonal dummies to assess the impact of the recent crisis (2008-2009).

Having specified the deterministic components, the next step is to test the number of cointegrating vectors or relationships for each industry sector y_t series. The maximum of the likelihood approach of cointegration is based on the relationship between the rank (Π) of a matrix and its characteristic roots or eigenvalues, which are different from zero. The rank of the long-run impact matrix Π gives the

[95] Johansen (1994) proposed a procedure appropriately specifying the deterministic components (constant and linear trend).

Johansen proposed likelihood ratio (LR) statistics for the number of cointegrating relationships as LR statistics for determining the rank of Π. The null for both statistics is that, there are r cointegrating vectors at most while the alternative is that, there are cointegrating vectors grater than r. In the present study each y_t is a 4x1 vector, and Γ_i and Π are (4x4) coefficient matrices. As explained earlier in the methodology chapter, Johansen (1988, 1995) and Johansen and Juselius (1990) propose two statistics of likelihood ratio tests for the number of cointegrating relationships based on the characteristic vectors: the trace and the max. The trace tests the null that there are at most r cointegrating vectors, against the alternative that the number of cointegrating vectors is greater than r, and the max tests the null that the number of cointegrating vectors is r, against the alternative of r + 1.

There are several asymptotic distributions in the literature including Osterwald-Lenum (1992) Johansen (1995), and MacKinnon et al (1999) which provide critical values for the trace and max statistics. The Johansen's (1995) distributions are updated versions of Osterwald-Lenum (1992), which was the most widely used distribution until just recently[96]. However, because the specified model includes level seasonal or impulse dummies, the critical values underlying the Johansen trace test are affected and thus the tabulated critical values cannot be used. The asymptotic distributions or critical values used for the trace tests of cointegration vectors (relations) for this study are based on the 95 per cent of the Gamma approximation of Doornik (1998), denoted by $C_{95\%(p-r)}$. The Gamma approximation is very close to the quantiles of the asymptotic distribution of Osterwald-Lenum's (1992), but as Boswijk and Doornik (2005, p.797) state, the Gamma Distribution 'provides an accurate approximation, with the benefit that p-values and quantiles are readily available'. If the statistic is smaller than the critical values (Gamma approximation) the null cannot be rejected and this indicates that there is no long-run relationship among the variables. In the present study, to test for bivariate and multivariate cointegration relationships between the industry indices of the US and emerging markets, only the trace test is applied for each

[96] Johansen and Juselius (1990) also present critical values.

industry sector using the above empirical model (unrestricted constant and restricted trend), with and without dummies for comparative or contrasting analysis[97]. The null hypothesis to be tested is that no long-run relationships exist between the emerging and US industry sectors as measured by the number of cointegrating vectors. From a US investor's point of view, diversification gains from these emerging industry sectors are limited when the null of no cointegration is significantly rejected.

To begin with, it is interesting to first explore how the industry sectors of the individual emerging markets of different geographic regions are linked with the US industry sectors. Johansen cointegration tests are used in order to obtain the cointegration ranks. In other words, the trace tests are implemented for bivariate cointegration relationships between all pairs of similar industries for each of the emerging and US industry sector indices. A bivariate cointegration analysis is of interest to examine whether the industry sectors of a particular emerging market can provide long-run diversification gains to US investors. Table 7.1 reports the trace results for the cointegration rrelationships between pairs of the intra sector price indices for the proposed empirical model of cointegration tests with and without exogenous dummies as well as the used lag orders. The trace statistics are calculated to test for the various null and alternative hypotheses. That is, the null $r = 0$ is tested against the alternative that $r > 0$; $r = 1$ is tested against the alternative $r > 1$; and so forth. The null of no cointegration can be rejected when the result of the (trace) test statistics is greater than the corresponding critical value of the Gamma distribution which has been in this study.

As the results in the table show, no bivaraite cointegration relationships are found for all cases without seasonal dummies. The only exception is the case of the US and Malaysian telecommunications industry sectors which shows a negligible relationship. However, when seasonal dummies are included in the testing model the hypothesis of zero cointegration between all pairs of the US and the emerging

[97] As Cheung and Lai (1993, p. 324) point out, 'the trace test is found to be more robust for both skewness and excess kurtosis in the residuals than the maximal eigenvalue test'.

markets' industry sectors is rejected in most tests. Banking is the only industry sector where no cointegration relationship is found between all three emerging countries and the US when the seasonal dummies are incorporated in the empirical model. On the other hand, the alternative hypothesis of two cointegration relationships could not be rejected in the cases of the South African financial services and the Brazilian industrial goods when exogenous dummies are included in the testing model. However, for relatively large tests, as in the present study, such results can be considered as a statistical nuisance, and generally the results of the bivariate tests should be viewed with caution.

Next, multivariate cointegration tests are conducted between each industry sector for the US and the three emerging countries/markets in a multivariate framework. Multivariate tests are able to capture any long-run relationships among any subset of variables. Table 7.2 reports the results of the trace statistics for the multivariate cointegration tests of the employed empirical models for the ten industry sectors of the four markets. The lag lengths in the cointegration tests are discussed in the last sub section and reported in the last column of the table. As can be seen from the table, the null of no cointegration relationships could not have been rejected in all cases when dummies are excluded from the testing model. On other hand, the null of no cointegration relationships are rejected in all cases when the dummies are augmented in the same testing model. With exogenous dummies, the strongest cointegration relationships occur among the food and beverages sectors, with two cointegration relationships, while only one cointegration relationship is found in all the remaining industry sectors. Overall, the multivariate test results also provide a picture of more segmentation among the US and the three emerging markets industry sectors than long run linear relationships. That is, no cointegration relationships are found between the US and emerging markets against Gamma approximations without exogenous dummies in all cases.

Table 7.1: The Trace test results for bivariate co-integration relations between the US and emerging countries' Industry Sectors

		Hypotheses			Cointegration relations	
Industry Sector	Markets	Null	Alternative	Without Dummies	With Dummies	Adopted lag Length
Banking	US Brazil	r = 0 r = 1	r > 0 r > 1	10.713 3.064	21.980 7.364	SIC (0)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	11.8799 3.456	20.927 7.823	SIC(1)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	13.591 2.445	25.039 10.646	SIC (0)
Basic Resources	US Brazil	r = 0 r = 1	r > 0 r > 1	18.618 7.430	27.160** 11.218	LR(6)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	17.011 4.743	22.110 8.009	LR(3)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	17.902 4.953	23.128 11.296	SIC(0)
Chemicals	US Brazil	r = 0 r = 1	r > 0 r > 1	19.039 2.547	22.631 4.210	SIC(0)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	18.390 7.194	24.124 9.011	LR(3)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	13.355 2.087	29.431** 9.602	SIC(0)
Construction and Materials	US Brazil	r = 0 r = 1	r > 0 r > 1	17.489 1.674	23.900 4.260	AIC/SIC(0)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	8.771 3.858	18.644 4.158	SIC(0)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	17.423 3.094	29.742** 11.300	SIC(0)
Financial Services	US Brazil	r = 0 r = 1	r > 0 r > 1	13.814 2.915	24.236 8.788	SIC(1)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	15.525 4.427	22.415 9.880	SIC(1)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	22.736 2.234	35.901** 15.540**	SIC(0)
Food and Beverage	US Brazil	r = 0 r = 1	r > 0 r > 1	21.605 5.510	28.654** 5.755	AIC(1)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	14.381 4.583	28.305** 7.579	LR/SIC(1)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	19.291 8.820	38.185** 8.560	AIC(2)
Industrial Goods and Serices	US Brazil	r = 0 r = 1	r > 0 r > 1	22.789 5.677	37.783** 14.032**	AIC(3)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	13.849 2.292	27.811** 11.117	AIC(3)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	21.780 7.687	25.795** 12.218	SIC(0)

Table 7.1: Continues

		Hypotheses			Cointegration relations	
Industry Sector	Markets	Null	Alternative	Without Dummies	With Dummies	Adopted lag Length
Personal and H/H Goods	US Brazil	r = 0 r = 1	r > 0 r > 1	17.040 7.619	37.259** 10.006	LR(3)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	19.254 3.479	33.092** 7.794	LR/AIC(1)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	18.105 3.022	27.517** 5.207	LR/AIC(3)
Retail Retail	US Brazil	r = 0 r = 1	r > 0 r > 1	14.558 7.253	24.901 7.157	AIC(3)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	18.256 7.282	23.596 7.070	SIC/AIC(1)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	19.246 7.003	31.773** 11.931	AIC(3)
Telecommu-nications	US Brazil	r = 0 r = 1	r > 0 r > 1	19.141 7.108	27.6596** 10.5439	LR(3)
	US Malaysia	r = 0 r = 1	r > 0 r > 1	25.819** 5.731	33.000** 10.740	LR(9)
	US S. Africa	r = 0 r = 1	r > 0 r > 1	19.447 8.255	24.390 8.212	LR(8)

Table Notes:
Only the critical value of 95% significant level is reported for the bivariate cointegration tests.
The ** indicate a rejection of the null hypothesis of no cointegration at 95% significant level of the Gamma Approximation which is used for this study. Asymptotic distributions of Gamma Approximation at 95% (C95%) are 25.18, and 12.20 for zero and one cointegrations.
The adopted lags for cointegration tests correspond to the optimal lags of the un-differenced VAR model whose optimal order is one greater than the VEC model (VAR-1), and are reported in the last column of the table. Lag selection methods are discussed in 7.2.3.
LR: The likelihood ratio. AIC: The Akaike information criterion. SIC: The Schwartz information criterion

In addition, although the empirical objective of this research is to examine the interdependence among the US and the emerging countries' industry sectors, a separate cointegration test for the emerging markets' industry relations is also conducted. There are two main reasons for conducting separate tests for the emerging countries industry sectors. The first is to eliminate the effect, or weight, of the US on the eventual industry relations. Secondly, separate tests for the industry sectors of emerging markets are very useful as they have different economic, legal, development, and trading characteristics. If cointegration relationships among the industry sectors of the emerging markets are found, then the effect of the US is limited, while no cointegration relationships will indicate the influence of the US on these market industry sectors (similar to national level markets as reported in the literature). Table 7.3 presents the results of the multivariate cointegration tests for the emerging industry sectors. As the results in the table show, similar to other tests, no cointegration relationships are found among the emerging markets' industry sectors without exogenous dummies. However, cointegration relationships are found between six out of ten emerging market industry sectors when seasonal dummies are including in the testing model. Although the later results may indicate that the US influence on these markets is limited in the crisis period, one has to take extra caution as the US equity markets has frequently been demonstrated to have the most important influence on global financial markets.

Table 7.2: The Trace test results for multivariate co-integration relations between the US and emerging countries industry sectors

		Hypotheses		Cointegration relations		
Industry Sector	Markets	Null	Alternative	Without Dummies	With Dummies	Adopted lag orders
Banking	US	r = 0	r > 0	39.645	48.989	SIC(0)
	Brazil	r = 1	r > 1	23.898	32.037	
	Malaysia	r = 2	r > 2	13.122	18.871	
	S. Africa	r = 3	r > 3	4.381	8.625	
Basic Resources	US	r = 0	r > 0	54.517	61.903	SIC(0)
	Brazil	r = 1	r > 1	31.358	38.719	
	Malaysia	r = 2	r > 2	14.555	21.021	
	S. Africa	r = 3	r > 3	4.961	9.188	
Chemicals	US	r = 0	r > 0	51.871	77.096**	AIC(1)
	Brazil	r = 1	r > 1	27.265	41.384	
	Malaysia	r = 2	r > 2	9.841	17.849	
	S. Africa	r = 3	r > 3	2.492	7.507	
Construction and Materials	US	r = 0	r > 0	45.155	53.058	SIC(0)
	Brazil	r = 1	r > 1	24.086	27.696	
	Malaysia	r = 2	r > 2	10.297	9.603	
	S. Africa	r = 3	r > 3	3.172	23.562	
Financial Services	US	r = 0	r > 0	56.236	67.066**	AIC(2)
	Brazil	r = 1	r > 1	23.605	32.156	
	Malaysia	r = 2	r > 2	8.961	17.404	
	S. Africa	r = 3	r > 3	3.758	3.833	
Food and Beverage	US	r = 0	r > 0	61.672	93.109**	AIC(1)
	Brazil	r = 1	r > 1	29.788	45.919**	
	Malaysia	r = 2	r > 2	14.591	14.453	
	S. Africa	r = 3	r > 3	5.172	4.566	
Industrial Goods and Services	US	r = 0	r > 0	50.122	65.404**	AIC(1)
	Brazil	r = 1	r > 1	28.715	37.883	
	Malaysia	r = 2	r > 2	15.815	19.434	
	S. Africa	r = 3	r > 3	15.815	7.314	

Table 7.2 continues

Personal and H/H Goods	US Brazil Malaysia S. Africa	r = 0 r = 1 r = 2 r = 3	r > 0 r > 1 r > 2 r > 3	45.767 18.897 10.423 2.290	62.825** 27.886 13.868 7.235	AIC(1)
Retail	US Brazil Malaysia S. Africa	r = 0 r = 1 r = 2 r = 3	r > 0 r > 1 r > 2 r > 3	62.760 37.517 15.193 4.507	74.019** 38.690 17.621 4.351	SIC(0)
Telecommu-nications	US Brazil Malaysia S. Africa	r = 0 r = 1 r = 2 r = 3	r > 0 r > 1 r > 2 r > 3	62.152 29.188 15.673 5.212	73.163** 37.098 18.460 5.646	AIC (1)

Table Notes:
The adopted lag orders are chosen using the lag selection methods discussed in sub-section 7.2.3. Only the critical values of 95% significant level of the Gamma Approximation (Doornik, 1998) are reported for the multivariate tests. The ** indicate a rejection of the null hypothesis of no cointegration at 95% significant level of the Gamma Approximation. Asymptotic distribution of Gamma Approximation: $C_{95\%:}$ 62.81, 42.06, 25.18, and 12.20

To summarise, the results of the linear cointegration tests in this section seem to support more segmentation than integration among the industry sectors of the US and the emerging countries under the benchmark model, that is, when exogenous dummies are excluded from the testing. In theory, segmentation implies that the US investors could gain much more by diversification through investing in various industry portfolios, except in the very few cases where cointegration relationships have been found. This also could be true for investors from emerging countries investing in the US market, or other emerging markets. Nevertheless, as can be seen from the results in the tables 7.1-7.3, seasonal dummies have an effect on the cointegration relationships between the industry sectors Indexes. In other words, the Inclusion the shift dummy in the tests results many non cointegrated variables in the benchmark model are now significantly cointegrated. The test results of this study is somewhat in line with Luintel and Paudyal (2006) who employed a similar approach for testing cointegration relations between various stock price and commodity price indices and various industry groups, and have shown that, integration dominates when unrestricted seasonal dummies are inroporated In the empirical model.

The evidence of cointegration relationships from the seasonal dummy incorporated model could be an indication several implications. Firstly, it indicates the presence of common factors which limit the amount of independent variation among the industry sector indexes. In other words, there is a common, such

Table 7.3: The Trace test results for multivariate co-integration relations among The emerging countries' (Brazil, Malaysia, and South Africa) industry sectors

		Hypotheses		Cointegration relations		
Industry Sector	Markets	Null	Alternative	Without Dummies	With Dummies	Adopted lag orders
Banking	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	25.350 13.598 7.403	33.493 17.641 7.742	LR(3)
Basic Resources	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	34.382 13.576 4.546	42.662** 20.176 8.260	AIC(1)
Chemicals	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	30.929 8.88 2.866	50.252** 25.738** 5.993	SIC/AIC (0)
Construction and Materials	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	25.605 10.273 3.159	32.394 9.197 3.169	SIC(0)
Financial Services	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	27.193 14.358 3.623	39.485 14.768 3.615	AIC(1)
Food and Beverage	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	38.294 12.015 4.918	47.729** 11.556 4.574	AIC(1)
Industrial Goods and Services	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	30.054 13.673 3.639	42.176** 22.911 7.229	LR/AIC(3)
Personal and H/H Goods	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	20.424 9.288 2.023	30.756 17.174 7.533	SIC/AIC (0)
Retail	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	37.896 18.802 3.931	45.875** 19.064 3.629	SIC(0)
Telecommu-nications	Brazil Malaysia S. Africa	r = 0 r = 1 r = 2	r > 0 r > 1 r > 2	41.733 21.033 4.489	55.700** 20.328 5.840	SIC/AIC (0)

Table Notes:
The most appropriate lag order is chosen using the lag selection methods discussed in sub-section 7.2.3. As in the other tests, only the 95% of Gamma Approximation are reported.
$C_{95\%:}$ 42.06, 25.18, and 12.20

an arbitrage activity, that brings the industry sectors of the US and the emerging markets together in the long run. Secondly, the elimination of the arbitrage opportunity indicates inefficiency in these sectors equity markets in the sense advocated by Fama (1965). Thirdly, it also indicates that, the potential benefits of long-run across region sectors diversification would be limited since the systematic country risk could not be eliminated. The result is also in contrast to the previous evidence obtained from cointegration tests under the conventional model (without exogenous dummy), which no cointegration relationships between industry sectors across markets were found and hence implies market efficiency. The concept of efficient market is described as a market consisting of a large number of profit maximisers and in which prices will reflect all information available, so that no profit opportunities are left to be exploited.

The failure to find cointegrating relationships across sectors demonstrates that the sample the markets under the conventional mdel have not moved together in an equilibrium relationship. However, it does not mean that, there could be no sub-periods during which the indices may have moved together. As Luintel and Paudyal (2006, p.16) point out, 'the non cointegrations in the benchmark model may be attributed to structural instability in the long-run relations'. Thefere, to further examine the dynamics of long-run relationships and the time-varying character of the long run relationships between the industry sectors of the US and the emerging markets, the next section presents graphical analysis of the multivariate recursive cointegration method proposed by Hansen and Johansen (1999) as wellas the rolling cointegration analysis neither of which has not previously been used for sector level studies. As discussed in chapter five the recursive cointegration analysis is applied to examine the stability of the cointegration relationships over each data point during the sample period, while the rolling tests are used to examine the degree of convergence during different sub-samples of the full sample.

7.3 Time variation in the long run relationships between the US and emerging countries industry sectors: Evidence from Recursive and Rolling Cointegration Analysis

7.3.1 Recursive cointegration analysis

As mentioned in chapter five, to gain insight into the dynamic evolving process of cointegration relationships between the US and emerging industry sectors, recursive and rolling window estimations are applied in this thesis. The Recursive cointegration analysis is applied to examine the stability of the cointegration relationships over each data point during the sample period. This approach of cointegration analysis is often implemented using the cointegration rank constancy test or the eigenvalue constancy test based on the Z-representation or R-representation, and relies on the Johansen's cointegration test. It is performed for an initial period and then recursively updated as new data are added to the initial sub-sample. According to Juselius (2006, p.150), various tests based on the eigenvalues (recursively calculated from the trace statistics, recursively calculated from the eigenvalues for long-run parameters constancy or the log transformed eigenvalues, and the fluctuations test) 'provide more detailed information about constancy/non-constancy of the individual cointegration relations'[98]. In the present study, the recursively calculated trace statistic is applied for the constancy of cointegration relationships between the industry sector indices of the study.

The starting point of recursive cointegration analysis, or (rolling estimation) is to determine a solution for the maximum likelihood estimator of the cointegrating rank, $\Pi=\alpha\beta$, of the VEC representation in equation 7.2 (without the dummy components) by solving for the eigenvalues as

[98] In other words, 'various versions of these tests make sense as stability tests', (Lütkepohl and Krätzig, 2004, p. 140).

$$\left|\lambda S_{11} - S_{01}\frac{1}{S_{00}}S_{10}\right| = 0 \quad (7.4)$$

where eigenvalues give $1 > \hat{\lambda}_1 >,...,\hat{\lambda}_p$, and $\hat{\lambda}_{p+1} = 0$. The eigenvalues equation of (7.4) can be used in various ways to form recursive tests. For instance, one could use the p−r smallest non-zero eigenvalue and apply the recursive trace test for rank constancy. The rank stability tests can also be based on recursive calculation of the largest eigenvalues (λ_i), a procedure which provides information about the adjustment coefficients α_i and the cointegrated vectors β_i. As mentioned above, the rescaled recursively calculated trace statistic is used for the constancy test cointegration relationships as follows

$$\lambda(r) = [-t_1.\sum_{i=1}^{r}\ln(1-\hat{\lambda}_i)]/C_{95}\%$$, for r =1, 2,...p, and t_1 =T_1,….,T (7.5)

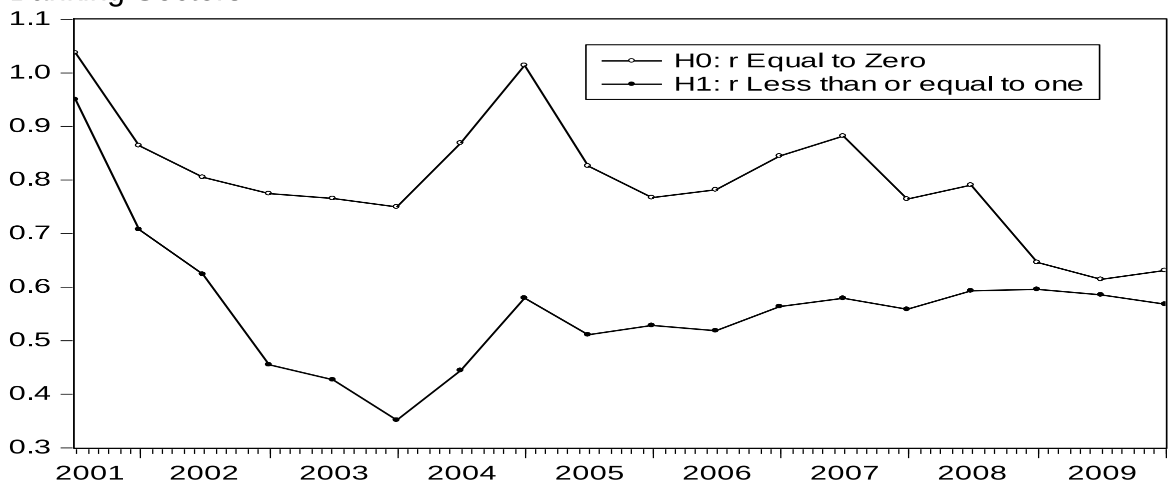
where T is the number of observations, and C95% is the Gamma distribution's 95% critical value. The null hypothesis to be tested is the existence of stable long-run relationships (as measured by the number of cointegrating vectors) between emerging and US industry sectors in each time period.

As Hansen and Johansen (1999) suggest, a graphical procedure can be presented to assess the constancy across time of the long-run relationships in the cointegrated vector autoregressive model. Using an expanding window, the trace statistics are calculated, adding one observation at a time and then dividing the trace statistic by its 95% critical value obtained from Doornik's (1998) Gamma. A year and a half, or seventy-eight weekly observations (from 04/01/2000 to 26/06/2001), are used as the initial estimation period for all tests, and then six months weekly subsamples are added through a full sample of the research. An upward slope indicates rising co-movement, while a downward slope reveals declining co-movement between the industry sectors of the US and the three markets. That is, for a given time period, if the rescaled trace statistic is above point one, regardless of the sub-period for which it has been estimated, then the null hypothesis of non-cointegration is rejected, if however, it is below one, the null is accepted. Moreover, the slope of the rescaled trace statistic determines the direction of co-movements between the variables.

Figures 7.11 to 7.20 illustrate the time path of the multivariate recursive trace test for zero and one cointegration relationships, scaled by the 95 per cent critical value of the gamma approximation. To conserve space, only the multivariate recursive trace tests are presented for each industry sector of all four markets (US, Brazil, Malaysia and South Africa)[99]. Figures display the normalized trace tests on cointegration vectors (r) 0 and 1 with increasing sample size.are. The vertical axes show the values of the trace test statistics scaled by the 95 percent critical value of Gamma distribution (Doornik 1998). A value greater than 1 indicates a rejection the hypothesis of no cointegration relationship at the 95% significance level. As in the Johansen's tests for cointegration relationships (table 7.2), the AIC and SIC have been used to determine the optimal lag lengths for recursive cointegration analysis. The choice of selected lag orders was also determined by the need for uncorrelated residuals. As can be seen from

Figures 7.11 to 7.20: Time varying cointegration relationships between industry sectors: Evidence from the recursive estimations

Figure 7.11: Recursive tests for time varying cointegration relations between Banking Sectors



99 Multivariate tests 'can capture any long-run relationships (or the evolution of such relationships for recursive multivariate cointegration tests) between or among any subset of these markets', Yang et al (2004, p. 242).

Figure 7.12: Recursive tests for time varying cointegration relations between Basic resources Sectors

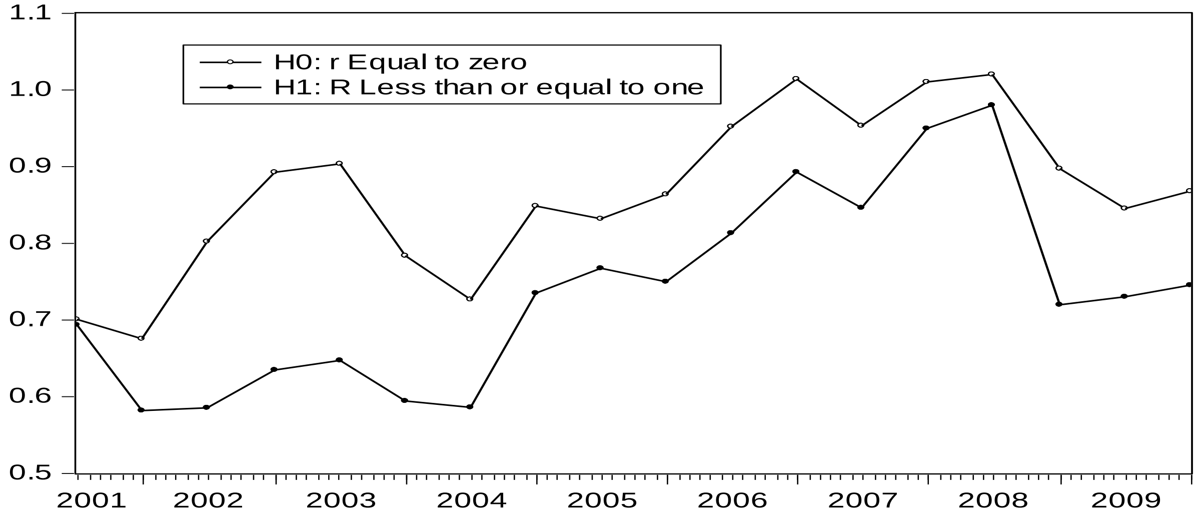


Figure 7.13: Recursive tests for time varying cointegration relations between Chemicals Sectors

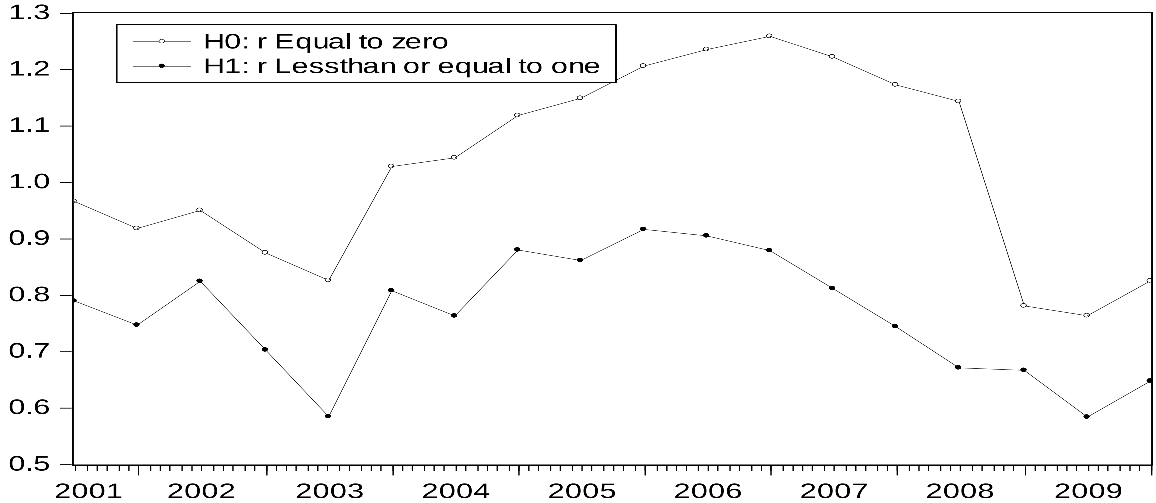


Figure 7.14: Recursive tests for time varying cointegration relations between Construction and Materials Sectors

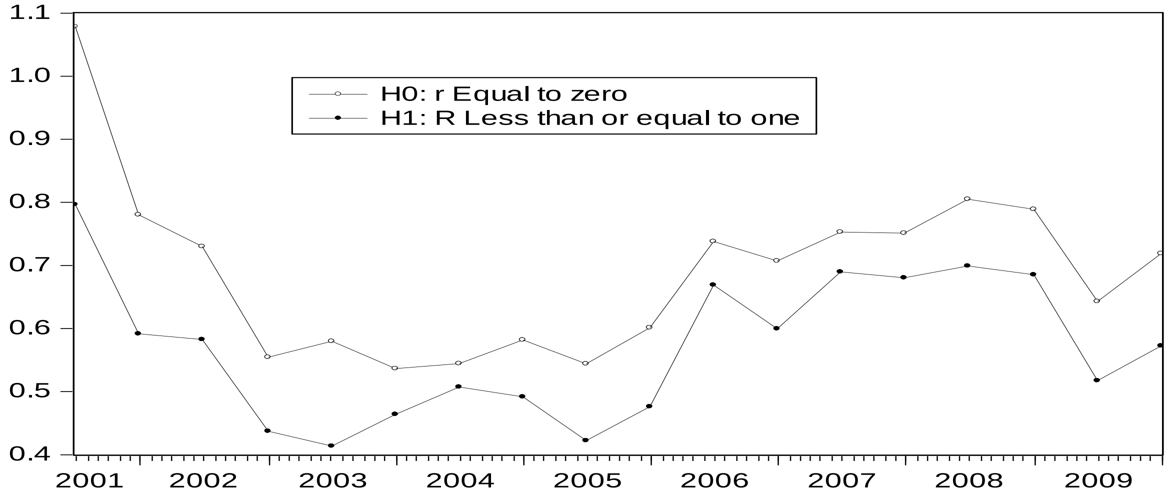


Figure 7.15: Recursive tests for time varying cointegration relations between Financial Sectors

