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Stock Market Volatility, Business Cycles and the Recent Financial Crisis: Evidence from Linear and Non-Linear Causality Tests

By

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ABSTRACT

FACULTY OF BUSINESS AND LAW

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STOCK MARKET VOLATILITY, BUSINESS CYCLES AND THE RECENT FINANCIAL CRISIS: EVIDENCE FROM LINEAR AND NON-LINEAR CAUSALITY TESTS

Sarosh Shabi

The relationship between stock market volatility and the business cycle is macro-financial as it links the fields of financial markets and macro-economics. This relationship links to theories of rational expectations/efficient market hypotheses and asset pricing theory. This thesis investigates the long-run relationship between stock market volatility and business cycles by means of linear and non-linear bivariate and multivariate causality tests. Moreover, it investigates the impact of the recent global financial crisis on the stock market volatility (SMV) and business cycles (BC) relationship. The contributions of this research to the literature include: a) analysing the non-linear causal relationship between stock market volatility and the business cycle; b) exploring the cross-country causality between these variables; and c) looking at the impact of the financial crisis on the said relationship. To the best of our knowledge this is the first time that any of these three aspects of the relationship between stock market volatility and the business cycle have been studied. The countries investigated are the US, the UK, Canada, and Japan (among the developed countries) and Brazil, Malaysia and Turkey (from the developing countries). Monthly data from January 1990 to December 2011 are applied in the empirical investigation. Stock market volatilities are estimated using the GARCH model, and industrial production indices are used for the business cycles. Bivariate non-linear causality tests are conducted by means of the Diks and Panchenko (2006) and Hiemstra and Jones (1994) methods. Non-linear multivariate tests are conducted by means of the Bai et al. (2010) method. Multivariate tests investigate the cross-country spill-over between two countries, with the US as the main country.

The results indicate that a non-linear causal relationship does exist between stock market volatility (SMV) and business cycles (BC). There is strong evidence to suggest that the SMV-BC relationship is not limited to within country only, as we find significant cross-country causal relationships. Both linear and non-linear bivariate causality tests indicate evidence of a stronger causality between variables when the financial crisis is taken into consideration. Also, both the linear and non-linear multivariate tests indicate that the US has a greater impact on the SMV and BC of developed countries than developing countries. And this impact has further increased during the recent financial crisis. The findings from this research have implications not only for investors and portfolio managers, but also for economists and policy makers. In addition, the research results signal that in countries such as the UK, inclusion of the US stock market as a business cycle indicator, in addition to the UK's own stock market, may be beneficial in identifying the turning points of the UK's business cycle, and vice versa.

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DECLARATION OF AUTHORSHIP

I, SAROSH SHABI 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.

STOCK MARKET VOLATILITY, BUSINESS CYCLES AND THE RECENT FINANCIAL CRISIS: EVIDENCE FROM LINEAR AND NON-LINEAR CAUSALITY TESTS

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. Parts of this work have been published as: [please list references below]:
    i. Choudhry, T.; Shabi, S.; Papadimitriou, I.F (2013) "Stock Market Volatility, Business Cycles and the Financial Crisis: Evidence from Linear and Non-Linear Causality Tests", European Business Research Conference, Rome, Italy September 2013

Signed:..

Date:...

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Chapter 1: Introduction

1.1 Background

The business cycle can be seen as the pulse of an economy. The cycles are the fluctuations in economic activity, and their movement indicates the direction of economic growth. Throughout the history of macroeconomics, business cycles have been heavily researched. Economists have developed theories and models to study various aspects of business cycles; predicting their turning points, analysing the patterns and exploring the causes of these cycles. However, even after more than a century of research, business cycles are still not perfectly understood or predictable, because of the changing dynamics of the world.

Over time, economies around the globe have gradually moved away from a bank-based financial system to a stock market-based financial system[1], and significant capital formation is sourced from these markets. Financial market indices, such as the S&P 500, FTSE 100 and Nikkei 225, have become international benchmarks and are followed closely by investors, market participants and other groups. With the ever changing economic and world conditions, and the increasing significance of the stock markets, the returns and volatility in these markets have found a link to the business cycles in the macro-financial literature.

The motivation of this thesis is to analyse the causal relationship between the business cycle and stock market volatility. The relationship between the business cycle and the stock market depicts the interaction between the macro-economy and finance (financial market). It can be viewed as a straightforward connection where one of the two variables co-integrates, causes or forecasts another, but there are various viewpoints as to why this relationship exists. The most popular explanation, to summarize, is that at increased levels of uncertainty, volatility in the stock market affects investors' and firm's decisions concerning investment and employment, and consumers' consumption. This in turn leads to a variation in profitability and output

[1] The UK was the first country to have a stock market based financial system, created in the 19th century after the industrial revolution, with the US following in the 20th century (Mayer and Vives, 1995).

growth at the firm level and adds up to affect the economic productivity of a country; that defines the business cycle. In the opposite direction, productivity growth is looked at as an important health check of the country; if output growth is expected to increase, it is an indication of businesses thriving, an increase in aggregate demand, and an increase in investment and share values. These links are explained at length in the Theoretical Background (chapter 2). The above relationships among the variables are characterised for an economy under normal conditions. But if the country is hit by a financial crisis, as in the recent global financial crisis, the relationship between the variables may not hold as expected. The findings from this research thus have implications for investors, market participants, policy makers and academics.

1.2 Literature Review

This research builds on existing literature that discusses the interaction of stock market returns/volatility and the macro-economy (specifically GDP, industrial production, output etc.). These strands of literature can be categorised as papers that: 1) present relationships and/or cointegration between the underlying variables; 2) show the direction of the relationship, one variable leading to another; 3) demonstrate the impact of new information on stock returns and/or the business cycle; 4) indicate the importance of cross-country variables; or 5) look at the influence of the financial crisis on any of these factors. Studies have been conducted on different sets of variables, using various models, time spans and data sets. Some of the more prominent ones are Schwert (1989); Fama (1990); Schwert (1990a); Ahn and Lee (2006); Bloom et al. (2009); Giannellis et al. (2010) and Kanas and Ioannidis (2010).

In the literature that examines these variables in an international context, there is a huge amount of research available on equity spill-overs, such as Koutmos and Booth (1995), Kanas (1998), Baele (2005), Diebold and Yilmaz (2009b), Balakrishnan *et al.* (2011), and Entorf *et al.* (2012), that mainly discuss how the stock returns/stock market volatility in one country influences or impacts stock returns in other stock markets. This strand has also been expanded to look at the second moment, or conditional volatility, of stock markets. Then there is another group of studies which looks at the integration or synchronisation of business cycles across countries, such as Kose *et al.*

(2003a), Yilmaz (2010a), Sinha and Sinha (2010), Lombardi *et al.* (2011), Ayhan Kose *et al.* (2011), and Bordo and Helbling (2011a).

Stock market volatility and business cycles are deemed to be related within the country, according to the literature stated above, and also there is evidence of equity spill-over and business cycle spill-over. It would not be wrong to expect a causal relationship between the stock market volatility of one country and the business cycle of another country, especially as the world is becoming more integrated with the endlessly increasing financial, trade and economic ties between countries. With the recent financial crisis having emanated in the US and engulfed many parts of the world the interrelationship and dependence between countries becomes even more prominent. The theoretical links for this possibility are further explained in the theoretical background (Chapter 2). To the best of our knowledge, the causal relationship between stock market volatility and business cycles has not been analysed across countries, whether before or during the crisis. Thus there is a gap in the literature that this research aims to fill.

1.3 Objectives

This thesis examines the causal relationship between business cycles and stock market volatility in various bivariate and multivariate settings using both linear and nonlinear Granger causality tests. This research aims to explore the causal relationship in various dimensions: i) intra country, or within the same country; ii) across countries, to figure out the possible spill-over between the stock market volatility of one country and the business cycle of another country, and vice versa; and iii) the impact of the global financial crisis on the stock market volatility and business cycle relationship.

1.4 Research Questions

The thesis explores four research questions. 1) Do changes in stock volatility within a country Granger cause changes in a country's own business cycle, and vice versa, in linear and non-linear frameworks? 2) Do changes in the stock market volatility of one country Granger cause changes in the business cycle of other countries, and/or changes in the business cycle of one country cause changes in the stock market volatility of other countries? 3) Has the recent financial crisis had an impact on the causal relationships in 1 and 2? 4) Does the spill-over effect of the stock market volatility and business cycles relationship vary between developed and developing countries?

1.5 Methodology

The variables of interest in this research are ‘changes in the business cycle’, represented by changes in the index of industrial production, and ‘changes in stock market volatility’, estimated using an Asymmetric GARCH model. The dataset includes eight countries, namely Brazil, Canada, China, Japan, Malaysia, the US, the UK and Turkey. These countries have been chosen from different regions across the world based on their economy (developed and developing) and their importance in their respective regions, based on the level of exposure to the recent financial crisis in relationship to the US. The data runs for the period Jan 1990 to Dec 2011 with monthly frequency for both the stock market index and industrial production index.

Granger causality tests have been used both in linear and nonlinear models in bivariate and multivariate settings. Linear causality has been tested based on the usual Granger tests (1969), and for nonlinear bivariate tests two benchmark studies, Hiemstra and Jones (1994) and Diks and Panchenko (2006), are adopted. For the cross-country causality, multivariate nonlinear causality is based on Bai *et al.* (2010), who have extended the Hiemstra and Jones (1994) test statistic to a multivariate setting. To our knowledge, non-linear causality has not been tested on these variables before, in either a bivariate or multivariate framework.

1.6 Results

The results from this research show that there is a causal relationship between stock market volatility and business cycles in both linear and non-linear frameworks. However, the direction and strength of the causality vary from country to country. In the case of Canada, a strong linear feedback effect is reported between Canadian stock market volatility and its business cycle for both the pre-crisis and including the crisis periods.

The Japanese stock market volatility and business cycle show linear independence of each other for both sample periods. The stock market volatility and business cycle show strong linear mutual dependence (feedback effect) for the full sample period, whereas there is weaker evidence of the feedback effect in the pre-crisis period in the UK. A strong linear feedback effect is reported for the US for the full sample period, however, in the pre-crisis period, stock market volatility significantly Granger causes the business cycle.

The US stock market volatility and business cycle show bidirectional linear causality with stock market volatility and business cycles in Canada, Japan and the UK for the pre-crisis period. However, the incidence of bidirectional causality (feedback) effect is reported in fewer cases for the full sample length. For instance, significant feedback effects between US stock volatility and the business cycles of Japan and the UK are reported, whereas for the US business cycle and the stock market volatilities of Canada, Japan and the UK, mixed results are documented.

Based on the multivariate causality analysis, the spill-over effect is significant from the US stock market volatility and business cycles after inclusion of the financial crisis period for Canadian and Japanese stock market volatility and business cycles, respectively. Moreover, the UK's business cycle has also been affected by this spill-over effect. Before the financial crisis episode, however, these relationships hold in the case of Canada only, and UK and Japanese variables are affecting the US stock market volatility and business cycle, respectively. The change in the causal direction is explained by the US being the epicentre of the recent global meltdown, and investment losses in the US market from corporate giants around the globe resulting in increased stock volatilities and prolonged recessions in these countries.

In developing countries, a strong causal relationship between stock market volatilities and business cycles is found at the first difference levels. A comparison of results for both sample lengths, reveals that the causal relationships have significantly changed in Malaysia after including the financial crisis period as the bidirectional causality changes to unidirectional, from stock market volatility to business cycle only. In the case of Brazil and

Turkey the bi-directional causal relationship remains relatively consistent over both the sample lengths.

Nonlinear bivariate causality results under Diks and Panchenko (2006) show evidence of nonlinear causality in the case of Malaysia, from stock market volatility to the business cycle across both samples, but no instance of nonlinear causality between the variables is reported for Brazil or Turkey using both data samples. Under the Hiemstra and Jones (1994) model, evidence of nonlinear causality is found only in the case of Malaysia. No instance of nonlinear causality between the variables is reported for Brazil or Turkey using both data samples.

In cross-country causality, US stock market volatility is observed to lead the business cycles of all three developing countries, i.e. Brazil, Malaysia and Turkey, and stock market volatilities of these countries also affect the US business cycle in the pre-crisis period. The cross-country spill-over effect is reported for Brazil, Malaysia and Turkey with at least one or more instances of spill-over being documented. However, in the full sample, stronger bi-directional causality or feedback is evident in the cases of Brazil and Malaysia only, which shows the significance and influence of the US stock market and business cycle on the developing countries. Turkey shows the least linear dependence against the US, however its stock market volatility shows some evidence of causing the US business cycle. These findings contribute significantly towards the literature on the cross-country spill-over between stock market volatility and business cycles because evidence in this context is non-existent to the best of the author's knowledge.

Evidence of nonlinear cross-country causality for developing countries is found only in two cases, i.e. the US stock market volatility and business cycle jointly affecting Brazilian stock market volatility. Similarly, after the financial crisis this relationship only holds in a few cases, showing the spill-over between stock market volatility and business cycles across the US and these developing countries.

1.7 Implications of the Research

The findings have implications for investors, portfolio managers and market participants as it helps them in understanding the market dynamics and the inter-relationships between stock market volatility and business cycles within and across countries. This knowledge can enable them to make prudent investment decisions and diversification strategies and to hedge their portfolios against changing domestic and international financial and economic dynamics.

The findings of international causal relationships between the variables are also of significance to policy makers. Based on this evidence, the policy makers have to devise policies to effectively deal with the cross-country spill-overs influencing their domestic financial markets and economies. It may also be time to think of adding another factor to the current business cycle indicators – the stock market volatility of another country, such as the US, in addition to the country's own stock market volatility

1.8 Structure

This thesis has been organized into seven chapters. This first chapter is the introduction to the research, with a brief background, objectives for carrying out this research, questions to be explored, summary of results, and layout. The second chapter is the 'Theoretical background', that explains the intricate relationships between stock market volatility and business cycles within the country and across economies. This chapter also discusses the reasoning behind this work and how it fills the gap in the existing literature. The third chapter is the 'Literature Review' that narrates the work that has previously been done on the relationship of stock market volatility and business cycles. However, it should be noted that literature specifically looking at the non-linear causal relationship between stock market volatility and business cycles (whether within country or across counties) is currently non-existent. Nevertheless, this chapter gives a feel of the existing aspects explored in previous research work and brings out the missing links. Chapter four is the 'Data and methodology' and gives the unit roots for variables, stock market volatility estimations and causality tests for all four hypotheses, and descriptive statistics of the data. It also explains the linear and non-linear causality tests at length. The Fifth and Sixth chapters are the 'Results and Findings' for the developed and developing countries, respectively, which explain the results of the causality tests conducted in various linear and non-linear, bivariate and multivariate settings. The seventh and the final chapter is the ‘Conclusion’, which, as the name signifies, concludes the research and also highlights its implications and points out the possible future areas for further research on this subject.

1.9 Summary

Stock market volatility and business cycles are at the epicentre of economics and finance in recent times, with many groups of academics, researchers, investors and policy makers making resources available to uncover the underlying dynamics and intricacies in order to better understand and accurately forecast the future direction of these two variables. This research combines both the variables in a causal relationship analysis using various bivariate and multivariate settings, and applying both linear and nonlinear econometric models to analyse the interdependencies between the two variables. This analysis is further expanded around the globe by including both developed and developing countries from different regions, such as Brazil, Canada, China, Japan, Malaysia, the UK, the US and Turkey. Analysis shows that the relationship between stock market volatility and the business cycle is significant both intra country and across economies, generating useful insights and implications for policy makers, investors, regulators and academics.

Chapter 2: Theoretical Background

This chapter builds the framework for the research topic and explicates the variables of interest - business cycles and stock market volatility - and the inter-relationships between them. It includes discussion on the recent financial crisis, how it affected various regions of the globe and its role in affecting the association between the said variables. It explains the reasons why the causal relationship may be expected and what factors lead to this connection. The chapter also discusses the hypotheses to be tested in detail and the significance of the research.

2.1 Business Cycles

There has been more than a century of research done on different aspects of economics in the hope of deciphering the codes of macro-economy. But, in spite of all the theories, models and the mass of literature, economists and experts have not yet been able to forecast economic cycles with any real certainty, nor have they been able to discern absolute reasons for what triggered or caused the cycles each time. A comprehensive text on macroeconomics is impossible without a mention of, or a discussion about, business cycles. Similarly, the existing research literature on economic fluctuations and business cycles is enormous. Some papers focus on theories explaining the fluctuations in the economic activity, whereas others have investigated ways of systematically identifying and measuring business cycles, such as Burns and Mitchell (1946) and research by the National Bureau of Economic Research. The first working definition for the business cycle was given by Burns and Mitchell in 1946, and has been widely acknowledged by economists in the literature.

"Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own." (Burns and Mitchell, 1946 p.3)

The definition highlights the important features of business cycles, which are: 1) business cycles are varying fluctuations in economic activity/productivity (output) over a period of time; 2) there are different stages of business cycles; 3) these variations are recurrent; and 4) at irregular intervals (spaced at different frequencies); 5) cycles bear many similarities across countries and over time (Zarnowitz, 1993; Diebold and Rudebusch, 1996). Every cycle is unique as it may differ from its preceding or subsequent cycle in its duration, depth and dispersion - the three D's of the business cycle (Dore, 1993; Kacapyr, 1996). No two cycles have ever happened of the same duration, due to which it is difficult to predict the turning points of business cycles with certainty. Although the duration varies from cycle to cycle, business cycles clearly differ from other short-run erratic fluctuations in economic variables as by rule business cycles are longer (over several years), larger and more widely diffused (Zarnowitz, 1992).