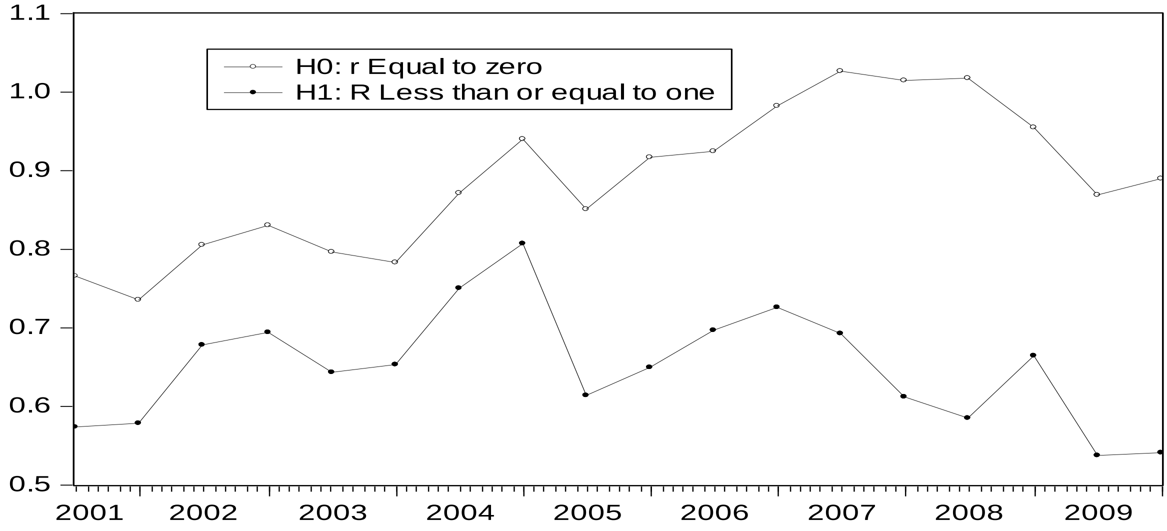


Figure 7.16: Recursive tests for time varying cointegration relations between Food and Beverage Sectors

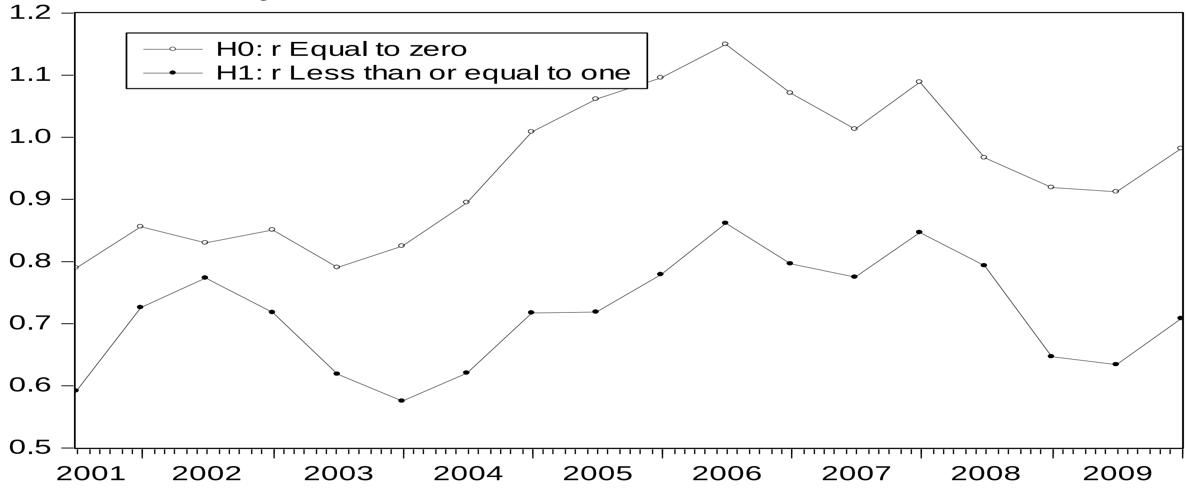


Figure 7.17: Recursive tests for time varying cointegration relations between Industrial Goods Sectors

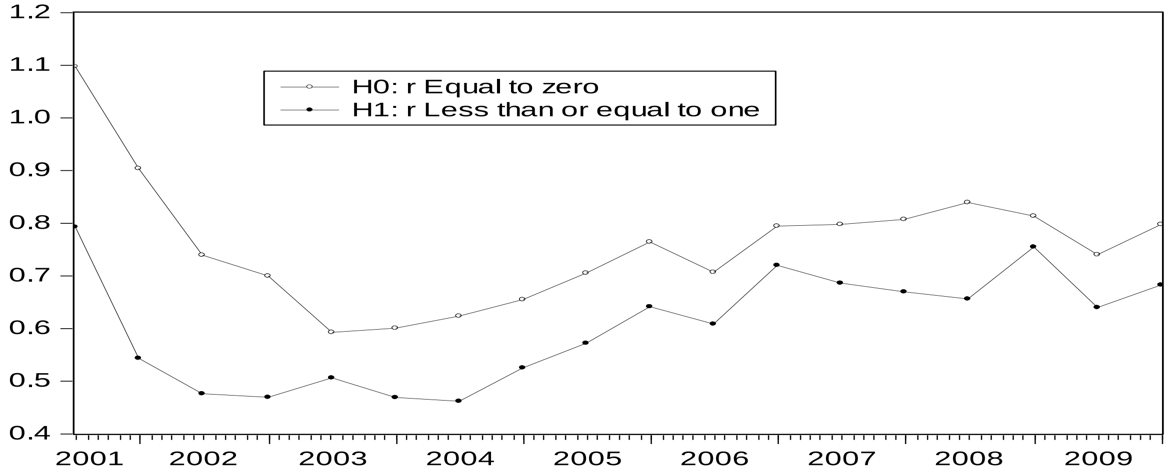


Figure 7.18: Recursive tests for time varying cointegration relations between Personal and H/H Goods Sectors

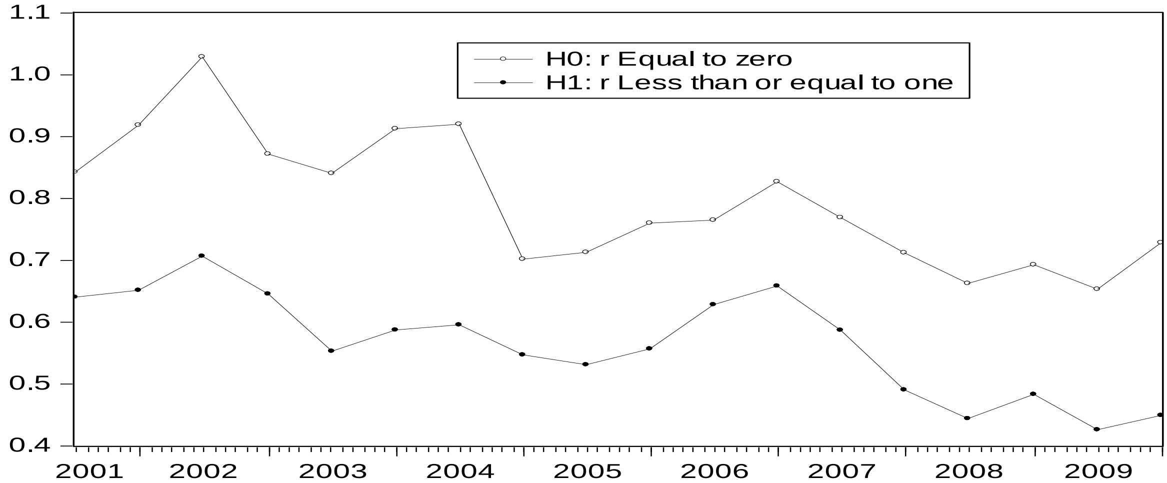


Figure 7.19: Recursive tests for time varying cointegration relations between Retailing Sectors

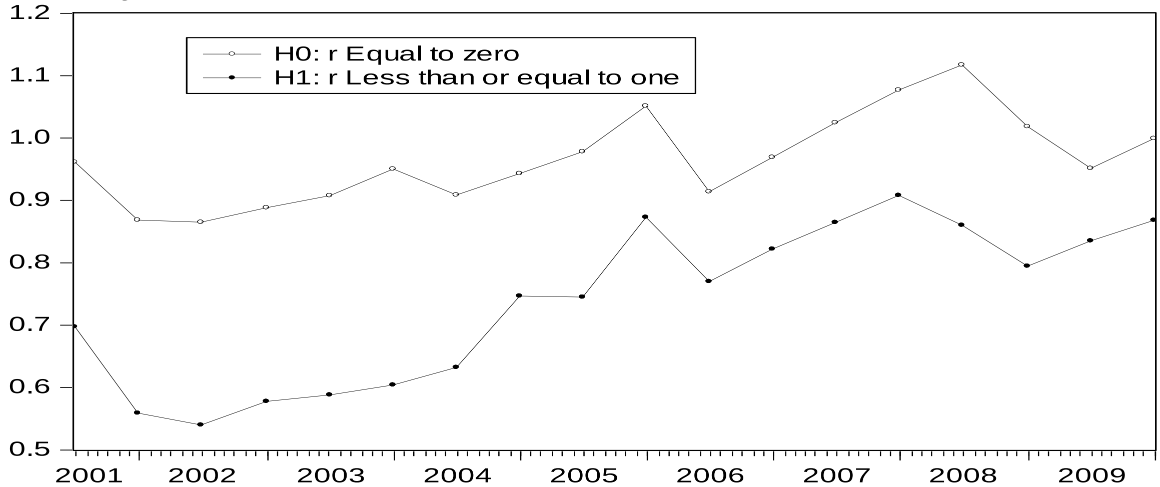
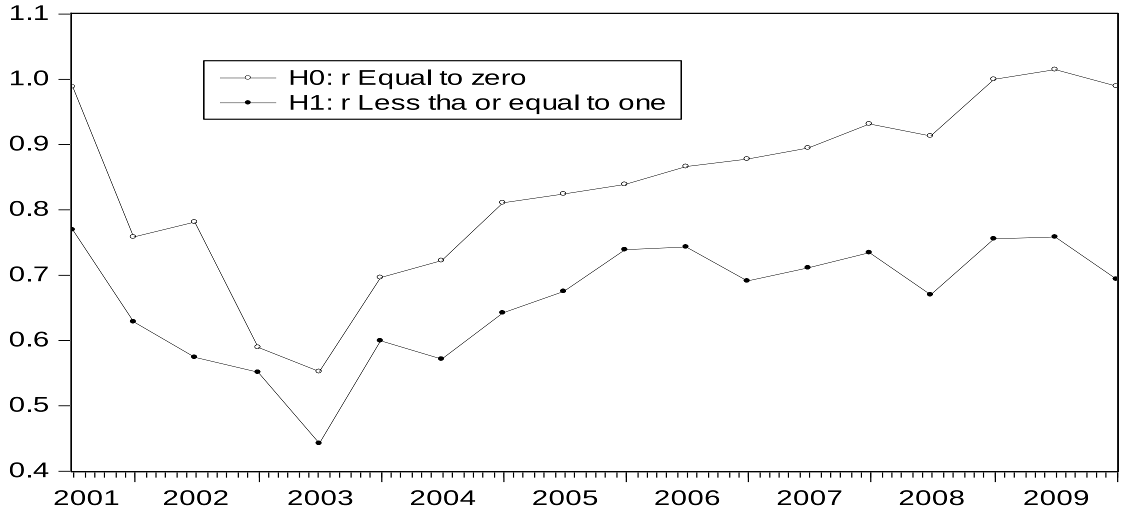


Figure 7.20: Recursive tests for time varying cointegration relations between Telecommunications Sectors



the graphs, the time varying relationships among the industry sectors under study vary across industry sectors as provided by the recursive trace test results. In other words, the recursive cointegration test results suggest that the null hypothesis of no cointegration cannot be rejected for most industry sectors in many sub sample periods on the trace tests. However, there also exist reasonably substantial periods where the null hypothesis of no cointegration is clearly rejected. Overall, the following conclusions can be made:

Banking: relationships at the beginning of the sample period (i.e. first subsample) and around the mid-2000s (2004 to be precise), but decreased relationships by the late 2000s. *Basic resources:* relationships in some periods in the second half of the 2000s. However, such relationships reversed by the late 2000s. *Chemicals:* cointegration relationships exist in each subsample from 2003 through to the second half of 2008. However, such relations declined in the late 2000s. *Construction materials*: relationships only in the first subsample, while declining and rising relationships exist in the remaining sub-periods. *Financial services*: similar to the baking sectors. *Food and beverage*: relationships from the second half of 2004 through to the end of 2008, while such relationships decreased in 2009. *Industrial goods:* relationship at the first subsample, and decreasing and increasing in other sub-samples. *Personal and household goods*: relationship in 2002, and decreasing in all other periods. *Retail:* relationship in mid 2000s, and decreasing and increasing in other sub-samples. *Telecommunications:* unlike other sectors understudy, relationships exist between telecommunications in the late 2000s sub-samples, which have been rising since about 2004.

To summarise, the recursive cointegration analysis seems to be more informative than the standard Johansen cointegration method to the extent that they reveal the stability or instability of the cointegration relationships. In the present study, as the above graphs indicate, it is unlikely that there exist two or more cointegrating relationships between any of the industry sectors in the study during the entire sample period or any sub-periods. Furthermore, the graphs of the rescaled trace tests indicate decreased levels of co-movements for most industry sectors during the crisis of the late 2000s compared to the other periods.

7.3.2 Rolling cointegration analysis

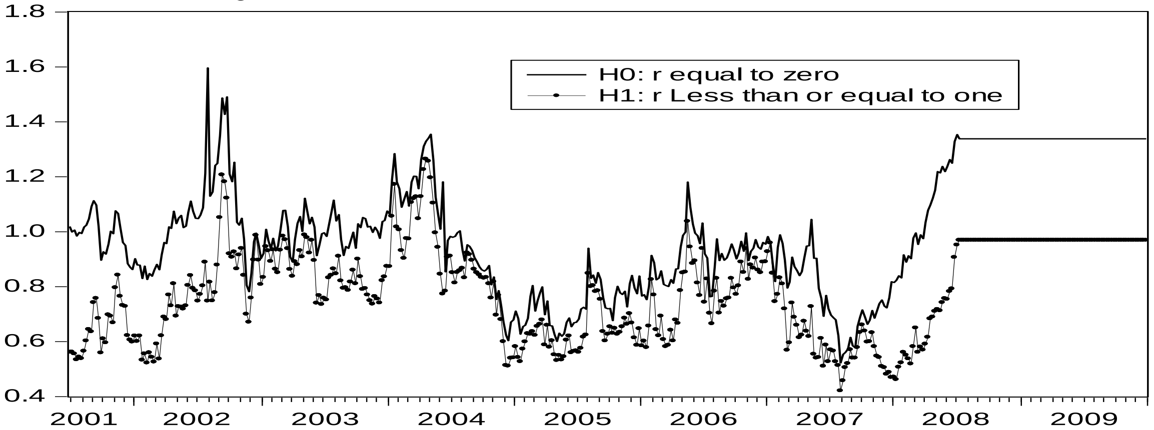
To gain insight into the dynamic evolving process of cointegration relationships between the US and emerging industry sectors, recursive and rolling window estimations are applied in this thesis. The rolling window technique allows for the emergence of a clearer picture of the possible dynamic linkages among the stock markets as, although the sample size remains unchanged, the sample period moves ahead by one observation at a time. In other words, as Mylonidis and Kollias (2010, p. 2060) point out, 'the rolling estimation with a fixed-length window can ensure that the effects of regime shifts are isolated and can be used to track possible structural breaks'. In this study, the rolling cointegration tests are calculated for a rolling 78 observation**s** (or a year and half weekly series) time window by adding one observation to the end and removing the first observation and so on. That is, starting with observations 1–78, we calculate the first trace test statistics, then the secod trace test for observations 2–79, then 3–80 for the third trace test etc until the full sample is used.

As in the case of recursive, the trace statistics obtained from the rolling cointegration tests are scaled by the adjusted critical values at the 95% significance level of the Gamma distribution (Doornik, 1998) which has been used in this thesis. Fiures 7.21-7.30 display multivariate rolling cointegration estimations. The figures report the of the normalized trace tests on cointegration vectors (r) 0 and 1 of rolling estimations with increasing sample size. The vertical axis of each graph shows the values of the trace test statistics scaled by the 95% critical value of Gamma distribution. Lag lengths used in the Johansen cointegration tests (table 7.2) for cointegration relationships were again used to determine optimal orders for the rolling cointegration estimations. The choice of selected lag orders was determined by the need for uncorrelated residuals. A value that is above point one of the graphs (greater than 1) for the series indicates a rejection of the hypothesis of no cointegration in any particular sub period.

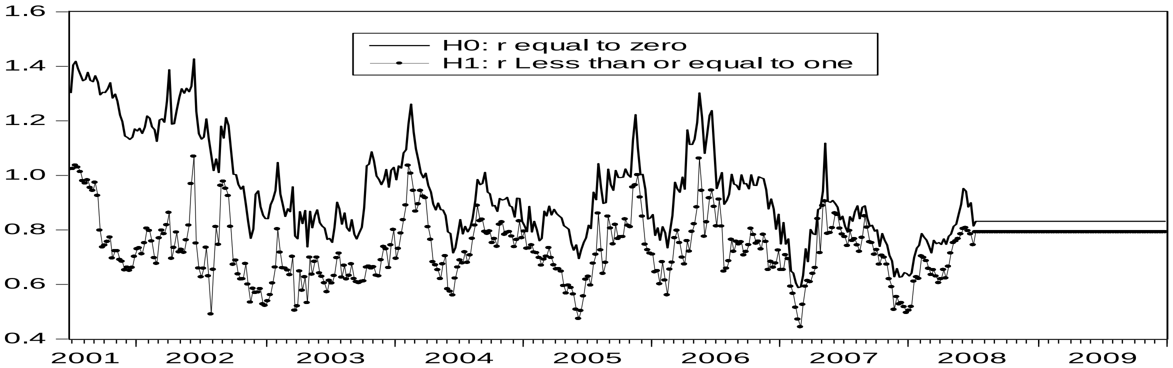
As can be seen from the graphical displays of the normalized trace statistics of rolling estimations can provide essential information about the time varying pattern of the number of cointegrating vectors. As the results of rolling cointegration tests suggest the majority of the sub sample periods the null hypothesis of no cointegrating vectors could be rejected under the trace test statistics for most industry sectors. Specifically, the test results indicate that most cross market sectors share most one cointegrating vector in nearly all sub-periods, that is, the null hypothesis H0: r = 0 is strongly rejected. A number of cross market sectors also shere two cointegration vectors in some periods. Overall, as the graphs show, there are sub-samples of cointegration relationships among many sectors and some periods of no cointegrations. Furthermore, the graphs of the rescaled trace tests show similar pattern of co-movements for most industry sectors during the crisis of the late 2000s compared to the other periods.

Figures 7.21 to 7.30: Time varying cointegration relationships between industry sectors: Evidence from rolling cointegration estimations

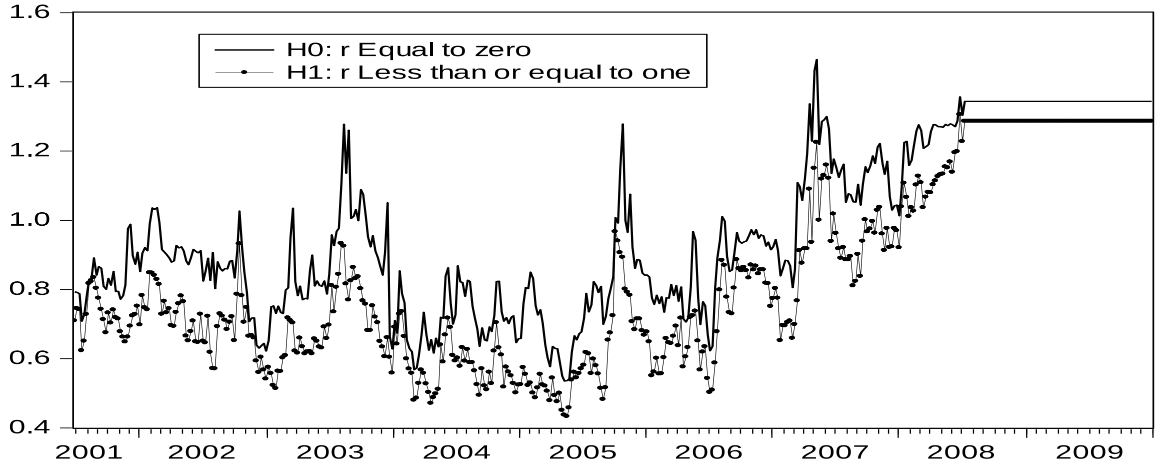
Figre 7.21: Rolling Window estimation for time varying cointegration relations between Banking Sectors



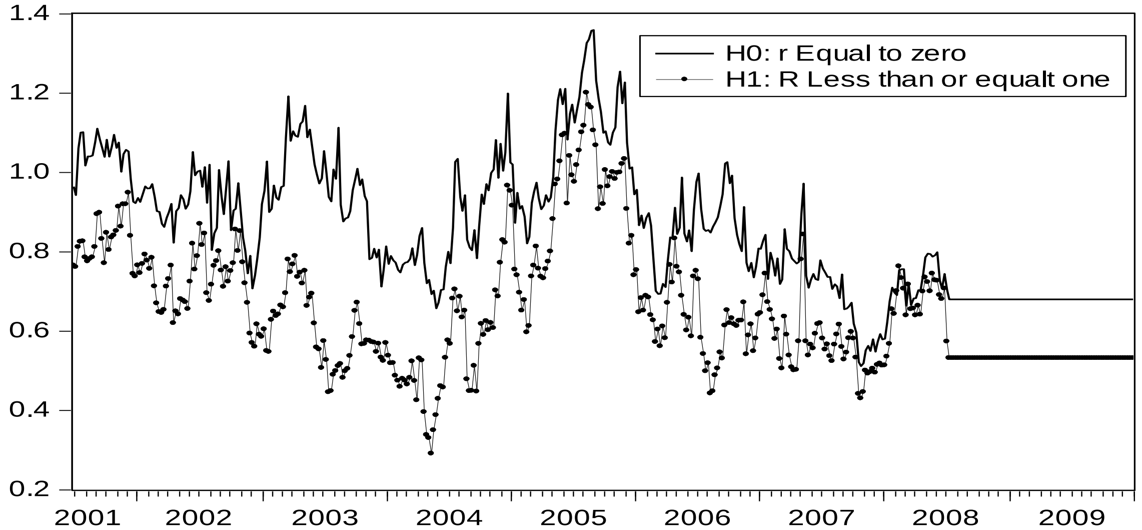
Figre 7.22: Rolling Window estimation for time varying cointegration relations between Basic Resources Sectors



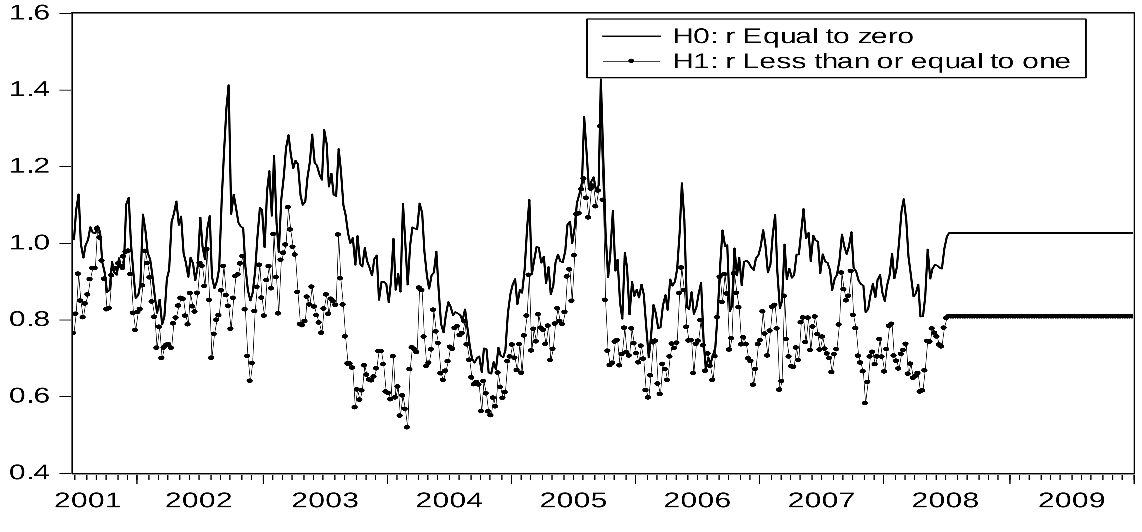
Figre 7.23: Rolling Window estimation for time varying cointegration relations between Chemical Sectors



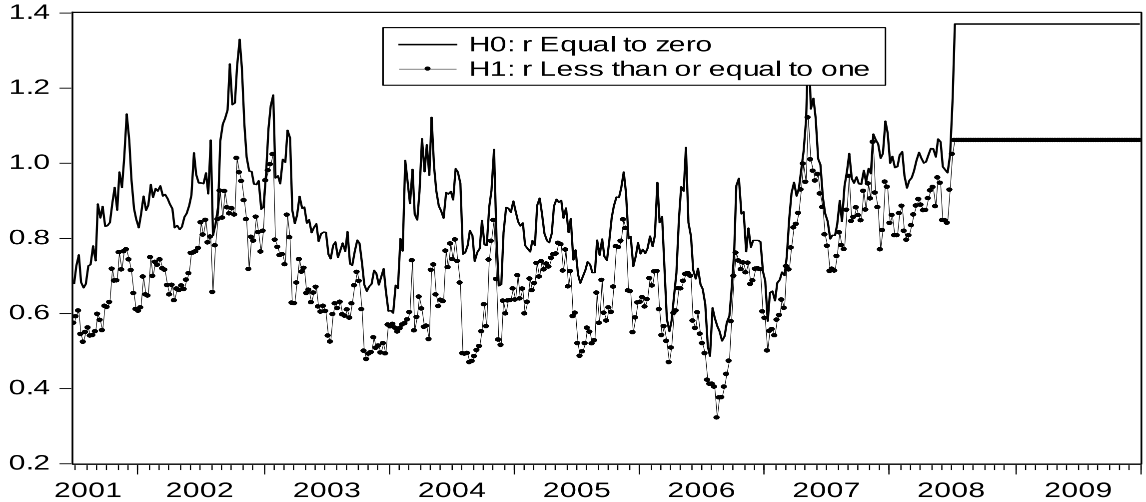
Figre 7.24: Rolling Window estimation for time varying cointegration relations between Construction and Materials Sectors



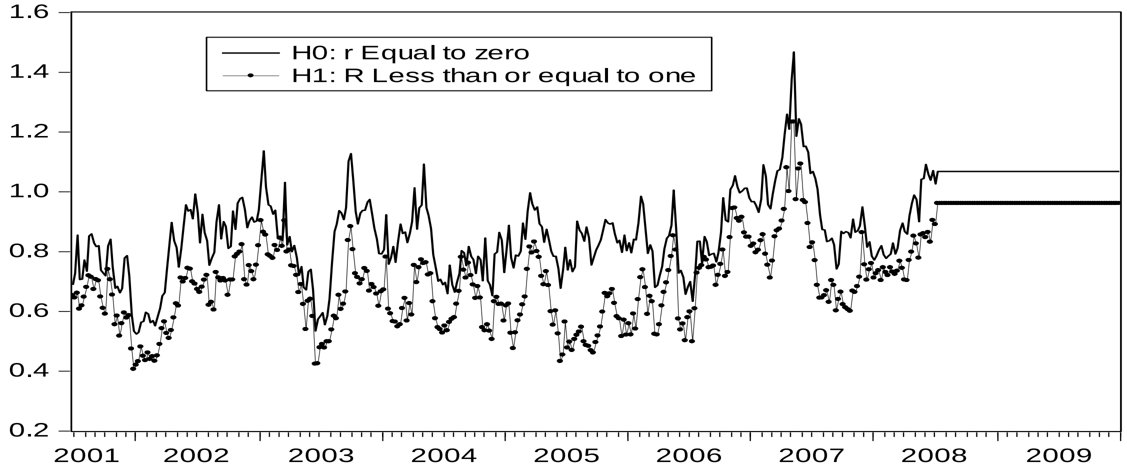
Figre 7.25: Rolling Window estimation for time varying cointegration relations between Financial Service Sectors



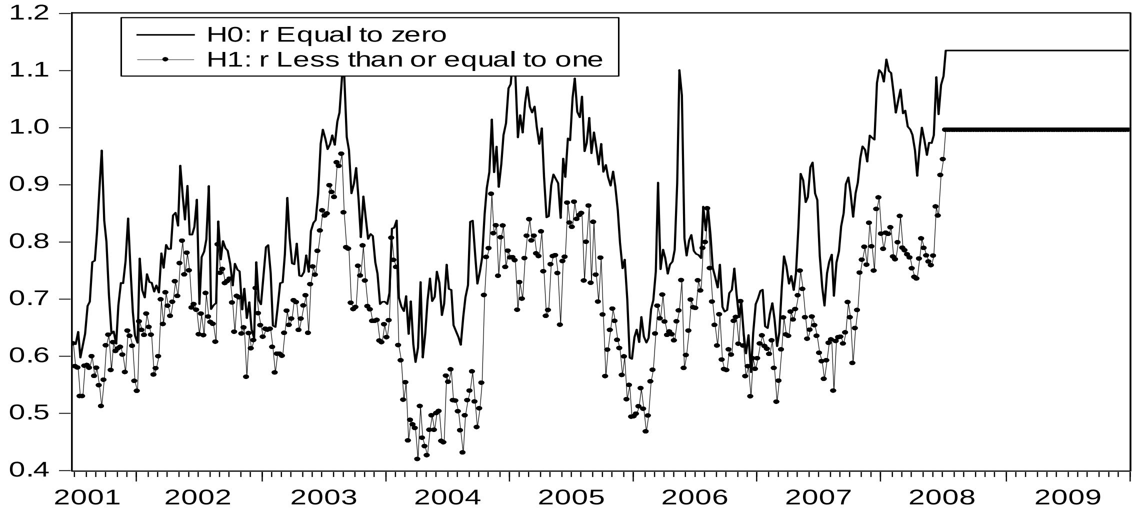
Figre 7.26: Rolling Window estimation for time varying cointegration relations between Food and beverage Sectors



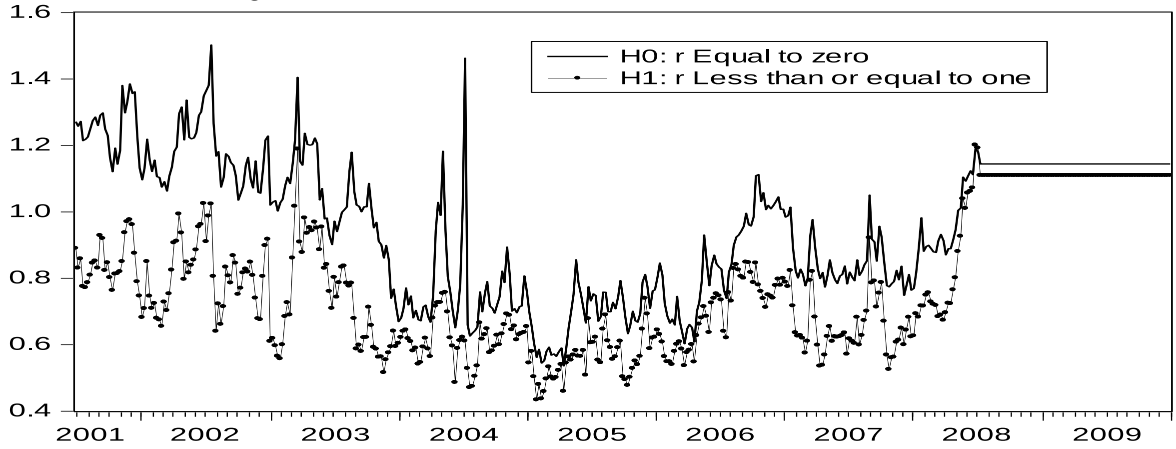
Figre 7.27: Rolling Window estimation for time varying cointegration relations between Industrial Goods Sectors



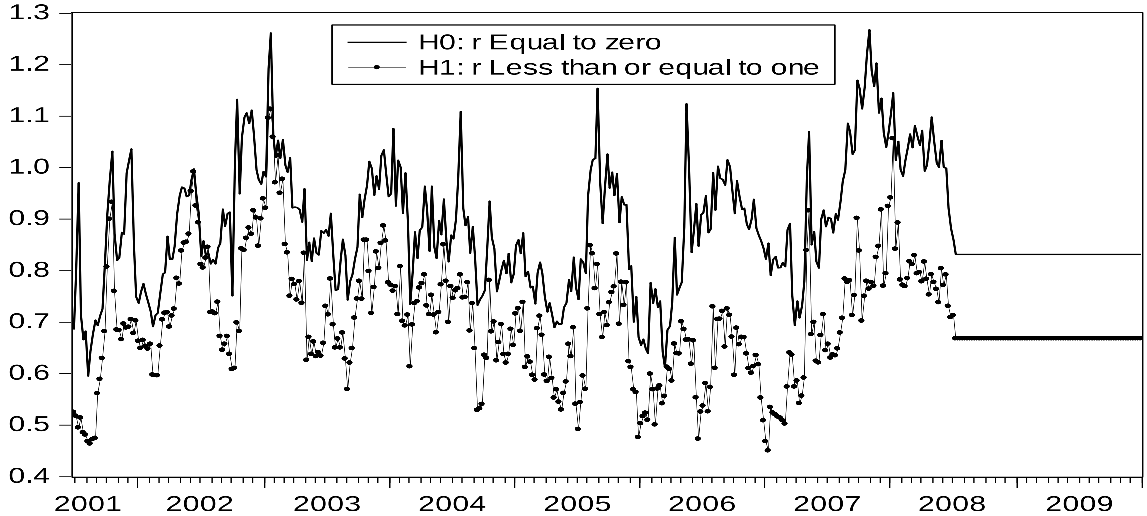
Figre 7.28: Rolling Window estimation for time varying cointegration relations between Personal and H/H Goods Sectors



Figre 7.29: Rolling Window estimation for time varying cointegration relations between Retailing Sectors



Figre 7.30: Rolling Window estimation for time varying cointegration relations between Telecommunications Sectors



7.4 Rank Tests for Nonlinear Unit Roots and Cointegrations: Testing Procedures and Results

As discussed in the methodology chapter suggests (section 5.4), due to various market frictions, the distribution of many asset price changes is often found to be highly leptokurtic, an indication of nonlinear behaviour. Conventional linear methods such as the unit root and cointegration tests can suffer from a failure to pass the normality tests by ignoring the nonlinear nature found in many financial time series, which can lead to the misleading conclusion that no long-run relationships exist between stock markets series. As a result, the possibility of nonlinear relationships among financial markets has been receiving greater attention in recent years. Specifically, attempts to model the nonlinearity cointegration relationships using several nonlinear methodologies have been presented in recent time series literature. To test nonlinear cointegration relationships between international sector indices, this thesis employs the nonparametric procedures proposed for nonparametric tests for unit roots by Breitung and Bierens (1997) and the rank tests for nonlinear cointegration (Breitung 2001) which is based on the difference between the sequences of ranks[100]. This section discusses the testing procedures of the rank tests for the price indices of the industry sectors in the research and presents their empirical results.

7.4.1 The Rank Test Results for Nonlinear Unit Roots

As reported in section two (7.2.1) of this chapter, the results of conventional unit root tests; ADF, DF-GLS and KPSS, show that the industry indices under study are all I(1). In this section, to motivate the tests for nonlinear cointegration relationships, the order of integration of the industry sector indices is further examined using the rank test (Breitung and Gourieroux 1997) for nonlinear unit roots. In other words, as discussed in the methodology chapter (equations 5.24 and 5.25) the order of integration of their monotonic transformations is tested using the 'uniform' version of the score statistics *(Uni)* and 'inverse normal scores' *(Ins).* The results of the rank test are then compared to those from the three linear unit root tests; the ADF test, the DF-GLS test, and the KPSS test. The null hypothesis of nonstationarity or unit root is rejected if the test statistic is smaller than their respective critical values under both versions of the score statistics as tabulated by Breitung and Gourieroux (1997, in appendix B).

Appendix C reports the results of the rank tests for nonlinear unit root tests for the price levels and first differences of the US and the three emerging markets'

[100] The rank test for nonlinear cointegration relations is applied to all series regardless of whether the linear cointegration hypothesis is rejected or accepted.

industry sector indices. As the results show, the null hypothesis of nonstationarity cannot be rejected in all cases of the price levels in both test statistics, with the exception of only three out of eighty tests (Brazilian Industrial goods, Malaysian Basic Resources and South African Financial Services), under the '*Uniform'* version of the score statistics in which such a hypothesis is rejected. On the other hand, the nonstationarity is strongly rejected in every case of the first differences in both tests in favour of the alternative stationary series. This implies that the transformed series are all characterised as difference stationary rather than trend stationary, and therefore the industry indices under study are likely to show nonlinear random walk processes. Overall, the results of the rank test are complimentary to those from the three linear unit root tests; the augmented Dickey-Fuller (ADF) test, the Elliott, Rothenberg, and Stock's (ERS, 1996) DF-GLS test, and the Kwiatkowski, Phillips, Schmidt, Shin (KPSS) test presented in the last section. Since the variables of interest were found to have nonlinear unit roots, the next empirical analysis (presented in the next subsection) is to investigate the cointegration relationships for the industry sectors among the US and the three emerging countries in the study.

7.4.2 Empirical results of rank and score tests for Cointegrations and Neglected nonlinearity

7.4.2.1 Rank Statistic tests for cointegrations

As detailed in the methodology chapter, in addition to Johansen's linear cointegration tests, this thesis applies Breitung's (2001) methodology to examine the existence of nonlinear cointegration relationships between the industry sector indices of the US and the emerging countries in the study. Breitung proposes two kinds of rank statistics for linear cointegration relationships in the bivariate and multivariate tests. In addition, Breitung developed another test (score) statistic to distinguish linear from under rank statistics. In this thesis, following the few empirical works (Li, 2006, Onour, 2008) which applied this methodology for national stock markets, these testing statistics are first applied for the industry prices in the study to test for bivariate and multivariate cointegration relationships[101]. The null hypothesis of no cointegration between the industry sectors of the US and the emerging countries in the study is rejected if the results of the test statistics are smaller than the critical values. To begin with, the κ_T and ξ_T type rank statistics, as specified in equations (5.28) to (5.29), (5.30) to (5.31), and (5.32) to (5.33), are tested for bivariate cointegration relationships among the industry sectors[102].

Table 7.4 presents the empirical results of these test statistics, both versions correlations adjusted and unadjusted. As the results in the table show, the κ_T and ξ_T rank test statisticsshow different results under the unadjusted and adjusted correlation tests.)[103]. In other words, as the results in the table show, cointegration relationships exist between the seven industry sectors for the US and one more emerging market as the rank test statistics reject the null hypothesis of no cointegration at the 5% or 1% significance levels when the tests (κ_T and ξ_T) are not adjusted. On other hand, the bivariate results of the correlation adjusted κ_T and ξ_T rank statistic tests indicate that there is no significant evidence of cointegration relationships for most industry sectors. Under the adjusted tests, Chemical sectors are the only industry sector that shows significant cointegration relationships with the US and all emerging countries, while Food and Beverages, and Personal and Household Goods indicate cointegration relationships for the US and Brazil, and the US and Malaysia.

In addition, the correlation adjusted version of Breitung's (2001) multivariate rank test statistics (as specified in equation 5.37 of the methodology chapter) is also employed to test for bivariate cointegration relationships among the industry

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[101] Li (2006) also presents short but interesting mathematical derivations of a simple theoretical model that motivates the nonlinear relationships among stock indexes from different countries.

[102] In the rank methodology for cointegration, a lag structure or deterministic terms do not need be estimated.

[103] The correlation coefficients (ρ_T), between a pair of ranks, which are not reported, are found to be between 0.185 and 0.53.

sectors in the research. As in the case of Johansen's ML approach, the multivariate version of the rank test statistics can be applied to both bivarariate and multivariate cases. Therefore, to complement and compare with the κ_T and ξ_T tests, the rank test statistics are applied for bivariate cointegration relations between the emerging markets and the US industry sectors. As in the κ_T and ξ_T type of tests, the null hypothesis of no cointegration relationships between the variables is rejected if the results of the test statistics are smaller than their respective critical values (Breitung (2001, table 1). As described in the methodology chapter, the residuals of the rank regression specified in equation (5.37) is written as $\hat{\psi}_t^R = R_T(y_t) - \beta R_T(z_t)$ where β is the least squares estimate from a regression of $R(y_t)$ on $R(x_t)$. The *k* is the number of the cointegration relationship which is one less than the number of variables in which their relationship is examined. Treating each market as the dependent in turn (in the estimation of the equation), the bivariate cointegration test results with $\Xi^*[k=1]$ are reported in table 7.5. As the results in the table show, the rank statistic provides strong support for correlation adjusted tests of the ξ_T type statistic at the 5% significant level as there are only a few detected cointegration relationships with the same industry sectors. Nevertheless, the results from the above (rank) test statistics are in contrast to those results provided by the trace statistics for bivariate cointegration relationships as presented in table 7.1. Under the trace tests of without dummies only one case of a cointegration relationship is reported, in the Telecommunications industry sector between the US and Malaysia.

Next, analogous to the Johansen's trace test, the rank test can be used for testing multivariate cointegration relationships among the US and emerging markets' industry sectors in the study where now k = 3, that is, $\Xi^*[k=3]$. The residuals in equation (5.37) are now $\hat{\psi}_t^R = R_T(y_t) - \beta_1 R_T(z_1) - \beta_2 R_T(z_2) - \beta_3 R_T(z_3)$ as detailed in the methodology chapter for each test of the US and emerging markets' industry sectors. Furthermore, each market's sector is treated as a dependent variable in turn. Table 7.6 presents the results of the rank statistic for multivariate cointegration tests. Overall, as the results in the table indicate, even after taking each market industry sector as the dependent variable, only seven (two in each of the Banking, Industrial Goods, and Telecommunications industries, and one in the Chemicals industry) out of forty tests are found to have cointegration relationships. Such results are in contrast to the findings of the Johansen's trace tests without dummy variable, were no cointegration relationships between sector indices were found in all cases. However, many sectors such as Chemicals, Financial Services, Food and Beverage, Industrial Goods, Personal Household Goods, and Retailing which were found to have cointegration relationships under the Johansen's trace tests with dummies show no similar results under the multivariate version of the Breitung's rank test statistic. Banking, and Contruction and Materials are detected to have cointegration relationships under the Breitung's rank test statistic. Such cointegration relationships have not been found under the Johansen's trace statistics with or without dummy variable.

Finally, as in the case of Johansen's test, the multivariate rank statistic is also applied to the emerging markets' industry sectors (without the US) where now k = 2 and $\hat{\psi}_t^R = R_T(y_t) - \hat{\beta}_1 R_T(z_1) - \hat{\beta}_2 R_T(z_2)$ for each industry sector. Table 7.7 reports the results of the multivariate rank statistics for the emerging countries' industry sectors. As can be seen from the table, the results of the rank tests are in contrast to the results of Johansen's maximum likelihood (trace) statistic for cointegrations (reported in table 7.3). In the trace tests, no cointegration relationships were found between the emerging markets industry sectors without dummies. In contrast, cointegration relationships are detected in four industries (Banking, Chemicals, Constructions, and Telecommunications) under the rank tests in line with the Johansen's trace results with dummies. These results represent a somewhat surprising outcome which also implies that the role of the US is irrelevant. That is, there are long run relationships among some emerging countries' industry sectors (for example the baking) which were not found under Johansen's trace statistics. Next, to examine the nature of the detected cointegration relationships, score tests for neglected nonlinearity is employed.

Table 7.4: The results of κ_T and ξ_T rank statistics for bivariate cointegration relationships between the US and emerging industry sectors

		Unadjusted Tests		Correlation Adjusted Tests			
Industry Sector	Markets	κ_T	ξ_T	κ_T^*	ξ_T^*	κ_T^{**}	ξ_T^{**}
Banking	US-Br	0.9349	0.1412	0.8432	0.1149	0.8515	0.1290
	US-ML	0.9215	0.1286	0.7506	0.0853	0.7523	0.0900
	US -SA	0.7835	0.0869	0.6994	0.0692	0.7076	0.0786
Basic Resources	US-Br	0.6534	0.0395**	0.7348	0.0499	0.7726	0.0661
	US-ML	0.8927	0.1004	0.6384	0.0513	0.6448	0.0577
	US -SA	0.5345**	0.0230***	0.5287	0.0225	0.5497	0.0287
Chemicals	US-Br	0.4176***	0.0160***	0.3396**	0.0106***	0.3451**	0.0123***
	US-ML	0.5747*	0.0190***	0.4191	0.0101***	0.4207	0.0109***
	US -SA	0.4176***	0.0219***	0.3476**	0.0152**	0.3496**	0.0166**
Construction Materials	US-Br	0.5536	0.0144***	0.4497	0.0095***	0.4523	0.0104***
	US-ML	0.9061	0.1480	0.7985	0.1149	0.8057	0.1284
	US -SA	0.5019**	0.0210***	0.5992*	0.0300	0.6046	0.0335
Financial Services	US-Br	0.7931	0.0957	0.7926	0.0956	0.8085	0.1131
	US-ML	0.7625	0.1162	0.5816	0.0676	0.5837	0.0724
	US -SA	0.6705	0.0615	0.6289	0.0541	0.6370	0.0619
Food and Beverages	US-Br	0.4617***	0.0216***	0.3964	0.0159**	0.4003	0.0179**
	US-ML	0.5977	0.0244**	0.4970	0.0169**	0.4977	0.0176**
	US -SA	0.5670	0.0342**	0.4735	0.0238	0.4768	0.0263
Industrial Goods	US-Br	0.4157***	0.0166***	0.4143	0.0165**	0.4264	0.0203*
	US-ML	0.7701	0.0733	0.7148	0.0631	0.7212	0.0705
	US -SA	0.5556	0.0553	0.6058	0.0657	0.6278	0.0829
Personal and H/H Goods	US-Br	0.4253**	0.0217***	0.4435	0.0236	0.4501	0.0273
	US-ML	0.4559**	0.0281**	0.3301**	0.0147**	0.3310**	0.0156**
	US -SA	0.5192**	0.0173***	0.4941	0.0156**	0.4988	0.0175**
Retail	US-Br	0.6034	0.0619	0.4235	0.0305	0.4300	0.0353
	US-ML	0.8218	0.1562	0.4982	0.0574	0.4995	0.0609
	US -SA	0.6724	0.0536	0.4587	0.0250	0.4649	0.0286
Telecommu-nications	US-Br	0.7663	0.0729	0.6751	0.0566	0.6890	0.0671
	US-ML	0.7874	0.0954	0.6084	0.0570	0.6094	0.0596
	US -SA	0.8448	0.1612	0.8227	0.1529	0.8300	0.1705

Table Notes

Critical values of the κ_T and ξ_T test statistics

	κ_T	ξ_T	κ_T^*	ξ_T^*
10%	0.6442	0.0573	0.394	0.0232
5%	0.5524	0.423	0.3635	0.0188
1%	0.4220	0.238	0.3165	0.0130

κ_T^{**} and ξ_T^{**} have the same critical values as κ^* and ξ^* respectively

Critical values are tabulated in Breitung (2001, table 1)

Only 5 percent level is reported. The ** indicates the significance at 5%.

Table 7.5: The Rank test results for bivariate cointegration relationships between the industry sectors of the US and each of emerging countries

Industry Sector	Markets	$\Xi^{*}[k=1]$
Banking	USA,Brazil	0.1174
	USA-Malaysia	0.0897
	USA -S. Africa	0.0712
	Brazil-USA	0.1351
	Malaysia-USA	0.0968
	S. Africa- USA	0.0758
Basic Resources	USA-Brazil	0.0484
	USA-Malaysia	0.0566
	USA -S. Africa	0.0226
	Brazil-USA	0.0547
	Malaysia-USA	0.0533
	S. Africa- USA	0.0231
Chemicals	USA-Brazil	0.0105***
	USA-Malaysia	0.0101***
	USA -S. Africa	0.0147**
	Brazil-USA	0.0109
	Malaysia-USA	0.0104
	S. Africa- USA	0.0159
Construction Materials	USA-Brazil	0.0097***
	USA-Malaysia	0.0972
	USA -S. Africa	0.0299
	Brazil-USA	0.0096
	Malaysia-USA	0.1210
	S. Africa- USA	0.0301
Financial Services	USA-Brazil	0.0546
	USA-Malaysia	0.0735
	USA -S. Africa	0.0545
	Brazil-USA	0.1103
	Malaysia-USA	0.0728
	S. Africa- USA	0.0587
Food and Beverages	USA-Brazil	0.0158**
	USA-Malaysia	0.0167**
	USA -S. Africa	0.0237
	Brazil-USA	0.0166**
	Malaysia-USA	0.0177**
	S. Africa- USA	0.0253

Table 7.5: Continues

Industry Sector	Markets	$\Xi^{*}[k=1]$
Industrial Goods	USA-Brazil	0.0166
	USA-Malaysia	0.0629
	USA -S. Africa	0.0641
	Brazil-USA	0.0169
	Malaysia-USA	0.0704
	S. Africa- USA	0.0729
Personal and H/H Goods	USA-Brazil	0.0239
	USA-Malaysia	0.0153**
	USA -S. Africa	0.0158**
	Brazil-USA	0.0241
	Malaysia-USA	0.0148**
	S. Africa- USA	0.0158**
Retail	USA-Brazil	0.0294
	USA-Malaysia	0.0566
	USA -S. Africa	0.0244
	Brazil-USA	0.0348
	Malaysia-USA	0.0724
	S. Africa- USA	0.0276
Telecommunications	USA-Brazil	0.0607
	USA-Malaysia	0.0618
	USA -S. Africa	0.1550
	Brazil-USA	0.0582
	Malaysia-USA	0.0601
	S. Africa- USA	0.1855

Table Notes
Tests are based on the rank statistic specified in equation (5.37)
Critical values of the rank statistics: $\Xi^{*}[k=1]$
10% : 0.0248, 5%: 0. 0197, 1% : 0136
Critical values are tabulated in Breitung (2001, table 1)
Only 5 percent level is reported. The ** indicates the significance at 5%.

Table 7.6: The rank test results for multivariate cointegration relationships between the US and emerging countries' industry sectors

		Cointegration Relations
Industry Sector	Markets	$\Xi^{*}[k=3]$
Banking	US, BR, ML, SA	0.0241
	BR, US, ML, SA	0.0108**
	ML, US, BR, SA,	0.0113**
	SA, US, BR, ML	0.0139
Basic Resources	US, BR, ML, SA	0.0195
	BR, US, ML, SA	0.0299
	ML, US, BR, SA,	0.0383
	SA, US, BR, ML	0.0166
Chemicals	US, BR, ML, SA	0.0092***
	BR, US, ML, SA	0.0178
	ML, US, BR, SA,	0.0145
	SA, US, BR, ML	0.0257
Construction Materials	US, BR, ML, SA	0.0126**
	BR, US, ML, SA	0.0080***
	ML, US, BR, SA,	0.0938
	SA, US, BR, ML	0.0214
Financial Services	US, BR, ML, SA	0.0495
	BR, US, ML, SA	0.0408
	ML, US, BR, SA,	0.0379
	SA, US, BR, ML	0.0337
Food and Beverages	US, BR, ML, SA	0.0142
	BR, US, ML, SA	0.0229
	ML, US, BR, SA,	0.0234
	SA, US, BR, ML	0.0276
Industrial Goods	US, BR, ML, SA	0.0167
	BR, US, ML, SA	0.0163
	ML, US, BR, SA,	0.0191
	SA, US, BR, ML	0.0185
Personal and H/H Goods	US, BR, ML, SA	0.0145
	BR, US, ML, SA	0.0239
	ML, US, BR, SA,	0.0153
	SA, US, BR, ML	0.0164
Retail	US, BR, ML, SA	0.0255
	BR, US, ML, SA	0.0234
	ML, US, BR, SA,	0.0490
	SA, US, BR, ML	0.0221
Telecommunications	US, BR, ML, SA	0.0422
	BR, US, ML, SA	0.0125**
	ML, US, BR, SA,	0.0096***
	SA, US, BR, ML	0.0242

Table Notes

Critical values of the rank statistics: $\Xi^{*}[k=3]$

10% : 0.0160 , 5%: 0.0137 , 1% : 0.0100

Critical values are tabulated in Breitung (2001, table 1). 5 and 1 percent levels are reported for multivariate rank tests. The ** and *** respectively significance at 5% and 1% levels

Table 7.7: The rank test results for multivariate cointegration relationships between the emerging countries industry sectors

		Cointegration Relations
Industry Sector	Markets	$\Xi^{*}[k=2]$
Banking	BR, ML, SA	0.0128**
	ML, SA, BR	0.0114***
	SA, BR, ML	0.0232
Basic Resources	BR, ML, SA	0.0332
	ML, SA, BR	0.0621
	SA, BR, ML	0.0323
Chemicals	BR, ML, SA	0.0248
	ML, SA, BR	0.0153**
	SA, BR, ML	0.0257
Construction Materials	BR, ML, SA	0.0127**
	ML, SA, BR	0.1033
	SA, BR, ML	0.0140**
Financial Services	BR, ML, SA	0.0408
	ML, SA, BR	0.0338
	SA, BR, ML	0.0522
Food and Beverages	BR, ML, SA	0.0321
	ML, SA, BR	0.0291
	SA, BR, ML	0.0299
Industrial Goods	BR, ML, SA	0.0524
	ML, SA, BR	0.0193
	SA, BR, ML	0.0186
Personal and H/H Goods	BR, ML, SA	0.0203
	ML, SA, BR	0.0188
	SA, BR, ML	0.0215
Retail	BR, ML, SA	0.0225
	ML, SA, BR	0.0490
	SA, BR, ML	0.0243
Telecommunications	BR, ML, SA	0.0111***
	ML, SA, BR	0.0093***
	SA, BR, ML	0.0279

Table Notes

Critical values of the rank statistics: $\Xi^{*}[k=2]$. The ** indicates the significance at 5% level.

7.4.2.2 The Score Statistic tests for Neglected Nonlinearity Cointegrations

When cointegration relationships among variables, $R_T(y_t)$ and 6R_T( ) are detected, then the nature of the cointegration relationship is determined using Breitung's (2001) score statistics for neglected nonlinearity as detailed in the methodology chapter. The null hypothesis of linear against non-linear cointegration is then tested in three steps. First, as explained in chapter five, a linear cointegrating equation is estimated by regressing y_t on a constant and z_t , adjusted for autocorrelation, and endogenous regressors based on the Dynamic Ordinary Least Squares (DOLS) method of Stock and Watson (1993) as specified in equation (5.40) of the methodology chapter. Second, the residuals from the linear cointegrating equation are regressed on the same regressors and the rank transformation R_T (), as in equation (5.41), hence embedding the alternative hypothesis of neglected non-linearity. Finally, the score test statistic, TxR^2, is computed where R^2 is the coefficient of determination of equation (5.41). The null hypothesis of no nonlinear relationship is rejected in favour of the alternative hypothesis of linear relationship if the computed statistic exceeds the χ^2 critical values with *K* degree of freedom (where k is the number of integrated regressors) under the null hypothesis of linearity.

In this research, the statistics for cointegrations and neglected non-linearities are tested in row prices of industries in which cointegration relationships have been detected, and lag orders of five and four were chosen for the lagged regressors of levels and the first differences, respectively [104]. When significant nonlinear cointegration relationships are found, it implies that the portfolio choice available to US investors becomes narrower than when only conventional linear cointegration tests are considered. Tables 7.8 to 7.10 present the combined results of the score statistics for neglected nonlinearity as well as the rank test results for those sectors in which evidence of cointegration relationships were detected. Table 7.8 presents the results of the bivariate tests. As the table shows, out of the seven tests where cointegration relationships were detected only two cases, in the Chemicals industry, are found to be characterised by nonlinearity (nonlinear cointegrations) where TR^2 tests exceed the χ^2 critical values at the 1% significant level.

[104] The experience from previous tests in this study suggests that short lags are appropriate. Serial autocorrelations based on the Durbin -Watson (DW) statistic were checked in each test of both estimations (equations 5.40 and 5.41) and no problems were found.

Table 7.8: The rank test results of bivariate cointegration relationships and the score statistic for neglected nonlinear cointegrations

		Cointegration relations	Neglected nonlinearity
Industry Sector	Markets	$\Xi^{*}[k=1]$	*TxR*^{2}
Chemicals	US, BR	0.0105***	21.218***
	US, ML	0.0101***	15.861***
	US, SA	0.0147**	1.653
Construction	US, BR	0.0097***	3.739
Food and Beverages	US, BR	0.0158**	0.4881
	US, ML	0.0167**	1.920
	BR, US	0.0166**	0.295
	ML, US	0.0177**	0.729
Personal and H/H Goods	US, ML	0.0153**	1.534
	US, SA	0.0158**	2.853
	ML, US	0.0148**	0.021
	SA, US	0.0158**	0.283

Table Notes
** and *** indicate the significance at 5% and 1% levels respectively

Next, where multivariate cointegration relationships have been detected, the nature of the cointegration relationships, or neglected nonlinearity, is tested. Specifically, score tests based on equations (5.46) and (5.47) are conducted for the cases where cointegration relationships between the US and emerging countries' industry sectors are found under Breitung's rank test statistic. The neglected nonlinearity tests with all possible sets of rank series enable to identify the source of nonlinearity. Table 7.9 presents the results of the multivariate neglected nonlinearity tests between the US and the emerging markets' industry sectors. As the test results in the table show, there is evidence of nonlinear cointegration relationships among the Chemicals industries, a result which supports the findings of the bivariate tests. Also, there are nonlinear cointegrations for Banking and Telecommunications only when the Brazilian and Malaysian markets are treated as the dependent variables, a result which conflicts with the trace statistic results. Finally, as in the linear case, the score statistic is employed to test possible nonlinear cointegrations between industries from the emerging countries in which cointegration relationships have been detected under the rank tests. As before, the combined results of the cointegrations and the neglected nonlinear tests of the cases where cointegration relationships were found are reported in table 7.10.