Theories and models on the business cycle have been presented, contradicted, rejected and renewed. Two such models that have received much attention in the literature are the New Classical theory and Keynesian theory. Within the New Classical theory, Real Business Cycle models have been much celebrated. The models that followed New Classical theory presumed business cycle fluctuations were attributed to exogenous, random and identifiable shocks. The Keynesian theory, on the other hand, supported the endogenous models driven by lags and non-linearity. (Zarnowitz, 1992)

Business cycles cannot be observed directly; therefore, these economic fluctuations are studied using the macroeconomic variables that indicate the cycle (known as business cycle indicators). In the US, the National Bureau of Economic Research (NBER) officially determines and announces the business cycle turning points, in post period[2]. In the US there have been 33 cycles reported by NBER since 1854 to date. The identification of turning points is based on cycle leading indicators such as real GDP, real income,

[2] The announcement for the June 2009 trough was made on September 2010, which is the latest announcement made by the NBER Committee, and the December 2007 peak in December 2008. (NBER)

unemployment, industrial production, and wholesale-retail sales. They look at a recession as a significant decline in economic activity spread across the economy, lasting more than a few months and normally visible by these variables. These macro-economic variables exhibit similar economic trends, i.e. expansion (going from trough to peak) or recession (moving from peak to trough). Moreover these factors are all inter-linked and closely move together. When real GDP declines during economic downturn, there is a decline in most factors, including industrial production, corporate profits, personal income, consumer spending and investment spending, except for unemployment, which rises (Mankiw, 2011).

In the literature, output (industrial production and GDP) has been a more preferred choice of variable for measuring business cycles. Industrial production and Gross Domestic Product are both pro-cyclical (in direction) and coincident (in timing) (Kettell, 2001), which make them ideal for replicating economic fluctuations. However, the official measures for GDP are only available quarterly, whereas the figures for industrial production are supplied at monthly intervals by the government. As a general rule, the greater number of data points observed in an interval enables the capture of the pattern of the cycle in more detail and makes it easier to date turning points of the business cycle (Jacobs, 1998). In addition, industrial production is the most cyclical component of GDP (Artis, 2003), thus Industrial Production may have leverage over GDP in the frequency of available data.

There has been an immense amount of research done on the why, when and how of these business cycles. In the quest of finding the triggering cause, economists have evaluated a mass of variables on the micro and macro level. In past decades, some researchers have also looked in the financial system for potential variables that may play a role in causing the business cycles, or help in predicting the cycle at least. But economists found it hard to accept the connection between financial markets and macro-economic fluctuations until the 1980's. However, over the past two decades the acceptability of the link has grown due to the frequent coinciding of recessions and financial crises.

2.2 Stock Market

In the financial system, the stock market's importance cannot be denied. It is a major part of the financial system and knits firms, financial institutions and investors together. The situation in the stock market is gauged by the stock prices, returns and volatility. Investment management is dependent on the mean-variance theory and derivatives valuation requires reliable volatility estimates (Gregoriou, 2009). Investors, policy makers, portfolio managers, risk arbitrageurs and other market participants give weight to volatility estimates as the barometer of the vulnerability of the financial market and the economy (Poon and Granger, 2003). Prices of the shares that trade on the stock market fluctuate and the causes/sources of these fluctuations may be firm-specific factors (e.g. profitability, dividends etc.) or may come from the wider world of economy, politics and any other factor that influences investors' expectations or perceptions about the stock's value (Gregoriou, 2009).

Huang and Kracaw (1984), referred to stock prices as a reflection of the market values of claims against the output. Variation in the stock prices (volatility) is the natural response of a financial market to new information that usually arrives in clusters (Engle, 2011). Prices reflect market expectations of the future course of the economy (Schwert, 1990a). Gregoriou (2009), summarizes the different angles of this phenomenon as the volatility in the stock market mirrors: 1) fundamentals, 2) information, and 3) market expectations. These three features are inter-connected with each other. The intensity of fluctuation in the share prices may be defined by whether the volatility is fundamentally justified or the result of unjustified collective irrational trading (Raunig and Scharler, 2010). In an efficient market, any changes or new information is reflected in the prices instantaneously, not allowing unjustified price variability to be sustained, and the market moves from one state of equilibrium to another. Higher volatility depicts a higher frequency of large positive or negative price changes, whereas lower volatility means that deviations from expected price changes, on average, are small (Raunig and Scharler, 2010).

Stock volatility varies over time and displays patterns in its movements (Schwert, 1990c). Stock market volatility can be estimated and forecasted using a variety of models, which can capture the stylized features of volatility. For instance, stock volatility (of the US) has been found to bear characteristics of long memory and structural change (Beltratti and Morana, 2006). The models have become more sophisticated over the years as we move from the historical volatility model to variants of autoregressive models (ARCH and GARCH extensions) and regime switching models etc., all competing to be recognised as the best estimate of volatility. For the purpose of this research, we need to estimate the volatility methods for the current and past time period and so we explain the volatility estimation methods at length in the methodology chapter.

In order to get a flavour of the kind of movement stock volatility and growth in industrial production show together, we plot these two time series for the US and the UK, as an example. The simple graphs below show the patterns in the movement of both time-series.

Figure 2.1 Industrial Production Growth vs. Stock Market Volatility - US

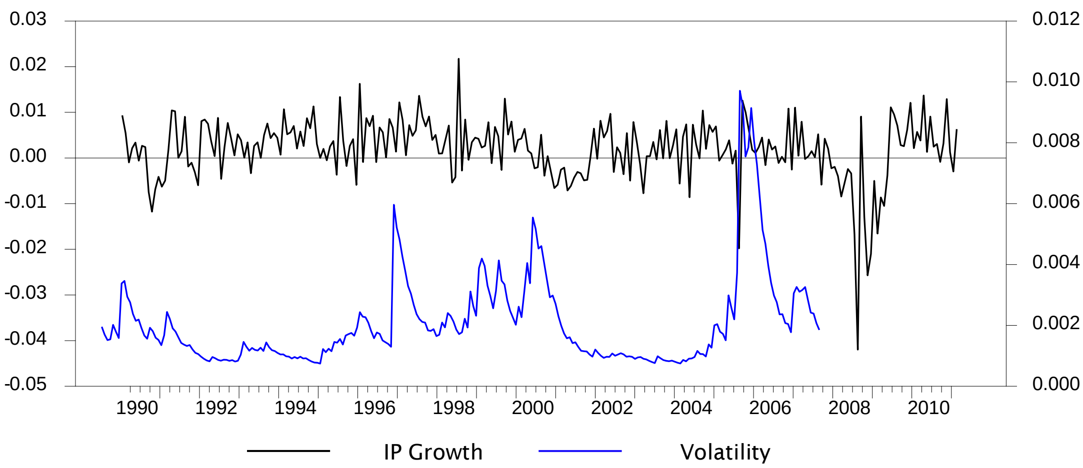
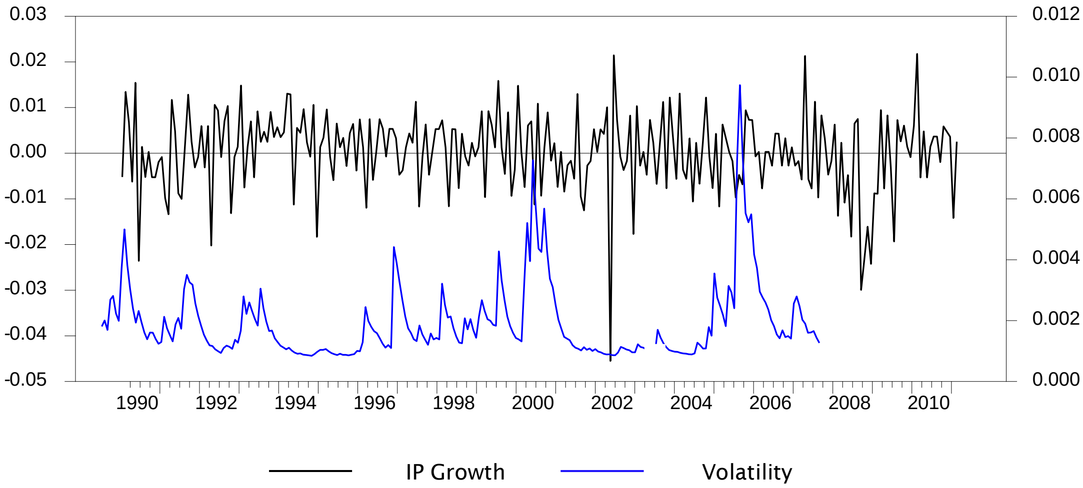


Figure 2.2: Industrial Production Growth vs. Stock Market Volatility - UK



The graphs show the business cycle (measured by changes in industrial production) and the stock market volatility (asymmetric volatility) movement over time (1990 - 2012). The time period when volatility has been high in the stock market mostly coincides with the periods of low industrial production growth. Thus, a coincidence of high stock volatility and low production growth can be observed. There have been three severe dips in industrial production growth, in 1990, 2002 and 2008. After viewing the discernible pattern between the two time series, we now look at the theoretical explanation for the connection between stock market returns and the business cycle in the next section.

2.3 Business Cycles and Stock Market Relationship: Theoretical Reasoning

The relationship between the business cycle and the stock market depicts the interaction between the macro-economy and finance (financial market). It can be viewed as a straightforward connection, where one of the two variables co-integrates, causes or forecasts another. However, behind the apparent connection between the stock market and the business cycle, there are numerous deep-rooted complex interactions among the variables that create this relationship, understanding this requires in-depth analysis. This research follows mainstream academic finance in taking up the 'functionalist paradigmatic approach'[3]. In the functionalist paradigm the world of finance is regarded as an environment of reality that can be understood and explained in terms of cause and effect (Ardalan, 2003). This approach emphasizes the significance of order, equilibrium and stability in society, and these are the premises for the theories stated later. It further assumes that the investors (individuals) in the stock market would take on a passive role, they do not outperform the market and their behaviour is being determined by the economic environment (Ardalan, 2005). Stock market prices/returns are included in the business cycle's forecasting estimations for empirical reasons too. For example, stock prices/indices are real figures that are available over a

[3] In the mainstream academic finance, none of the research papers have employed any of the other three paradigms. All the theories and research follow the functionalist paradigmatic approach. (Ardalan, 2003, 2005)

long span of time on a consistent and continuous basis. Thus, the data doesn't depend on survey or consensus as in other macro-economic variables; stock market data is reliable, free from judgemental bias and also doesn't require interpolation (Shapiro, 1988).

The stock market and business cycle relationship is linked to theories of 'rational expectations/efficient market hypotheses (EMH)' and 'asset pricing theory (APT)'. The reason for this can be understood by looking at these concepts more closely. EMH assumes that prices rapidly adjust and reflect the new information on its arrival as a consequence of changes in expectations. In an efficient capital market, information is available to all investors at the same time and they cannot consistently earn excess returns (risk adjusted) to the average market returns (Fama, 1970; Fama, 1991). Asset pricing theory, in addition to assumptions of EMH, also assumes that investors are rational and risk averse. Investors cannot influence the prices in the market and their investment is well diversified across a range of investments. In the context of these theories, the changing prices signal the arrival of information, thus one can gather the information set that the prices foretold.

This use of rational expectations was done by Veronesi (1999) in a closely related area, who presented a rational expectations equilibrium model of asset prices to study the varied reaction of stock prices to news in different regimes. He found that stock prices overreacted to good news in bad times. The rational expectations concept was also used by Blanchard (1981), who developed an extension of the standard IS-LM model to explain the inter-relationship of output and stock prices. The IS-LM model assumes that output is determined by aggregate demand and that over time the price level adjusts to its equilibrium value only. However, Blanchard's model emphasizes the relationship between output and asset value, rather than output and interest rate, as in the IS-LM model. He has shown that an expansionary policy shock leads to expectations about changes in real interest rates and profitability. In response, asset prices change, which further impacts the wealth spending. This further pumps up the supply and elevates the equilibrium output that justifies the initial rise in stock prices. In this manner, output supply adjusts to demand shifts. Asset prices act as a major predictor of future output but are not caused by the changes in output because output and asset prices both respond to the economic environment in Blanchard's model. In the past two decades there has been much advancement in investment literature and the theory of irreversible investment under uncertainty. Bernanke (1983a) was the first to apply this theory to business cycle analysis.

The equilibrium asset pricing model has been used in its dividend discount form for linking the macro-economy to stock market volatility, such as in Fama (1990) and Schwert (1990c). Prices reflect the value of future dividends today. Dividends are dependent on earnings, which are based on the output. Thus, variation in prices can be seen as a possible change in future dividends and output. It is believed that if discounted future dividends determine the prices of stocks at present, then variations in output would cause volatility in the stock prices. This view is mostly employed in determining the causality or predictability of stock volatility from macro-economic variables such as output (Schwert, 1990a). Thus, using Schwert's (1990a) approach of describing the relationship between stock prices and economic activity, a simple form of the discounted cash flow model is given below:

$$P_t = \sum_{n=1}^{\infty} \frac{E(D_{t+n})}{(1 + i_{t+n})^n} \tag{1}$$

In the above equation, P_t refers to the fundamental stock price which equals the present value of the future cash flows; $E(D_{t+n})$ are the cash flows to the shareholders expected in period t+n, and i_{t+n} is the discount rate. The fundamental (fair) value of the firm's share equals the expected present value of the firm's future expected dividend pay-outs. Companies are expected to perform better during expansion resulting in greater earnings, greater returns on companies' shares and higher dividend payments to investors. By contrast, if it is expected that the economy may go into recession, there would be lower returns on shares and lower dividends[4] and uncertainty would increase. If cash flows follow AR(1),

$$(D_t - \mu_d) = \varphi\,(D_{t-1} - \mu_d) + u_t \tag{2}$$

[4] Unless companies stop investment in projects and direct the money intended for expansion into dividends.

In the above equation, D_t are cash flows at time t; μ_d is the long term mean expected cash flows; φ is the autoregressive coefficient; D_{t-1} is the first lag of cash flow (cash flows at t-1); u_t is the random error or disturbance term, then the stock price and the variance of the stock price is,

$$P_t = \left[\frac{\varphi_d}{i}\right] + \left[\frac{\{\varphi(D_t - \mu_d)\}}{(1 + i + \varphi)}\right] \tag{3}$$

$$var(P_t) = var(u_t)\,\frac{\varphi^2}{[(1 + i)^2 - \varphi^2]} \tag{4}$$

Where $var(P_t)$ is the variance of stock price; $var(u_t)$ is the variance of the error term and the rest of the terms are as described above. These associations show that volatility in the stock market is proportional to the volatility in cash flows, if cash flows follow a constant parameter ARMA process and discount rates are constant over time. In the present value model, the real activity and discount rates vary with the variation in future expected cash flows (Schwert, 1990c).

Investors base their decision making according to their perceptions about future cash flows and discount rates. Investors' expectations about the economic situation and the cash-flows resulting from that economic state are reflected in the stock prices and resultant stock returns affected through their decisions. Conditional volatility of stock returns reveals uncertainty about (the process that generates) future cash payoffs and discount rates and the future course of the economy (Casarin and Trecroci, 2007). As aggregate uncertainty (about the economic activity) rises (or falls), conditional volatility responds by perking up (or down). Fornari and Mele (2009) and Mele (2008) build the link between financial volatility and economic volatility, by showing that stock market volatility is countercyclical. According to them, the neoclassical model of asset pricing, based on the assumption of rational expectations, helps in showing the countercyclical behaviour of stock volatility over the business cycle (Mele, 2008). They show that, if risk premia are counter-cyclical and asymmetric, and stock price and price-dividend ratio are pro-cyclical, then stock volatility is counter-cyclical (higher in recessions and lower in booms). The high volatility during a recession has been found previously by Schwert, (1990c), Hamilton and Lin, (1996) and Bittlingmayer, (1998).

Why the causal relationship can be expected, and the logical sequence from an increase in volatility to the impact on the business cycle is described next. At increased levels of uncertainty, volatility in the stock market affects investors' and firms' decisions about investment and employment, and consumers' consumption. The changes in the macroeconomic variables cause a variation in profitability and output growth at the firm and aggregate level, which defines the business cycle. The rise in stock market volatility affects investor confidence, consumer spending, companies' expansion and investment, employment and, in turn, real output, leading to reduced economic growth.

2.3.1 Consumption:

The reaction of investors to stock market volatility can be viewed using the 'uncertainty hypotheses' and 'wealth effect'. According to Romer (1990), an increase in stock market volatility causes uncertainty about future macroeconomic behaviour and future wealth, supporting the uncertainty hypothesis. Upon the uncertainty shock, the interest rate drops lowering the returns on savings and making investment very risky (Bloom, 2007). This, together with the reduction in resources spent on capital and labour adjustment, is viewed as a signal of consumption becoming cheap, leading consumers to consume rather than save for the uncertain future. Thus, consumption shoots up immediately. However, it doesn't remain high for long but falls below average consumption over the next three quarters (Bloom, 2007). This leads to a decline in demand for consumer durable goods in the long-run. The fall in consumption as a consequence of an increase in stock volatility has been confirmed again by Raunig and Scharler (2011) using a more recent data set.

The fall in consumption in the long-run may also be due to investors' reduced wealth (concept of wealth effect). Although Romer's (1990) results show that the 'wealth effect' of the stock market on real activity is insignificant or minimal, Fama (1990), Schwert (1990a) and Mauro (2003) are all proponents of this concept, by which the increased volatility in the stock market, drop in share prices, and lower returns therefrom cause investor's to lose part of their wealth, putting a strain on consumption over the longer time period. The decrease in consumption leads to a drop in aggregate demand for investment goods by individuals and households. The interdependencies in the stock market and real economy are found to exist through affecting the balance sheets of households and firms in the US and the UK (Giannellis *et al.*, 2010).

2.3.2 Investment

When the demand for consumption drops, and uncertainty heightens, the firms become cautious and defer investment and hiring. Building on Bloom *et al.'s* (2009)[5] concept, firms defer the decision making of expansion or contraction, and investment in current systems and investment in new projects is withheld. There is a drop in capital creation due to a hold on investment projects. The increase in volatility may also affect the risk aversion of financial intermediaries and investors whose willingness to lend reduces in uncertain times, increasing the cost and reducing the quantity of available credit. Moreover, in the financial markets, if stock holders are dependent on financing their positions (i.e. borrow to invest) the stock volatility would further affect their investment decision.

2.3.3 Employment

Hiring of new work force (labour), or filling up the vacancies created in the normal course of time, is delayed due to the state of uncertainty. The exiting labour are not laid off, but rather kept engaged in tasks other than mainstream production. In normal times (less uncertainty), high productivity is maintained at all times; unproductive firms face contraction and productive firms expand as the capital and labour are reallocated and resources are efficiently utilized. However, during increased uncertainty there is a state of hiatus, due to which the reallocation of resources freezes and hiring stops (Bloom *et al.*, 2009). The unemployment rate rises far above its usual level during a severe economic slump but also cannot decline below a certain level in economic booms.

2.3.4 Output

As all firms postpone investing and hiring and stop using resources efficiently, there is a sudden decline in total hours worked. The output of the company

[5] Bloom (2009) has explained the impact of uncertainty shocks at the firm level, industry level and aggregate level.

falls and profitability becomes questionable. The reduction in productivity of most firms implies a decline in the aggregate industrial production and growth in the economy. Lesser earnings imply less dividends and little amount of money available for expansion, again limiting the scope for economic growth. However, once the uncertainty declines, there is a rebound in output as firms try to meet the pent-up demand for hiring and investment and productivity returns to its long-run trend after experiencing a drop. (Bloom *et al.*, 2009) This is how volatility in the stock market reflecting uncertainty leads to both decline and increase in output in the form of a cycle. All these factors together are an inter-linked chain of happenings that can be a major cause of slump in the business cycle.

Another angle for viewing the relationship is to take the stock market as a transmission channel through which one country's business cycle affects another country's economy, i.e. the business cycle of one country influences another country's business cycle through its stock market (Sandra, 2007). The basic proposition for this investigation is that during the current financial crisis stock markets around the globe declined significantly, which led researchers to explore the possibility that stock markets, especially the US market, along with other channels such as trade, foreign direct investment and bank lending, were transmitting shocks to the international business cycles. However, the impact of financial markets on the international business cycles in this study remained uncertain. Recently, Espinoza *et al.* (2012) studied the impact of one country's business cycle on another country's business cycle by adding financial variables to the analysis. Their results suggested no improvement in the forecasts of business cycles based on the international business cycle alone. However their analysis was limited to the linear framework only.

2.4 Financial Crisis

2.4.1 The Crisis - Magnificence and Debacle

The financial crisis of 2007-2011 has been enormous in its magnitude and scope. The crisis has been extraordinary in all its dimensions and rightly considered to be the worst crisis in the past 80 years (since the Great

Depression of 1929-1930)[6]. The crisis emanated in the US in Aug 2007, rapidly engulfed Europe, and spun around the globe as a full scale global financial crisis, leading to the deepest and most persistent trough in the global business cycle since World War II (Kamin and DeMarco, 2012). The segments of the crisis have also been termed as, liquidity crisis, credit crisis, sub-prime crisis etc., in the literature. All of this happened almost simultaneously, and the financial system nearly collapsed, as in the span of a few months the world experienced unprecedented collapse in trade and activity (Gorton, 2010). The scale of the current crisis can be imagined by an example given by Roubini (2010)[7] that compares the size of the rescue packages required to save a few companies in the US against IMF's package presented for saving South Korea after the Asian Financial Crisis: as of November 2011, the Federal Reserve had injected an enormous 29 trillion dollars to stabilise the US financial system through loans, guarantees, and outright purchases of distress assets that were in excess of double the current US GDP (Felkerson, 2011).

Research on the financial crisis has found it hard to pin down the definite causes (Gorton, 2010). However, there is a vast amount of literature that focuses on the time line of events, the consequences and repercussions of the crisis on different areas and the lessons for the future. In this section we intend to give a summary of how the crisis unfolded affecting the equity sector and economic activity, and describing some significant statistics along the way.

2.4.2 The Crisis - Why and How

The crisis started becoming apparent with the banking panic on the 9th August 2007. This was unlike the past banking panics of the US as it was a mass run

[6] According to Schwert (2011) the comparisons of the current financial crisis with the Great Depression are exaggerated or misguided, especially if stock prices and volatility are used as an indicator of its extent.

[7] According to Roubini (2010), during the Asian financial crisis (1997-98), South Korea (a developing economy) was presented the grand sum of 10 billion dollars for its salvage by IMF. After a decade, as a result of the current financial crisis, the amount the US government has paid to private firms for their bailouts is extraordinary in its comparison: 40 billion to Bear Stearns, 200 billion to Fannie Mae and Freddie Mac, 250 billion to AIG and the troubled asset relief program for banks of 700 billion, and a sum of 1 trillion dollars for the European Union-International Monetary Fund allocated for the rescue of European countries.

of companies and institutional investors on the financial firms[8] (Gorton, 2010). But the analyses of past events reveal that the path for the crisis was paved much earlier in 2004, when the companies started becoming highly leveraged. The equity values became a thin silver lining on the balance sheets, as the debt to equity ratios rose to 40:1 compared to a previous high of just 15:1 (Blundell-Wignall *et al.*, 2008). There is general agreement that the current financial crisis has resulted due to a combination of credit boom and asset (housing) bubble as the initial and prominent causes in the US. It is, however, incorrect to blame sub-prime mortgages for all the problems around the world (Dwyer and Lothian, 2011). The US subprime crisis may be seen as a mere trigger for the global bank run and financial crisis, rather than a fundamental driver of it (Kamin and DeMarco, 2012). With the passing of time, and more research carried out on every aspect of the crisis, analysts agree that there were more deep rooted causes that paved the way for the financial tsunami and the inevitable global recession (Blundell-Wignall and Atkinson, 2008; Blundell-Wignall *et al.*, 2008).

2.4.2.1 Housing Crisis:

There was a fundamental mispricing in capital markets (real-estate bubble). The housing prices had, on average, almost doubled from 1995 to 2006. The events that signalled the crisis started happening in the first quarter of 2006 (Acharya *et al.*, 2009). The real-estate prices started falling (a 20% fall from 2006 to 2008) against the expectation of appreciation in the housing prices. Many homeowners had bought their houses with borrowed money and now they owed more in mortgages than the value of their possession (the asset bubble had burst). This then led to mortgage defaults and home foreclosures and the selling of houses in the market for mortgage servicing. The sub-prime mortgages were designed around this expectation of appreciation, as they required refinancing in a short period to avoid the jump in mortgage rate. The expectation turned bad and debts soared in the balance sheets. With assets losing their value and debts escalating, it didn't take much time for the silver equity lining to fade away.

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[8] The banking panics in the US of 1907 and earlier were characterized by individual investors having a run on banks.

2.4.2.2 Sub-Prime Crisis:

The subprime mortgage market was booming between 2001 and 2006. Angell and Rowley (2006), Kiff and Mills (2007) and Demyanyk and Van Hemert (2011) have shown that this upsurge was due to the so called private-label mortgage-backed securities[9]. There was an increase in the market share of subprime mortgages from 8% in 2001 to 20% in 2006 (in the securitised mortgages market from 54% in 2001 to 75% in 2006) (Demyanyk and Hemert, 2011). This drastic increase was due to the growing demand for higher-yield securities among investors, leading to increased investment in these securities. Another key factor for growth in the mortgage market was the off-balance sheet mortgage securitisation, which had increased at a fast pace prior to 2007.[10] The Federal Reserve and other central banks have been held partially responsible for providing easy money[11] to banks that then issued cheap loans with an artificially low Fed. funds target. Fed and other regulators have also been criticized for allowing poor underwriting standards in the mortgage market and supporting financial innovations without realizing the repercussions.

In the last quarter of 2006, as the housing market started showing the stress signs, financial institutions owning the mortgage-backed securities incurred huge losses or went bust. Approximately six million sub-prime borrowers could not honour their payments (Felsenheimer and Gisdakis, 2008). Ownit Mortgage Solutions was the first subprime lender to go bust, in the last quarter of 2006, followed by the second-largest sub-prime lender, New Century Financial, in April 2007. The collapse of New Century Financial alone led to 3,200 people losing their jobs (Felsenheimer and Gisdakis, 2008). However, the outstanding subprime mortgages in 2007, being approx. $1.2 trillion, were not huge enough to have alone caused the entire banking system of $20 trillion (sum of traditional and parallel banking) to topple down (Gorton, 2010).

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[9] These were characterised by no credit protection from Government Sponsored Enterprises such as Fannie Mae and Freddie Mac.

[10] SEC for investment banks had initiated the “consolidated supervised entities program” which allowed the investment banks to increase their off-balance sheet mortgage securitization by manifolds and exploit it as a key driver to jump their revenues and share prices in a short span of time

[11] The Fed had set the Fed fund rate down to 1 percent until 2004.

The sub-prime mortgage crisis had begun, primarily affecting the investment and merchant banks and later engulfing commercial banks into the crisis. This further worsened the financial condition in terms of liquidity and investors' confidence, leading to the drying up of both money and capital markets, changing from a subprime to a full scale global credit/financial crisis (Felsenheimer and Gisdakis, 2008).

2.4.2.3 Credit Crisis:

The waves of the credit crisis were felt in July 2007 with the default of the Credit Default Obligations (CDOs), as lenders demanded more collateral due to the increase in uncertainty (Felsenheimer and Gisdakis, 2008). For instance, Merrill Lynch, the creditors to Bear Sterns, managed two of their hedge funds and seized $800 million of their assets and tried to fire sell them, of which only one eighth could be sold as the declining worth of the assets became apparent. On 23 June 2007, Bear Sterns tried to salvage the hedge funds by pledging $3.2 billion in loans. By the next month, the funds had lost 90% of their value and on June 20, 2007 the two hedge funds managed by Bear Sterns collapsed. The banking panic, which started on Aug 9, 2007, revolved around the repo market (where the traders are institutional investors and firms), which is not insured (Gorton, 2010). There was a severe run on the assets of three SIVs of BNP Paribas, making it suspend redemptions on Aug 9, 2007.

The message was received by investors loud and clear. The asset backed commercial paper market, the repo market and all other short-term markets froze with the announcement, until the central bank had to inject more liquidity. The future months evidenced continual announcements of bankruptcies of sub-prime mortgages, write-downs by financial institutions etc. There were runs-on banks, cash was running out, placing extreme pressure on banks to remain liquid, and the liquidity crisis took its toll. Then Bear Sterns, the fifth largest investment bank that boasted investments from around the globe, was run over in the week of 10 March 2008. The bank had very high exposure to the sub-prime mortgage market and was highly leveraged. At the weekend, government officials engineered JPMorgan Chase's purchase of Bear Sterns by guaranteeing $29 billion of sub-prime backed securities to prevent it from going bust (Acharya *et al.*, 2009).

Inter-bank trust had diminished and perceived counter-party risk had increased immensely. For their survival, the financial institutions stopped credit creation. The demand for liquidity increased tremendously. This led a flight to quality, yields on most liquid government securities fell low and yield spread on bonds widened. Wholesale funding had disappeared as the credit market for hedge funds and other leveraged financial intermediaries diminished. The financial crisis escalated in September 2008 after the default of Lehman Brothers (a large US investment bank) and the rescue of American International Group (a US insurance company) and other bailouts across the US and Europe. Volatility in the financial market was surging due to deleveraging across the global financial system and the rapid decline in the financial markets (Blundell-Wingall *et al.*, 2008; Felsenheimer and Gisdakis, 2008; Acharya *et al.*, 2009; Hellwig, 2009).

The above facts were the triggering points of the global financial crisis, which to this date stands as the worst financial calamity observed in recorded economic history. The stock markets, as shown in Figure 4.5, show the volatility for the developed countries rising from the second half of 2007, indicating the surge in economic and financial uncertainty caused by the financial crisis. The crisis spread from the US to European countries and further around the world. The factors that contributed to the spread of the crisis, and the impact it had on various countries around the globe, are discussed in the following paragraphs.

2.4.3 Impact of the Financial Crisis on Economies around the World

The financial crisis originating in the US spread across borders and waters to the developing markets. This spreading of crisis has been referred to as contagion, or as spill-over, in the literature. The US economy was the epicentre of the crisis and has suffered massively, but Western Europe and developed Asia were also hit hard (IMF, 2009). The global interdependencies in the financial and real sectors were much greater than realized, and thus enabled the transmission of the crisis among countries (Kamin and DeMarco, 2012). The channels of transmission, finance and trade, are particularly emphasized in the literature, such as in Acharya *et al.* (2009), Balakrishnan *et al.* (2011), Claessens *et al.* (2011), Berkmen *et al.* (2012) and Chor and Manova (2011). Whereas, Kannan and Köhler-Geib (2009) emphasize that the uncertainty regarding the economic fundamentals was the cause of the spreading of the crisis.

2.4.3.1 Trade

As the financial crisis took its toll, the US and other major economies substantially reduced their imports. This resulted in a severe drop in consumption and demand for manufacturing (durable) goods from exporting countries (Berkmen *et al.*, 2009), the developing economies bearing a high export to GDP ratio being hit the hardest. The collapse in trade and output has been strikingly parallel (Blanchard *et al.*, 2010). Furthermore, the higher interbank rates of countries and the resultant tighter credit conditions have been found to hamper their international trade volumes (Chor and Manova, 2011).

2.4.3.2 Finance

Another direct source of impact was the reduction in FDI for developing economies. Chudik and Fratzscher (2011), find that a spill-over of the crisis to developed economies has been due to the tightening of liquidity conditions, whereas to developing economies the crisis has been transmitted through a rise in risk aversion and a re-pricing of risk.

2.4.3.3 Uncertainty

Kannan and Köhler-Geib (2009), show that an unanticipated crisis increases uncertainty (variance of investors' beliefs) in other countries. This high uncertainty regarding the fundamentals of the economy explains the quick transmission of the crisis contagion to other countries, in addition to other important channels of transmission, namely trade links with a country struck by crisis. This phenomenon was found in the recent crisis, as the crisis originating in the US had a significant impact on developing economies. Kannan and Köhler-Geib (2009) also find past stock market volatility to have a significantly positive effect on uncertainty.

An interesting development is that the financial crisis changed the decoupling phenomenon (business cycles of developing economies becoming unsynchronized with the OECD countries) that caught much attention prior to the escalation of the current global crisis. The business cycles of developed and developing economies, although affected differently by the financial crisis, are known to have moved closer, with the massive growth pattern of the developing markets slowing down. This economic integration and the effect of the crisis on interdependence has been studied by Kose *et al.* (2008); Dooley and Hutchison (2009) and Kim *et al.* (2011) among many others. However, as the crisis has calmed down, the developing economies, like China, are now trying to catch up with their previous growth trends (Fidrmuc and Korhonen, 2010). Different countries have reacted differently to the global financial crisis. Among the many factors that are responsible for this varied impact are the following: exposure to the extent of the financial integration it shares with foreign countries, the nature of the financial instruments traded with them (Milesi-Ferretti *et al.*, 2010), and the nature of exchange rates[12] in the home country (Berkmen *et al.*, 2009).

2.4.3.4 United Kingdom

Europe, and more specifically the UK, was hit by the crisis soon after the sub-prime crisis broke in the US in 2007. Firstly, UK banks operating in the US automatically received the blow; secondly, the business model[13] used in the UK was similar to the US model, which failed around the world; thirdly, of the total securitized sub-prime (related) US products, one third were sold to overseas investors; fourthly, due to an increase in the market risk and application mark-to-market accounting rule, the sliding asset (market) prices adversely affected the value of assets in the balance sheets of financial institutions globally (Blundell-Wignall and Atkinson, 2008). The UK cycle had been strongly correlated with the US even before the crisis hit, more than it had been with European countries. Thus, forecasts of the economy show fear that the crisis will leave the UK economy much worse. The UK economy was strongly hit by the crisis and it was struggling to recover from the impact even in 2011, when the unemployment rate touched 8.3% (2.63 million people unemployed). Market capitalization of UK listed companies as a percentage of GDP dropped from 137.2% (in 2007) to 49.4% (in 2011) (World Bank, 2012). However, as the

[12] Countries having less flexible exchange rates are known to have been affected more, whereas none of the least affected countries had a pegged exchange rate.

[13] Long-term assets were widely financed out of the funds from the short-term (specifically commercial paper) money market. It could not sustain the pressure of the liquidity crisis.

crisis neared its end, the figures were more positively revised and the economy is thought to have weathered the impact of the crisis better than some other major countries in Europe (Sentance *et al.*, 2012).

2.4.3.5 Japan

Japan's economy has been severely hit by the financial crisis. However, one of the possible indirect reasons for the outbreak of the current crisis quoted in the literature is Japan's close to zero interest rate and low exchange rate policy that it has employed to compete with challenges from China and the growing industrial economies. These policies are considered to have decreased the global cost of capital in financial markets via carry trades.