Table 7.9: The rank test results of multivariate cointegration and the neglected nonlinear cointegrations for US and emerging countries

		Cointegration relations	Neglected nonlinearity
Industry Sector	Markets	$\Xi^{*}[k=3]$	TxR^2
Banking	BR, US, ML, SA	0.0108**	11.209**
	ML, US, BR, SA,	0.0113**	4.507
Chemicals	US, BR, ML, SA	0.0092***	52.539***
Construction Materials	US, BR, ML, SA	0.0126**	5.073
	BR, US, ML, SA	0.0080***	7.704
Telecommunications	BR, US, ML, SA	0.0125**	23.476***
	ML, US, BR, SA,	0.0096***	17.699***

Table Notes
** and *** indicate the significance at 5% and 1% levels respectively

Table 7.10: The rank test results of multivariate cointegrations and the neglected nonlinear cointegrations for emerging countries

		Cointegration relations	Neglected nonlinearity
Industry Sector	Markets	$\Xi^{*}[k=2]$	TxR^2
Banking	BR, ML, SA	0.0128**	3.078
	ML, SA, BR	0.0114***	0.276
Chemicals	ML, SA, BR	0.0153**	1.807
Construction Materials	BR, ML, SA	0.0127**	3.468
	SA, BR, ML	0.0140**	2.383
Telecommunications	BR, ML, SA	0.0111***	2.964
	ML, SA, BR	0.0093***	7.185**

Table Notes
** and *** indicate the significance at 5% and 1% levels respectively

As the result in the table indicates, even though several cointegration relationships have been detected between emerging industry sectors using the rank statistic, no evidence of neglected nonlinearity is found, with the only exception of the Telecommunications industry when the Malaysian market is treated as the dependent.

To sumaise, the rank and score statistics tests (Breitung, 2001) have been used in this section to detect possible linear and nonlinear cointegrations in both bivariate and multivariate frameworks. Overall the rank statistic tests lead to additional sets of cointegration results both in bivariate and multivariate tests. Specifically, several bivariate cointegration relationships that the Johansen's trace statistic indicated are also detected by the rank tests. Moreover, more industry sectors exhibit multivariate cointegrations. This is particularly evident in the case of the emerging countries' industry sectors. Nevertheless**,** as the results in tables 7.8 to 7.10 indicate, although several cointegration relationships have been detected through the rank statistic, no significant evidence of neglected nonlinearity is reported, except in the case of the Chemicals industry. Therefore, as in the linear (trace) tests, it seems that segmentation rather than integration is more evident for this industry sector study.

7.5 Conclusion

The aim of this thesis is to investigate the degree of long run co-movements and dynamic linkages among the US stock market and three leading emerging markets (Brazil, Malaysia and South Africa) through the use of industry level price indices and linear and nonlinear econometric methodologies. The focus of this chapter has been on the long-run relationship among industry indices of the US and the three emerging countries using linear and nonlinear cointegration tests. For long run linear relationships, Johansen's (1988, and 1995) cointegration methodology is applied, which uses maximum likelihood estimators and testing cointegration through a vector autoregression (VEC) framework. Specifically, the trace statistic has been applied for various bivariate and multivariate long run relationship tests. As the results of the Johansen's trace statistic in the last section indicate, overall it seems that there is more segmentation among the industry sectors under investigation than when cointegration relationships were tested without exogenous dummies.

Conventional cointegration tests assume that the long-run equilibrium relationship between the economic variables in question is stable over the entire sample period. However, as discussed in section two of the chapter, the sample period of this study includes a somewhat volatile time period for the international stock markets due to global events. These events suggest that finding stable long-run relationships between the industry sectors of the US and emerging markets in the study may prove unlikely. In other words, there may be a period of time in which long-run relationships did exist, while there may also be a period where no long run relationships exist. As a result, this thesis examines the time varying long-run relationships between the US and the emerging markets; industry sectors by applying recursive cointegration analysis as proposed by Hansen and Johansen (1999) as well as rolling cointegration estimations.

The recursive cointegration test results displayed by figures 7.11-7.20 suggest that, the null hypothesis of no cointegration cannot be rejected for most industry sectors in many sub sample periods on the trace tests. However, there also exist reasonably substantial periods where the null hypothesis of no cointegration is clearly rejected. The rescaled graphs of the trace tests also indicate although sometimes significant, decreasing levels of co-movements during the crisis of late 2000s among most sectors. In addition, rolling cointegration tests have been conducted to examine the degree of dynamic convergence between the US and emerging countries industry sectors during different sub-sample periods of the full sample. As the graphical displays of trace test statistics show, rolling fixed length window estimations provide essential information about the time varying pattern of the number of cointegrating vectors. The rolling cointegration tests suggest the majority of the sub sample periods the null hypothesis of no cointegrating vectors could be rejected under the trace test statistics for most industry sectors. Nevertheless, as can be seen from figures 7.21-7.30 there exists several periods, were the null hypothesis cannot be rejected and the variables do not appear to exhibit long-run relationships.

As discussed in the methodology chapter, various market frictions, including transactions costs and information frictions, can prevent the linear models converging to long run equilibrium in financial markets. These problems can undermine the results of the linear cointegration tests and may call for econometric methods that do not rely on the assumptions of linearity and normal distribution. The investigation of the nonlinear cointegrating behaviour of financial assets has been based on a variety of econometric models. To further examine the long run relationships between the emerging and US stock industry sectors, this thesis also applies relatively new techniques such as the rank and score tests proposed by Breitung (2001). Breitung's methodology can be used first to detect relationships among time series variables in linear settings using the rank statistics, and then to test the nature of the nonlinear relationships or neglected nonlinearity under score statistics. Although the rank statistic tests lead to additional sets of [linear] cointegration results both in bivariate and multivariate tests, only a few cases of nonlinear cointegration relationships are found among the industry sectors of the US and the three emerging countries.

In summary, as the results of both techniques (linear and nonlinear) for cointegration relationships indicate, there are more segmentations than integration between the US and the emerging countries' industrial sectors. Neverthless, as Li (2006, p.195) summarises, 'the linear and nonlinear test techniques are better treated as supplements to, rather than substitutes for, each other'. The implication of segmented sectors implies [in theory] that a portfolio diversification opportunity could be available to US investors by investing in these emerging countries' industrial sectors. In addition to the examination of the long-run co-movements, this thesis also explores the short-run dynamic linkages by examining causality relationships and between the US and emerging markets' industry sectors using various non causality tests. Testing dynamic and asymmetric causality linkages will be the focus of the next chapter.

CHAPTER 8:
Empirical Results of Dynamic Linkages between the US and the emerging Industry Sectors

8.1 Introduction

As mentioned before, the aim of this thesis is to search for more concrete evidence for the interdependence between the US stock market and three leading emerging markets (Brazil, Malaysia and South Africa) through the use of ten industry sector prices and various empirical techniques including linear and nonlinear econometric methodologies. In addition to testing for long run dynamic relations, this thesis also examines possible short- run dynamic relationships between the industrial sectors of these markets. The present chapter presents the testing procedures and empirical results of linear and nonlinear causality tests, as well as dynamic transmissions using the generalised impulse response analysis. To investigate the causality linkages among the industry sectors in the study, bivariate linear and nonlinear causality tests are conducted with symmetric and asymmetric analysis. The investigation of linear and nonlinear Granger causality linkages between international industry sectors in both symmetric and asymmetric analysis represents an important empirical advancement of this thesis.

Granger causality analysis provides useful information about the sector return dynamics linkages. In this thesis, since no long run or cointegration relationships were found between the US and the emerging industry sectors, linear Granger-causality relations are first tested by applying the ordinary first differenced VAR model to find the direction of causality linkages within the series. Standard Granger non-causality tests assume that the *VAR* model's parameters remain constant over time. However, as discussed earlier in chapter seven and other places of the thesis, this assumption which may not hold for the sample period of this research. Therefore, time varying causality tests between industry sector returns are to be conducted through rolling window Granger causality analysis. In addition, this thesis also investigates asymmetric dynamic causality relationships between the industry sectors of the emerging countries and the US markets[105]. Specifically, following Hatemi (2012a), the possibility of asymmetric (positive or negative) Granger causal relationships between the industry sectors under study is investigated. To determine the nonlinear causal relationship between international industry sector returns, this thesis also applies the bivariate noisy Mackey-Glass (M-G) in its symmetric and asymmetric versions. The principle advantage over simpler VAR alternatives is that the non-linear Mackey–Glass terms are able to filter the more difficult dependent dynamics within a time series (Kyrtsou and Labys, 2006, p.262).

As discussed in previous chapters, another empirical objective in this thesis is partly motivated by the need to extend empirical work of industry sectors and examine the impact of the late 2000s economic and financial crisis on international industry equity relations. The crisis of the late 2000s has resulted the collapse of several large financial institutions, the rescue of banks by national governments, and downturns in stock markets around the world. Thus, taking the crisis of this period into account, this thesis investigates shifts in correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 economic and financial crisis[106]. In other words, for a comparative analysis, two period samples are examined using data series of 2004-2006 and 2007-2009 are conducted. The work of this chapter is structured as follows. Sections two and three report the empirical results of linear and [symmetric] nonlinear Granger causality tests. Section three also reports the test results of univariate nonlinear dependencies, while section four presents the results of asymmetric tests for linear and nonlinear causality relationships between the returns of the industry sectors in the study. Next, section five presents the test results of the recent crisis using testing procedure discussed in chapter five. Finally, section six summarises the work of the chapter.

[105] Methodologies of causality linear and nonlinear tests, as well as asymmetric causality analysis were discussed in chapter five.

[106] The literature of 2007-2009 crisis has been growing rapidly in recent years. Mishkin (2011) is one of the papers which present a detailed review.

8.2 Empirical results of Linear Causality Relations

8.2.1 Linear Granger Causality test relationships

The first step of analysing short-run dynamic linkages is to conduct linear Granger causality tests. Although Granger causality analysis is commonly used in the literature of finance and macroeconomic studies, there seems to be little or no use of such a methodology in micro-analysis of international stock market relations. As discussed in chapter five, linear Granger causality test examines whether past values of one variable can help explain current values of a second variable, conditional on past values of the second variable. This subsection presents the testing procedures and empirical results of the conventional linear Granger causality tests among industry sectors in the study. Granger causality requires that all data series involved are stationary. In this study, a battery of unit root testing procedures, including the conventional ADF (Dickey-Fuller, 1981), the modified DF (DF-GLS), the KPSS (Kwiatkowski, et. al.1992) and nonlinear unit root tests based on rank statistics **(**Breitung and Gourieroux, 1997) have been conducted. As the unit root test results in chapter seven show, all industry indices follow an I(1) process in the sense there are unit roots in all level series while the first differenced series are all stationary. In addition, given the results of the unit roots, the maximum likelihood approach of cointegration (Johansen 1988, 1991, 1995, and Johansen and Juselius, 1990) was applied to the log levels of the series. As the test results in the same chapter (chapter seven) have shown, no cointegration relationships were found between endogenous variables (when the tests are conducted without exogenous dummies) for all industry sector price indices[107]. As Masiha and Masih (2002, p. 76) point out, 'the absence of cointegration simply rules out the existence of a long-run equilibrium tending relationship, but does not invalidate any short-run relationships, which may arise due to profit-seeking opportunities in transactions'.

[107] However, a weak cointegration relationship was found between the US and Malaysian telecommunication sectors.

Chapter 8

Having determined that the series are all level stationary, and that no cointegration relationships between the price indices of all industry sectors in the study were found, a first differenced VAR model is estimated and used to examine the linear Granger interactions among all sectors. That is, the following bivariate VAR models of the first differenced sector price indices in logarithm form as in equations 5.49a and 5.49b of chapter five are estimated

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_i x_{t-p} + \varepsilon_t \qquad (8.1)$$

$$x_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-p} + \varepsilon_t \qquad (8.2)$$

where x_t and y_t are the industry sector price indices, and p is the lag length of x and y. To implement the Granger tests for vectors of different time series the OLS estimation is first used to estimate the parameters in the VAR model for the industry sectors in each test. In these models, the null hypothesis for causality is that the estimated coefficients of the lagged independent variables are jointly zero. For example, in equation (8.1) the null hypothesis in the Granger causality test is that x does not cause y, which is represented by H_0: $=\beta_1 = \beta_2 = \beta_i=0$. Similarly, the null hypothesis that, y does not cause x in equation (8.2) is that all β_j are zero which is equivalent to failing to reject causality from y_t to x_t. Bidirectional causality is said to exist with Granger causality runs in both directions.

It is common to set all the equations in VAR to possess the same lag length for each test. Furthermore, as noted from tests in previous chapters, short lags are most appropriate for this study. Therefore, following the suggestions of the Akaie Information Criterion (AIC) and the Schwarz Information Criterion (SIC), which are in favour of short lag lengths, lag orders of between one to three lags and based on (AIC) or (SIC) were used for all tests[108]. To identify the linear causal

[108] All test results indicate that serial correlations in the residuals of the individual regressions were not problematic according to DW statistics.

relationships between the series in the VAR models, a number of test statistics have been suggested and used in the empirical literature. In the present study, the significance tests of the lags of the regressing variables, that is, the coefficients of the lagged independent variables, is based on the standard *F* distribution defined as follows

$$F = \frac{(RSS_1 - RSS_2)/p}{RSS_1/(T - p - p - 1)} \tag{8.3}$$

where RSS_1 and RSS_2 are the sum of the squared errors from the ordinary least squares (OLS) regressions, T is the total number of observations, and p represents the number of lags for the variables. The test has an asymptotic *F* distribution with *n, T-2p-1* degrees of freedom. Alternatively, one could use the Wald statistics of the OLS test, which follows a χ^2 distribution with degrees of freedom equal to the number of restrictions and corresponds to the standard F test, or one could also the likelihood ratio (LR) statistics to examine the short-run causality. The linear VAR system is a symmetric model in the sense that the responses to positive and negative shocks are not separated. The issue of asymmetric effects on causality relationships are discussed in section four of this chapter.

Table 8.1 reports the empirical results from the VAR linear Granger causality tests based on the first differenced VAR model. The significance levels of 1 and 5 per cent are reported. Overall, based on the results in the table, the null hypothesis that the emerging industry sectors do not Granger-cause the US sectors should not be rejected at any conventional level of significance. In other words, there are no unidirectional causalities running from the emerging markets' sectors to the US industrial sectors in all tests. On the other hand, there some evidence of linear Granger causality relationships between the US sectors indices and the emerging markets' sector indices. That is, out of sixty tests there are only sixteen cases of unidirectional causalities running from the US industry sectors to the emerging countries industrial sectors.

As can be seen from the results of the table, the unidirectional causalities running from the US industrial sectors to the emerging markets sectors vary. For example, there exist unidirectional causalities running from the US to Malaysia in all industrial sectors except the personal and household goods sector. In the case of Brazil, there are five unidirectional causality relationships with the US sectors, namely; Chemicals, Financial services, Industrial goods, Retail, and Telecommunications, while there are only two (Chemicals and Food sectors) unidirectional causalities in the case of South Africa. In summary, as the results in the table indicate, although there are some significant short-run linear casualties between several industry sectors across markets, the overall causality relationships are not strong under the conventional linear Granger causality test. Another way to examine the Granger causality relationships between the industry sector returns is to conduct varying causality tests. The next sub-section presents graphical displays of the time varying results through rolling window estimations. Furthermore, since no causality relationships were not found for most industry sectors under the VAR linear tests nonlinear causality tests are conducted. Section three of this chapter resprts the results of nonlinear causality tests. Further analysis of causality tests is to be presented later in the chapter to assess the effect of recent financial crisis on industry sector linkages.

Chapter 8

Table 8.1: VAR Granger Causality Results

Sector	Markets	Testing Hypothesis	F- Statistic	Causality Decision
Banking	US, Brazil	US ←Brazil	3.5496(0.0601)	NGC
		Brazil ←US	0.9551(0.3288)	NGC
	US, Malaysia	US ←Malaysia	2.7848 (0.0957)	NGC
		Malaysia ←US	18.3625(0.0000)**	GC
	US, S. Africa	US← S. Africa	2.1796(0.1404)	NGC
		S. Africa ←US	0.20854(0.6481)	NGC
Basic Resources	US, Brazil	US ←Brazil	0.9652 (0.3263)	NGC
		Brazil ←US	3.8046(0.0516)	NGC
	US, Malaysia	US ←Malaysia	2.3538(0.1255)	NGC
		Malaysia ←US	16.7765(0.0000)**	GC
	US, S. Africa	US← S. Africa	0.5071(0.4767)	NGC
		S. Africa ←US	0.0244 (0.8759)	NGC
Chemicals	US, Brazil	US ←Brazil	1.6684 (0.1895)	NGC
		Brazil ←US	6.3136(0.0122)*	GC
	US, Malaysia	US ←Malaysia	1.7276(0.1787)	NGC
		Malaysia ←US	10.7648(0.0000)**	GC
	US, S. Africa	US← S. Africa	1.8048(0.7199)	NGC
		S. Africa ←US	3.0767(0.0469)*	GC
Construction & Materials	US, Brazil	US ←Brazil	2.2893(0.1023)	NGC
		Brazil ←US	3.1985(0.0742)	NGC
	US, Malaysia	US ←Malaysia	1.0552(0.3048)	NGC
		Malaysia ←US	17.9906(0.0000)**	GC
	US, S. Africa	US← S. Africa	3.842(0.010)	NGC
		S. Africa ←US	1.932(0.123)	NGC
Financial Services	US, Brazil	US ←Brazil	2.3417(0.1265)	NGC
		Brazil ←US	4.1519 (0.0421)*	GC
	US, Malaysia	US ←Malaysia	1.0003 (0.3684)	NGC
		Malaysia ←US	14.8275(0.0000)**	GC
	US, S. Africa	US← S. Africa	0.265(0.6068)	NGC
		S. Africa ←US	0.8649(0.3527)	NGC
Food & Beverage	US, Brazil	US ←Brazil	0.855(0.464)	NGC
		Brazil ←US	2.4182(0.1205)	NGC
	US, Malaysia	US ←Malaysia	0.0860(0.7693)	NGC
		Malaysia ←US	10.507(0.0012)**	GC
	US, S. Africa	US← S. Africa	0.7310(0.4819)	NGC
		S. Africa ←US	5.5991(0.0039)**	GC
Industrial Goods	US, Brazil	US ←Brazil	0.6081(0.4358)	NGC
		Brazil ←US	9.7883(0.0018)**	GC
	US, Malaysia	US ←Malaysia	2.0382(0.131314)	NGC
		Malaysia ←US	9.3934 (0.0000)**	GC
	US, S. Africa	US← S. Africa	1.07634(0.3415)	NGC
		S. Africa ←US	1.4616 (0.2328)	NGC

Table 8.1: Continues

Sector	Markets	Null Hypothesis:	F- Statistic	Causality Decision
Personal & H/H Goods	US, Brazil	US ←Brazil	2.607(0.051)	NGC
		Brazil ←US	2.484(0.060)	NGC
	US, Malaysia	US ←Malaysia	0.5320(0.4660)	NGC
		Malaysia ←US	3.7127(0.0545)	NGC
	US, S. Africa	US← S. Africa	0.2228(0.6371)	NGC
		S. Africa ←US	1.4210(0.2337)	NGC
Retail	US, Brazil	US ←Brazil	1.9635(0.1617)	NGC
		Brazil ←US	9.4160(0.0022)**	GC
	US, Malaysia	US ←Malaysia	1.6670 (0.1910)	NGC
		Malaysia ←US	14.4986(0.0000)**	GC
	US, S. Africa	US← S. Africa	0.0146 (0.9036)	NGC
		S. Africa ←US	0.9850 (0.3214)	NGC
Telecomm-unications	US, Brazil	US ←Brazil	2.1699 (0.1152)	NGC
		Brazil ←US	3.3138(0.0371)*	GC
	US, Malaysia	US ←Malaysia	0.3653(0.6941)	NGC
		Malaysia ←US	7.0890(0.0009)**	GC
	US, S. Africa	US← S. Africa	2.6338(0.1052)	NGC
		S. Africa ←US	0.7516 (0.3863)	NGC

Table Notes:
The *and**denote respectively statistical significance at the 1 and 5 percent levels
The figures shown in parenthesis are probability values.
Eviews econometric application is used for all tests causality in this table
The ← arrow indicates the direction of linear Granger causality between market sectors
GC = Granger causality relationship. NGC = No Granger causality relationship.

8.2.2 Time varying causality relations: Evidence from Rolling Window analysis

In chapter six, time varying cross correlations among industry sectors of the study was examined using the rolling correlation analysis technique. In addition, the stability or time variation of the long-run relationships between the industry sectors price indices has been investigated using recursive and rolling window cointegration analysis. As mentioned before, another way to examine the causality between the industry sector returns is to test whether the causality linkages have been changing over time. This thesis applies rolling window estimations to examine the time varying nature of the Granger causality relationships between the industry sectors in the study. The rolling window estimations allow us to examine how sensitive the Granger causality tests are to the particular sample used. The rolling tests are calculated using a fixed length window of a 52 rolling observations (approximately 1 calendar year) time window by adding one observation to the end and then removing the first observation, and so on. That is, starting with observations 1–52, then 2– 53, 3–54, and so on, until the sample is exhausted and the last possible sample observations are calculated.

As noted before, the standard Granger non-causality tests assume that the *VAR* model's parameters remain constant over time. Structural changes in data series over the sample period may shift the parameters and the pattern of the causal relationship may change over time**.** The rolling window approach is more robust to the possibility of structural breaks in the data and allows one to measure the dynamic convergence in industry return indices over time. A Gauss code of Bootstrap simulations for a bivariate non-causality test, developed by Hill (2012) is performed for each window for each VAR model in differences[109]. Since there are so many estimations for different industry sectors, the optimal lag values vary. Lag orders of one or two and based on either SIC or AIC order selections are used for all VAR estimations**.** The choice of lag selections was partly determined by need of the estimated models passing no residula auto-correlations. Next, the Ljung-Box Q tests with five lags are performed on the residuals of the VAR order estimations. The probability value of the LB Q statistic is used for the rolling window analysis of the causality relations. A higher p- value indicates lower or declining causality relationships between the US and industry sector returns, while a lower p- value reveals a higher or rising causality linkage. In other words, for a given time period, if the probability value reaches point one there is no causality relationship, while a zero probability value means that there is a strong Granger causality relationship in that sub-period.

Figures 8.1 to 8.10 present the probability values of the LB- Q statistic of rolling test results for time varying Granger causality relationships between intra-industry sectors of the study over the sample period. The vertical exes measure time

[109] This GAUSS code for rolling window analysis of time varying causality test is available from the web-site of Jonathan Hill at www.unc.edu/~jbhill/software.htm.

varying correlations coefficients. Each point in the time series plots shows the lag order selected for the window ending in the observation corresponding to that point. To conserve space and reduce the burden of graphs the yearly rolling causality tests between the three emerging markets are not reported. As can be seen from the figures, the rolling window estimations for causality relationships provide generally better pictures on the short run co-movements between the industry sectors under study. As the graphs show, the probability values are well above zero in most cases which means generally weaker and unstable Granger causality linkages in most of the industry sector returns under study. Nevertheless, there several cases where the probably values reach close to zero which implies the existence of Granger causality relationships in these respective periods. In summary however, there is some evidence of a time-varying type of causality relationships between the US and the emerging countries industry sectors in various sub-samples. On the other hand, as can be seen from the figures there are some sharp changes in some sectors's graphs, which might due partly to the different lag lenths used for VAR estimations. That is, the VAR model was estimated for different lag lengths, considering also that the Schwartz Bayesian Criterion (SBC) and the Akaike Information Criterion (AIC) suggested different lag structures within each sector's test.

Figures 8.1 to 8.10: The rolling test results for time varying causality relationships between the intra-industry sectors of US and the emerging markets: P-Values

Figure 8.1: Rolling Granger causality relationships between Banking sectors

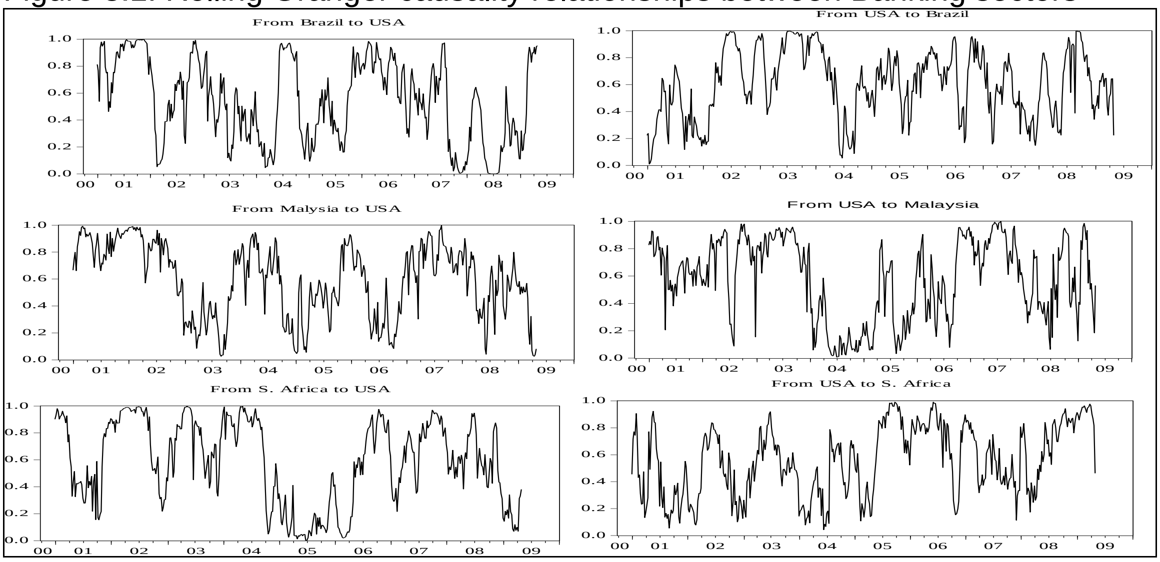


Figure 8.2: Rolling Granger causality relationships between Basic resources sectors