Japanese stock prices surged in summer 2007 but with the outbreak of the sub-prime crisis in the US the prices dwindled down, straining commercial banks and limiting their willingness to lend. Furthermore, a sudden rise in oil prices added to the sluggishness of industrial activity that showed a sharp decline (Nov 2008, 100 to Feb 2009, 70). Market capitalization of Japanese listed companies as a percentage of GDP dropped from 102.2% (in 2007) to 60.3% (in 2011) (World Bank). Japan faced a massive decline in exports attributed to demand and trade drying up world-wide. The total value of exports dropped enormously by Jan 2009, to 50% of their value in Sept 2008. Japanese exports of information technology and durable goods fell drastically, and car exports alone fell by 65% during Sept 2008 to Jan 2009 (Sommer, 2009). Matters became worse with the appreciation of the yen by 30% during the same time span. Amiti and Weinstein (2009), show that exporting firms' inability to get trade financing from the banks and other financing institutions that were unsecured creditors to the collapsed Lehman Brothers contributed to the falling exports[14]. Japan had one of the worst five collapses in output in 2009. Although exports had significantly recovered by Oct 2009, Japan then had a severe earthquake and the Fukushima nuclear disaster in March 2011. This led to a supply shock, unlike the demand shock from the financial crisis, and the export figures fell even below the lowest value during the crisis (Ando and Kimura, 2011).

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[14] Japanese banks, such as Aazoro and Mizuho, got a direct impact from the collapse of Lehman as these were two of the largest five unsecured creditors, and together had an exposure of 1 billion dollars.

2.4.3.6 Canada

The Canadian economy has strong economic and financial links with the US, for instance a quarter of Canadian business funds are raised from the US alone (Klyuev, 2008). Bayoumi and Swiston (2008), have shown that a 1 percentage change in US GDP shifts Canadian GDP by ¾ per cent in the same direction. Duttagupta and Barrera (2010), find that US GDP growth explains half of the volatility in Canadian GDP growth rate in the long-run, evidencing the business cycle spill-over. Canada is highly vulnerable to the economic and financial conditions in the US. But the Canadian banking system, contrary to the US, is much more concentrated and heavily regulated (Bordo *et al.*, 2011). Thus, these differences in the historical banking system are thought to have played a key role in Canada's capital market being one of the least affected around the globe. The World Economic Forum has given it first place (among 134 countries) for the effectiveness of its banks in 2008 (WEF, 2008). Canada is characterized by a conservative residential mortgage market, where only 5% of mortgages were non-prime (US: 25%) and of which only 25% were securitized (US: 60%). However, the growth in real GDP dropped from 2.7% in 2007 to 0.5% in 2008 and market capitalization of Canadian listed companies as a percentage of GDP dropped from 153.5% (in 2007) to 66.8% (in 2008) (World Bank, 2012).

2.4.3.7 Malaysia

Malaysia was one of the most adversely affected Asian economies, but compared to other economies its downturn is quite moderate. Market capitalization of Malaysian listed companies as a percentage of GDP dropped from 174.4% (in 2007) to 84% (in 2008) (World Bank, 2012). Malaysia has been able to largely avoid the impact of the financial crisis on its capital markets due to two reasons. Firstly, it had little exposure to the financial derivatives where the crisis originated. Secondly, after the harsh experiences of the Asian financial crisis, Bank Negara Malaysia (the central bank) has been very effective in maintaining the financial sector, which continued through the recent global crisis. FDI substantially reduced in 2008 and 2009 (IMF, 2009). On the manufacturing side, the contraction in aggregate demand due to the sudden drop in exports has burdened the economy. However, the contagion effect took longer to affect the Malaysian macro-economy and the impact was only seen in late 2008. Malaysia's output (GDP growth rate) fell substantially from 4.8% in Q3:2008 to -6.2% in Q1:2009. However, the unemployment rate has been quite stable throughout the crisis period (2008: 3.3%, 2009: 3.6% and 2010: 3.3%).

2.4.3.8 Brazil:

Brazil is the world's tenth biggest economy, and entered into a more vigorous growth cycle in 2006. The companies operating were financially sound, the consumer debt was low and the liabilities were short-term. Brazil and its industries felt the impact of the financial crisis in the last quarter of 2008. There was a drop in demand for capital goods (exports) which, together with the credit squeeze, caused a 21% drop in industrial production and a 2.9% drop in GDP between October and December 2008 (de Barros, 2010). Market capitalization of Brazilian listed companies as a percentage of GDP dropped from 100.3% (in 2007) to 35.7% (in 2008) (World Bank). It had a very high foreign portfolio investment in its stock market by international investors seeking high returns on highly liquid assets. Because of losses in the global financial markets, these investors began liquidating their financial assets in Brazil. Thus, the pressure kept building, resulting in the stock market losing half its value and its currency dropping by 53% against the dollar. However, the country has come out of the crisis relatively quickly and has continued to grow.

2.4.3.9 Turkey

Turkey's economy has suffered a severe downturn overall due to the current financial crisis. Although Turkey's banking sector has been strong enough to weather the effect of the current crisis due to having undergone drastic restructuring, improved regulation and supervision after the 2001 crisis[15], the industrial production dipped significantly along with a huge decline in demand for Turkey's exports in the first quarter of 2009. The unemployment rate increased from 9.2% in June 2008 to 13% in June 2009, as 400,000 jobs were

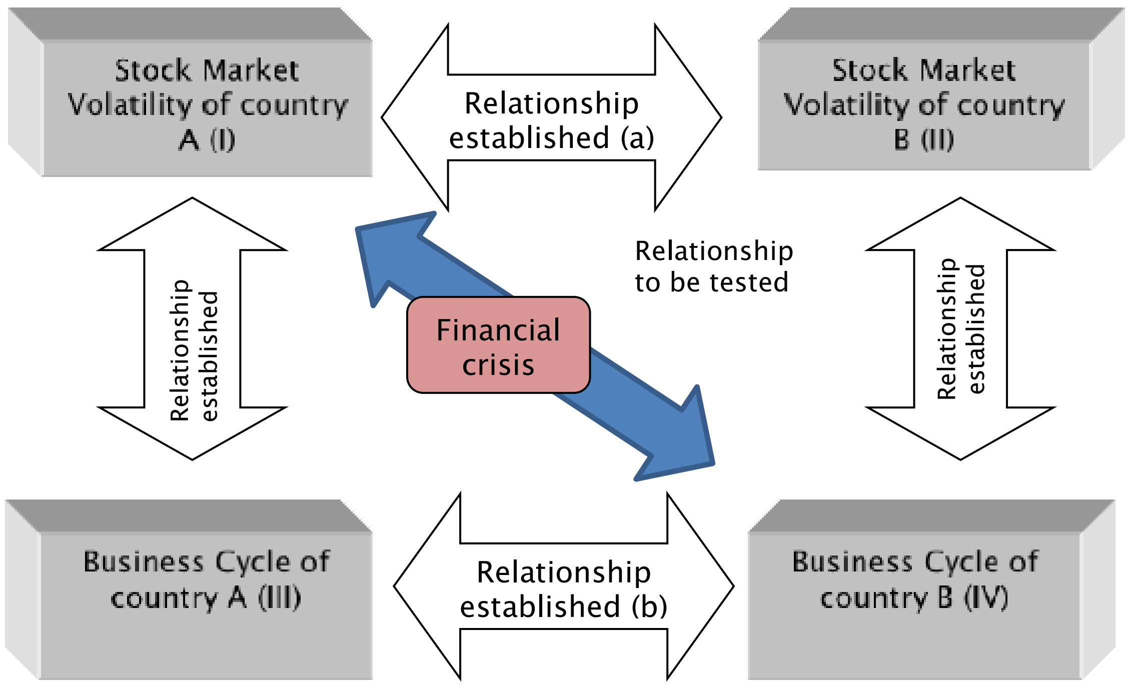
[15] The banking sector not bearing any flaws in the structure, and having maintained a balance between financial deepening and excessive risk-taking during the credit boom, was resilient to the effect of the global financial crisis. It had virtually no exposure to the US sub-prime crisis, and no dependence on international wholesale funds. The liquidity remained high, e.g. in 2009, no bank had a capital adequacy ratio of less than 13%.

lost in the manufacturing sector (hit hardest) alone. Istanbul Stock Exchange Index lost 55% of its value during July 2007- March 2009. Market capitalization of Turkish listed companies as a percentage of GDP dropped from 44.3% (in 2007) to 16.1% (in 2008) (World Bank, 2012).

2.5 Research Plot – Stock Market and Business Cycle Links

Stock markets and the real economy interact between themselves and in doing so display inter-connections. Figure 2.3 is a graphical presentation of the relationships that will be discussed and analysed in the course of this research, and thus bears significance for visualising the causal connections that will follow in the proceeding discussion. The stock market volatility and business cycle have four kinds of causal relationships that interest us.

Figure 2.3: Stock market volatility and Business Cycle Relationship



2.5.1 Relationship (I-II): International Stock Markets

Due to the globalization and integrated nature (bearing financial, regional and political ties) of countries and the international stock markets at present, investors and market participants are alert to any significant information created in foreign markets. In integrated financial markets, assets with identical risk carry the same expected returns irrespective of their domicile. Thus, volatility in the stock market of country A can, and is found to be, transmitted to the stock market of country B. Returns-spill-over are found to differ from volatility-spill-over as stock returns evolve slowly into cycles and are transmitted across markets, whereas stock volatility spill-overs show eruptions linked to economic events (Diebold and Yilmaz, 2009a). Interdependence (volatility spill-over) between national stock markets has been tested empirically in numerous papers and proved to exist among equity markets of many countries around the globe.

Hamao *et al.* (1990) found volatility transmissions between the US and the UK and the Japanese stock markets. Koutmos and Booth (1995), in addition, found the daily volatility spill-over among these countries to be asymmetric, i.e. shocks due to bad news transmitting more than those due to good news. Also the US, UK and Japan have become more interdependent in the post 1987 crash period. Arshanapalli and Doukas (1993) found similar results, the US having a strong influence on the UK, French and German markets, but not on Japan. Karolyi (1995) studied the US and Canada and found the presence of asymmetric volatility transmission of stock volatility from the US to Australian and Singapore markets. Kanas (1998) also found some asymmetric volatility transmission among the equity markets of London (UK), Frankfurt (Germany) and Paris (France). In *et al.* (2001) recorded increased interdependencies and volatility spill-over in Asian markets during the Asian crisis of 1997-98, confirming that investors responded to news originating in both local and foreign markets asymmetrically. Karunanayake and Valadkhani (2011) and Baele (2005) focused on the Western European countries that underwent financial and economic monetary integration. Baele found increased spill-over of shocks during times of high volatility among the EU markets, and also evidence of contagion from the US to these markets.

Apart from interdependence among developed equity markets, there is evidence of return/volatility spill-overs across developed and developing economies. Balakrishnan *et al.* (2011), using a financial stress index, demonstrated that financial stress spiking in developed economies transmits strongly and quickly to developing economies, this phenomenon has been strengthened due to the increasing financial linkages between developed and developing economies. John Wei *et al.* (1995) found significant return and volatility spill-overs from developed markets (the US, UK and Japan) to developing stock markets (Taiwan and Hong Kong). After the Asian financial crises of 1997-98, these unidirectional return spill-overs changed into bidirectional spill-overs for some countries (such as the UK and Taiwan), indicating that the developed economies are giving more weight to the prices and returns in these developing markets (Wang and Firth, 2004). The horizontal line (a) on Figure 2.3 signifies the inter-relationship between international stock markets.

2.5.2 Relationship (III-IV): Integration of the Business Cycle

In the US in the late 1990s, the economy was booming as productivity growth surged due to technological advancements. The growth was considered sustainable and continuing, so the global demand pumped up and the stock market quickly inflated to match the trend. The stock market bubble could not sustain and burst, making the economy tumble (Sandra, 2007). The synchronicity of economic slump across many industrialised countries puzzled many, and thus researchers focused more on international business cycles to seek answers. Over the past decades, globalization has resulted in enhanced economic and financial ties among countries. International trade and financial flows among countries have risen in the search for high return, low diversified risk; to gain specialization in production by benefitting from cost effective and efficient factors of production in other regions; and to achieve global dominance in financial markets (Sinha and Sinha, 2010). The horizontal line (b) on Figure 2.3 indicates the integration of business cycles across countries.

The economic and financial interdependencies among countries increases the sensitivity to industry-specific, external and global shocks. These widen the channels of shock transmission and make them more prone to external and global shocks. Financial and macroeconomic fluctuations (depending on the volume) spread across the countries, referred to as spill-over/contagion, and result in synchronization/convergence of the business cycles (Kose *et al.*, 2003b; Sinha and Sinha, 2010). Yilmaz (2010b) reported that fluctuation occurs in business cycle spill-over in an upward trend over time. Lombardi *et al.* (2011) found that real economic shocks transmit from the US to Japan and the Euro area. Yilmaz (2010b) has shown that the US and Japan are the main transmitters of shocks to countries around the world, since 1980 and 1970 respectively. Bordo and Helbling (2011b) declare that there has been increasing synchronisation between business cycles over the twentieth century during four exchange rate regimes, unlike the studies that have only related this phenomenon to more recent decades. Business cycle convergence has mixed results in the literature based on the level of development, the nature of the shocks and the pattern of specialization in the different countries and data sets chosen (Kose *et al.*, 2012).

Another aspect of the synchronization between business cycles is between developed and developing economies. High growth in China and other developing economies was in contradiction to the concept of synchronisation of international business cycles among developed and developing economies. The growth in these developing economies remained unaffected by the slow-downs in developed countries in spite of sharing trade links with them. It led to the dialogue of the decoupling of the business cycle of developing economies from that of the developed countries. During the current financial crisis, the decoupling phenomenon was considered to be on weak ground, but as the crisis is softening, the discussion on decoupling is reviving (Kose *et al.*, 2012). In another study, Kose *et al.*, (2012) have shown that, over time, the financial indices of developed and developing economies have become more correlated, but the correlation between output indices of two groups has lowered.

2.5.3 Relationship (I-III / II-IV): Stock Market Volatility and the Business Cycle

These relationships are indicated by the vertical arrows in Figure 2.3. Three types of relationships are evidenced to exist between stock market volatility and business cycles: 1) correlation/co-integration, 2) predictability, or forecasting ability, and 3) linear causality, running from stock market volatility to the real economy and vice versa within the same country. Co-integration between stock returns/volatility and industrial production has been found by Cheung and Ng (1998), Jay Choi *et al.* (1999), McMillan (2005) and Ratanapakorn and Sharma (2007).

The variability in stock prices is taken as an 'information variable'[16] based on the 'lagged information hypothesis', where historical information is reflected in the asset (stock) prices that contain predictive content for real activity (Blanchard, 1981; Huang and Kracaw, 1984; Hassapis and Kalyvitis, 2002). This strand of research has been extended as a number of macro-economic and financial variables have been tested for their ability to forecast and indicate future economic activity, such as in Chauvet (1998), and Srivastava (2009). The emphasis in this line of research is on forecasting economic activity and business cycle turning points. There are some studies that have examined the reasons for variations in stock returns (e.g. Schwert (1990c)) and have searched for macro-economic variables as indicators to forecast stock return/volatility, or as a possible cause of it, such as Errunza and Hogan (1998), Rodríguez *et al.* (2002), Pierdzioch *et al.* (2008), and Paye (2010) who looked at the phenomenon on various data sets in various countries.

[16] Real economic activity has been estimated and measured using a variety of economic and financial variables in the literature.

There are studies that have looked at the relationship between two time series in terms of news announcements, i.e. macroeconomic news in one market causing variations in stock volatility of equity markets across countries. For example, Becker *et al.* (1995) found increased volatility in UK stock returns (for 30 minutes) surrounding US news announcements. Entorf *et al.* (2012) emphasized the news element of business cycle forecasts on stock returns and volatility.

However, some researchers have also looked at the causal relationship between stock returns/volatility and economic activity (output) and believe that the stock market may actually be causing the business cycles, and vice versa, such as Lee (1992), Ahn and Lee (2006), Beltratti and Morana (2006) and Kanas and Ioannidis (2010). Fama (1990) and Schwert (1990b) found future production growth to cause variations in stock returns. Diebold and Yilmaz (2008a) found macroeconomic volatility (GDP or IP) to cause volatility in the stock market. Examples of some studies that show causality running from stock return/volatility to output growth are Schwert (1990c), Jay Choi *et al.* (1999) and Hassapis and Kalyvitis (2002). Ratanapakorn and Sharma (2007) differentiated between causality in the short and long-run, and found that macroeconomic variables only cause stock prices in the long-run, whereas causality from stock prices to IP only follows in the short-run. Giannellis *et al.* (2010), in addition, looked at the volatility spill-over between stock markets and real economy sectors.

Due to the nature of the two time series, i.e. stock market volatility and output growth, non-linear causality is expected to exist in addition to the linear causal relationship. But non-linear causality is yet to be tested between the two variables. Thus, the first set of hypotheses for this thesis (1a and 1b) aim to establish this relationship.

2.5.4 Relationship (II-IV): Stock Market Volatility affecting Business Cycles across countries

Keeping in mind the evidence available on the above two types of relationships, this research aims to determine and explore the causal relationship (I-IV) between the stock market volatility of country A and the business cycle of country B. Canova and De Nicolo (1995) were one of the first studies that examined this relationship in the international context. They found that innovations to foreign production influence domestic production, and as stock prices reflect output, foreign production affects the domestic stock prices too. Nasseh and Strauss (2000) found that the industrial production of Germany was co-integrated with the stock prices of four European countries. Kanas and Ioannidis (2010), as a part of their study, found that the UK's price-economic growth relationship and the industrial production growth in the UK are being influenced by stock prices in the US. Espinoza *et al.* (2012) made an attempt to forecast the business cycles of the US and the Euro area using financial variables alongside the cross–country business cycle. Although the financial variables didn't improve the forecast, they pointed out that this could be due to the linear nature of the model used. These studies hint at the possible relationship of stock volatility and the business cycle across borders. Among the financial variables, stock market returns/volatility generally appears to demonstrate considerable significance for predictive power within the country and across countries (Entorf *et al.*, 2012).