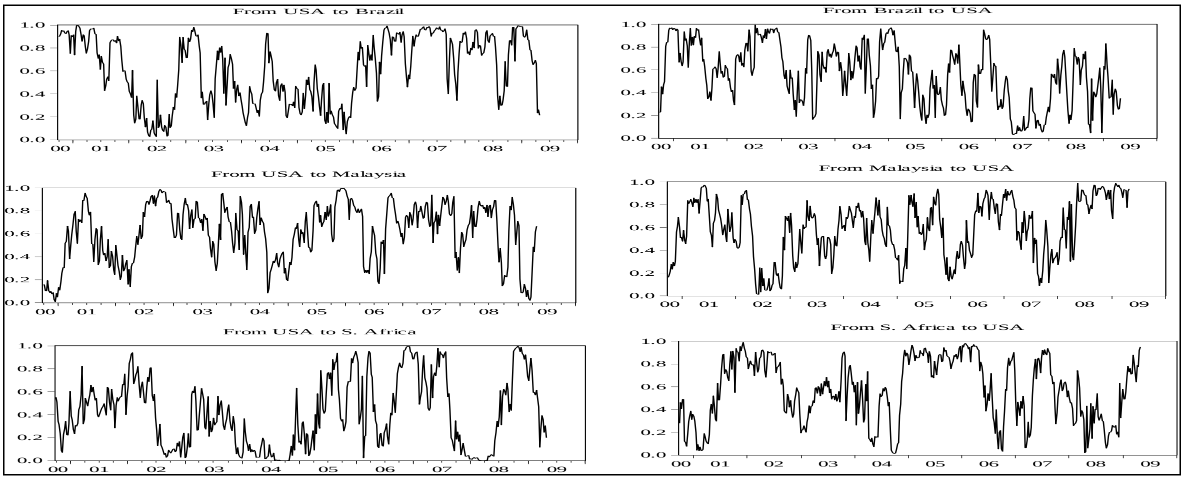


Figure 8.3: Rolling Granger causality relationships between Chemical sectors

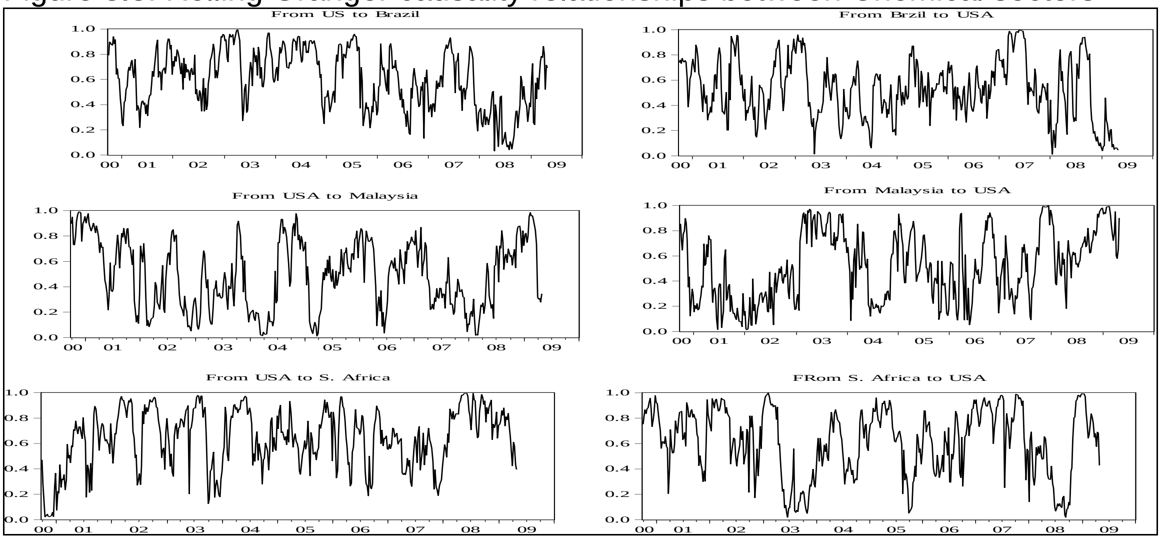


Figure 8.4: Rolling Granger causality relationships between Construction sectors

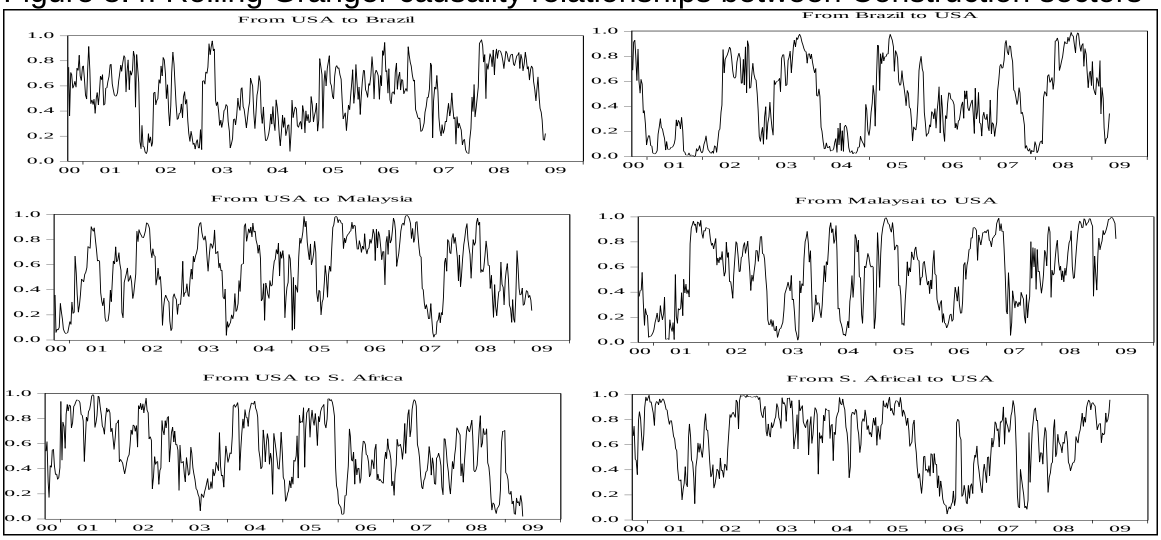


Figure 8.5: Rolling Granger causality relationships between Finance sectors

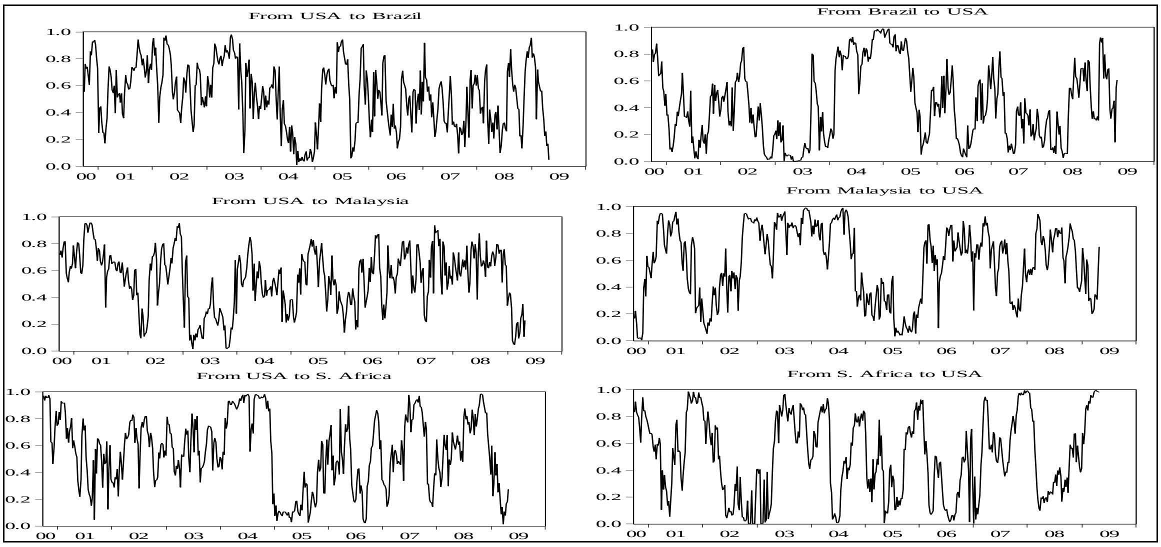


Figure 8.6: Rolling Granger causality relationships between Food sectors

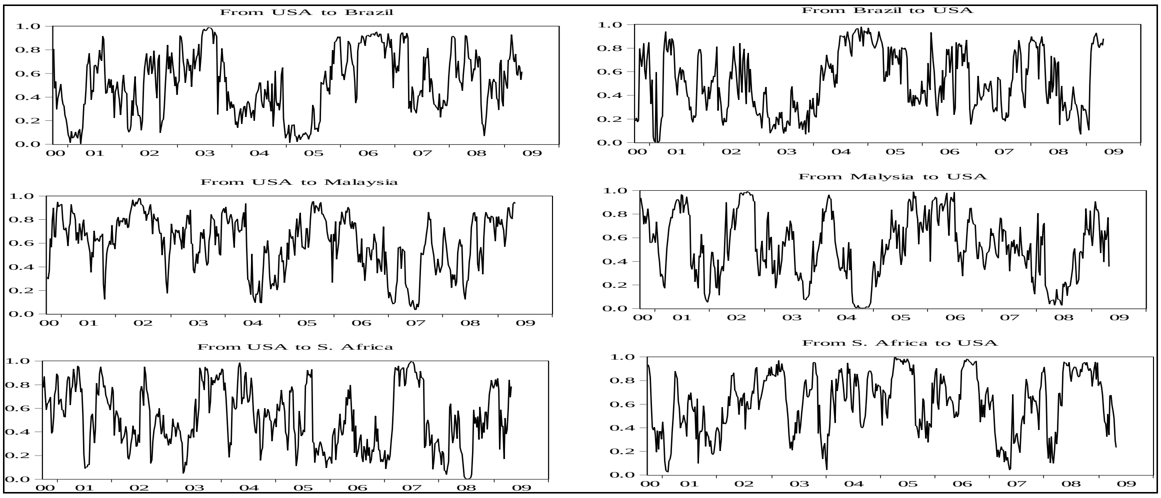


Figure 8.7: Rolling Granger causality relationships between Construction sectors

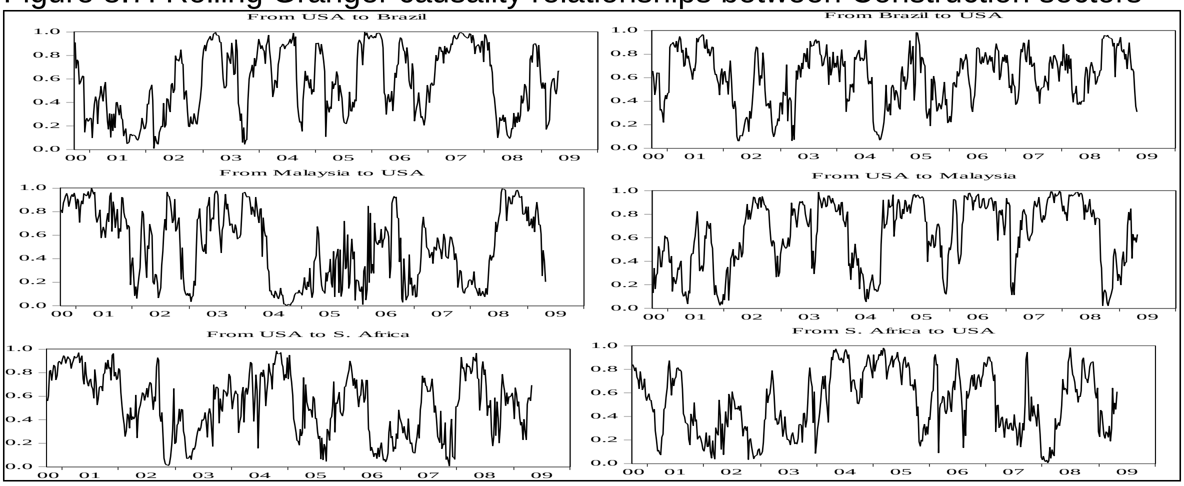


Figure 8.8: Rolling Granger causality relationships between Personal & H/H sectors

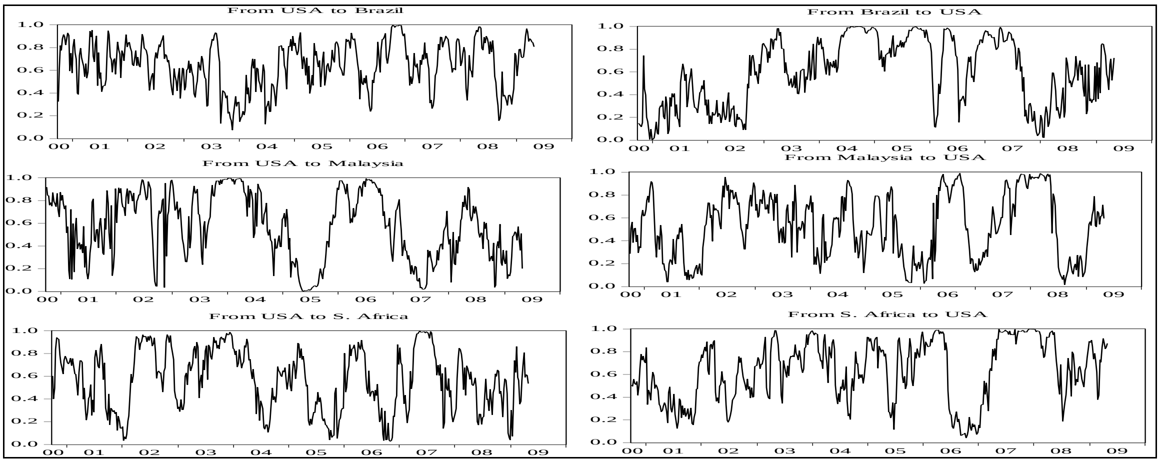


Figure 8.9: Rolling Granger causality relationships between Retail sectors

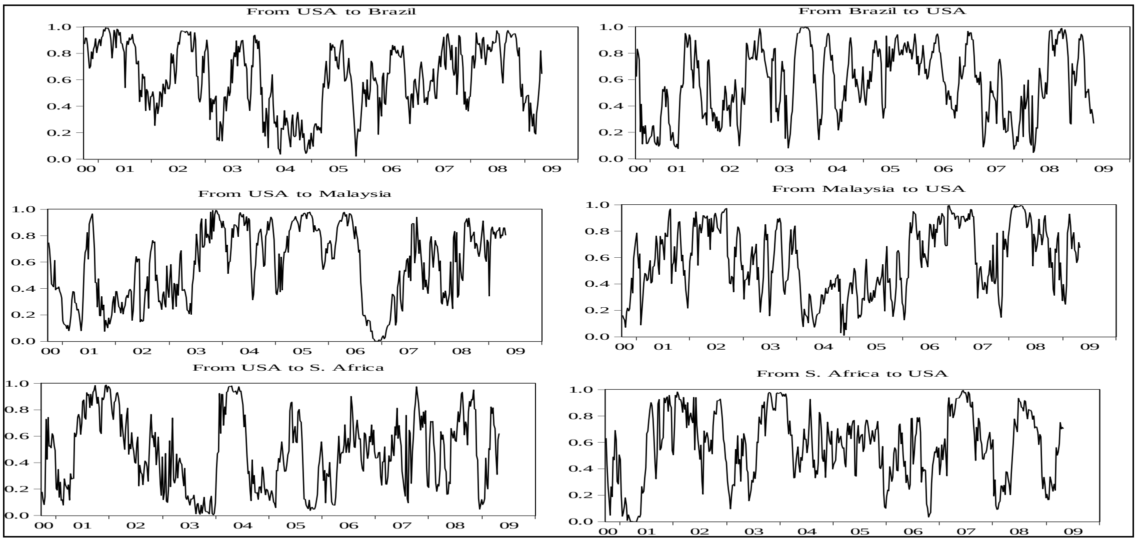
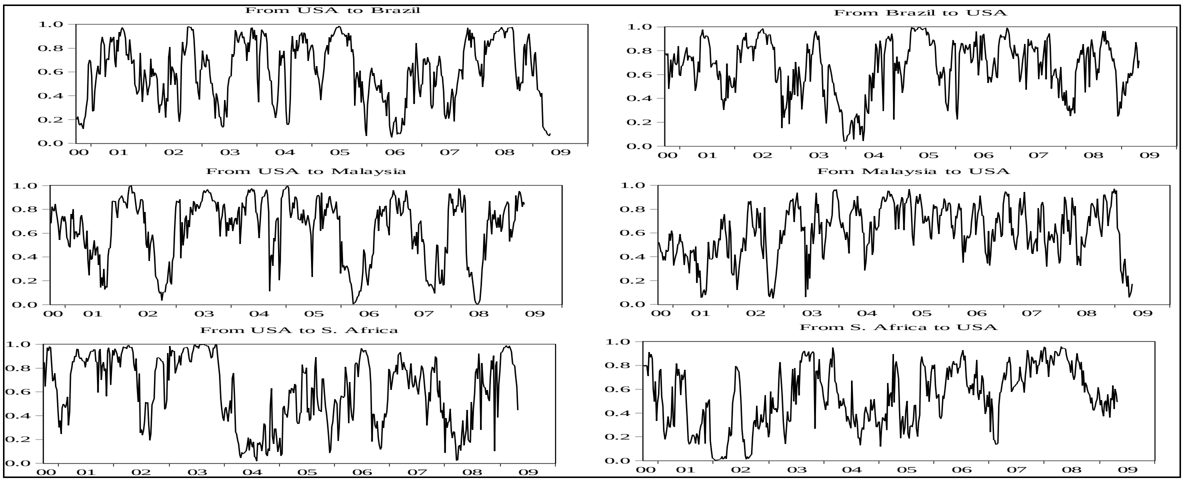


Figure 8.10: Rolling Granger causality relationships between Telecommunication sectors



Chapter 8

8.3 Nonlinear Causality relationships between the US and emerging sector returns: Testing procedures and empirical results

The recent focus on non-linear relationships in stock price co-movements is motivated by the richer types of asset behaviour provided by non-linear models. As mentioned in the methodology chapter, numerous models for nonlinear causality approaches have been presented in the literature. In particular, numerous empirical studies in financial markets have employed the Baek and Brock (1992) and Hiemstra and Jones's (1994) nonparametric Causality methodology for nonlinear causality relationships among assets in international financial markets. Nevertheless, there seems no study so far that has undertaken nonlinear causality testing for micro-analysis at either the firm or industry sector level. In this thesis, to examine nonlinear short-run causality, this study uses the nonlinear Granger causality test referred to as the bivaraite noisy Mackey-Glass model, proposed by Kyrtsou and Labys (2006), and further developed by Hristu-Varsakkeis and Kyrtsou (2008, 2010). According to Kyrtsou and Labys (2006, p. 262), 'the identification of significant Mackey-Glass terms could mean that a non-linear feedback law is the generating mechanism of inter-dependences'. In contrast to the modified model (Baek and Brock, 1992, and Hiemstra and Jones, 1994) which is applicable to the residuals of a VAR model, the Mackey–Glass (M-G) model can be applied directly to the original returns series. Before testing the M-G model for nonlinear causality relationships between industry sectors in the study, the nonlinear dependence behaviour of the individual return series are tested.

8.3.1 Tests results for nonlinear dependencies

To check the nonlinear dependencies for the industry sector returns, this thesis employs the McLeod and Li (1983) test for squared residuals, Engel's (1982) test for ARCH effect and the BDS test for randomness independence or nonlinear dependence as used by Brock et al (1996) applying these tests to the residuals of autoregressive AR (p) modelling or to the residuals of the GARCH filtering procedure. These tests (and others) require that any linear dependencies of the estimated residuals are first removed before the non-linear dependencies are conducted. Thus, prior to testing the nonlinearity behaviour of the industry returns series, an autoregressive fitting procedure of p lags, AR(p), is first applied to the returns series to remove the linear dependencies, as follows[110].

$$r_t = \alpha_0 + \beta \sum_{p=1}^{r} r_{t-p} + \varepsilon_t \qquad (8.4)$$

where $r_{i,t}$ represents the returns of the price indices in sector i, and $\varepsilon_t \sim N(0, \sigma_t^2)$. For the linear dependence test, an appropriate lag length must be chosen for the linear model. The choice of AR lag length can be made on a number of theoretical grounds, including the Box- Jenkins interactive procedure, or the use of various information criteria such as Schwarz's Bayesian Information Criterion (Schwarz, 1978) and Akaike's information criterion (Akaike, 1974), or the maximization of R^2.

To investigate the nonlinearities for the international industry indices the following testing procedures are undertaken. Firstly, the best fit linear autoregressive AR (p) model in 8.4 is used to remove any linear dependence in the return series. An AR of up to 5 lags is considered for each return series, and then the optimal lag length based on the Schwartz information criterion (SIC) is chosen for each return series. The Schwartz criterion is said to have better large sample properties under the null hypothesis of a linear generating mechanism compared to the alternative choices. Next, the Ljung–Box Q-test is used to determine whether any linear dependency remains in the residuals of the AR estimation.

Appendix D reports the results of the linear and nonlinearity tests for the residuals of the linear models. The returns series are not reported but available on request. As the results (derived from the residuals of the linear models) indicate, linear

[110] All price indices and first differences (or returns) were also tested for the presence of unit root using a number of statistical tests. As reported in the empirical chapter, the log-levels series were found to be I(l) in all cases while nonstationarity in the first differenced series was strongly rejected

dependence is not a problem for any of the returns series against the 1% to 5% significance levels of the adjusted LBQ (5) tests. Furthermore, residual autocorrelations based on the DW test were found not to be a problem in the estimated AR(P) model for all industry sector returns of each market in the research. Next the nonlinear tests are conducted using the McLeod and Li (1983) test, the Engle's (1982) Lagrange Multiplier (LM) test, and the BDS Brock et al (1996) test. The McLeod and Li (1983) test, which is based on the Ljung-Box modified Q^2 test, looks at the autocorrelation function of the squares of the pre-whitened data, and tests whether the first *p* lagged autocorrelations for the squared residuals are collectively small in magnitude. As the fourth columns of the table indicate there is strong evidence of nonlinear dependencies in the squared returns for nearly every industry sector for all markets. Similarly, the results of the ARCH test [ARCH (5)] reveal an ARCH effect in the residuals of the linear models for almost every industry sector in all markets. That is, as the results of the linear AR (P) fitting models indicate, the ARCH effect is present in most residuals of the industry sector return series of the study. The ARCH test results, distributed as $\chi^2(5)$, are in line with many previous studies that have shown the presence of ARCH effects in various financial markets such as Brooks (1996) and Ramchand and Susmel (1998). Next, for robust testing, following the lead of Brooks (1996) and Opong et al (1999), the independence or nonlinearity behaviours of the industry sector returns are examined by applying the BDS test to the residuals of the fitted AR(p) model for each industry return series.

The BDS statistic measures the statistical significance of the correlation dimension calculations, and, as in other tests, it is also necessary to remove or filter out of the series any linear dependences before applying the BDS statistic. That is, once any linear dependence is removed from the data, any remaining dependence should be due to a nonlinear data generating process. This study follows the lead of frequently cited Brock et al. (1991), and Hsieh (1991) of selecting the ranges of *m, δ,* for a given N. In the literature, common choices of *δ* are 0.75, 1, and 1.5. According to Brock et al (1991) when 500 or more observations are prepared and the embedding dimension *m* is in the range of 2 *to* 5, then the value of δ is selected as a half. In this research, the value of δ equals to 0.75σ (δ=0.75σ) and the embedding dimension of 6 is used. The σ represents the standard deviation of the filtered data. The tested null hypothesis is that each industry sector indices is IID, and the null can be rejected with 95% confidence when the estimated value Z, the BDS statistic, exceeds 2.0 (or 1.96). Columns five to ten provide the values of the BDS statistics. It can be seen that the IID assumption is rejected for the chosen values of 0.75σ and the embedding dimensions for the entire examined industry sector return series.

As the results of the linear AR (P) fitting models indicate, the ARCH effect is present in most residuals of the industry sector return series in the study. Thus, in an attempt to filter out the heteroskedasticity in the behaviour of the industry return residuals, they are further examined by augmenting the chosen AR(P) model for each return series with a GARCH(Generalized Auto-Regressive Conditional Heteroskedasticity) filtering procedure of the following format

$$r_t = a_0 + b\sum_{p=1}^{r} r_{t-p} + u_t, u_t \approx (0, \hat{\lambda}_t) \qquad (8.5)$$

where $\hat{\lambda}_t = a_0 + a_1 + \hat{\lambda}_{t-1} + a_2 u_{t-1}^2$

To evaluate whether the GARCH (1,1) model adequately captures the nonlinear structure in the return series, the BDS test is then applied to the standardised residuals of the return GARCH as a misspecification test[111]. In general, the results of the Garch (1,1)- AR(p) model fitting process, which have not been presented **to** conserve space**,** appear to have successfully removed the ARCH effects in many cases. However, as the results of the BDS test on the GARCH residuals indicate, there still exists some degree of non-linearity of an unknown form. In summary, as the results of these test statistics indicate, significant nonlinear dependencies in the return series for all industry sectors when AR (P) filtering is applied[112]. The

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[111] Alternatively, one can apply it to the logarithms of squared standardized residuals

[112] Also, as reported in chapter seven, unit root test results from the ADF, DF-GLS, KPSS and KSS test statistics show that sector price indices are non-stationary in price levels and stationary in first differenced or returns.

result indicates that nonlinear information might not be fully uncovered by the traditional linear Granger causality test. Therefore, testing for non-linear causality relationships is conducted in this thesis using the bivaraite noisy Mackey-Glass (M-G) model.

8.3.2 Empirical results of symmetric nonlinear causality Relationships: Evidence from the Mackey-Glass (M-G) model

The Mackey-Glass model for nonlinear causality test involves testing whether the past values of a variable such as y_t have predictive non-linear effect on the current value of another variable such as $x_{t,}$ and vice versa. Under the M-G framework, one begins by selecting the delay parameters τ_1, τ_2, c_1, and c_2. In this thesis, the optimal delay parameters τ_1, and τ_2, are determined on the basis of Schwarz information criterion (SIC). Next, the M-G model that best fits the given time series is estimated using ordinary least squares and then the F-test statistic as defined in equation (5.59) and reproduced here

$$S_f = \frac{(S_c - S_u)/k}{S_u/(N-m-1)} \approx F_{k,N-m-1} \qquad (8.6)$$

If the calculated statistics exceed a specified critical value, then the null hypothesis that y_t does not nonlinearly cause x_t is rejected. Then the p-value for the F-test is calculated. As Hristu-Varsakelis and Kyrtsou (2008) show, the P-value is obtained from

$$p = 1 - F^{cdf}_{nrest\,r,N-nfree-1}(S_F, n_{rest\,r}, N - n_{free} - 1) \qquad (8.7)$$

The null hypothesis for no causality is rejected if $P < 0.05$ in favour of the alternative hypothesis[113].

[113] Note: The nonlinear Granger causality test is applied to all return series of the study regardless of whether the linear causality hypothesis is rejected or accepted.

Table 8.2 reports the results of nonlinear Granger causality relationships between the US and the emerging countries industry sectors. As can be seen from the table, overall there are no significant nonlinear Granger causality relationships between the industry sectors under study. As in the linear case, the nonlinear causality results indicate that under the M-G model the null hypothesis that industrial sector returns of the three emerging countries markets do not Granger cause the US sector returns should be accepted in nearly all cases. However, in contrast to the conventional linear model, the M-G model uncovers two cases of unidirectional nonlinear causality relationships running from the emerging markets' industrial sectors to the US sectors. In particular, as can be seen from the results in the table, there is unidirectional nonlinear causality from South Africa to the US in the case of Basic resources, and Construction and Materials from Brazil to the US. There is also one case of a unidirectional nonlinear causality relationship, in the case of the Personal and Household sector running from the US to Malaysia, which was not reported under the conventional linear model. To summarise, under the Mackey-Glass (M-G) model of nonlinear (symmetric) causality test, there exist nonlinear Granger causality relationships which are weaker than under the conventional Granger linear model. In other words, the results from the standard VAR model provide more evidence of bidirectional causality between the returns of US and the emerging economies than the Mackey-Glass (M-G) model. Nevertheless, the Mackey-Glass (M-G) model uncovers few cases of unidirectional nonlinear causality linkages that were not found under the conventional linear VAR model.

Table 8.2: Symmetric nonlinear Granger causality relationships: Evidence from the Mackey-Glass (M-G) model

Sector	Markets	Testing Hypothesis	Input Parameters	F-Statistics	P-Value	Causality Decision
Banking	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=1,\tau_2=2,c_1=1,c_2=2$	1.9398	0.1643	NGC
		Brazil $\leftarrow$ US		0.0316	0.8589	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=1,\tau_2=1,c_1=2,c_2=2$	0.2235	0.6366	NGC
		Malaysia $\leftarrow$ US		0.7669	0.3816	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=2,\tau_2=2,c_1=2,c_2=1$	0.1855	0.6669	NGC
		S. Africa $\leftarrow$ US		1.2682	0.2606	NGC
Basic Resources	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=1,\tau_2=1,c_1=2,c_2=1$	1.3637	0.2434	NGC
		Brazil $\leftarrow$ US		2.1001	0.1479	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=1,\tau_2=2,c_1=1,c_2=2$	0.1651	0.6847	NGC
		Malaysia $\leftarrow$ US		0.7015	0.4027	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=1,\tau_2=1,c_1=2,c_2=1$	4.7656^{*}	0.0295	GC
		S. Africa $\leftarrow$ US		0.8447	0.3585	NGC
Chemicals	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=3,\tau_2=1,c_1=2,c_2=2$	1.7703	0.1839	NGC
		Brazil $\leftarrow$ US		0.2423	0.6228	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=2,\tau_2=1,c_1=1,c_2=2$	0.5970	0.4401	NGC
		Malaysia $\leftarrow$ US		2.1374	0.1444	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=1, \tau_2=1,c_1=1c_2=1$	0.0322	0.8576	NGC
		S. Africa $\leftarrow$ US		0.7736	0.3795	NGC
Construction & Materials	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=2,\tau_2=1,c_1=3,c_2=2$	4.6126^{*}	0.0322	GC
		Brazil $\leftarrow$ US		0.1310	0.7176	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=2,\tau_2=1,c_1=3,c_2=2$	0.1203	0.7288	NGC
		Malaysia $\leftarrow$ US		0.1856	0.6668	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=2,\tau_2=2,c_1=2,c_2=2$	0.1942	0.6596	NGC
		S. Africa $\leftarrow$ US		1.2925	0.2561	NGC
Financial Services	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=2,\tau_2=2,c_1=2,c_2=1$	1.5645	0.2116	NGC
		Brazil $\leftarrow$ US		0.1563	0.6927	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=2,\tau_2=2,c_1=2,c_2=2$	1.4886	0.2230	NGC
		Malaysia $\leftarrow$ US		1.2165	0.2706	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=1,\tau_2=3,c_1=2,c_2=1$	0.7880	0.3751	NGC
		S. Africa $\leftarrow$ US		1.6285	0.2025	NGC
Food & Beverage	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=2,\tau_2=1,c_1=3,c_2=1$	0.1110	0.7392	NGC
		Brazil $\leftarrow$ US		0.0195	0.8889	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=2,\tau_2=1,c_1=2,c_2=1$	1.7947	0.1810	NGC
		Malaysia $\leftarrow$ US		1.7446	0.1871	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=2,\tau_2=2,c_1=2,c_2=2$	0.5974	0.4399	NGC
		S. Africa $\leftarrow$ US		1.0655	0.3024	NGC
Industrial Goods	US, Brazil	US $\leftarrow$ Brazil	$\tau_1=1,\tau_2=1,c_1=1,c_2=1$	0.0048	0.9447	NGC
		Brazil $\leftarrow$ US		0.3914	0.5318	NGC
	US, Malaysia	US $\leftarrow$ Malaysia	$\tau_1=1,\tau_2=1,c_1=2,c_2=2$	1.6207	0.2036	NGC
		Malaysia $\leftarrow$ US		1.7997	0.1803	NGC
	US, S. Africa	US $\leftarrow$ S. Africa	$\tau_1=1,\tau_2=2,c_1=2,c_2=1$	1.6993	0.1930	NGC
		S. Africa $\leftarrow$ US		1.0063	0.3163	NGC

Table 8.2: Continues

Sector	Markets	Testing Hypothesis	Input Parameters	F-Statistics	P-Value	Causality Decision
Personal & H/H goods	US, Brazil US, Malaysia US, S. Africa	US ⟵Brazil Brazil ⟵US US ⟵Malaysia Malaysia ⟵US US⟵ S. Africa S. Africa ⟵US	τ_1=1τ_2=1, c_1=2,c_2=1 τ_1=1τ_2=2, c_1=2,c_2=1 τ_1=1τ_2=2, c_1=1,c_2=1	1.5952 0.0039 1.0532 5.0173* 0.2569 0.1255	0.2072 0.9500 0.3052 0.0255 0.6125 0.7233	NGC NGC NGC GC NGC NGC
Retail	US, Brazil US, Malaysia US, S. Africa	US ⟵Brazil Brazil ⟵US US ⟵Malaysia Malaysia ⟵US US⟵ S. Africa S. Africa ⟵US	τ_1=2,τ_2=1,c_1=2,c_2=1 τ_1=1,τ_2=1,c_1=3,c_2=2 τ_1=1,τ_2=2,c_1=2,c_2=2	0.0798 0.2388 0.7928 2.2694 0.4311 0.0010	0.7777 0.6253 0.3737 0.1326 0.5117 0.9746	NGC NGC NGC NGC NGC NGC
Telecomm-unications	US, Brazil US, Malaysia US, S. Africa	US ⟵Brazil Brazil ⟵US US ⟵Malaysia Malaysia ⟵US US⟵ S. Africa S. Africa ⟵US	τ_1=1 τ_2=1 c_1=2,c_2=1 τ_1=1,τ_2=2,c_1=1,c_2=1 τ_1=1,τ_2=2,c_1=2,c_2=1	0.1717 0.0016 1.7290 1.0689 0.000 0.2107	0.6787 0.968 0.1891 0.3017 0.9955 0.6464	NGC NGC NGC NGC NGC NGC

Table Notes:
Input Parameters for all tests have been selected on the basis of Schwarz information criterion (SIC).
The arrow indicates the direction of nonlinear Granger causality relationship between sector markets.
The tests for symmetric nonlinear Granger causality relationships are performed using a modified Matlab code kindly written by Drs Varsakelis and Kyrtsou who developed the empirical model, and kindly provided by Professor Emmanuel Anoruo from Coppin State University (USA).
GC = Granger causality relationship. NGC = No Granger causality relationship.

8.4 Asymmetric effects on Linear and nonlinear causality relations between the US and emerging industry sector returns

As discussed before, a major contribution of this thesis is to conduct linear and nonlinear causality analysis to examine the dynamic interdependence between the US and the emerging countries industry sectors. Thus, to examine further the causality linkages between industry sector indices and diversification implications, the linear and nonlinear Granger causality tests are extended through investigations of asymmetric causality analysis proposed by Hatemi (2012a) and Hristu-Varsakelis and Kyrtsou (2008).

8.4.1 Empirical results of Asymmetric effects on the linear Granger causality relationships

In the conventional Granger causality test presented in the last section, there is no separation between the causal impact of positive and negative shocks. As discussed in chapter five, market frictions including asymmetric information phenomenon can induce asymmetric adjustments to equilibrium and causal effects. In this thesis, following Hatemi (2012a), the possibility of asymmetric (positive or negative) causal relationships between the industry sectors under study is investigated through the cumulative sums of possible positive and negative shocks, as has been detailed in chapter five[114]. Tables 8.3 and 8.4 present the results of asymmetric (positive and negative) causality tests based on bootstrap simulations as proposed by Hatemi (2012a). As the results in these tables indicate, shocks have resulted in more asymmetric Granger causality relationships than under the conventional VAR causality tests especially in the case of negative shocks. As the results of the positive asymmetric causality tests (table 8.3) indicate, only the US industry sectors are impacting the emerging markets' sectors.

In other words, the null hypothesis that the emerging countries sectors are not affecting the US sectors cannot be rejected at the one and five per cent significant levels of the bootstraps distributions in all positive asymmetric causality tests. The (positive) effect of a shock is most noticed in the Banking, Chemicals, Industrial goods, and Telecommunication sectors with between two and three unidirectional causalities running from US industrial to the emerging markets sectors. On the other hand, the results in table 8.4 show more unidirectional and bidirectional causality relationships in the case of negative asymmetric tests. Specifically, there are more unidirectional causalities running from the US to the emerging markets in most of the industrial sectors, and several cases of bidirectional asymmetric causality relationships. As can be seen from table 8.4, the cases of bidirectional asymmetric causalities are; Chemical, Financial services, and Industrial goods

[114] The asymmetric character of returns and the underlying correlations in financial markets have been examined in the literature by others (see Hatemi (2012a for citations).

between the US and Brazil, Banking and Basic resources between the US and Malaysia, and Construction and Materials between the US and South Africa.

Table 8.3: The test results of positive asymmetric linear causality relationships

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV 1%	Bootstrap CV 5%	Causality Decision
Banking	US, Brazil	US ←Brazil	0.029	7.838	4.012	NGC
		Brazil ←US	0.001	6.824	3.457	NGC
	US, Malaysia	US ←Malaysia	0.005	5.499	3.442	NGC
		Malaysia ←US	12.893**	9.120	4.137	GC
	US, S. Africa	US← S. Africa	0.273	5.597	3.928	NGC
		S. Africa ←US	9.037**	6.000	3.549	GC
Basic Resources	US, Brazil	US ←Brazil	0.390	7.427	4.497	NGC
		Brazil ←US	2.113	6.433	3.985	NGC
	US, Malaysia	US ←Malaysia	0.234	7.010	3.935	NGC
		Malaysia ←US	5.201*	8.880	4.076	GC
	US, S. Africa	US← S. Africa	0.657	8.256	4.452	NGC
		S. Africa ←US	0.036	6.617	3.982	NGC
Chemicals	US, Brazil	US ←Brazil	0.731	6.506	4.115	NGC
		Brazil ←US	4.779*	7.370	3.558	GC
	US, Malaysia	US ←Malaysia	0.407	5.838	3.552	NGC
		Malaysia ←US	4.403*	6.501	3.951	GC
	US, S. Africa	US← S. Africa	2.753	6.684	3.872	NGC
		S. Africa ←US	1.039	6.914	3.573	NGC
Construction & Materials	US, Brazil	US ←Brazil	1.624	6.701	4.066	NGC
		Brazil ←US	3.415	6.487	3.682	NGC
	US, Malaysia	US ←Malaysia	0.055	6.944	4.268	NGC
		Malaysia ←US	0.937	6.738	3.465	NGC
	US, S. Africa	US← S. Africa	0.544	6.622	4.134	NGC
		S. Africa ←US	0.752	6.782	3.714	NGC
Financial Services	US, Brazil	US ←Brazil	0.129	6.672	3.969	NGC
		Brazil ←US	1.108	6.685	3.687	NGC
	US, Malaysia	US ←Malaysia	2.366	10.288	5.860	NGC
		Malaysia ←US	12.895**	10.267	5.686	GC
	US, S. Africa	US← S. Africa	0.243	6.432	3.546	NGC
		S. Africa ←US	1.332	6.690	4.159	NGC
Food & Beverage	US, Brazil	US ←Brazil	2.772	7.135	3.901	NGC
		Brazil ←US	0.530	6.259	3.720	NGC
	US, Malaysia	US ←Malaysia	1.127	7.701	3.902	NGC
		Malaysia ←US	3.478	8.014	3.948	NGC
	US, S. Africa	US← S. Africa	0.027	7.936	3.680	NGC
		S. Africa ←US	0.040	7.074	3.823	NGC

Table 8.3: Continues

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV		Causality Decision
				1%	5%	
Industrial Goods	US, Brazil	US ←Brazil	0.413	7.347	3.847	NGC
		Brazil ←US	5.989*	7.046	4.318	GC
	US, Malaysia	US ←Malaysia	0.098	7.076	3.712	NGC
		Malaysia ←US	7.086**	6.354	3.520	GC
	US, S. Africa	US← S. Africa	0.000	7.027	3.756	NGC
		S. Africa ←US	0.576	7.065	4.110	NGC
Personal & H/H Goods	US, Brazil	US ←Brazil	2.476	7.354	3.774	NGC
		Brazil ←US	1.967	6.015	3.874	NGC
	US, Malaysia	US ←Malaysia	0.186	6.864	3.922	NGC
		Malaysia ←US	0.126	6.692	3.663	NGC
	US, S. Africa	US← S. Africa	2.580	6.643	3.952	NGC
		S. Africa ←US	0.642	8.098	3.648	NGC
Retail	US, Brazil	US ←Brazil	2.584	7.369	3.757	NGC
		Brazil ←US	2.939	6.654	3.890	NGC
	US, Malaysia	US ←Malaysia	1.206	6.259	3.846	NGC
		Malaysia ←US	6.888*	7.903	3.887	GC
	US, S. Africa	US← S. Africa	0.801	7.410	4.355	NGC
		S. Africa ←US	0.488	6.795	3.626	NGC
Telecommu-nications	US, Brazil	US ←Brazil	3.192	7.885	4.083	NGC
		Brazil ←US	8.458**	6.728	4.202	GC
	US, Malaysia	US ←Malaysia	0.104	7.889	4.014	NGC
		Malaysia ←US	4.731*	7.238	4.185	GC
	US, S. Africa	US← S. Africa	0.484	7.327	4.132	NGC
		S. Africa ←US	7.582**	6.667	3.493	GC

Table: Notes:
Used lags are based on Information criterion proposed by Hatemi-J Criterion (HJC)
Test Value: Modified Wald Test based on bootstrap simulations as proposed by Hatemi (2012a).
Hatemi's bootstrap critical values of 1 and 5 percent levels are reported.
The *and**denote a rejection of no causality hypothesis respectively at the 1 and 5 percent levels
A Gauss code written by Hatemi-J (2011a) is used to implement the asymmetric causality tests.
The ← arrow indicates the direction of linear causality between market sectors.
GC = Granger causality relationship. NGC = No Granger causality relationship.

Table 8.4: The test results of negative asymmetric linear causality relationships

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV		Causality Decision
				1%	5%	
Banking	US, Brazil	US ← Brazil	0.501	8.866	4.145	NGC
		Brazil ← US	6.023*	8.617	3.556	GC
	US, Malaysia	US ← Malaysia	6.616*	12.166	6.531	GC
		Malaysia ← US	12.191*	14.367	6.709	GC
	US, S. Africa	US ← S. Africa	0.360	7.508	4.109	NGC
		S. Africa ← US	0.202	8.608	3.300	NGC
Basic Resources	US, Brazil	US ← Brazil	0.243	7.702	5.546	NGC
		Brazil ← US	18.899**	9.435	6.009	GC
	US, Malaysia	US ← Malaysia	7.165*	9.987	6.302	GC
		Malaysia ← US	37.767**	9.928	6.249	GC
	US, S. Africa	US ← S. Africa	0.656	8.729	3.862	NGC
		S. Africa ← US	1.268	8.207	4.323	NGC
Chemicals	US, Brazil	US ← Brazil	12.747**	9.534	6.097	GC
		Brazil ← US	8.960*	9.496	6.291	GC
	US, Malaysia	US ← Malaysia	4.104	11.870	6.372	NGC
		Malaysia ← US	23.877**	9.854	6.258	GC
	US, S. Africa	US ← S. Africa	4.676	11.934	7.995	NGC
		S. Africa ← US	17.390**	14.207	8.046	GC
Construction & Materials	US, Brazil	US ← Brazil	0.198	9.028	3.271	NGC
		Brazil ← US	1.050	10.577	3.419	NGC
	US, Malaysia	US ← Malaysia	3.616	9.480	5.884	NGC
		Malaysia ← US	36.424**	8.982	5.886	GC
	US, S. Africa	US ← S. Africa	11.383*	13.660	8.024	GC
		S. Africa ← US	29.401**	13.838	8.466	GC
Financial Services	US, Brazil	US ← Brazil	9.284*	9.800	6.022	GC
		Brazil ← US	17.974**	10.884	6.139	GC
	US, Malaysia	US ← Malaysia	5.483	10.762	6.341	NGC
		Malaysia ← US	41.285**	8.938	5.893	GC
	US, S. Africa	US ← S. Africa	4.900	8.752	3.887	NGC
		S. Africa ← US	0.740	7.340	3.374	NGC
Food & Beverage	US, Brazil	US ← Brazil	0.802	7.914	3.841	NGC
		Brazil ← US	3.809	7.325	3.844	NGC
	US, Malaysia	US ← Malaysia	0.585	9.034	3.482	NGC
		Malaysia ← US	8.779*	8.662	3.757	GC
	US, S. Africa	US ← S. Africa	8.209	11.957	8.260	NGC
		S. Africa ← US	26.711**	11.248	7.323	GC
Industrial Goods	US, Brazil	US ← Brazil	12.440*	12.667	8.203	GC
		Brazil ← US	7.530*	13.391	7.744	GC
	US, Malaysia	US ← Malaysia	5.031	10.614	6.206	NGC
		Malaysia ← US	19.878**	10.371	6.273	GC
	US, S. Africa	US ← S. Africa	0.027	6.852	3.913	NGC
		S. Africa ← US	0.186	6.070	3.835	NGC

Table 8.4: continues

Sector	Markets	Testing Hypothesis:	Test Value	Bootstrap CV		Causality Decision
				1%	5%	
Personal & H/H Goods	US, Brazil	US ←Brazil	0.465	6.196	3.787	NGC
		Brazil ←US	5.130*	6.860	3.943	GC
	US, Malaysia	US ←Malaysia	0.008	6.346	4.000	NGC
		Malaysia ←US	4.643*	7.163	3.839	GC
	US, S. Africa	US← S. Africa	0.143	8.265	4.055	NGC
		S. Africa ←US	1.708	7.953	4.252	NGC
Retail	US, Brazil	US ←Brazil	3.049	8.273	3.818	NGC
		Brazil ←US	10.992**	7.908	3.932	GC
	US, Malaysia	US ←Malaysia	1.913	10.291	6.601	NGC
		Malaysia ←US	20.760**	11.347	6.059	GC
	US, S. Africa	US← S. Africa	0.468	7.474	3.868	NGC
		S. Africa ←US	0.015	6.422	3.665	NGC
Telecomm-unications	US, Brazil	US ←Brazil	0.396	7.866	4.246	NGC
		Brazil ←US	4.610*	7.054	4.140	GC
	US, Malaysia	US ←Malaysia	0.057	8.930	4.269	NGC
		Malaysia ←US	9.289**	6.118	3.697	GC
	US, S. Africa	US← S. Africa	1.066	7.014	3.801	NGC
		S. Africa ←US	0.440	6.893	3.834	NGC

Table Notes: See table 8.3

8.4.2 Empirical results of Asymmetric effects on the nonlinear Granger causality relationships

In this subsection, the nonlinear causality tests of the last section are extended using the Mackey-Glass (M-G) model as described in chapter five. ‘Regardless of the causality relationships identified in the pair x_t and y_t, [of the Mackey-Glass model] we would like to know whether those relationships hold when conditioning for positive or negative returns’ (Hristu-Varsakelis and Kyrtsou, 2008, p.3). In other words, lack of or ‘detection of a causality relationship does not give information on whether a positive or negative shock has significant predictive value’. Therefore, asymmetric nonlinear causality tests are conducted for the industry sector return series. In other words, similar to the linear asymmetric causality of the last section, the shock (positive or negative) effect on the returns are separated for testing the asymmetric nonlinear causality linkages between the US and emerging markets industry sectors. For example, tests are conducted to see whether positive returns in the US series exhibit a Granger cause effect on the emerging industry return series. The procedure is then repeated, with the order of the series reversed, that is, whether positive returns in the emerging return series exhibit a Granger cause effect on the US sector return series. The same testing procedure is then applied to non-positive (negative) return series.

Tables 8.5 and 8.6 report the results of asymmetric (positive and negative) nonlinear Granger causality relationships. As can be seen from the tables, there are more asymmetric nonlinear causality relationships than under the case of symmetric nonlinear Granger causality tests of the last section. Furthermore, in contrast to the asymmetric causality relationships under the linear model, there are many emerging markets industrial sectors that show positively nonlinear Granger causality with the US industrial sectors. In addition, there are several cases of bidirectional positive asymmetric nonlinear causal relationships between industry sector returns of the United States and the emerging markets for the period under study. These cases are; Food and Beverage between the US and Brazil, Financial services and Industrial goods sectors between the US and South Africa. Overall, the positive asymmetric tests uncover extra nonlinear causality relationships between the US and the emerging countries' industrial sectors, which have not been found under the VAR linear model. As for the case of negative asymmetric tests of linear Granger causality, there are significant numbers of unidirectional nonlinear causality relationships that run both from the US industrial sectors and the emerging countries sectors. There are also several cases of bidirectional nonlinear causalities such as Basic resources between the US and Malaysia; Chemicals between the US and Brazil and the US and South Africa; and Financial services and Industrial goods sectors between the US and South Africa. Overall, as in the case of linear tests, the asymmetric tests (positive and negative) under the Mackey-Glass (M-G) model uncover more nonlinear causality relationships than symmetric tests (linear and nonlinear). Furthermore, there are more cases of bidirectional non causality relationships (positive or negative) under the Mackey-Glass model tests than asymmetric tests under the conventional linear asymmetric tests.

Table 8.5: The test results of positive asymmetric Nonlinear Causality Relationships

Sector	Markets	Testing Hypothesis	F-Statistics	P-Value	Causality Decision
Banking	US, Brazil	US ⟵Brazil	29.1989**	0.0000	GC
		Brazil ⟵US	3.1103	0.0784	NGC
	US, Malaysia	US ⟵Malaysia	3.5016	0.0619	NGC
		Malaysia ⟵US	1.2735	0.2596	NGC
	US, S. Africa	US⟵ S. Africa	0.2042	0.6515	NGC
		S. Africa ⟵US	0.6538	0.4191	NGC
Basic Resources	US, Brazil	US ⟵Brazil	46.7854**	0.0000	GC
		Brazil ⟵US	3.7278	0.0541	NGC
	US, Malaysia	US ⟵Malaysia	19.4982**	0.0000	GC
		Malaysia ⟵US	1.6633	0.1977	NGC
	US, S. Africa	US⟵ S. Africa	27.7202**	0.0000	GC
		S. Africa ⟵US	2.3390	0.1268	NGC
Chemicals	US, Brazil	US ⟵Brazil	0.3239	0.5695	NGC
		Brazil ⟵US	0.3977	0.5286	NGC
	US, Malaysia	US ⟵Malaysia	1.5483	0.2140	NGC
		Malaysia ⟵US	4.1774*	0.0415	GC
	US, S. Africa	US⟵ S. Africa	11.9501**	0.0000	GC
		S. Africa ⟵US	2.1541	0.1428	NGC
Construction & Materials	US, Brazil	US ⟵Brazil	2.9810	0.0848	NGC
		Brazil ⟵US	14.9929**	0.0000	GC
	US, Malaysia	US ⟵Malaysia	0.1238	0.7251	NGC
		Malaysia ⟵US	1.0940	0.2961	NGC
	US, S. Africa	US⟵ S. Africa	0.9591	0.3279	NGC
		S. Africa ⟵US	2.4166	0.1207	NGC
Financial Services	US, Brazil	US ⟵Brazil	1.2461	0.2648	NGC
		Brazil ⟵US	11.4507**	0.0000	GC
	US, Malaysia	US ⟵Malaysia	3.5210	0.0612	NGC
		Malaysia ⟵US	0.2171	0.6414	NGC
	US, S. Africa	US⟵ S. Africa	40.4066**	0.0000	GC
		S. Africa ⟵US	6.7087**	0.0099	GC
Food & Beverage	US, Brazil	US ⟵Brazil	4.3714*	0.0370	GC
		Brazil ⟵US	9.1817**	0.0026	GC
	US, Malaysia	US ⟵Malaysia	2.3408	0.1266	NGC
		Malaysia ⟵US	2.1476	0.1434	NGC
	US, S. Africa	US⟵ S. Africa	3.0821	0.0798	NGC
		S. Africa ⟵US	5.3283*	0.0214	GC
Industrial Goods	US, Brazil	US ⟵Brazil	14.0312**	0.0000	GC
		Brazil ⟵US	2.6250	0.1058	NGC
	US, Malaysia	US ⟵Malaysia	8.7173**	0.0033	GC
		Malaysia ⟵US	0.0052	0.9425	NGC
	US, S. Africa	US⟵ S. Africa	26.3625**	0.0000	GC
		S. Africa ⟵US	8.3485**	0.0040	GC

Table 8.5: Continues

Sector	Markets	Testing Hypothesis	F- Test	P-Value	Causality Decision
Personal & H/H Goods	US, Brazil	US ←Brazil	15.2799**	0.0000	GC
		Brazil ←US	0.1669	0.6831	NGC
	US, Malaysia	US ←Malaysia	0.2916	0.5895	NGC
		Malaysia ←US	7.9755**	0.0049	GC
	US, S. Africa	US← S. Africa	5.9718**	0.0149	GC
		S. Africa ←US	0.0965	0.7561	NGC
Retail	US, Brazil	US ←Brazil	0.0334	0.8550	NGC
		Brazil ←US	2.9496	0.0865	NGC
	US, Malaysia	US ←Malaysia	1.7685	0.1842	NGC
		Malaysia ←US	0.3824	0.5366	NGC
	US, S. Africa	US← S. Africa	17.2413**	0.0000	GC
		S. Africa ←US	3.1195	0.0780	GC
Telecomm-unications	US, Brazil	US ←Brazil	0.4555	0.5000	NGC
		Brazil ←US	0.9512	0.3299	NGC
	US, Malaysia	US ←Malaysia	2.9591	0.0860	NGC
		Malaysia ←US	0.0247	0.8752	NGC
	US, S. Africa	US← S. Africa	10.2583**	0.0014	GC
		S. Africa ←US	0.0000	0.9998	GC

Table Notes:
Input Parameters: Same as in table 8.6
The ← arrow indicates the direction of linear causality between market sectors.
The * and ** indicate a rejection of the null hypothesis of no nonlinear causality relationship at the 5% and 1% significance levels.
GC = Granger causality relationship. NGC = No Granger causality relationship.
The tests for asymmetric nonlinear Granger causality relations are performed using a Matlab code written by Drs Varsakelis and Kyrtsou (2008) who proposed the asymmetric version of the M-G model for nonlinear causality test. The code was kindly provided by Professor Emmanuel Anoruo.

In summary, an interesting finding that emerges from this study is that many of industry sector returns respond asymmetrically to both positive and negative shocks in linear linar and nonlinear. These empirical findings are somewhat in line with theoretical expectations. As Hristu-Varsakelis and Kyrtsou (2008, p. 1) state, ‘asymmetric causality testing can reveal interesting information about the inherent dynamics of the processes studied’. The empirical results are also in line with a recent study by Hatemi (2012b) who examined causality relations between the stock markets of US and United Arab Emirates (UAE) finds segmentation under the standard (VAR) symmetric causality tests, whereas these are linked when the asymmetric version of causality tests are implemented. A possible source of asymmetric causal relationships may arise from the transmission of industry price shocks caused by the highly volatile changes in stock market price indices in late

2000s. The result suggests that one should account for the sign of shock effects when examining dynamic causalities and its implication for portfolio diversification.

Table 8.6: The test results of negative asymmetric Nonlinear Causality Relationships

Sector	Markets	Testing Hypothesis	F-Statistics	P-Value	Causality Decision
Banking	US, Brazil	US ← Brazil	4.4380^{*}	0.0356	GC
		Brazil ← US	1.1910	0.2756	NGC
	US, Malaysia	US ← Malaysia	1.0999	0.3085	NGC
		Malaysia ← US	0.9485	0.3306	NGC
	US, S. Africa	US ← S. Africa	0.9406	0.3326	NGC
		S. Africa ← US	0.0089	0.9251	NGC
Basic Resources	US, Brazil	US ← Brazil	2.5760	0.1091	NGC
		Brazil ← US	15.9546^{**}	0.0000	GC
	US, Malaysia	US ← Malaysia	5.4489^{*}	0.0200	GC
		Malaysia ← US	17.4934^{**}	0.0000	GC
	US, S. Africa	US ← S. Africa	1.4537	0.2285	NGC
		S. Africa ← US	10.7795^{**}	0.0011	GC
Chemicals	US, Brazil	US ← Brazil	4.5920^{*}	0.0326	GC
		Brazil ← US	14.0934^{**}	0.0000	GC
	US, Malaysia	US ← Malaysia	0.5831	0.4455	NGC
		Malaysia ← US	0.4973	0.4810	NGC
	US, S. Africa	US ← S. Africa	6.9931^{**}	0.0084	GC
		S. Africa ← US	4.4026^{*}	0.0364	GC
Construction & Materials	US, Brazil	US ← Brazil	0.0262	0.8714	NGC
		Brazil ← US	22.6470^{**}	0.0000	GC
	US, Malaysia	US ← Malaysia	0.0884	0.7664	NGC
		Malaysia ← US	2.9113	0.0886	NGC
	US, S. Africa	US ← S. Africa	7.9126^{**}	0.0051	GC
		S. Africa ← US	2.0626	0.1516	NGC
Financial Services	US, Brazil	US ← Brazil	4.4842^{*}	0.0347	GC
		Brazil ← US	0.2368	0.6267	NGC
	US, Malaysia	US ← Malaysia	0.0304	0.8618	NGC
		Malaysia ← US	7.1245^{**}	0.0078	GC
	US, S. Africa	US ← S. Africa	5.9076^{*}	0.0154	GC
		S. Africa ← US	5.2249^{*}	0.0227	GC
Food & Beverage	US, Brazil	US ← Brazil	2.0310	0.1547	NGC
		Brazil ← US	8.4105^{**}	0.0039	GC
	US, Malaysia	US ← Malaysia	0.0059	0.9387	NGC
		Malaysia ← US	0.6147	0.4334	NGC
	US, S. Africa	US ← S. Africa	0.1985	0.6561	NGC
		S. Africa ← US	13.3187^{**}	0.0003	GC

Table 8.6: Continues

Sector	Markets	Testing Hypothesis	F-Test	P-Value	Causality Decision
Industrial Goods	US, Brazil	US ←Brazil	1.0649	0.3026	NGC
		Brazil ←US	7.9878**	0.0049	GC
	US, Malaysia	US ←Malaysia	6.8633**	0.0091	GC
		Malaysia ←US	0.9211	0.3376	NGC
	US, S. Africa	US← S. Africa	7.3222**	0.0070	GC
		S. Africa ←US	5.0446*	0.0251	GC
Personal & H/H Goods	US, Brazil	US ←Brazil	1.7903	0.1815	NGC
		Brazil ←US	4.9451*	0.0266	GC
	US, Malaysia	US ←Malaysia	0.0087	0.9255	NGC
		Malaysia ←US	2.9520	0.0864	NGC
	US, S. Africa	US← S. Africa	1.4358	0.2314	NGC
		S. Africa ←US	2.2737	0.1322	NGC
Retail	US, Brazil	US ←Brazil	3.7081	0.0547	NGC
		Brazil ←US	0.3564	0.5508	NGC
	US, Malaysia	US ←Malaysia	0.0757	0.7833	NGC
		Malaysia ←US	0.2358	0.2358	NGC
	US, S. Africa	US← S. Africa	0.0033	0.9540	NGC
		S. Africa ←US	11.2864**	0.0000	GC
Telecomm-unications	US, Brazil	US ←Brazil	0.1114	0.7387	NGC
		Brazil ←US	5.5734*	0.0186	GC
	US, Malaysia	US ←Malaysia	4.6214*	0.0320	GC
		Malaysia ←US	1.0596	0.3038	NGC
	US, S. Africa	US← S. Africa	3.0226	0.0827	NGC
		S. Africa ←US	6.5245*	0.0109	GC

Table Notes: See table 8.9

8.5: The Linkages between the US and Emerging Markets' Industry Sectors before and during the 2007-2009 Financial Crisis: Empirical Results and interpretation

8.5.1 Cross correlations

The recent economic and financial crisis that originated from the US in 2007 has become a global financial turmoil and affected many economies around the world. Such crisis can change the correlation between cross-border financial markets rapidly. In other words, as discussed in earlier in chapters, various studies have indicated that financial crisis is often associated with increase in both cross-correlations among stock indices. Therefore, understanding and monitoring the correlation and dynamics linkages between the industry sectors of US and the three emerging countries in this study, especially during crisis era, is important for portfolio decisions and asset allocations for international investors as well as for policy makers. Thus, as noted in chapters one and five, this thesis investigates cross correlations and the dynamic causality linkages among the industry sectors of US and the emerging equity markets in the study (Brazil, Malaysia, and South Africa) before and during the 2007-2009 financial crisis. Specifically, for a comparative assessment, a two period cross correlation and causality tests are conducted using data series of 2004-2006 and 2007-2009. Tables 8.7 and 8.8 present the results for the two period's correlation tests. As before, the correlations between the emerging are also reported in the tables.

As noted from chapter 6 (table 6.1), the industry sector return correlations for US and the three emerging of this study (Brazil, Malaysia, and South Africa) were all positive and significant at a higher than 1% level over the full sample period (04/01/2000–29/12/2009). In this section, as can be ssen from table 8.7 the return correlations of the pre crisis period (2004–2006) are overall close to those of full sample. In the pre crisis period, the highest correlation coefficient (0.756) is between basic resources sectors of US and Brazilian markets. In the same period, the banking sector returns of US and Malaysia show the lowest correlation coefficient (0.027). However, as the results in table 8.8 show, in the crisis period (2007–2009), cross correlations of sector returns have increased considerably for all industry sectors. In this period, the highest correlation coefficient (0. 878) occurs between the basic resources sectors of US and Brazil, while the lowest correlation coefficient (0.203) is between food and beverage sectors of Malaysia and US. In addition, there are also strong correlations among many of the emerging economies industry sectors. Overall, the result from the crisis perid is in line with the earlier cited literature as well as a number of recent studies (i.e. Kassim, 2010 and Zhang et al, 2013), and supports the notion that financial market crisis induces increased correlations. The higher correlations also imply that benefits of cross market sector diversifications have declined substantially since the 2007 when the current crisis started in US.