Current financial literature has a gap in that it does not explain the spill-over, causal (linear or non-linear) effect, of the stock market volatility of one country on the business cycles of other countries that share regional, political, financial and trade ties with one another. Thus, in this thesis we test multivariate non-linear causality among the variables. We believe that when uncertainty in one country's economy increases, and is reflected in the stock market by an upsurge in volatility, the investors, consumers and firms across other countries are conceptually expected to respond as follows:

Response of Investors and Consumers: The investors do not want to save (invest) more as the markets become risky and the returns don't match the heightened risk. The investors cannot turn to shift their investment to other markets as, due to volatility spill-over, other stock markets also bear uncertainty and increased stock market volatility. This reduces investor and consumer confidence, in addition to the loss on their investments. If investors from around the globe are holding a significant proportion of their investment portfolio in a single economy, or a few markets that bear positive return-correlations, the decline in that specific market(s) could decrease consumers' wealth around the globe. This in turn will result in decreased consumption over the long-run, after an initial surge, and a drop in the demand for durable goods. (Bloom, 2007; Aruoba *et al.*, 2010)

Response of Companies: We build on Bloom (2007) and Bloom *et al.'s* (2009) concept of the effect of uncertainty on consumption, investment and employment. With globalization, companies have expanded their operations across the globe, with manufacturing plants based in many countries. With an increase in uncertainty, which is reflected on the stock market by increased volatility, companies try to put a hold on expansion, restrict hiring (and replacement of existing labour) and delay investment in new projects. This leads to a cut in the total hours worked and reduced output at the manufacturing units in various countries. When all the companies have a reduction in productivity, it affects the industrial production of the countries where the manufacturing plants are based. The decline in output leads to a downturn in the business cycle.

2.5.5 Relationship (I-III/II-IV) During the Financial Crisis

With the current financial crisis at play during the time of this research, the worst since the 1930s, causality has to be evaluated during both the crisis and the non-crisis time. The second set of hypotheses (2a, 2b, 3a, 3b, 4) is designed to test whether the financial crisis affected the linear and non-linear causal relationships between stock volatility and the business cycle in both developed and developing economies. With the growing financial and global integration, no country could remain secluded from the events around the world, as countries are tied together through financial and trade ties. The recent financial crisis has affected some countries more than others depending on the country's inter-dependence on the US, or other crises-hit countries, and the stability and strength of its internal economic and financial system etc. According to Schwert (2011), the stock volatility has been high during the crisis period, but the heightened volatility was not as long lived as in the Great Depression. Yilmaz (2010b) reported that the business cycle spill-over has increased tremendously since September 2008 due to the global crisis, with the intensity highest in Dec 2008. Moreover, the business cycle spill-over during the 2008-2009 crisis has been mainly from the US to industrialised countries. Chinzara (2011), using South Africa, found that volatility in the macro-economy and stock market increased tremendously during the financial crisis and made the influence of the former on the latter more pronounced. We will look further at how industrial production and the stock market responded during the span of the current financial crisis.

2.6 Impact of the Financial Crisis on Industrial Production and the Stock Market

The crisis of 2007 led to a massive decline in world industrial production and an enormous drop in equity valuations. Stock markets showed the huge impact of the crisis right from the time the crisis sparked. Many companies depend on the financial system for financing their short-term liquidity and for expansion. When the financial system became less viable, the profitability of companies became dubious. The equity prices responded to the financial news almost simultaneously. From Feb 2007, the share values were escalating. On October 2007, global equity market capitalization was $59[17] trillion (an all-time high) but was wiped away to a little above $29 trillion by Nov, 2008 (Exchanges, 2012). The share prices started to fall from early 2008 in various countries, but the real equity disaster took place over 31 trading days (Sept - Oct 2008) as almost all indices collapsed by 30-40%[18]. The companies lost their share value and investors lost their wealth in investments. Due to increasing correlations among international markets during the crisis, the diversification strategy became void and the markets collapsed in tandem (Bartram and Bodnar, 2009). The world is still struggling in January 2014, after more than 6 years, but the global equity capitalization has largely recovered, with a latest figure of $57.17 trillion.

The extremely high stock return volatility reflected spiked uncertainty that caught much attention and prompted speculation of the economic consequences of the crisis (Schwert, 2011). Thus, stock return volatility resulted in busted investors and reduced consumer confidence and consumer spending. The demand for durable goods dropped significantly; putting a strain on companies' profitability, demand for imports and output. However, the market did not expect the volatility to be sustained for long (Schwert,

[17] Aggregate figure for all member stock exchanges.
[18] From 15 September 2008, the day Lehman Brothers filed for bankruptcy, to the end of 27 October 2008, during which AIG was bailed out.

2011) and thus the volatility dwindled down after peaking in November 2008. Although it did perk up twice afterwards (to 10% higher), the markets had already started stabilizing (Bartram and Bodnar, 2009).

As the crisis emanated from the US, the NYSE has been leading the global market in unfolding the uncertainty, and new relevant information from the US markets has been followed by markets around the world. This was examined by Cheung *et al.*, (2009), showing that during the crisis, the interrelationship between the US and other global markets, such as the UK and Japan, had a short-term causal relationship and a long-term co-integrating equilibrium, as this becomes stronger it confirms the presence of the contagion effect.

Figure 2.4: Stock Market Volatility in Developed Countries

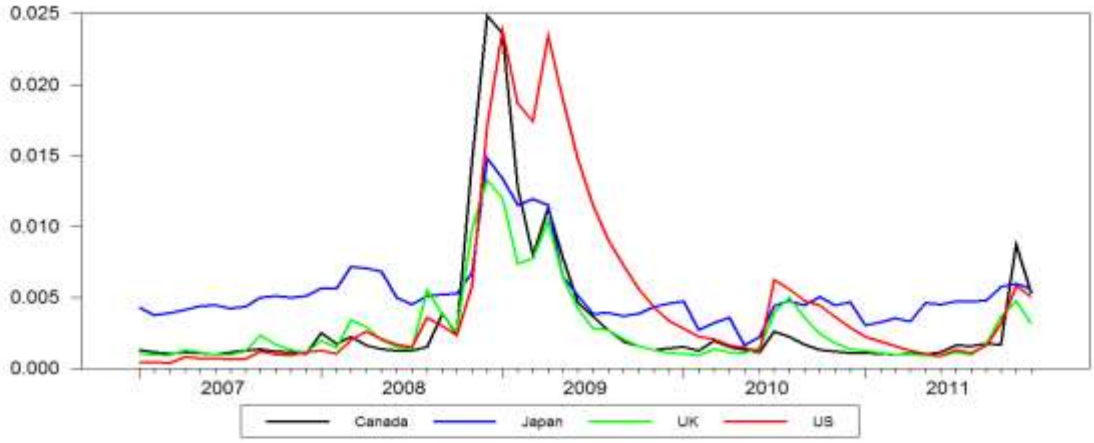


Figure 2.4 shows the conditional volatility of stock market volatility in the US, UK, Japan and Canada from January 2007 to December 2011. The stock market indices data has been obtained from DataStream.

Figure 2.5: Stock Market Volatility in Developing Countries

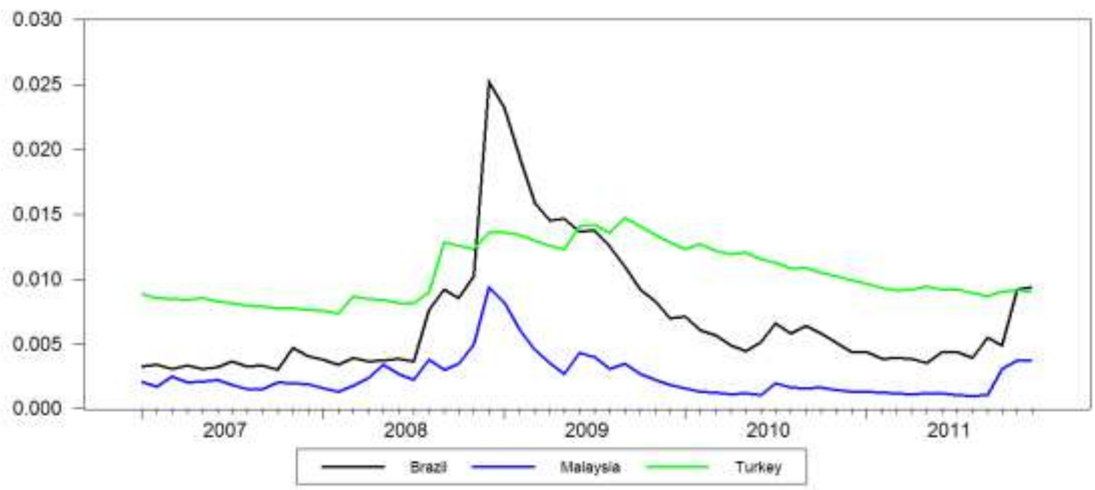


Figure 2.5 shows the conditional volatility of stock market volatility in Brazil, Malaysia, and Turkey from January 2007 to December 2011. The stock market indices data has been obtained from DataStream.

The aggregate demand for imports dipped due to the economic downturn around the globe, particularly in developed countries. Due to the greater possibility of credit defaults and the longer time span involved in international trade transactions, exporters are majorly dependent on trade financing, therefore, the lack of trade financing had a major hit on exports (Amiti and Weinstein, 2009). Moreover, the halt in credit creation on the supply (producer) side had a direct impact on the exports potential due to the excessive decline in external finance, including trade finance (Chor and Manova, 2010). As a consequence, the international trade flows lowered, compromising imports to the US and other developed countries. The output dropped due to the reduced demand for commodities and the shrinkage of available financing for running the production units. The massive drop in output showed in the third quarter of 2008 onwards, in most of the countries around the world (Chor and Manova, 2010).

Figure 2.6: Industrial Production - Developed Countries (Log)

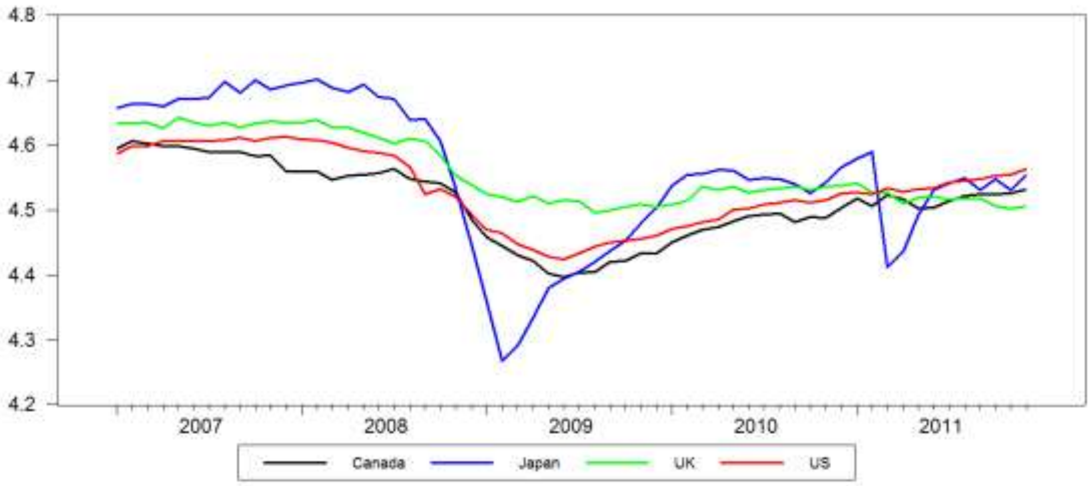


Figure 2.6 shows the industrial production growth in the US, UK, Japan and Canada from January 2007 to December 2011. The industrial production data has been obtained from DataStream.

Figure 2.7: Industrial Production - Developing Countries

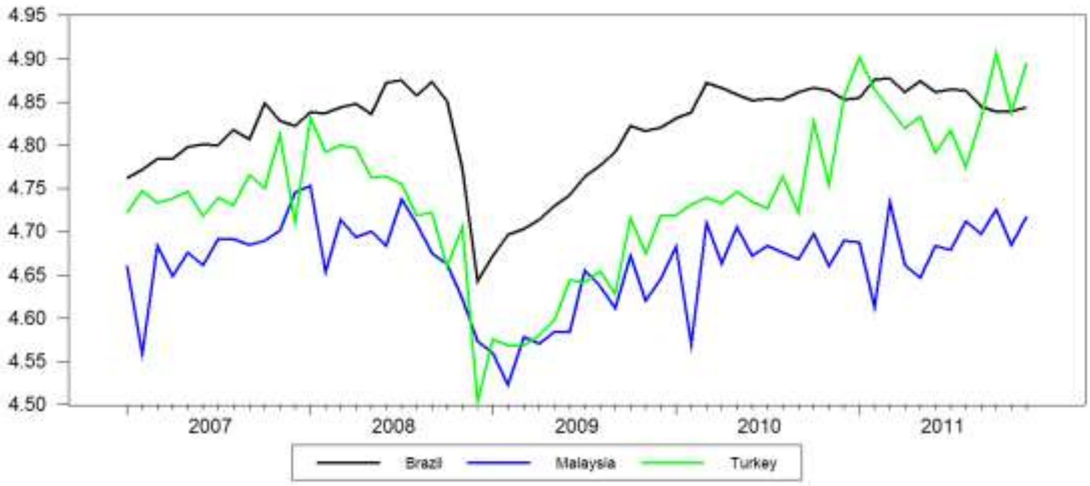


Figure 2.7 shows the industrial production growth rate in Brazil, Malaysia and Turkey from January 2007 to December 2011. The industrial production data has been obtained from DataStream.

2.7 Hypotheses

The research questions have been translated into two sets of hypotheses given below. The hypotheses can be explained through Figure 2.3, in which the two variables, changes in stock market volatility and the business cycle, can depict a number of relationships within the same country and across the countries.

2.7.1 Establishing Causal Relationship between Changes in Stock Market Volatility and the Business Cycle

Hypothesis 1a: There is a linear causal relationship between changes in Stock Market volatility and Business Cycles.

Hypothesis 1b: There is a non-linear causal relationship between changes in Stock Market volatility and Business Cycles

These alternative hypotheses aim to detect the causal direction between changes in stock market volatility and business cycles. The level of economic activity (expansion and recession) is critically viewed by investors as an indicator of macroeconomic prosperity, or otherwise. The stock market can be viewed as a reflector of the anticipations of the economy as a whole about future economic conditions. Economic activity carries news about future events that is absorbed by the market participants and gets reflected in the share prices (Bowden and Martin, 1995), thus affecting the returns and the volatility. The volatility, being a signal of uncertainty, affects the consumption, investment and output in the economy, causing the business cycle to move.

There is evidence that stock market volatility can predict variations in business cycles, such as in Fama (1990), Schwert (1990a) and Jay Choi *et al.* (1999). Whereas some more papers, such as Mauro (2003), Duca (2007), Beltratti and Morana (2006), Shyu and Hsia (2008), Kanas and Ioannidis (2010), show that stock market returns/volatility actually cause these changes in the business cycles. In the opposite direction, there is little evidence on the feedback causality from the output to stock market volatility as part of a number of macroeconomic variables, such as Beltratti and Morana (2006) and Engle *et al.* (2009). In addition, it has been shown that expansionary times are characterized by higher returns and less volatility in the stock market, whereas during recession returns on stocks are low and volatility is higher (Schwert, 1990), (Schwert, 2011).

The purpose of testing the linear and/or nonlinear relationship between the two time series is to establish grounds for testing the other hypotheses (2a, 2b, 3a, 3b, 4). The non-linear causal relationship between the two time series, i.e. changes in the business cycle (BC) and changes in stock market volatility (SMV), has not been determined in any of the research known to us. The reason for believing that the two time series may bear a non-linear causal relationship (1b), in addition to a linear relationship (1a), is that there exists evidence in the literature, such as Hsieh (1991) and Andreou *et al.* (2000), that financial time series, especially stock market prices, exhibit non-linear features. Similarly, Hiemstra and Jones, (1994) found nonlinearity in the stock-volume relationship and Kanas (2005) found that nonlinearity better explains the stock price-dividend relationship. Therefore, it can be rightly expected that the conditional variance of stock market returns based on stock prices bears nonlinear features. Stock return (or volatility) and industrial production need to be modelled in a non-linear multivariate setting (Andreou *et al.*, 2000). Thus, in the causal setting, hypothesis 1a alone may not fully explain the causal relationship.

2.7.2 Spill-over Effect of BC-SMV Relationship

Hypothesis 2a: A linear causal relationship exists between changes in the stock market volatility of country A and changes in the business cycle of country B.

Hypothesis 2b: A non-linear causal relationship exists between changes in the stock market volatility of country A and changes in the business cycle of country B.

These alternative hypotheses are unique to this research and are intended to test the transmission effect of changes in the stock market volatility and business cycle relationship on the business cycles of related economies. The null hypotheses for the cross-country effect, 2a and 2b, is that there is no causal relationship between changes in the stock market volatility of country A and/or changes in the stock market volatility of country B with the business cycle of country B for both parametric and nonparametric tests. The relationship needs to be tested in a multivariate setting as the assumption is that changes in the business cycle of country B is being caused by changes in the stock market volatilities of countries A and B. The difference between the two statements is that 2a tests for the linear relationship whereas 2b tests for the nonlinear relationship using the residuals of the linear causality relationship.

We expand on the reasons explained in Section 1.5.3 for bivariate causality between changes in stock market volatility and the business cycle in a single country, and examine the cross-country relationship between these variables in a multivariate model. The factors that get added in the assessment of the cross-country relationship include globalisation (financial and economic linkages), the spill-over of changes in volatility in international equity markets and the co-movement of international business cycles.

From the discussion on Figure 2.3, the following relationships become visible. International stock markets tend to move together, and changes in volatility get transmitted across the borders to other stock markets. With the advent of globalisation, business cycles have become more integrated resulting in business cycle transmission across countries. Therefore, the above discussion can be concluded to: 1) changes in the stock market volatility of one country (A) transmits to another stock market (B); 2) the business cycle of one country (A) is getting synchronized with the business cycle of another country (B); and 3) changes in the stock market volatility of country (A) causes its own country's business cycle (A) (based on literature and the result of the first hypothesis). These were the possible relationships drawn in Figure 2.3.

An assumption can be made, in view of all these relationships, that changes in the stock market volatility in country A does not relate to changes in business cycles of its own country alone, but rather this relationship may have a spill-over effect on the fluctuations in the stock markets and business cycles of countries (B etc.) that share financial or economic ties with the country under study. In other words, causality (linear and/or non-linear) runs between changes in stock market volatility in country A and the changes in the business cycle of country B, which are hypotheses 2a and 2b.

2.7.3 Financial Crisis

Hypothesis 3: The current financial crisis (2007-2011) has an effect on hypotheses 1 and 2.

This hypothesis is meant to test the relationship between the two main variables, changes in stock volatility and the business cycle, taking into account another factor – the financial crisis. The financial crisis has been discussed at length in Section 2.4. This research is being conducted at a time when the financial markets across the globe are experiencing the worst financial crisis since the Great Depression. The current financial crisis has left the asset and commodity prices depreciated (after the initial asset bubble burst), record high figures of bankruptcy and distressed companies, massive numbers of individuals have been laid off (unemployment is on the rise) and a decline in economic growth around the globe. It is highly appropriate to consider how a financial crisis of such magnitude changes the relationships that exist in normal times. Therefore, the aim is to study how the linear and non-linear causal relationship between the stock market volatility of country A and the business cycle of country B differs in the pre-crisis period and during the current financial crisis (2007-2011).

The relationships that exist in a stable economy may or may not pertain in an economy marked by crisis. According to Schwert (1990c), on average the stock prices decline before and at the time of the crisis and the return volatility increases after the crisis. At the onset of, and during, financial crisis, the circumstances of the financial markets and the economy become extraordinary. Thus, going back to our variables, given that changes in stock volatility does cause changes in business cycles, at a time of financial crisis the elevated volatility may result in a deeper dip in the business cycle. Research on previous financial crisis episodes indicates that during financial crisis, the business cycle falls below its pre-crisis level.

Therefore, the aim of Hypothesis 3 is to evaluate whether the bivariate and multivariate causality tests will give the same results during the global financial crisis as in normal times. We are taking into account the impact of the recent global financial crisis on the relationship of our key variables, but not significantly looking at the previous crises that have punctuated financial history as the previous crises are no match to the current crisis in every aspect.

2.7.4 Spill-over Effect of BC-SMV Relationship: Developed and Developing Countries Comparison

Hypothesis 4a: The linear causal relationship between the changes in stock market volatility of developed country A and the changes in the business cycles of developed country B is stronger compared to the relationship between changes in stock market volatility of developed country A and changes in the business cycles of developing country C.

Hypothesis 4b: The non-linear causal relationship between the changes in stock market volatility of developed country A and the changes in business cycles of developed country B is stronger compared to the relationship between changes in stock market volatility of developed country A and changes in the business cycle of developing country C.

Alternative hypotheses 4a and 4b explain the sensitivity of business cycle fluctuations in developing countries to the changes in stock market volatilities in the developed countries. The difference between the two hypotheses is that 4a aims to test the linear causal relationship whereas 4b assumes a non-linear causal relationship. These hypotheses have significance as we expect that the impact of an increase in stock return volatility, or changes in the business cycle of the developed country (e.g. the US), will differ on a developed economy's activity (e.g. the UK, Japan and Canada) than on a developing economy (e.g. Brazil, Malaysia and Turkey). In other words, based on our assumption that how a country responds to the volatility or business cycle spill-over from across borders and markets is dependent on its economic and financial ties with the country originating the spill-over, the economic activity in the developed economies is expected to be affected more by the news generated in other developed countries, as the financial and trade linkages and interactions they share with each other make them more sensitive to the changes in stock volatility and business cycles across borders.

These hypotheses are an extension of hypothesis 2.6.2. The data here is sub-categorized to distinguish the impact for developed and developing economies. Although there is research available on the volatility spill-over/ transmission across international equity markets of developed economies and developing economies (Wang and Firth, 2004), and also on the growing integration between developed and developing economies, we have not come across any work that looks at the transmission of volatility from the stock markets of developed countries to the economic activity (output) of developing counties, which makes this preposition one not tested before. Why this relationship is expected can be found in the discussion on return and volatility spill-over across international equity markets and the justification of the macro-financial connection extending beyond borders in Sections 2.5.1-2.5.3. If the data confirms that stock market volatility and/or the business cycle in the developed countries spills across borders to show greater influence on developed countries' stock market volatility or business cycles, the null hypothesis cannot be accepted.

We expand on the idea of Bloom (2007), which has been presented in the justification for the first hypothesis. The increased volatility would make companies and investors (local and international) cautious of an upcoming downturn in the business cycle. Companies may freeze their investment in new projects and employment, to keep resources at hand rather than expanding their productivity. Most of these companies do not have production units within the same country, rather they have manufacturing plants in different parts of the world. These manufacturing facilities will have to pause on hiring man power and would delay filling any natural vacancies being created. Therefore, the manufacturing process may slow down in the plants in the other countries, leading to reduced industrial productivity. Thus, changes in stock market volatility may have a spill-over effect on business cycles across borders and vice versa.

The developed countries, like the US, UK, Japan and Canada, are more integrated by shared financial and trade ties. The developing countries, like Brazil, Malaysia and Turkey, are connected with the developed countries through their exports and direct foreign investment, but the integration of these countries with the US is still less than that of the developed countries.

2.8 Reasons for Interest in the BC and SMV Relationship

The predictive or causal relationship between changes in stock volatility and business cycles has implications for the wider financial and economic world, due to the intricate relationship between the two variables having its roots in macroeconomics and finance. In order to comprehend these dynamic inter-relationships and the trends involving stock markets, much research is undertaken by researchers in academia and research based organizations e.g. NBER, IMF. The results of these studies and theories are used to build models and devise strategies for the firms and market participants to rightly anticipate and respond to the business cycle movements. Similarly, the growing financial system and its importance in an economic context have required researchers to focus on the dynamics of financial markets and their inter-links with the economy. This piece of research contributes significantly to the theory and empirical work done in this field.

The findings of this research will benefit policy makers, financial and economic analysts, risk-managers and portfolio managers. Policymakers are interested in identifying variables that affect economic productivity, in order to better forecast or manipulate the variables leading to expansion/recession and make informed decisions for the health and direction of the economy (Ahn and Lee, 2006). If the results of the study are as expected, the policy makers shall have to protect real activity from instability shocks through implementing monetary policy framework with flexible inflation targeting, adjusting interest rates upwards when stock prices rise and vice versa. (Giannellis *et al.*, 2010)

The investors, traders, portfolio managers, speculators and other stock market participants want to discover the factors surrounding stock prices and volatility (that comes from uncertainty). The reason for their interest is simple. Investors want to earn returns in the financial markets, portfolio managers wish to earn by managing the portfolios for the investment companies and helping their investors in achieving their desired returns. Furthermore, investors try to diversify their risk by investing in other stock markets across borders. Speculators aim to beat the market by taking positions at the best prices in stocks and options. Many professionals have come up with models that they claim work best in predicting the market trends and thus earning profits in the financial markets. The factors that forecast stock volatility become state variables in an investors' portfolio decisions for effective asset allocation (Paye, 2010). With the results of this research, the element of occasional irrationality in decision making can be minimized as the consequences of volatility in the financial markets will be considered.

When macroeconomic information (regarded as indicators of future stock movements) is released, the investors can use this relationship as a risk management technique for stress-testing and calculating value-at risk over the longer term (Paye, 2010). The volatility fluctuations in the stock market of a foreign country, e.g. the US, and the domestic country, e.g. the UK, will signal the direction of the economy of the domestic country, e.g. the UK.

Theoretically, if the economy is going into recession, investors can sell short in the stock market and benefit even from recessionary times by closing out the short position near the trough. Similarly, at the onset of economic recovery or expansion, investors can take long positions at the low prices and sell when the business cycle reaches its peak to earn profits.

The research findings can help in revamping the leading indicators of business cycles. Macroeconomic and financial variables (including various monetary aggregates and stock prices) have become components of the index of leading (business cycle) indicators. However, changes in the conditional volatility of the cross-country stock market, in addition to the country's own stock market volatility, has not previously been used as a direct indicator. Thus, if this research proves that changes in stock volatility of country A happen to cause changes in the business cycle of country B, with its inclusion into the series of indicators, leading economic indices will become more efficient at predicting the turning points of the business cycle (of country B).

Lastly, the findings of this work can be built on by academic research. The cross-country spill-over of the stock market volatility and business cycle relationship has not received any major recognition so far in the literature. However, in the present times, with frequent episodes of turbulent financial markets, frequent downturns in economies around the world and growing integration in world economies, and also increasing talk of contagion/spill-over, it is time to realize the power of the financial system. It will be useful to appreciate that one volatile financial (stock) market can cause waves in the economies of related countries, and similarly changes in the other countries' economy can influence the stock market volatility in the home country.

Chapter 3: Literature Review

3.1 Introduction

Finance and macroeconomics are two distinct fields, however some subjects are covered in both. Yet the perspective or the treatment of those subjects is often different in each field; the stock market is one such example. The stock market is the most significant market in finance, yet in macroeconomics it did not receive due credit for its link to economic activity until the late 1980s. Macroeconomists have not been particularly keen to consider the stock market as the sole significant predictor of the future course of the economy, but yet they did not disregard stock prices and returns in their estimations of business cycle turning points.

This chapter discusses the relationship between the stock market and the macro-economy (and its components) as has been researched in various contexts using different models and a variety of data sets. Economic activity (real activity) reflects aspects of production, consumption and investment. The variables that are used to represent the real activity are numerous, such as industrial production, GDP, GNP, interest rate, inflation rate, unemployment and real exchange rate etc. The health of the economy, based on these factors, is assessed by the level of activity, i.e. expansion/recession (boom/bust). The theory of the wealth effect claims a positive correlation between current stock 'returns' and future real activity; whereas the theory of uncertainty effect believes the stock 'volatility' affects the real activity (Romer, 1990).

In the literature, the influence of macroeconomic variables on the stock market has been examined for various reasons, and interpreted in different ways accordingly. Specifically in our area of interest, some of the theoretical objectives for examining this relationship in the literature are: 1) Determining the factors that help in forecasting stock prices/returns; 2) Testing the efficiency of the stock market (if the lag effect of macroeconomic variables impacts the stock returns, the informational efficiency of the stock market is challenged according to the 'Efficient Market Hypothesis' proposed by Fama (1970); and 3) Evaluating the causes for volatility in the stock market and how to deal with these.

In the literature, only a few researchers have looked at this relationship with respect to the prevalent state of economy, expansion and recession, such as Hamilton (1989) and Schwert (1990a). The majority of authors have linked the stock returns/volatility to macroeconomic variables, based on the time-invariant framework.

We elaborate, from the literature, the following four aspects of the relationship between the stock market and the real activity.

- Stock prices/returns as leading indicators, or the cause, of economic activity (with the emphasis on output/production)
- Determining the cause of the variation in stock prices/returns and, having found causes, their predictive content in the macro-economy.
- Stock market volatility leading to variations in economic activity or transmission of volatility from the macro-economy to the stock market. (Second moment of distribution- volatilities)
- Evaluating the stock market and business cycle relationship, taking into account the financial crisis

Uncertainty may originate in the stock market and transmit to economic activity, or uncertainty may arise due to anticipations about economic activity that finds its way into the stock market. However, there may be exogenous variables causing variation both in stock markets and in economic variables that determine the business cycle (Bittlingmayer, 1998; Chauvet, 1999). Nevertheless, the stock market is still known to predict the turning points of the business cycle. Baro (1989) found that stock market performance (one year lagged value of annual returns) successfully predicted eight out of nine recessions from 1926-1987, however it also wrongly predicted three more recessions during this period. The volatility in the stock market is countercyclical but this alone does not imply that volatility in the stock market encodes information about the formation of the business cycle, i.e. it can anticipate the business cycle or that it causes the boom-bust cycles (Fornari and Mele, 2009).

3.2 Theoretical and Econometric Models

This section discusses the relationship between the stock market and macroeconomic variables based on the development of theoretical and econometric models. It covers studies, over a span of time, which have introduced or developed new models describing the relationship between the two time series.

In the field of economics, Blanchard (1981) used a standard IS-LM model to show how output, the stock market, and the interest rates respond to the effects of monetary and fiscal shocks. The IS-LM model assumes that output is determined by aggregate demand and the level of prices can only adjust to its equilibrium value over time. IS-LM emphasizes the relationship between output and interest rates, whereas Blanchard's model focuses on the relationship between stock prices and output. In the context of the model, the asset prices are likely to forecast future output, but are not caused by the changes in output, as both variables are likely to respond to changes in the economic environment.

Chen *et al.* (1986) is one of the main papers that explore the effect of macroeconomic variables, including industrial production, on the stock market returns. The study was focused on the US, using a multivariate arbitrage model. They found a number of economic variables, including industrial production, to significantly explain the expected stock returns. However, their results did not support the consumption-based asset-pricing model as the consumption variable was found insignificant in the analysis. They concluded that stock prices/returns are exposed to systematic economic news and prices vary depending on the exposure to these shocks. This line of study was followed by many researchers over the years, by varying the variables, using different models and by experimenting on various data sets.

On the econometric front, Hamilton (1989) modelled quarterly real GNP using the regime switching process. He presented the phases of the business cycle, expansion and contraction, as two different economic regimes. He proposed that real output growth may follow one of two separate auto-regressions based on the state of the economy. The shift between the two-regimes will be determined by the outcome of an unobserved Markov Chain. He found that the recessions usually have shorter duration than the expansions. Hamilton and Lin (1996), based on data from the US, confirmed Schwert's finding that stock volatility is primarily driven by economic recessions. They used a time-series model that they believed was better at forecasting both stock volatility and economic turning points.

Romer (1990) has been frequently quoted in the literature for the theoretical explanation she has provided on the link between stock volatility, the estimated magnitude of wealth effect and uncertainty. She argues that increased stock market volatility causes uncertainty about future wealth, which leads to a decline in demand for consumer durable goods. Her results, based on a study spanning the period of 1891 to 1986 in the US, support the "uncertainty hypothesis", according to which, increased volatility leads to increased uncertainty about the future economy that negatively affects the consumption and investment spending, resulting in reduced aggregate demand. But her findings show that the 'wealth effect' of the stock market on real activity is insignificant or minimal.

Cochrane (1991) introduced a production based asset pricing model (using producers and production functions) in place of a consumption based asset pricing model. This study was based on US quarterly data from 1947:Q1 to 1987:Q4. The analysis shows that stock returns and investment returns are equal. The concept is used to give partial equilibrium explanations for the predictability of stock returns, which helps in forecasting real variables including investment and output (GNP), comparatively large movements of which determine the direction of business cycles.

The Engle *et al.* (2006) study is another well-regarded development on the econometric methodology of dealing with variables of interest. Their study was based on daily stock market returns and macroeconomic variables data for the US from 1885-2004. They have revisited Schwert's work of why volatility varies over time by using a new model that combines features of Spline-GARCH and MIDAS filtering. Spline-GARCH is different to conventional GARCH and other stochastic volatility models as it allows for unconditional volatility to change over time. This new class of model further enables them to distinguish between short and long-term sources of volatility and also links them to macro-economic variables. Engle *et al.* (2006) report that macroeconomic volatility (including industrial production and producers' price index) drives stock market volatility in the US.

Engle and Rangel (2007), using the exponential spline model for 50 countries with daily data (1885-2004), show that macroeconomic variables, including GDP growth, can explain the rise in stock volatility.

Engle *et al.* (2009) developed another model to examine the economic sources of volatility in line with Schwert's (1990c) work. The new model is the MIDAS-GARCH and links the macro-economic variables to the long-term component of volatility. It uses a mean reverting daily GARCH process and a MIDAS polynomial, which applies to monthly, quarterly or bi-annual macroeconomic variables. This characteristic is very useful when comparing data of two or more different frequencies. This model is claimed to have many advantages over the specification and process used by Schwert. They have examined the one-way predictive ability of macroeconomic variables for stock market volatility and found that both the level and volatility of industrial production growth contain information about financial volatility.

Casarin and Trecroci (2007) examine the relationship of stock (financial) volatility and business cycle volatility, using a Bayesian framework to time-series modelling. The backdrop of their work is that the tremendous increase in stock prices in the 1990s is believed to be the cause of a chain of events. Broad macroeconomic risk estimated by the business cycle volatility decreased, probably leading to the decline in equity premium and thus the decreased stock volatility. The results are based on quarterly data of the US from 1966, Q2 to 2003, Q3. The analysis comprises of two sets of variables: 1) stock index returns and, based on these, dividend yield and price-to-earnings ratio; and 2) industrial production, non-residential investment expenditure, real personal consumption expenditure and output gap. Their results show that the volatilities of both S&P and IP remained low for a greater time span. Stock volatility and business cycle volatility rise exclusively around episodes of contraction in GDP such as in 1990-91 and 2001. However, as this research dates only until 2003, the changing dynamics due to the recent turmoil in the financial markets and real economy have not been analysed.