Table 8.7: Cross Correlations between the Industry sector returns of 2004-2006

	Market				
Industry Sector	Market	Brazil	Malaysia	South Africa	USA
Banking	Brazil	1.000 - -			
	Malaysia	0.114(1.42)	1.000 - -		
	S. Africa	0.**410**(5.56)**	0.027(0.33)	1.000 - -	
	USA	0.387(5.21)**	0.179(2.26)	0.192(2.42)	1.000 - -
Basic Resources	Brazil	1.000 --			
	Malaysia	0.197 (2.50)**	1.000 --		
	S. Africa	**0.620** (9.80)**	0.207 (2.63)**	1.000 - -	
	USA	**0.756** (14.35)**	0.252 (3.23)**	**0.645**(10.48)**	1.000 - -
Chemicals	Brazil	1.000 - -			
	Malaysia	0.184 (2.33)**	1.000 - -		
	S. Africa	0.303 (3.95)**	0.284 (3.67)**	1.000 - -	
	USA	0.**490** (6.97)**	0.162(2.03)*	0.**402** (5.45)**	1.000 - -
Construction and Materials	Brazil	1.000 - -			
	Malaysia	0.347 (4.60)**	1.000 - -		
	S. Africa	0.304 (3.96)**	0.265 (3.41)**	1.000 - -	
	USA	**0.504** (7.25)**	0.356 (4.74)**	0.**434** (6.00)**	1.000 - -
Financial Services	Brazil	1.000 - -			
	Malaysia	0.320 (4.19)**	1.000 - -		
	S. Africa	0.**448** (6.22)**	0.243 (3.11)**	1.000 - -	
	USA	0.**487** (6.93)**	0.296 (3.85)**	0.377 (5.05)**	1.000 - -
Food and Beverages	Brazil	1.000 - -			
	Malaysia	0.317 (4.14)**	1.000 - -		
	S. Africa	0.483 (6.85)**	0.322 (4.22)**	1.000 - -	
	USA	0.259 (3.33)	0.205 (2.60)**	0.163 (2.06)*	1.000 - -
Industrial Goods and Services	Brazil	1.000 - -			
	Malaysia	0.322 (4.22)**	1.000 - -		
	S. Africa	**0.431** (5.93)**	0.207 (2.63)**	1.000 - -	
	USA	**0.549** (8.16)**	0.233 (2.98)**	0.355 (4.72)**	1.000 - -
Personal and Household Goods	Brazil	1.000 - -			
	Malaysia	0.022(0.28)	1.000 - -		
	S. Africa	0.338 (4.45)**	0.032(0.40)	1.000 - -	
	USA	0.322 (4.23)**	0.043 (5.35)**	0.203 (2.57)**	1.000 - -
Retailing	Brazil	1.000 - -			
	Malaysia	0.077 (0.969)	1.000 - -		
	S. Africa	**0.455** (6.35)**	0.104 (1.30)	1.000	
	USA	0.366 (4.89)**	0.170(2.14)*	0.235 (3.00)**	1.000 - -
Telecommuni-cations	Brazil	1.000 - -			
	Malaysia	0.197 (2.50)**	1.000 - -		
	S. Africa	0.354 (4.69)**	0.173 (2.18)*	1.000	
	USA	0.384 (5.16)**	0.145 (1.82)*	0.166 (2.09)*	1.000 - -

Table notes: Bolded text indicates strong and significant correlation coefficients (40% or more), while* and ** denote significance at the 5% and 1% significant levels respectively.

Table 8.8: Cross Correlations between the Industry sector returns of 2007-2009

	Market				
Industry Sector	Market	Brazil	Malaysia	South Africa	USA
Banking	Brazil	1.000 - -			
	Malaysia	0.**481**(6.84)**	1.000 - -		
	S. Africa	0.**623**(9.93)**	**0.498**(7.15)**	1.000 - -	
	USA	**0.532**(7.83)**	0.278(3.61)*	**0.462**(6.48)**	1.000 - -
Basic Resources	Brazil	1.000 --			
	Malaysia	**0.555** (8.30)**	1.000 --		
	S. Africa	**0.751** (14.17)**	**0.597** (9.27)**	1.000 - -	
	USA	**0.878** (22.84)**	**0.482** (6.85)**	**0.724**(13.06)**	1.000 - -
Chemicals	Brazil	1.000 - -			
	Malaysia	**0.532** (7.84)**	1.000 - -		
	S. Africa	**0.581** (8.90)**	0.**549** (8.18)**	1.000 - -	
	USA	0.**702** (12.27)**	**0.505**(7.29)**	0.**620** (9.85)**	1.000 - -
Construction and Materials	Brazil	1.000 - -			
	Malaysia	**0.438** (6.07)**	1.000 - -		
	S. Africa	**0.417** (5.72)**	**0.487** (6.94)**	1.000 - -	
	USA	**0.640** (10.37)**	**0.402** (5.46)**	0.**570** (8.64)**	1.000 - -
Financial Services	Brazil	1.000 - -			
	Malaysia	**0.559** (8.40)**	1.000 - -		
	S. Africa	**0.672** (11.31)**	**0.536** (7.91)**	1.000 - -	
	USA	0.**701** (12.24)**	0.331 (4.37)**	0.**584** (8.96)**	1.000 - -
Food and Beverages	Brazil	1.000 - -			
	Malaysia	0.393 (5.33)**	1.000 - -		
	S. Africa	**0.521** (7.60)**	**0.415** (5.69)**	1.000 - -	
	USA	**0.531** (7.80)**	0.203 (2.58)**	**0.465** (6.55)**	1.000 - -
Industrial Goods and Services	Brazil	1.000 - -			
	Malaysia	**0.528** (7.74)**	1.000 - -		
	S. Africa	**0.693** (11.96)**	**0.496** (7.11)**	1.000 - -	
	USA	**0.731** (13.34)**	0.371 (4.97)**	0.**691** (11.89)**	1.000 - -
Personal and Household Goods	Brazil	1.000 - -			
	Malaysia	0.377(5.07)**	1.000 - -		
	S. Africa	**0.421** (5.78)**	0.305(3.99)**	1.000 - -	
	USA	**0.527** (7.73)**	0.151 (1.90)*	**0.400** (5.44)**	1.000 - -
Retailing	Brazil	1.000 - -			
	Malaysia	**0.852** (20.24)**	1.000 - -		
	S. Africa	**0.598** (9.30)**	**0.837** (19.04)**	1.000	
	USA	**0.423** (5.82)**	**0.694**(12.01)**	**0.794** (16.29)**	1.000 - -
Telecommuni -cations	Brazil	1.000 - -			
	Malaysia	0.372 (5.02)**	1.000 - -		
	S. Africa	**0.510** (7.40)**	**0.438** (6.06)**	1.000	
	USA	**0.535** (7.88)**	0.236 (3.03)**	**0.530** (7.78)**	1.000 - -

Table notes: See table 8.7

8.5.2 Causalities linkages: Evidence from Toda and Yamamoto approach with bootstrap distributions

The results of the correlation matrix between sector return series in the last sub-section provide insight that the correlations between the industry sectors of US and the three emerging economies before and during recent financial crisis (2007-2009), and have indicated sharply increased correlations during the crisis period as table 8.8 shows. A simple investigation of the cross correlation between sector return series can also provide important information for the Granger causality linkages, which will be taken in this sub-section. In other words, in addition to the standard cross correlation tests, tests for dynamic causality relations for the two periods (2004-2006 and 2007-2009) are undertaken in this thesis using Toda and Yamamoto (1995) approach for testing non causality with bootstrap distributions as proposed by Hacker and Hatemi (2006) as discussed in chapter five. The Toda and Yamamoto (1995) approach is based on the modified Wald (MWALD) statistic for test non causality. However, according to Hacker and Hatemi (2006) the MWALD statistic tends to reject easily the null hypothesis of causality when the error terms are non-normal and autoregressive conditional heteroscedasticity (ARCH) exists. To remedy this problem, these authors proposed critical values based on a test of leveraged bootstrap simulations which according to them leads to a less bias in statistical inference'. As Hacker and Hatemi (2006) show, the modified Wald test based on a bootstrap distribution exhibits much smaller size distortions compared to the use of asymptotic distributions. The optimal lags orders (p) for all tests have been selected using the Schwarz information criterion (SIC). The choice of selected lag orders was also determined by the need of uncorrelated residuals under LM tests.

Tables 8.9 and 8.10 present the results of two period's causality tests. As before, only the causality linkages between the industry sectors of US and the three emerging economies are reported. The two tables reveal contrasting causality results. As table 8.9 shows there are only three cases of unidirectional casuality relations in the pre-crisis period. These three cases of cuaslaities are recorded one case in the basic resources sectors which run from US to Malaysia and two

Table 8.9: Causality Tests Based on Toda and Yamamoto approach with bootstrap distributions: 2004-2006

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV		Causality Decision
				1%	5%	
Banking	US, Brazil	US ⟵Brazil	0.402	6.172	3.686	NGC
		Brazil ⟵US	0.215	6.510	4.052	NGC
	US, Malaysia	US ⟵Malaysia	0.609	6.972	4.090	NGC
		Malaysia ⟵US	0.002	6.343	3.539	NGC
	US, S. Africa	US⟵ S. Africa	0.540	7.281	3.804	NGC
		S. Africa ⟵US	2.965	7.846	3.883	NGC
Basic Resources	US, Brazil	US ⟵Brazil	0.580	6.133	3.741	NGC
		Brazil ⟵US	1.913	5.848	3.735	NGC
	US, Malaysia	US ⟵Malaysia	0.001	6.722	3.656	NGC
		Malaysia ⟵US	8.975**	7.619	3.894	GC
	US, S. Africa	US⟵ S. Africa	1.213	6.218	3.515	NGC
		S. Africa ⟵US	0.338	5.853	3.311	NGC
Chemicals	US, Brazil	US ⟵Brazil	0.000	7.134	3.929	NGC
		Brazil ⟵US	0.381	8.468	4.031	NGC
	US, Malaysia	US ⟵Malaysia	0.001	8.018	3.936	NGC
		Malaysia ⟵US	3.790	6.258	4.016	NGC
	US, S. Africa	US⟵ S. Africa	0.886	6.955	3.842	NGC
		S. Africa ⟵US	0.117	6.881	3.837	NGC
Construction & Materials	US, Brazil	US ⟵Brazil	3.528	7.557	3.971	NGC
		Brazil ⟵US	4.196*	7.508	3.682	GC
	US, Malaysia	US ⟵Malaysia	0.123	7.172	4.124	NGC
		Malaysia ⟵US	4.534*	6.819	3.589	GC
	US, S. Africa	US⟵ S. Africa	0.251	6.134	3.541	NGC
		S. Africa ⟵US	0.172	6.929	3.690	NGC
Financial Services	US, Brazil	US ⟵Brazil	0.000	6.410	3.839	NGC
		Brazil ⟵US	0.751	6.372	3.688	NGC
	US, Malaysia	US ⟵Malaysia	0.200	7.878	4.378	NGC
		Malaysia ⟵US	0.308	6.576	3.700	NGC
	US, S. Africa	US⟵ S. Africa	0.000	6.741	3.965	NGC
		S. Africa ⟵US	1.670	7.809	3.714	NGC
Food & Beverage	US, Brazil	US ⟵Brazil	1.747	8.656	5.939	NGC
		Brazil ⟵US	4.719	9.220	6.582	NGC
	US, Malaysia	US ⟵Malaysia	2.955	9.570	6.555	NGC
		Malaysia ⟵US	2.328	10.724	6.418	NGC
	US, S. Africa	US⟵ S. Africa	4.435	9.132	5.722	NGC
		S. Africa ⟵US	0.226	9.884	5.741	NGC
Industrial Goods	US, Brazil	US ⟵Brazil	0.354	9.244	6.363	NGC
		Brazil ⟵US	0.034	9.924	6.325	NGC
	US, Malaysia	US ⟵Malaysia	2.707	9.762	6.141	NGC
		Malaysia ⟵US	0.722	11.531	6.034	NGC
	US, S. Africa	US⟵ S. Africa	3.439	9.819	6.209	NGC
		S. Africa ⟵US	1.098	10.637	6.436	NGC

Table 8.9: Continues

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV		Causality Decision
				1%	5%	
Personal & H/H Goods	US, Brazil	US ⟵Brazil	0.115	8.030	3.944	NGC
		Brazil ⟵US	1.804	6.307	3.757	NGC
	US, Malaysia	US ⟵Malaysia	0.070	6.823	3.919	NGC
		Malaysia ⟵US	1.448	7.599	3.814	NGC
	US, S. Africa	US⟵ S. Africa	0.143	7.292	4.185	NGC
		S. Africa ⟵US	2.906	7.293	4.048	NGC
Retail	US, Brazil	US ⟵Brazil	0.323	6.435	3.873	NGC
		Brazil ⟵US	0.027	6.642	3.733	NGC
	US, Malaysia	US ⟵Malaysia	0.174	7.469	3.918	NGC
		Malaysia ⟵US	0.856	6.318	4.421	NGC
	US, S. Africa	US⟵ S. Africa	0.052	7.811	4.081	NGC
		S. Africa ⟵US	0.243	7.567	4.164	NGC
Telecommu-nications	US, Brazil	US ⟵Brazil	1.536	5.899	3.966	NGC
		Brazil ⟵US	1.960	6.696	3.946	NGC
	US, Malaysia	US ⟵Malaysia	0.071	6.939	4.106	NGC
		Malaysia ⟵US	0.106	6.573	4.276	NGC
	US, S. Africa	US⟵ S. Africa	0.325	7.015	4.016	NGC
		S. Africa ⟵US	0.623	6.290	4.006	NGC

Table: Notes:
Used lags are based on the Schwarz information criterion (SIC).
Test Value: Modified Wald Test based on bootstrap simulations as proposed by Hacker and Hatemi (2006a). Due to space consideration, only the bootstrap critical values of 1 and 5 percent levels are reported.
The *and**denote a rejection of no causality hypothesis respectively at the 1 and 5 percent levels
A Gauss code written by Hackerand Hatemi (2009) was used to implement these causality tests.
The ⟵ arrow indicates the direction of linear causality between market sectors.
GC = Granger causality relationship. NGC = No Granger causality relationship.

cases in the construction and materials sectors which also run from US to Brazil and Malaysia respectively. In contrast, there are significant changes in the causal relationships between the industry sectors of US and the three emerging markets during the crisis period. In other words, as can be seen from table 8.10, forteen causality relations are recorded in the crisis period tests compared to only three in pre-crisis period. As the results in the table indicate, withthe exception one bidirectional in the case of US and South African telecommunication sectors, the causality relationships of the crisis period are are also found to be unidirection running from US sectors to the emerging economies's industry sectors. Moreover, the most of recorded unidirectional causalities, that is, eight of the forteen cases, are found to run from the US industry sectors to Malaysian sectors.

Table 8.10: Causality Tests Based on Toda and Yamamoto approach with bootstrap distributions: 2007-2009

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV 1%	Bootstrap CV 5%	Causality Decision
Banking	US, Brazil	US ←Brazil	0.321	6.102	3.515	NGC
		Brazil ←US	0.468	7.663	4.258	NGC
	US, Malaysia	US ←Malaysia	0.603	6.693	3.766	NGC
		Malaysia ←US	10.047**	7.256	7.733	GC
	US, S. Africa	US← S. Africa	0.136	7.708	3.957	NGC
		S. Africa ←US	0.937	6.150	3.795	NGC
Basic Resources	US, Brazil	US ←Brazil	1.488	7.826	4.171	NGC
		Brazil ←US	2.135	7.048	4.374	NGC
	US, Malaysia	US ←Malaysia	0.809	7.025	4.091	NGC
		Malaysia ←US	8.701**	7.967	4.125	GC
	US, S. Africa	US← S. Africa	0.489	6.309	3.770	NGC
		S. Africa ←US	0.100	6.966	3.989	NGC
Chemicals	US, Brazil	US ←Brazil	0.373	7.579	4.004	NGC
		Brazil ←US	0.333	6.923	3.859	NGC
	US, Malaysia	US ←Malaysia	3.205	7.696	3.966	NGC
		Malaysia ←US	10.113**	6.648	3.960	GC
	US, S. Africa	US← S. Africa	0.153	7.392	4.145	NGC
		S. Africa ←US	0.873	6.910	4.316	NGC
Construction & Materials	US, Brazil	US ←Brazil	0.661	11.83	6.484	NGC
		Brazil ←US	1.341	14.285	6.482	NGC
	US, Malaysia	US ←Malaysia	1.335	10.016	6.085	NGC
		Malaysia ←US	6.292*	9.642	6.519	GC
	US, S. Africa	US← S. Africa	1.117	9.705	6.216	NGC
		S. Africa ←US	7.603*	10.117	6.595	GC
Financial Services	US, Brazil	US ←Brazil	1.400	9.602	6.300	NGC
		Brazil ←US	2.491	10.187	6.187	NGC
	US, Malaysia	US ←Malaysia	1.702	9.405	6.332	NGC
		Malaysia ←US	17.484**	9.526	5.899	GC
	US, S. Africa	US← S. Africa	5.835	10.100	6.133	NGC
		S. Africa ←US	4.032	9.764	6.387	NGC
Food & Beverage	US, Brazil	US ←Brazil	4.037	9.126	5.861	NGC
		Brazil ←US	0.474	8.677	6.218	NGC
	US, Malaysia	US ←Malaysia	0.256	9.770	6.280	NGC
		Malaysia ←US	17.532**	9.751	3.948	GC
	US, S. Africa	US← S. Africa	0.016	10.390	6.289	NGC
		S. Africa ←US	21.920**	9.872	6.213	GC
Industrial Goods	US, Brazil	US ←Brazil	3.772	9.298	6.213	NGC
		Brazil ←US	2.947	9.933	6.498	NGC
	US, Malaysia	US ←Malaysia	0.757	9.834	6.016	NGC
		Malaysia ←US	6.398	10.036	6.808	NGC
	US, S. Africa	US← S. Africa	1.151	10.852	6.713	NGC
		S. Africa ←US	6.279	9.665	6.529	NGC

Table 8.10: Continues

Sector	Markets	Testing Hypothesis	Test Value	Bootstrap CV		Causality Decision
				1%	5%	
Personal & H/H Goods	US, Brazil	US ⟵Brazil	0.732	6.989	4.168	NGC
		Brazil ⟵US	4.634*	7.895	3.716	GC
	US, Malaysia	US ⟵Malaysia	0.261	7.049	4.302	NGC
		Malaysia ⟵US	11.304**	6.154	3.866	NGC
	US, S. Africa	US⟵ S. Africa	0.069	6.824	3.913	NGC
		S. Africa ⟵US	15.105**	7.172	3.781	NGC
Retail	US, Brazil	US ⟵Brazil	0.421	7.342	3.939	NGC
		Brazil ⟵US	2.829	7.065	4.060	NGC
	US, Malaysia	US ⟵Malaysia	0.242	7.467	4.097	NGC
		Malaysia ⟵US	11.893**	6.245	3.779	GC
	US, S. Africa	US⟵ S. Africa	0.145	7.377	4.248	NGC
		S. Africa ⟵US	2.187	7.380	4.198	NGC
Telecommu-nications	US, Brazil	US ⟵Brazil	1.883	6.602	4.024	NGC
		Brazil ⟵US	1.052	6.978	3.736	NGC
	US, Malaysia	US ⟵Malaysia	2.085	7.863	4.120	NGC
		Malaysia ⟵US	2.539	6.298	3.380	NGC
	US, S. Africa	US⟵ S. Africa	9.932**	7.015	4.148	GC
		S. Africa ⟵US	6.918*	7.457	3.758	GC

Table: Notes: See table 8.9

Furhermore, as one might expect, the US industry secotrs are found to be the most influential sectors before and during the crisis period. The reults might also due to the fact that the global financial crisis of 2007 -2009 has had its origin in the US market. The increased causalities under the crisis period are also in line some previous studies including among others, Yang et al (2003), Hatemi et al (2006) and more recently Kassim (2010), who also incorporate the effect of financial crisis to the level of integration among stock markets under study.

8.6 Conclusion

The empirical objective of this thesis is to assess the degree of interdependence between industry sector indices between the US and the industry sector indices of three leading emerging countries; Brazil, Malaysia and South Africa. The focus of this chapter has been to examine the short run dynamic relationships between the industry sector indices of these markets employing linear and nonlinear Granger causality analysis. Granger causality analysis provides useful information about the sector return dynamic linkages. In this study, since the entire sector indices are non-stationary in levels but the first-differenced, and no cointegration relationships between sectors were found, the Granger causality relationships are investigated using first differenced series and the standard VAR model for each industry sector. As reported in section two of the chapter (table 8.1), the causality relationships between the industry sectors under study were overall weak under the conventional VAR model. That is, out of sixty tests, only sixteen cases of unidirectional causalities mainly from the US sectors to the emerging sectors have been found.

In addition, to extend the time varying analysis in chapter six, the linear Granger-causality tests were complemented with time varying causality tests based on rolling windows analysis of VAR estimations. The probability value of the LB Q statistic is used for the rolling window analysis of the causality relationships. A higher p- value indicates lower or declining causality relationships between the US and an industry sector returns while a lower p- value reveals a higher or rising causality linkage. As graphs 8.1 to 8.10 show, the probability values varies and are often well above zero which imply weak and unstable Granger causality linkages for most cases between the US and the emerging countries industry sector returns. Nevertheless, as one can see from the graphs there are several cases where the probability values are close to zero for certain periods and thus indicate some degree of causality relationships.

As discussed in chapter five, nonlinear nonlinearities in the dynamic linkages between economic and financial variables have been receiving increasing attention recently in the econometric time series literature, and stock market data may exhibit highly non-linear dependencies, which cannot be captured by the linear Granger-causality tests. Therefore, this thesis also conducts nonlinear causality tests employing a more recently developed nonlinear causality methodology which is also capable of capturing the effect of economic shocks on the causality among variables being either positive or negative. Specifically, unlike many of the earlier studies that applied other well known nonlinear models (i.e.

Hiemstra and Jones, 1994) for testing causality relations between international stock markets, this thesis applies the bivarite noisy Mackey-Glass (M-G) model which was introduced in economic and financial studies by Kyrtsou and Terraza (2003) and Kyrtsou and Labys (2006) to examinine the nonlinear causality relationships between the returns of US and the emerging economies. As mentioned above and discussed in chapter five, the Mackey-Glass (M-G) model is capable of conditioning on the samples of the causing variable being either positive or negative. As reported in table 8.2, no significant nonlinear causality relationships were found under the symmetric version of the Mackey-Glass (M-G) model. In other words, as the results in the table indicate, out of sixty tests only three cases of weak unidirectional nonlinear casualties (two from the emerging markets and one from the US) were found under the symmetric version of the Mackey-Glass (M-G) model.

To further examine the causality linkages between the industry sector indices and the diversification implications, the linear and nonlinear Granger causality tests are extended through investigations of asymmetric causality analysis utilizing techniques proposed by Hatemi (2012a) and the asymmetric of the Mackey-Glass (M-G) model (Varsakelis and Kyrtsou, 2008). Testing the asymmetric effect on linear and nonlinear causality relationships for industry sector indices represents a major empirical novelty of this thesis. Tables 8.3-8.4 and 8.5-8.6 report the results of the asymmetric causality (linear and nonlinear) tests respectively. Overall, as the results in these tables indicates, asymmetric tests have resulted in more unidirectional causality relationships than under the conventional Granger causality model and the symmetric version of nonlinear causality tests. In addition, several cases of bidirectional non-causality relations (positive or negative) were found under the asymmetric version of the Mackey-Glass model.

The sample data series coverers a period in which the interest of micro studies on international equity markets has been growing, and also includes more recent years of extreme economic and financial crisis. Hence, another empirical advancement of this thesis is to investigate separately shifts in correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 financial crisis. Specifically, In addition to the standard cross correlation analysis, causality tests for the the periods are undertaken in this thesis using Toda and Yamamoto (1995) approach for testing non causality with bootstrap distributions proposed by Hacker and Hatemi (2006) using data series of 2004-2006 and 2007-2009. Section five of this chapter presents the results of the pre and during crisis periods. The empirical results of this section suggest increased cross correlations and causality relationships among the industry sectors during the crisis of the sample period than pre-crisis period of the same sample. Overall however, the weak causality relationships between the industry of US and the emerging countries in the study remain weak which also indicate diversification benefits still available for US investors.

CHAPTER 9:
Conclusion and Suggestions for further Research

9.1 Review of research objectives

The objective of this thesis is to re-investigate the interdependence (integration and dynamic linkages) among international equity markets at industry level by examining large numbers of heterogeneous industry (super) sectors. Specifically, the thesis assesses the degree of interdependence between industry sectors price indices of developed and emerging countries. It uses industry super sector price indices of US, the world's largest economy, and the industry sectors of three leading emerging countries; Brazil, Malaysia and South Africa. These markets have relatively large numbers of industry sectors and thus represent their respective economies (developed and emerging) in terms of capitalisation or turnover according to the Industry Classification Benchmark. Moreover, the selected national stock markets represent different continents between which are various levels of economic ties. Furthermore, as these markets are from geographically diversified regions and represent different sizes of global economies, they can be considered to be a reasonable portfolio diversification opportunity in international industry sectors. It is thus interesting to know whether markets with different industrial structures will move together more closely at industry level, or may have dynamic linkages. A disaggregation approach at the industry sector level is likely to capture the main differences across national markets. The sample period of the research covers from January 4, 2000 to December 29, 2009 with 522 weekly observations and includes the recent economic and financial crisis. This final chapter summarises the work of the thesis and points to possible future directions of research developing from the main findings presented in the thesis.

The focus on the industry sector relationships in a global context is important for international diversification strategies as the extent to which industries in different markets are linked is likely to be related to the differing nature of the national economies, the extent of multilateral and bilateral trade liberalisation, and capital flows and control (Carrieri et al, 2004 and others). Despite the importance of the issue, the studies that address industry level interdependence, or the issue of which sectors co-move across industries at a global level are relatively small compared to national level studies. To examine the degree of international stock market interdependence at an industry level, the existing studies on industry level interdependence have been done mainly on geographical groups or certain markets, such as markets in developed countries and Europe. However, empirical analysis consisting of only a few countries or a particular group of markets is insufficient for a portfolio diversification strategy aimed across countries and industries. Furthermore, almost all of the existing literature, like the unit root or stationary tests, cointegration analysis, and the tests for dynamic causality linkages, are all built on the basis of linear framework. In addition, as mentioned in previous chapters, the sample period of the study includes the economic and financial crisis of the late 2000s. Therefore, as to be discussed further in the subsequent sections, this thesis differs from previous studies in several aspects by offering extensive empirical analysis on industry sector relations including the recent period of economies and financial crisis, which represents a clear contribution to the existing literature.

9.2 Summary of the results and implications

As mentioned above, a number of major empirical analyses are addressed in this thesis for the interdependence between the industry sectors of United States of America and the three economies in the study (Brazil, Malaysia, and Sout Africa). The first empirical analysis in the thesis employs several related empirical methods to study the co-movements between industry sector returns. Such methods include standard cross correlation analysis, time varying correlations and time varying return co-movements using the rolling correlation analysis, time varying coefficients or *beta* convergence applying state space framework, and Kalman filtering methods. Since international diversification benefits depend on the correlation between assets across markets and the initial step of co-movements between sector returns, the thesis first conducts s simple cross correlation analysis. The cross correlation results indicate a weak linear association between the sectors of the markets considered in the study over the sample period. Most estimated correlation coefficients are lower than 50 per cent while only a very few industry sectors indicate around 50 per cent or more. The initial return co-movement tests also looked for time-varying relationships among international industry sectors by examining time varying cross correlations and beta convergences. The time variation correlations are examined through rolling window estimations whilst the time varying betas are investigated using simple time series regressions based on the state space model and the Kalman filter framework. Graphical analysis based on the rolling window estimates indicate high instability in the correlations between the industry sectors of the US and the emerging countries under study over the sample period. As an alternative procedure to model time-varying betas for the industry sectors under study, time series regressions are conducted through a state space model and via Kalman filtering. As the results of the regressions indicate, there is generally unstable beta convergence among the returns of the US and the emerging countries industry sectors over the sample period. Overall, the result of the time varying beta analysis reaffirms the view that relationships between global financial markets tend to be quite volatile over time and particularly high in a time of high financial turbulence.

Secondly, linear and nonlinear cointegration tests were implemented to look for long run equilibrium relationships between the price indices of the industry sectors across markets. For long run linear relationships, Johansen's trace statistic was applied for various bivariate and multivariate long run relationship tests. As the results of the trace statistics indicate, overall it seems that there is more segmentation than integration among the industry sectors under investigation when the cointegration relationships were tested without exogenous dummies. Conventional cointegration tests assume that the long-run equilibrium relationship between the economic variables in question is stable over the entire sample period. Therefore, this thesis examines the time varying, or stability of long-run relationships between the US and the emerging markets industry sectors by applying recursive cointegration proposed by Hansen and Johansen (1999) as well as rolling cointegration estimations. The recursive cointegration analysis is applied to examine the stability of the cointegration relationships over each data point during the sample period, while the rolling tests are 'used to investigate the degree of convergence during different sub-samples of the full sample.

The recursive cointegration test results displayed by figures 7.11-7.20 suggest that, although there exist reasonably substantial periods where the null hypothesis of no cointegration is clearly rejected, no cointegration relations exixt for most industry sectors in many sub sample periods on the trace tests. Moreover, the rescaled graphs of the trace tests also indicate although sometimes significant, decreasing levels of co-movements during the crisis of late 2000s among most sectors. In addition, rolling cointegration tests have been conducted to examine the degree of dynamic convergence between the US and emerging countries industry sectors during different sub-sample periods of the full sample. The rolling cointegration tests suggest the majority of the sub sample periods the null hypothesis of no cointegrating vectors could be rejected under the trace test statistics for most industry sectors. Nevertheless, as can be seen from figures 7.21-7.30 there exists several periods, were the null hypothesis cannot be rejected and the variables do not appear to exhibit long-run relationships.

As discussed in the text, an important shortcoming labelled on the linear Vector Autoregressive (VAR) or vector error correction model (VECM) techniques is that linear vector error correction models assume frictionless markets and the adjustment for premiums is linear and symmetrical. In this case, conventional linear models such as the unit root and cointegration tests can suffer from the failure to pass the normality tests. In other words, ignoring the nonlinear nature of many financial time series, the conventional linear methods may lead to the misleading conclusion that no long-run relationship exist between stock markets series. To mitigate the shortcomings in the conventional models, an important recent development in the literature of time-series financial econometrics has been proposals of numerous nonlinear models that take nonlinearity in the dynamic relationships between variables of interest that cannot be adequately represented using a linear model. Thus, to further examine nonlinear long run relationships between the emerging and US stock industry sectors, this thesis also applies relatively new techniques such as the rank and score tests proposed by Breitung (2001). As reported in chapter seven (subsection 7.4.2.1) although the rank statistic tests lead to additional sets of linear cointegration results both in bivariate and multivariate tests, only a few cases of nonlinear cointegration relationships are found among the industry sectors of the US and the three emerging countries. Overall, the results of the linear and nonlinear tests for cointegration relationships indicate more sector segmentations than integration.

Thirdly, dynamic linkages are investigated through linear and nonlinear tests for Granger causality linkages. As a first step for testing for causality relations between the industrial sectors returns, the conventional linear Granger-causality tests are performed. As reported in chapter 8 (table 8.1), the causality relationships between the industry sectors under study are very weak under the conventional VAR model. To extend the time varying correlation analysis reported in chapter six, the linear Granger-causality tests were complemented with time varying causality tests based on rolling window analysis of the VAR estimations. By applying the rolling regression method, it might be possible to detect changes in the Granger causality, which indicates structural breaks in the linkages. Next, nonlinear causality tests based on return series and bivariate noisy Mackey-Glass (M-G) methodology are conducted. The Mackey-Glass (M-G) model is also capable of capturing the effect of economic shocks on the causality among the variables being either positive or negative.

To examine further the causality linkages between industry sector indices and diversification implications, the linear and nonlinear Granger causality tests are extended through investigation of the asymmetric causality analysis. As the results of all the causality tests (including the asymmetric tests) indicate, causality relationships between the US and the emerging markets are weak in all industry sectors in the study. Nevertheless, more causality relationships were found under asymmetric tests in both linear and nonlinear causality tests than symmetric models. The results of asymmetric causality analysis suggest that one should account for the sign of shock effects when examining dynamic causalities and its implication for portfolio diversification. A possible source of asymmetric causal relationships may arise from the transmission of industry price shocks caused by the highly volatile changes in stock market price indices in the late 2000s. Another empirical motivationof this thesis is to conduct separate analysis to investigate shifts in correlation patterns and the dynamic causality linkages between the US and emerging markets' industry sectors before and during the 2007-2009 Financial Crisis. Specifically, In addition to the standard simple cross correlation analysis, causality tests for the the periods are undertaken in this thesis using Toda and Yamamoto (1995) approach for testing non causality with bootstrap distributions proposed by Hacker and Hatemi (2006) using data series of 2004-2006 and 2007-2009. The empirical results of this section suggest increased cross correlations and causality relationships among the industry sectors during the crisis period of the sample period than pre-crisis period of the same sample.

The extended tests of the degree of integration or co-movement and the direction of the dynamic causality relationships between the industry sectors of US and emerging econmies that have been presented in this thesis will be important for international portfolio investors and corporations. The results of the correlation matrix between sector return series between the industry sectors of US and the three emerging economies have indicated, though increased during the crisis period, generally low in most sectors. The cross correlation results therefore indicate there are potential benefits for US investors in diversifying their portfolio investment across industry sectors of these emerging markets. Similarly, the results of both linear (without dummies) and nonlinear cointegration tests suggest no long-run long run relationships between the industry sectors of US and the three emerging economies exist. Such results can also be interpreted as long run potential diversifying gins for US investors in their portfolio investment across industry sectors of the emerging markets. Nevertheless, when seasonal dummies are incorporated in the (linear) cointegration tests the results indicate cointegrting relationships between several industry sectors which suggest decreasing diversification opportunities as a result of the seasonal dummies having an affect on industry sectoral co-movements. The results of the dynamic causality tests show that, although there are some significant short-run causal linkages (linear and nonlinear) between the US and the emerging markets' industry sectors, overall the causality linkages remain relatively weak. However, as indicated by the separate tests for cross correlations and dynamic causality relationships for the 2007-2009 crisis there is increased co-movement among the industry sectors during the crisis period. The increased cross correlations and dynamic causality relations also suggest less diversification gains in the crisis period.

In summary however, the micro market analysis in this study indicates that, the international investors may able to obtain diversification benefit by investing in the segmented sectors of the emerging markets. In other words, the empirical results of the research show relatively weak interdependence between the US and the emerging markets industry sectors especially in the pre- crisis period, which suggest potential diversification benefits available for US investors in diversifying their portfolio investment across industrial sectors of the emerging markets. The result also indicates that, though the emerging markets are open for international investors, there could still be other factors affecting portfolio diversification decisions in these markets. These factors might include; legal and regulatory frameworks, different industrial structural and cultural differences, and standard of transparency and internal control rules.

9.3 Short comings of the thesis

Although this thesis presents extensive empirical analysis, several shortcomings are worth acknowledging. For a comparative analysis of the equity market interdependence of the US and the emerging countries in this study, empirical tests of country level relationships in the same period could have provided a complete picture of these markets' equity market linkages. Another shortcoming of the thesis is its focus on only four markets; the sample size of this thesis could be increased to include more markets both from developed and emerging countries. For example, an investigation could be conducted examining the interdependence between fewer industry sectors of the three most active and matured markets, US, UK and Japan, and the emerging markets including Brazil, Malaysia and South Africa and other leading emerging countries such as India and Russia. As Ratner and Leal (2005, p. 244) state ‘the U.S., U.K. and Japan are the only countries with a substantial number of firms in virtually all sectors’. Also, sectoral components could have been more detailed by listing, for example, the number of companies in each industry sector across markets. In addition, for a comparative assessment, aggregate or national market level analysis could have provided additional weight to the empirical results.

This thesis is confined to the issue of the long run co-movements and dynamic price linkages amongst national stock markets or the *first moments* through industry sector prices. In financial markets, it is important for participants to understand the volatility transmission mechanism over time (and across sectors) in order to make optimal portfolio allocation decisions. The sample period of this study covers a somewhat volatile time period for the international stock markets. As the review of the series' empirical properties demonstrates (Chapter 4), the distributions of the return series under study are found to be highly leptokurtic; the squared series are significantly autocorrelated in nearly all the return series and exhibit a leverage effect. Therefore, another dynamic relation that has not been examined in this thesis is the *secod moments,* or how the volatilities of industrial sectors under study are linked to each other in different markets. These empirical properties could lead to alternative and more interesting modelling techniques.

9.4 Outlook for Further Research

As explained in the last section, an obvious shortcoming of the thesis is its focus on only four markets; the sample size of this thesis could be increased to include more markets both from developed and emerging countries. Also, to investigate the linkages among equity markets at industry sector level, two approaches can be taken. First, is the cross-sector linkages within a given country or currency area and, second approach is interdependence among equivalent sectors across countries, or intra-sectoral linkages. The focus of this thesis has been on second approach or the intra-sectoral interdependence between equivalent industries in different countries. However, in order to investigate the true long-run diversification benefits, one could consider the bivariate relationships among all industrial pairs within a particular country.

The empirical scope of this study could be advanced in different directions. Chapter six of the thesis examines the return relationships between the industry sectors of the emerging countries and the US by applying time varying correlations and beta coefficients. The time-varying beta tests can be extended in several directions. The introduction of the linear Gaussian state space model and the Kalman filter could also be extended for extensive and more advanced analysis that can then be connected to other empirical frameworks, including the Markov regime switching model. To test the long run linear equilibrium relationships between industry sectors, the thesis applies the conventional Johansen approach of cointegration which uses maximum likelihood estimators.

An important critique to note against the standard cointegration technique is that, it does not take into account various market frictions, including different types of legal and economic barriers and situations of asymmetric information, resulting in a need for transaction costs to make arbitrage across financial markets in different countries. The emergence of numerous non-linear models presented in recent decades expands the types of analysis that can be employed in the analysis of price asymmetry. The thesis employs the nonparametric cointegration test proposed by Breitung (2001). To extend the long run equilibrium tests for international industry sector prices, one could apply cointegration tests with multiple structural breaks or regime shift models such as regime shifting nonlinear cointegration models like threshold cointegration (TVEC) by Hansen and Seo (2002) or the Smooth Transition Vector Error Correction Model (STVECM) of Van Dijk et al (2002). Furthermore, one could apply cointegration models that allow structural change such residual based unit root tests proposed Gregory and Hansen (1996), or Tests for cointegration with two unknown regime shifts proposed by Hatemi (2008).

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Another important contribution of this thesis is to examine the causal relationships between international industry sector returns, applying both linear and nonlinear causality tests. For nonlinear causality analysis, this research applies the bivariate noisy Mackey-Glass (M-G) model, introduced to economic and financial studies by Kyrtsou and Terraza (2003), Kyrtsou and Labys (2006) and Varsakelis and Kyrtsou (2008). The nonlinear Granger causality test can be extended by applying various nonlinear causality models discussed in the literature, including, among others, well known nonlinear model of Hiemstra and Jones (1994), which has frequently been applied for testing causality relations between international stock markets. Other nonlinear time series models such as the Threshold vector autoregressive (TVAR) and the Smooth Transition autoregressive (STVAR) or Markov-Switching models could be alternative models for nonlinear causality relationships. In addition, one might also wish to conduct nonlinear causality tests based on multivariate GARCH models. Furthermore, in addition to the rolling window analysis presented in the thesis, one could model time varying causality tests by applying linear and nonlinear time-varying parametric models.

Furthermore, the finding of volatility clustering behaviour in the sector returns could be examined through conditional heteroskedasticity modelling, a key concept in many areas of finance and financial econometrics that can be used to model conditional regression coefficients in an indirect way. Within the versatile class of heteroskedasticity models, many different specifications that explicitly allow for particular empirical properties, such as fat-tailed distributions, leverage effects or volatility co-movements, could be considered. For example, one could investigate the financial spillover by looking at the changes of volatility correlation between the industry sectors of US and the emerging economies before and during financial crises. Multivariate Generalised Autoregressive Conditional Heteroskedasticity (MGARCH) methodology could be to examine the volatility transmissions between the sectors across markets.

Another empirical advancement of this thesis has been to investigate shifts in correlation patterns between the US and emerging markets' industry sectors before and during the 2007-2009 financial crisis. The results of simple correlation tests suggest increased co-movements among the industry sectors during the crisis of the sample period than pre-crisis period of the same sample. To further examine the effect of crisis, one could test the possibility of weather financial crisis had permanently changed the correlations between the industry sector returns of US and the emerging coutries.

APPENDICES

Appendix A: Industry Super-sectors, their industry groups, and descriptions

A1: Super sectors and their industry group

Super Sector	Main Industry
Automobiles & Parts	Consumer Goods
Banks	Financials
Basic Resources	Basic Materials
Chemicals	Basic Materials
Construction & Materials	Industrials
Financial Services	Financials
Food & Beverages	Consumer Goods
Health Care	Health Care
Industrial Goods & Services	Industrials
Insurance	Financials
Media	Consumer Services
Oil & Gas	Oil & Gas
Personal & Household Goods	Consumer Goods
Real Estate	Financials
Retail	Consumer Services
Technology	Technology
Telecommunications	Telecommunications
Travel & Leisure	Consumer Services
Utilities	Utilities

Sources: Guide to the Dow Jones Global Total Stock Market Indexes

Appendices

A2: Super sectors and their descriptions

Industry (Super) Sector	Description
Automobiles & Parts	Covers companies involved in the manufacture of cars, tyres and new or replacement parts. Excludes vehicles used for commercial or recreational purposes.
Banks	Contains banks whose business is primarily retail.
Basic Resources	Comprises companies involved in the extraction and basic processing of natural resources other than oil and gas.For example, Coal Diamonds & Gemstones, General Mining, Gold Mining, Platinum & Precious Metals
Chemicals	Encompasses companies that produce and distribute both commodities and finished chemical products.
Construction & Materials	Includes companies engaged in the construction of buildings and infrastructure, and the producers of materials and services used by this sector.
Financial Services	Comprises companies involved in corporate banking and investment services, including real estate activities.
Food & Beverages	Encompasses those companies involved in the food industry, from crop growing and livestock farming to production and packing. Includes companies manufacturing and distributing beverages, both alcoholic and non-alcoholic, but excludes retailers.
Health Care	Includes companies involved in the provision of healthcare, pharmaceuticals, medical equipment and medical supplies.
Industrial Goods & Services	Contains companies involved in the manufacturing industries and companies servicing those companies. Includes engineering, aerospace and defence, containers and packaging companies, electrical equipment manufacturers and commercial transport and support services.
Insurance	Encompasses companies who offer insurance, life insurance or reinsurance, including brokers or agents.
Oil & Gas	Covers companies engaged in the exploration, production and distribution of oil and gas, and suppliers of equipment and services to the industry.
Media	Companies that produce TV, radio, films, broadcasting and entertainment. These include media agencies and both print and electronic publishing.
Personal & Household Goods	Companies engaged in the production of durable and non-durable personal and household products, including furnishings, clothing, home electrical goods, recreational and tobacco products.
Real Estate	Combines real estate investment and services and real estate investment trusts
Retail	Comprises companies that retail consumer goods and services including food and drugs.
Technology	Companies providing computer and telecommunications hardware and related equipment and software and related services, including internet access.
Telecommunications	Includes providers of fixed-line and mobile telephone services. Excludes manufacturers and suppliers of telecommunications equipment.
Travel & Leisure	Encompasses companies providing leisure services, including hotels, theme parks, restaurants, bars, cinemas and consumer travel services such as airlines and auto rentals.
Utilities	Covers companies that provide electricity, gas and water services.

Sources: S&P Dow Jones Indices Sector Classification: Structure & Definitions (Online)

Appendices

Appendix B: The results of unit root and stationarity tests: The ADF, DF-GLS, and KPSS statistics

B.1 Unit root and stationary tests of the US industry sector price levels and first differenced

	Lags		ADF Test		DF-GLS Test		KPSS Test	
Sector Code	Lev el	1st Diff.	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
BNK	1	0	-1.3422	-25.6490***	-0.9803	-25.6870***	0.5190	0.0486***
BRS	1	0	-2.1372	-23.7165***	-1.7950	-21.1663***	0.2189	0.0643***
CHM	1	0	-2.9867	-23.6304***	-2.0242	-15.6067***	0.1570	0.0532***
CNM	1	0	-1.8403	-23.3920***	-1.8017	-21.3263***	0.3080	0.0786***
FNS	2	1	-1.4098	-27.9520***	-1.1436	-24.0810***	0.3669	0.0759***
FBV	2	1	-3.0660	-25.0709***	-2.7422	-8.2567***	0.1582	0.0323***
ING	1	0	-1.9110	-24.1266***	-1.7329	-18.6770***	0.2766	0.0846***
PHH	4	3	-1.9386	-22.7890***	-1.8578	-4.0290***	0.3675	0.0748***
RTL	2	1	-3.0406	-24.5428***	-2.0563	-24.1191***	0.2924	0.0698***
TLC	2	1	-2.1956	-24.2553***	-0.9710	-23.2582***	0.4413	0.1548*

B.2: Unit root and stationary tests of the Brazilian industry sector price levels and first differenced

	Lags		ADF Test		DF-GLS Test		KPSS Test	
Sector Code	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
BNK	4	3	-1.9934	-12.1838***	-1.3262	-8.8905***	0.3620	0.1088***
BRS	1	0	-2.2954	-23.2355***	-1.2071	-15.1021***	0.2570	0.1114***
CHM	4	3	-1.9991	-10.5850***	-1.7623	-9.9739***	0.2390	0.0843***
CNM	1	0	-0.7293	-23.3874***	-1.3598	-17.7958***	0.2892	0.1403***
FNS	4	3	-2.1702	-11.7666***	-1.3606	-4.7140***	0.3288	0.1131***
FBV	1	0	-2.0326	-24.4261***	-2.033	-15.0475***	0.2094	0.0556***
ING	4	3	-2.4702	-10.4867***	-0.8226	-8.3373***	0.3283	0.1337***
PHH	1	0	-2.4123	-24.8447***	-1.9233	-17.6970***	0.2475	0.0557***
RTL	1	0	-1.8236	-22.8112***	-1.0570	-19.1008***	0.3552	0.0978***
TLC	4	3	-2.0816	-1.6343***	-1.1134	-8.2467***	0.4058	0.0692***

Appendices

B3: Unit root and stationary tests of the Malaysian industry sector price levels and first differenced

	Lags		ADF Test		DF-GLS Test		KPSS Test	
Sector Code	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
BNK	3	2	-2.0748	-21.7906***	-1.5457	-7.5544***	0.2009	0.0612***
BRS	1	0	-2.4900	-20-9421***	0.9569	-19.5502***	0.2175	0.0853***
CHM	1	0	-2.2645	-22.1413***	-1.7080	-12.5410***	0.2636	0.0791***
CNM	1	0	-1.8391	-20.9048***	-1.1388	-20.6300***	0.2788	0.0670***
FNS	2	1	-2.5143	-20.1582***	-1.3332	-19.0333***	0.1526	0.0797***
FBV	2	1	-1.9162	-27.5664***	-1.3997	-25.4235***	0.2601	0.0708***
ING	1	0	-1.4998	-22.5972***	-1.5403	-21.9721***	0.2397	0.1063***
PHH	2	1	-2.3066	-27.5311***	-2.0264	-9.9496***	0.2440	0.0393***
RTL	1	0	-1.6413	-21.4482***	-0.5960	-17.3959***	0.4877	0.0639***
TLC	1	0	-2.4473	-22.6834***	-1.0243	-20.5479***	0.3986	0.0992***

B4: Unit root and stationary tests of the South African industry sector price levels and first difference:

	Lags		ADF Test		DF-GLS Test		KPSS Test	
Sector Code	Level	1st Diff.	Levels	1st Diff.	Level	1st Diff.	Level	1st Diff.
BNK	1	0	-2.0284	-24.9674***	-1.5855	-17.1608***	0.3363	0.1062***
BRS	2	1	-2.2301	-24.0908***	-2.2383	-23.9300***	0.3000	0.0434***
CHM	1	0	-1.5550	-21.9700***	-1.2414	-13.5883***	0.4275	0.1469*
CNM	1	0	-1.6656	-22.3722***	-1.3608	-11.4181***	0.2812	0.1126***
FNS	2	1	-2.3283	-22.5220***	-0.9196	-7.6157***	0.3202	0.1928*
FBV	1	0	-2.6370	-23.2491***	-1.1323	-17.7176***	0.3375	0.1493*
ING	2	1	-1.9454	-24.1913***	-1.3116	-18.0219***	0.3317	0.1286**
PHH	2	1	-1.4930	-27.9944***	-1.4084	-25.8595***	0.4114	0.1234**
RTL	2	1	-2.8142	-21.9541***	-0.7077	-13.5184***	0.2972	0.2140*
TLC	2	1	-1.9023	-24.5363***	-1.1806	-5.1445***	0.2894	0.1531*

Table Notes:

As mentioned in the text, a constant and a drift term or linear time trend are included in all three (ADF, DF-GLS, and KPSS) tests for testing non-stationarity and stationarity.

The critical values of the ADF test with trends are respectively -3.975, -3.418, and -3.131 at 1, 5, and 10 percent significant levels. The CVs of the DF-GLS test with trends are respectively -3.480, -2.890, and -2.570 at the 1, 5-, and 10 percent significant levels. The CVs of the KPSS test with trends are 0.2160, 0.1460, and 0.1190 respectively for 1, 5, and 10 percent significant levels. The *, **, and *** respectively indicate the significance at the 1%, 5%, and 10% levels. As the results in the tables show, the null hypothesis of the stationary series is rejected in all cases of price levels, and the statistical results support the alternative hypothesis of nonstationary series, while the opposite holds strongly for the first differences.

Appendix C: The results of nonlinear unit root tests: The rank test statistics

C1: The rank test for nonlinear unit root of the US industry sector prices

	$\pi_T(Uni)$		$\pi_T(Ins)$	
Sector Code	Levels	1st Differences	Levels	1st Differences
BNK	0.2321	0.0001***	0.250	0.0001***
BRS	0.1185	0.0001***	0.4267	0.0003***
CHM	0.1144	0.0001***	0.4119	0.0003***
CNM	0.1412	0.0001***	0.4203	0.0003***
FNS	0.2805	0.0000***	0.2525	0.0000***
FBV	0.1365	0.0001***	0.4062	0.0003***
ING	0.1598	0.0000***	0.3511	0.0001***
PHH	0.1639	0.0002***	0.3288	0.0002***
RTL	0.1820	0.0000***	0.3075	0.0000***
TLC	0.3253	0.0006***	0.2035	0.0004***

C2: The rank test for nonlinear unit root of the Brazilian industry sector prices

	$\pi_T(Uni)$		$\pi_T(Ins)$	
Sector Code	Levels	1st Differences	Levels	1st Differences
BNK	0.4618	0.0020***	0.1439	0.0006***
BRS	0.5337	0.0025***	0.1264	0.0006***
CHM	0.0886	0.0002***	0.4525	0.0012***
CNM	0.2778	0.0000***	0.2311	0.0000***
FNS	0.8757	0.0044***	0.0734	0.0003***
FBV	0.6627	0.0030***	0.1036	0.0005***
ING	0.0221***	0.0000***	0.7765	0.0015***
PHH	0.1810	0.0005***	0.3326	0.0010***
RTL	0.4704	0.0017***	0.1465	0.0005***
TLC	0.2044	0.0000***	0.2875	0.0000***

C3: The rank test for nonlinear unit root of the Malaysian industry sector prices

	$\pi_T(Uni)$		$\pi_T(Ins)$	
Sector Code	Levels	1st Differences	Levels	1st Differences
BNK	0.2347	0.0004***	0.3181	0.0005***
BRS	0.0193***	0.0000***	0.1706	-0.0003***
CHM	0.0941	0.0001***	0.2928	0.0005***
CNM	0.0480	0.0000***	0.2516	-0.0001***
FNS	0.0467	0.0000***	0.2444	0.0002***
FBV	0.1048	0.0003***	0.3017	0.0009***
ING	0.0701	0.0001***	0.2883	0.0003***
PHH	0.1413	0.0001***	0.2853	0.0002***
RTL	0.0467	0.0000***	0.2446	0.0001***
TLC	0.0655	0.0000***	0.2515	0.0000***

C4: The rank test for nonlinear unit root of the South African industry Sector Prices

	$\pi_T(Uni)$		$\pi_T(Ins)$	
Sector Code	Levels	1st Differences	Levels	1st Differences
BNK	0.2317	0.0004***	0.2966	0.0005***
BRS	0.1528	0.0003***	0.2933	0.0006***
CHM	0.1074	0.0001***	0.2945	0.0004***
CNM	0.0938	0.0003***	0.2843	0.0008***
FNS	0.0374*	0.0000***	0.2532	-0.0001***
FBV	0.0908	0.0002***	0.2681	0.0007***
ING	0.0884	0.0002***	0.2610	0.0005***
PHH	0.1447	0.0003***	0.2778	0.0006***
RTL	0.0594	0.0001***	0.2535	0.0005***
TLC	0.1415	0.0004***	0.2718	0.0008***

Table Notes:
The *Uni* and *Ins* statistics are reported in Table 6 of Breitung and Gourieroux (1997). The critical values with T= ∞ are used for the present tests. The CV of the 'Uni' rank test are 0.0250, 0.0362, and 0.0453 respectively for the 0.01, 0.05, 0.10 significance levels. The CV of the 'Ins' rank test are 0.0250, 0.0368, and 0.0464 respectively for the 0.01, 0.05, 0.10 significance levels.
*** and * respectively indicate the significance at the 1%, 5%, and 10% levels.

Appendix D: The results nonlinearity tests for the residuals of linear Models

D.1: Linear and nonlinear tests on residuals of AR(p) models for US Sector returns

			Tests for Nonlinear dependence						
	Tests for Linear dependence		LB-$Q^2(5)$	Arch Effect	BDS Test with Epsilon δ= 0.75σ Embedding dimension				
Sector Code	Lag	LB(5)		LM(5)	2	3	4	5	6
BNK	0	9.673	36.412	33.524	6.760	9.776	13.312	17.066	21.156
BRS	0	12.858	194.50	116.698	4.177	5.261	5.831	6.711	7.630
CHM	0	3.6936	124.45	72.103	6.716	9.177	10.417	11.527	13.098
CNM	0	10.064	172.78	92.389	7.173	8.157	9.471	10.340	11.299
FNS	1	6.848	155.95	52.245	6.716	9.177	10.417	11.527	13.098
FBV	1	7.581	167.70	90.947	5.581	7.319	9.133	10.294	11.384
ING	0	13.348	71.786	48.836	6.027	8.459	10.688	13.310	15.851
PHH	3	1.333	83.628	75.901	4.461	6.182	6.872	7.240	7.684
RTL	1	12.061	77.707	50.295	4.527	6.497	7.519	8.614	9.363
TLC	1	2.5828	29.004	20.584	4.300	7.071	8.615	10.265	11.365

D.2: Linear and nonlinear tests on residuals of AR(P) models for Brazilian Sector returns

			Tests for Nonlinear dependence						
	Tests for Linear dependence			Arch Effect	BDS Test with Epsilon δ= 0.75σ Embedding dimension				
Sector Code	Lag	LB(5)	LB-$Q^2(5)$	LM(5)	2	3	4	5	6
BNK	3	0.226	41.566	33.057	5.061	4.896	5.552	6.306	6.978
BRS	0	10.356	114.24	86.329	2.417	3.513	3.945	4.629	5.958
CHM	3	0.558	129.28	43.151	4.912	4.471	4.827	5.017	5.728
CNM	0	1.883	0.0048	0.164	3.012	3.247	4.060	4.487	4.985
FNS	3	0.904	175.19	66.051	4.961	5.469	6.113	6.810	7.254
FBV	0	10.592	16.117	14.337	3.819	4.156	4.699	5.273	6.125
ING	3	0.252	165.50	66.918	3.370	4.983	6.240	7.356	8.309
PHH	0	10.428	55.585	48.106	4.486	4.629	5.550	6.191	6.556
RTL	0	4.599	20.161	17.836	1.518	3.070	4.333	5.193	6.457
TLC	3	0.486	15.359	7.557	1.466	1.277	1.528	2.246	2.518

D.3: Linear and nonlinear tests on residuals of AR(p) model for Malaysian Sector returns

			Tests for Nonlinear dependence						
	Tests for Linear dependence			Arch Effect	BDS Test with Epsilon δ= 0.75σ Embedding dimension				
Sector Code	Lag	LB(5)	LB-$Q^2(5)$	LM(5)	2	3	4	5	6
BNK	2	3.016	17.152	19.619	2.233	2.281	2.864	4.325	5.200
BRS	0	12.691	43.834	39.748	3.348	4.683	5.363	6.048	6.286
CHM	0	4.044	68.719	46.704	5.596	6.824	7.508	7.964	8.254
CNM	0	7.832	33.902	24.732	5.169	6.686	8.343	9.811	10.951
FNS	1	6.269	13.232	10.805	3.684	4.650	5.360	6.107	6.450
FBV	1	4.260	95.505	93.974	6.113	7.623	8.736	9.762	10.778
ING	0	6.780	15.842	13.957	4.852	5.961	7.052	8.224	9.316
PHH	1	6.798	33.985	33.786	2.695	3.663	4.969	6.253	7.954
RTL	0	5.572	1.4551	1.148	4.702	6.298	7.302	7.627	8.468
TLC	0	1.714	9.6001	8.300	3.145	3.998	4.684	5.224	5.311

D.4: Linear and nonlinear tests on residuals of AR(p) model for South African Sector returns

			Tests for Nonlinear dependence						
	Tests for Linear dependence			Arch Effect	BDS Test with Epsilon δ= 0.75σ Embedding dimension				
Sector Code	Lag	LB(5)	LB-$Q^2(5)$	LM(5)	2	3	4	5	6
BNK	0	10.107	123.54	92.566	1.602	2.897	3.938	4.464	4.927
BRS	1	12.069	297.52	141.598	4.714	5.532	5.646	5.337	5.732
CHM	0	4.398	129.28	58.599	-0.084	1.774	2.126	2.170	2.124
CNM	0	6.274	167.82	98.137	4.338	5.716	6.482	6.921	7.844
FNS	1	6.480	104.65	85.557	0.931	2.801	4.087	4.938	5.724
FBV	0	7.486	101.54	85.497	1.032	2.242	2.732	3.143	3.612
ING	1	14.879	129.04	73.210	-0.085	-0.115	5.725	7.877	8.753
PHH	1	3.097	103.17	59.788	5.937	6.717	7.308	7.742	7.630
RTL	1	6.480	104.65	85.557	0.931	2.801	4.087	4.938	5.724
TLC	1	7.100	15.3	32.918	2.404	3.244	3.474	3.791	4.340

Table Notes:
$LBQ^2(5)$: The Ljung-Box statistic for squared return autocorrelations at lag 5 distributed as χ^2 with 5 degrees of freedom, and approximated to McLeod and Li (1983) Q(*m*) for nonlinearity dependence of the squared observations. The ARCH effect is tested using lagrange Multiplier (LM) test distributed as $\chi^2(5)$. The econometric application of Eviews was used for all tests of nonlinearity

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