Mele (2008), building on Schwert's findings, provided possible theoretical explanations and further empirical evidence for the stock market volatility and business cycle relationship using a tree model for the period January 1948 to December 2002. Mele finds the neoclassical model of asset pricing to be effective at explaining the countercyclical behaviour of stock market volatility (higher in recession and lower in boom) over the business cycle. The assumption is that risk-premia are counter-cyclical and asymmetric, whereas stock price and price-dividend ratio are pro-cyclical. The volatility in the risk-premia increases in bad times (rather than in good), which makes asset prices very responsive to the changes in economic conditions during recessionary times, thus leading to increased variation in price-dividend ratio and increased return volatility. The results of calibration and linear regression show that stock market volatility helps in forecasting the business cycle (industrial production growth). Similarly, in predicting stock market volatility, macroeconomic variables (inflation and industrial production growth) improve the forecasting results by 60% more than using past volatility information alone.

Yet another prominent study describing the link between variables, looking particularly at stock volatility in terms of uncertainty, is by Bloom *et al.* (2009), who suggested that time-variation in uncertainty is an impulse that drives the business cycle. They show that uncertainty (idiosyncratic and aggregate) is strongly counter-cyclical at the establishment, firm, industry and aggregate levels, as stock market volatility is higher by 42.2% during quarters marked as recessionary by NBER, indicating that macro-uncertainty is substantively higher during recessions. They used a dynamic general equilibrium model, calibrated on the Real Business Cycle Model but with a few changes. They treated uncertainty as an exogenous shock, with economic activity responding to it in the following manner. When uncertainty rises, the firms pause spending on investment and hiring. This reduces the hours worked and sharply hampers the output and productivity growth. As the uncertainty drops in the second quarter, the pent-up demand for new staff and new investments help in the rebound of productivity, as firms accelerate towards new thresholds. By the fourth quarter, the economic activity shoots above the long-run trend, and that continues for several quarters before returning to the average trend. A rise in uncertainty results in a substantial decline in aggregate economic activity. Moreover they also found that the presence of uncertainty shocks dampens the effectiveness of an expansionary policy.

Christiano *et al.* (2010) examine a risk shock that originates in financial markets and leads to fluctuations in business cycles. They employ a Dynamic Stochastic General Equilibrium Model and use US data to present their findings. They categorized the shocks into seven categories and looked at the contribution of each category of shock in GDP growth variation. They analysed the impact of these shocks during recession and crisis episodes of the 1990s and 2000. Their results show that shocks adversely affect consumption and investment, which implies that both of these are pro-cyclical. Corradi *et al.* (2012) devised a no-arbitrage model that explains the low-frequency stock volatility through business cycle factors (CPI and industrial production). They used a data set of 1950-2006 for their model and then tested if the model produces the same results as real data during the sub-prime crisis of 2007-2009. According to their model, the stock volatility and stock volatility risk-premiums[19] are driven by the business cycle factors. The model tracked the movement of stock volatility index (VIX)[20] and predicted that industrial production growth (a business cycle factor) can explain more than 85% of these variations. Over the period of the crisis, Jan 2007-March 2009, massive variations in the index can be tracked through volatility risk-premiums. In addition, the volatility risk-premium is reported to be more countercyclical than stock volatility. They conclude that stock volatility and volatility of risk premiums are both caused by business cycle factors.

3.3 News Announcements Effect

Much research has already been done on the news aspect of macroeconomic information. This line of research studies the impact of news of macroeconomic variables (including productivity, employment and inflation) on the stock market prices, returns and volatility. It tests different aspects of the stock market's reaction to macroeconomic news announcements, such as the

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[19] Volatility risk premium is defined by Coradi et. al (2012) as the difference between future market volatility under true probability and the risk neutral. It can be viewed as the quantified willingness of the representative agent to pay for insurance against the increase in volatility beyond his/her expectation. It is a general measure of risk-aversion.

[20] VIX is a volatility index, which shows the risk-adjusted expectation of future volatility in a month, maintained by the Chicago Board Option Exchange (CBOE).

nature and timing of the impact, the dependence of the impact on the state of the economy, and the international linkages determined by this relationship.

Huang and Kracaw (1984) proposed measuring the arrival of new information (relevant to changes in real output or employment) with stock return volatility instead of commodity prices. According to them, the volatility in the stock prices should reflect changes in the information arrival relevant to the output decisions. The empirical results, based on the Granger causality test, support the lagged information hypothesis. They found that US stock return volatility Granger-caused the level of aggregate output (measured by the log of real GNP and unemployment) during the period 1962-1978. McQueen and Roley (1993) show that the impact of macroeconomic news (industrial production, inflation and unemployment rate) on the stock market is dependent on the state of the economy. Before this study, most researchers could not find evidence of the stock market's response to macroeconomic news. During a strong economy, the news of higher than expected real activity results in lower stock prices, whereas if the same news arrives in a weak economic state, the stock price will increase. The findings are based on the data period of 1977: M9 to 1988: M5 for the US.

Becker *et al.* (1995), in order to identify the sources of international equity linkages, analysed the impact of macroeconomic news from the US (inflation and employment) on the US and UK stock return volatility, captured by stock index futures contracts. (The results were arrived at by running correlations and examining intraday volatility for stock future indices.) They found increased volatility in UK stock returns (for 30 minutes) surrounding US news announcements. Thus, the response of the UK stock market to US news is similar to the US market's reaction to its own news. Nikkinen *et al.* (2006) analysed the impact of US macroeconomic news announcements on 35 stock markets (their GARCH volatilities) around the globe with the objective of identifying integration among international equity markets. The results, using regression analysis, show that the G-7 countries, European countries other than the G-7, and selected Asian countries are integrated as they all respond to US macroeconomic news and don't provide much opportunity for diversification.

Kim (2003) studied the impact of international (US and Japanese) macroeconomic news on Hong Kong, South Korea and Australia during the period 1991-1999. They found the conditional volatilities in these markets to respond to international news about economic activity (including GDP, inflation and unemployment rate). Vrugt (2009) extended Kim's work by studying the impact of news on conditional and implied volatilities over a longer time period of 1996-2007. He found similar results, that US macroeconomic news was found to have a significantly large impact on conditional (GARCH) stock volatility in the said countries. Conditional variances are reported to increase between 28- 67% on the day of the news announcement.

Entorf *et al.* (2012) added to the previous literature on forecasting stock return/volatility by analysing high frequency business cycle data for Germany. They emphasized the news element of the macroeconomic variables on return and volatility, which can be significant for forecasting purposes. They examined the monthly news arrival of two business cycle forecasts[21] on the stock market index (DAX) at every 15 seconds. The analysis is based on data covering 2 Jan 2004 to 28 April 2006 and used the ARMA and GARCH models. The results show that stock returns immediately respond to the news in an asymmetric fashion, i.e. positive news shows a quicker and positive response in the stock returns, whereas bad news about the economic forecast is responded to with a lag.

3.4 Economic Activity to Forecast Stock Returns/Volatility

This section explains the use of economic activity, or more specifically the numbers of GDP and industrial production, to predict the returns or volatility in the stock market, and vice versa. Schwert (1988, 1990a) found that in the US during recession and periods of crisis, stock returns were low and volatility in stock returns was higher on average. Similarly, volatility in industrial production also remained high over recessions. This result, according to him, shows that the stock market is an important indicator of business cycles, and that volatility in the stock market can help in assessing the state of the

[21] Ifo Business Climate Index and ZEW Indicator of Economic Sentiment

economy. It also highlights that business cycles are asymmetric, as high volatility lasts for a shorter duration than the phase of low volatility. Schwert (1990a) arrived at these results using monthly data for a portfolio of US stocks for the period 1834 to 1986. He used two different statistical models, a linear AR model for conditional mean and standard deviations of stock returns, similar to Schwert (1988), and the second non-linear regime-switching Markov model, adapted from Hamilton (1989). On the econometric front, he found weak evidence that the Markov switching model added any incremental information to that provided by the autoregressive model. He showed that stock returns are a more reliable indicator when compared with stock volatility, and believed the latter could be used as an additional variable to assess the state of the economy.

Schwert (1990c) studied the factors responsible for changes in volatility over time. He believed that volatility in the macroeconomic variables may be the cause of this change, based on the present value model. In the present value model, the volatility of real activity and discount rates change with the variation in future expected cash flows. He found weak evidence of macroeconomic volatility in predicting future stock return volatility. In addition, the level of macroeconomic volatility explained less than half of the stock return volatility. However, the results indicated strong evidence for stock return volatility in predicting volatility in industrial production for the periods 1981-1987 and 1920-1952 using US data. Furthermore, Schwert showed that volatility (in the stock market and industrial production) is reliably high during recessions, indicating that stock market uncertainty is related to the level of economic activity. The possible reason for this is that stock prices fall prior to, and during, recessions, leading to a higher leverage during recessions that causes a rise in the volatility of leveraged stocks. However, in the couple of decades since then, there have been significant advancements in econometric methodology for volatility. One of the shortfalls of the Schwert, (1990c) model that is likely to have influenced the findings, is that the model did not account for the persistence properties of stock volatility, such as structural change and long memory (Beltratti and Morana, 2006).

Fama (1990) also evaluated the variation in expected returns and its possible causes. According to them, the possible sources of variation are: shocks to cash flows, or variation in the discount-rate due to the shock or time-varying element. The set of macroeconomic factors are considered to impact the stock prices either through future cash flows or the discount rate (risk-adjusted) in a standard discounted cash flow model. Fama (1990) used production growth rate as a proxy for shocks to the cash-flow. The study was based on US data for the period 1953-1987 using multiple regression tests. He finds high correlation between current stock returns and future production growth rates at monthly, quarterly and annual frequencies; which becomes stronger for longer horizons.[22] Thus, indicating that the stock prices reflect the value of cash flows at all future horizons. Future production growth rate explains 43% of the variance in stock returns, indicating that uncertainty arising about the future cash flows (carrying information about production) causes variations in the expected returns. Schwert (1990b) tested the stability of the relations explained by Fama (1990) after extending the data set to a century 1889-1988 for the US. He confirmed the results of a strong positive relationship between real stock returns and future production growth rates, even with a much larger data set.

Errunza and Hogan (1998) investigated whether macroeconomic volatility causes stock market volatility in seven of the largest European equity markets, namely, the UK, Germany, France, Italy, Switzerland, the Netherlands and Belgium, for the period January 1959 to March 1993, using VAR to test for linear Granger causality. The authors included the US in their analysis for comparison with the results of Schwert (1989b). They used industrial production as the proxy for real activity. Consistent with Schwert (1990c), they found that macroeconomic factors are not significant sources of stock return volatility for the US. Similarly, in the UK, Switzerland and Belgium, the return uncertainty doesn't reflect the fundamental uncertainty in the economy. For the other countries in the sample, return volatility predictions can be improved by including information about macroeconomic activity into forecasts. The response of stock return volatility to real and monetary volatility varies across countries. For Germany and France, monetary instability (monetary volatility) is an important factor, while for Italy and the Netherlands, industrial production is a significant factor. Impulse response analysis shows that in the countries

[22] Information about the production of a given period is spread over many past periods and affects the stock returns of all those periods. Returns of a given short-horizon have information about many future production growth rates. (Fama 1990)

where the stock market volatility is affected by the economic factors, the return volatility responds to the shocks with a 1-2 month lag.

Bittlingmayer (1998) found that in Germany, volatility has been higher before and during recession and stock volatility has been inversely related to output; volatility perks up when output declines. He presented a view that stock returns volatility and output may be simultaneously affected by an exogenous variable of 'uncertainty' (political as in the case of Germany). Prior studies on the US have referred to the generic uncertainty of an indeterminate source reflected in stock volatility, Bittlingmayer (1998) believes this uncertainty is caused by political shock.

Cheung and Ng (1998) looked at the long-run co-movement of stock prices and aggregate economic variables (including real output (GNP) and real consumption) that are considered to drive prices in the US, Japan, Italy, Canada and Germany. They devised an Error Correction Method that enables them to study both short-term and long-term variations in stock return. The results show that ECM provides incremental information on the stock return variation that was not covered by the commonly used proxies for time varying expected returns, as in Fama (1990). They also employ the Johansen (1991) procedure to test for the presence of co-integration, and find long-term co-movement in the stock returns and real activity for all five countries.

Jay Choi *et al.* (1999), based on the studies of Fama, (1990) and Schwert (1990), examined the relationship between real activity (industrial production) and stock returns. They ran error correction techniques and cointegrations on the G-7 countries. The results of Fama and Schwert are subject to limitation due to the in-sample OLS procedure, which selects regressors based on their goodness of fit. Jay Choi *et al.* (1999) used an out-of-sample procedure in addition to the in-sample process. The result of the in-sample cointegration shows significant positive co-movement between industrial production and the lag of stock returns at monthly, quarterly and annual frequencies. Regression with the error correction term shows that past stock returns cause the log of Industrial production at all frequencies for all countries, except Italy. These results conform to Fama and Schwert's findings, and support the forward-looking trend of stock prices. The out-of-sample procedure shows that stock returns are prescient of future industrial production growth in a few countries for a few frequencies, as sometimes future IP is so predictable that stock returns can only provide a minor contribution towards improving the forecast.

Binswanger (2001) used a very similar data set as Jay Choi *et al.* (1999), 1960-1999 in the G-7 countries. He ran the analysis using both GDP and industrial production (both figures quarterly) for presenting economic activity. He divided the set into sub-samples to measure if the relationship breaks down in the period of boom. His results of co-integration are different to Jay Choi *et al.* (1999) and do not support evidence of cointegration in the US for the said sample period between stock prices and real economic activity. Thus, they moved on to using OLS regressions instead of the error correction method. They found that for the entire sample period the relationship between stock returns and real activity, measured by industrial production/GDP, is significant, but when the time-series is divided into sub-samples, the relationship between the variables breaks down in the US and Japan in the early 1980s, and a temporary break down may have occurred in Canada and Germany too, but then the link revived for these countries in the 1990s. Biswanger attributes the structural break to the speculative bubble in the US and Japan over the 1980s.

Campbell *et al.* (2001) studied the pattern of realized volatilities by segregating the volatility into Firm, Industry and Market volatilities. Similar to the findings of Schwert (1990), they showed that market (and industry) variances over the period of 1926-1997 in the US have been quite stable and exhibit no significant trend. However, firm-level volatility moved significantly upwards, with volatility having more than doubled over this time span. The three volatility time series show a significant increase during economic downturns, and lead into recession. They indicated that volatility (especially industry level volatility) helps in predicting US GDP growth rate.

Hassapis and Kalyvitis (2002) found evidence that real stock returns are a good predictor of output growth (industrial production) in the G-7 economies (except Italy), and also that the two time series were highly correlated. The findings are based on the Vector Autoregressive (VAR) methodology. The Granger causality tests shows causality running from real stock prices to output for the US, UK, Japan and Canada for annual and quarterly frequencies, and for Germany based on the quarterly dataset. Analysis of exogenous shocks to real stock returns and growth show that positive shocks result in a positive change in output. The impact of shock on real stock prices shows on the output with a lag of 3-4 quarters on average. The effect of unanticipated shock in growth remains pronounced on the output for 2-3 quarters. In both cases the exception is Japan, where the output carries the effect of the shock for longer, and the shock in output negatively affects the future stock returns, lasting up to a span of 8-12 quarters, after which real stock prices return to the trend-line. Morelli (2002) investigated whether conditional macroeconomic volatility, based on variables including industrial production, can explain the conditional stock market volatility in the UK using monthly data over the period January 1967- December 1995. Conditional volatilities were calculated using ARCH and GARCH. The results show that volatility in the macroeconomic variables does not predict changing stock market volatility.

Davis and Kutan (2003) have done similar work to Schwert (1989) on an extended international data set (post 1957). They looked at the impact of movement in real output and inflation together on stock returns and conditional volatility using GARCH and EGARCH models. The results support Schwert's (1989) findings of only weak evidence for macroeconomic volatility having predictive powers for stock volatility. Out of 13 industrial and developing countries, industrial production has no effect on stock returns for any country except Israel. Volatility in output growth shows an influence on stock volatility for only four countries, and is also not very significant.

McMillan (2005) examined the long-run relationship between two macroeconomic variables (industrial production and 3 months interest rate) and US stock prices (S&P 500 index). The use of these macroeconomic variables is based on the concept of discounted cash flow, where a demand shock results in a future rise in industrial production, which increases the cash flow and the stock prices. Their findings are derived from VECM for co-integration using monthly data for the period 1970 to 2000. The results show that stock prices have a positive long-run relationship with industrial production and a negative relationship with the short-term interest rate. The author has also used the recursive cointegration test to show that the relationship between macroeconomic variables and stock prices substantially changes over time.

Beltratti and Morana (2006) studied the economic causes of volatility persistence following the work of Schwert (1990c). They have looked at the relationship of stock volatility and macroeconomic activity (comprising of output growth, inflation, federal funds rate, and money growth variables). They used a multi-component econometric model that takes care of structural breaks and estimates dynamics with different persistence characteristics. Unlike Schwert (1990c), they found that US stock market volatility is characterized by the presence of long memory and structural change. Thus, they believe this evidence, along with the advancements in econometric models of time-varying volatility since Schwert's original study, requires adopting newer methodology to deal with these aspects. Their analysis is based on Probit models and fractional cointegration analysis on data from the US, S&P500, for the period 1970-2001. They found that the high volatility regime has been unusually lengthy compared to in the past, qualifying Campbell *et al.'s* (2001) findings. Furthermore, they found bi-directional causality between volatilities in the stock market and macro-economy, in line with Schwert's findings, but they found that macroeconomic volatility exercises a strong influence on persistent and non-persistent stock volatility, whereas the causality from stock market volatility to macroeconomic volatility is only weak, which according to Schwert was the other way round.

Ratanapakorn and Sharma (2007) analysed the short-run and long-run relationship between macroeconomic variables and stock prices under a floating exchange rate regime. The macroeconomic variables selected were real economic activity, inflation, money supply, short and long-term interest and foreign exchange rates. The study was based on US data covering a span of 1975-1999. VECM together with Granger causality tests were used. A positive relationship was witnessed between stock prices and industrial production. On testing for short and long-term causality, all the variables were found to Granger-cause stock prices only in the long-run. However, short-run causality runs from stock prices to industrial production and other macro-economic variables. The presence of cointegration and causality again signal that the US stock market is not efficient, as the macroeconomic variables can be used to forecast the future stock prices.

Diebold and Yilmaz (2008b) studied the macro-financial relationship, to be able to predict GDP and return volatilities. They used data from 46 countries covering 1961: Q1 to 2003: Q3. They ran the analysis in two ways: firstly, following Schwert's technique of exploiting time-series volatility, estimating the VAR model for each country and conducting causality tests. The results based on this analysis are the same as Schwert's mixed results. Secondly, they coupled cross-section volatility analysis with time-series, using a fixed effects model. They found that the fundamental GDP volatility (of business cycles) causes volatility in the stock market, but evidence for reverse causation could not be found. Thus, according to them, real economic productivity acts as a leading indicator in predicting stock prices, and the variation in production growth is likely to cause volatility in the stock market.

Fornari and Mele (2009), in an examination of US post war data, found that financial volatility (uncertainty) is extremely informative for future economic activity. Their work also relates to Bloom (2009) and Bloom *et al.* (2009). Fornari and Mele (2009) defined volatility as the moving average of past absolute returns. They used monthly data of the US from January 1957 to September 2008. The aggregate stock volatility is negatively correlated with industrial production growth (one year), confirming the countercyclical features of stock return volatility. Volatility also decreases sharply as the economy goes into recession. The results show that stock volatility explains 30% (at the one year horizon) and 55% (at the two-year horizon) of the economic growth rate during the great moderation era. Stock market volatility, together with other components of financial volatility, explains 30% and 40% of growth at the one year and two years horizons. They further show that combining aggregate stock market volatility (aggregate risk) with term spread (risk-premium and monetary policy) improves the forecasting results for business cycles, and can reasonably track and predict. However, all the combinations of variables they tested do not give consistent results across all sample periods, which may suggest that the model is not as good as it first seems (Di Mauro *et al.*, 2011).

Campbell and Diebold (2009) found that the expected business cycle is an important predictor of excess return, which is in line with the concept that excess returns are counter-cyclical. They found that both risk and risk aversion contribute to this counter-cyclicality of expected excess returns. The results are based on variables estimated from survey data from 1952:Q1 to 2003:Q2 and multiple regression analysis.

Kanas and Ioannidis (2010) assessed the causal relationship between real stock prices and real activity, taking into account the issue of regime switching for the UK spanning the period 1946-2002. They defined a Markov Switching VAR model that allowed for univariate and bivariate regime switching. The results supported regime switching in the causality running from real stock returns to industrial production growth, making the causality vary across regimes. Real stock returns caused significant variation in industrial production growth only when the volatility (uncertainty) in the stock market is lower, the causality diminishes as uncertainty heightens. These results are similar to findings of Kim and In (2003) for the US showing that the lead-lag relationship (in terms of causality tests) is not constant and varies over time. The regime-independent causality could not be evidenced among the variables, in contrast to Hassapis and Kalyvitis (2002) and Jay Choi *et al.* (1999). But then Jay Choi *et al.* (1999) studied the data span 1957-1996, which is considered mostly a period of low volatility, for which Kanas and Ioannidis (2010) also find causality.

Raunig and Scharler (2010) discussed the relationship between stock market volatility and the business cycle by quoting evidence from literature, estimating simple statistics and presenting them on the charts. They estimated volatility using several models: historical volatility, GARCH, GJR and Implied volatility based on the volatility index for the US economy and stock market from 1960 to 2008 (196 quarters). However, they did not use any econometric model to show the link between the stock market and the business cycle. Raunig and Scharler supported the concept of the 'Uncertainty Hypothesis'. Raunig and Scharler (2011) estimated the impact of stock market volatility on consumption (durable and non-durable) and investment using post-war US data. They believed their results supported the view of 'Uncertainty Hypothesis', as the stock market volatility was found to substantially reduce consumption (especially of durable goods) and investment growth.

Croux and Reusens (2011) analysed the predictive power of stock prices for future domestic economic activity (GDP growth). The contribution of this paper has been the segregation of Granger causality in the frequency domain, slowly fluctuating components and quickly fluctuating components. The data comprises quarterly figures for the G-7 countries (varying start dates to 2010: Q2). Geweke's test of Granger causality with provision for frequencies is applied to a single country setting and a multi-country setting. The results confirm Granger causality from stock returns to GDP growth in both settings at the slowly fluctuating components, whereas the results are weaker at the quickly fluctuating components. The Pierce test was also conducted which yielded the same results. This research could only identify the strength of the predictive ability; it could not test the channels through which stock prices connect with real economic activity.

Building on Bloom's research, Bachmann and Bayer (2011) analysed whether shocks to a firm's profitability risk can cause major boom-bust business cycles. They used a heterogeneous firm dynamic stochastic general equilibrium model using the 'wait and see' investment property (used by Bloom) on German firm level data (1973-1998), broader in scope than the comparable US data set. The results show that firm-level shocks are responsible for only 15% of the volatility aggregate economic output. Thus, time-varying firm-level risk alone does not cause the year-to-year business cycle fluctuations. Even when time-varying risk is combined with aggregate productivity shocks, it doesn't produce realistic variations in the economic cycle.

Similar studies have been done on less developed markets that are not treated as main-stream international markets. Mehrara (2006) focused on Iran and found evidence of unidirectional causality from the economic variables (industrial production, money supply and value of trade balance) to the Iranian stock market volatility. She used the Granger causality test of Toda and Yamamoto (1995). According to Mehrara (2006), the fact that macro variables lead the stock prices indicates the informational inefficiency of the Tehran stock exchange. Rasiah (2010) looked at the relationship of macroeconomic activity (including industrial production, money supply, real exchange rate, and CPI) and the stock market for Malaysia over 1980 to 2006. They used cointegration techniques and vector error correction methods to find a positive long-run relationship between real stock returns and macroeconomic activity. Furthermore, generalized decomposition analysis shows that of all of these variables, CPI, money supply and real exchange rate have had a major influence on volatility in Malaysian stock prices. Shocks in the stock market are not found to impact the forecast variance of industrial production, which is a relatively exogenous variable. Wang (2010) studied the relationship between volatilities in the stock market and the macro-economy (CPI and GDP) in China from 1992 to 2008. They also considered the influence of the short-term interest rate on economic activity and the stock market. The volatility for each variable is calculated using the AR-EGARCH model, and the causal relationships are analysed using the lag-augmented VAR model. Wang could not find any significant relationship between stock volatility and volatility in real GDP. He attributes their results to the less efficient stock market of China due to its detachment from the main stream economy, unlike the US and related countries. He also explained the reasons that make the Chinese stock market not such a good representative of the Chinese economy.

3.5 Stock Returns/Volatility leading Macroeconomic Activity

Some research findings also suggest mixed results, or bi-directional causality, as in the following papers. Fischer and Merton (1985) explained the link between finance and the macro-economy based on the results of the VAR model. They argue that increases in the real value of the stock market index (stock prices) are powerful predictors of the growth rate of GNP and its components, investment (fixed and inventory) and consumption expenditure.

Lee (1992) examined the causal and dynamic relationships between real stock returns (NYSE), inflation, real interest rates and growth in industrial production (measure of economic activity). The findings are based on US data from Jan 1947 to Dec 1987 and the multivariate VAR model. He found stock returns to be positively correlated to growth in industrial production, indicating that a rise in real stock returns represents the expectation of an increase in industrial production growth. Real stock returns are found to explain 10.61% of the variance in industrial production, and the latter positively respond to variations in stock returns for the first 12 months, after which the impact dies out. These results support the view that the stock market rationally leads the changes in real economic activity, as held by earlier studies such as Schwert, (1990a) and Fama (1990).

Domian and Louton (1995) also build on the premise that the stock market predicts downturns in the economy and needs to be considered by forecasters. Their analysis is based on US data ranging from 1948 to 1992. They found that the unemployment rate suddenly perks up following negative stock returns, whereas the unemployment rate drops slowly subsequent to positive stock return shocks, showing an asymmetric relationship. Domian and Louton (1997), using US data, find that the predictive power of stock market returns for industrial production is asymmetric, i.e. negative shocks in stock returns have greater impact than positive shocks.

Estrella and Mishkin (1998) focused on predicting recessions, using out-of-sample performance. The recession variable was constructed using NBER dates. The analysis is based on quarterly data from the first quarter of 1957 to the first quarter of 1995. The results show that stock-prices act as a good predictor in the short-term horizon, especially for one, two or three quarters. However, over the long-term horizon the yield spread provides better predictive results. Thus, a combination of the two variables has the best predictive power (among the simple financial variables) for all horizons. The authors believe these financial variables can complement other macroeconomic indicators and the sophisticated models employed for predicting economic activity.

Chauvet (1999) tested their Markov Switching dynamic factors model using stock market fluctuations to predict the turning points of business cycles. He constructed two dynamic factors, a stock market indicator and a business cycle indicator. The two factors comprise of a number of financial (including stock returns) and economic (including industrial production) variables. The factors are allowed to switch non-synchronously over time. The data is based on monthly frequency from 1954: M2 to 1992: M12 for the US. The results support the hypothesis that the constructed stock market factor is more efficient at predicting business cycle turning points than Composite Leading Indicators in real time.

Ahn and Lee (2006) looked at the first and second moment relationship between the stock returns index and industrial production growth rate using GARCH (AR and VAR) and BGARCH (AR and VAR) models for five developed countries, the US, UK, Italy, Japan and Canada. The sample period for this research was 1975 to 2000. They found that increased volatility in real output is likely to be followed by high volatility in the stock market, and increased stock volatility is followed by high real output growth volatility. Yet their findings show a significant relationship between underlying variables only in the case of the US and Italy.

Duca (2007) investigated the causal relationship between stock market prices (indices) and the economy (GDP) using quarterly data of the US (1957-2005), Japan (1957-2004), the UK, France and Germany (1970-2004). The results of the Granger Causality test show unidirectional causality running from the stock market index to GDP in all the countries except Germany, where no causal relationship has been found between the two variables. Duca suggests that the absence of a causal relationship in the case of Germany may be due to its small market capitalization relative to the level of economic activity. The reason for the presence of causality has been linked to the present value model. Stock market prices may be causing GDP as expected future dividends are a good proxy of future economic activity. Prices of current stock are a reflection of the investors' demand and supply and thus information and expectations of future economic activity could be embedded in them.

Rahman (2009) studied the impact of industry-level stock return volatility (rather than aggregate market volatility) on the state of the economy through macroeconomic factors (GDP, inflation and unemployment). The study is based on Australian data for the period 1973 to 2004. The industry indices are taken at a daily frequency and are used to calculate realized quarterly industry volatility, following the procedure of Campbell *et al.* (2001). They used the nonparametric method of coincident indicators that shows that industry-level volatility is a leading indicator of the cycles of GDP and inflation. Using VAR based multi-step Granger causality tests and impulse response analysis they also find unidirectional causality from industry-level volatility to macroeconomic variables. In addition, it is shown that industry-level volatility carries better information about the future economic state compared to stock market volatility.

Fornari and Lemke (2010) forecast recession probabilities using a number of financial variables (including stock returns). The ProbVar model is used to forecast the business cycles for the US, Japan and Germany for the sample period 1960:Q1 to 2008:Q3. The results indicate that the model was a good fit for the US but did not work as well for Germany, and forecasts for Japan were the least accurate based on this model. However, the established finding that financial variables help in forecasting business cycles and downturns was confirmed by this study.

Giannellis *et al.* (2010) studied the short-run dynamic relationship between stock market and real activity using the Cross Correlation Function and EGARCH model. They analyse the volatility transmission between the stock market and the macro-economy in the US and the UK from January 1970 to December 2002. The results of the analysis show that the Industrial production growth rate leads the stock prices both in the US and the UK, whereas changes in stock returns do not lead to variations in industrial production growth. Also, when a significant positive and bi-directional volatility spill-over occurs between the two markets, an increase in stock return volatility leads to an increase in industrial production volatility, and vice versa. The volatility transmission is found to be asymmetric in the UK but not in the US, i.e. the volatility resulting from negative news transports quicker than the variation due to positive news. This finding is in line with the previous wisdom that there is high volatility in the stock market during recession. However, their findings do not explain the case of the current financial crisis of 2007-2011 as to how these two variables respond in the presence of crisis.

Vu (2014) reported that movements in output growth can be predicted by stock market volatility in a sample of 27 countries. This research based on a dynamic panel model, shows that stock market volatility appears to be a strong predictor of output growth in the succeeding one or two quarters. Further, increased level of stock market volatility is detrimental for output growth not only during the financial crisis period, but under normal circumstances as well.

Thus, literature on macro-financial relationships shows that results vary depending on the countries and time period analysed, the prevalent economic state and the econometric models used. However, it is evident that there exists some level of relation between stock return/volatility and economic growth, whether that be cointegration, causal relation or predictive ability. There is significant literature available on the interaction between the stock market and economic activity on forecasting and/or causing variation in one of the two variables. However, the gap in the literature is that almost all research focuses on linear relations, using a variety of models, but ignores the non-linear characteristic of return/volatility series. Thus, we test the non-linear causal relations among the said variables as in hypothesis 1. The next element that we incorporate in our framework is the influence of another country's stock volatility or macroeconomic activity on the domestic macro-financial relationship. Moreover, we make comparisons between the influence of a foreign country's variables on developed and developing countries.

3.6 Cross-Border Spill-over Effect of the Macro-Financial Relationship

While the literature has continued to expand in two distinct streams, there has been some thought towards combining the two sets of knowledge: i) a macro-financial link that examines the relationship between the macro-economy and stock market from different angles using various models; and ii) the growing connection between the stock markets and integration of business cycles across countries leading to return and volatility spill-overs. Researchers have recently looked at countries as part of the globe and have analysed their macro-financial linkage, where influences of other countries' financial markets and economy have been observed on the domestic relationships.

Canova and De Nicolo (1995) analyse the relationship between stock returns and real activity as an International General Equilibrium Model of the business cycle. The data set includes five countries, the US, UK, Germany, France and Italy, and an aggregate they call Europe, for the period 1973-1991. They proxy expected returns by dividend yield and proxy shocks to the expected future cash flows by GNP, following Fama (1990). They find that international data strengthens the relationship between domestic variables of stock returns and GNP growth. European lagged stock returns were found to explain European as well as US GNP growth rate, and US stock returns explain European GNP growth. However, future US GNP doesn't explain European stock returns. The cross-country spill-over of stock returns and real activity occurs through three possible international transmission channels studied. These channels are: shocks contemporaneously correlated across countries; production interdependencies; and consumption interdependencies. The impact of production interdependencies is important when the international cycle is driven by technology shocks, and the effect of consumption interdependencies is larger when government shocks drive the cycle. (Canova and De Nicolo, 1995).

David (2000) acknowledged the literature on the integration of international stock markets and the macro-financial relationship of macroeconomic variables and indicated the need for combining the two concepts. In his study he examined the co-integration or long-run relationship among macroeconomic variables (interest rates, industrial production and real exchange rate) and stock indices. The effect of these domestic macroeconomic variables, together with an international (with the US as representative of the global economic environment) and regional stock market was looked at on a domestic stock market, as it is supposed that the economic environment of the other country has been captured by the behaviour of that country's stock index. The study is conducted on the UK, Germany and France using the error or equilibrium correction model over the time period of 1980 to 1995, leaving out the 1987 crash. This research highlights key macroeconomic variables such as output, inflation and interest rate as significant determinants of stock market movements in the sample countries.

Nasseh and Strauss (2000) also found a significant integrating relationship between stock prices and industrial production in Europe using a multivariate co-integration framework. Their research focused on European countries (France, Germany, Switzerland, Italy, the Netherlands and the UK) for the period 1962-1995 with quarterly frequency. They found evidence of international spill-over, as an increase in industrial production in Germany brings variations in stock prices in four (out of five) economies. Furthermore, they used Variance Decomposition methods and found that domestic and international macro-economic activity can forecast (37%- 82%) stock prices after four years in the European countries studied. Thus, findings of this research support the results of Canova and De Nicolo (1995).

Aslanidis *et al.* (2008) studied the reasons for co-movement between stock prices across the US and the UK. Among the reasons highlighted was the role of macroeconomic information leading to interdependence. The results of time-varying conditional correlations show the US and UK equity markets being influenced by international financial and macroeconomic (interest rate, exchange rate and inflation) variables. However, the results indicated that from the year 2000 onwards, the economic variables alone do not explain the increasing correlation between the US and UK stock returns, as they did prior to this time.

Kanas and Ioannidis (2010) went one step further and examined the cross-country effect of US stock returns (lagged, real) on the industrial production growth of the UK. The data set covers the period 1946-2002. They employ the Markov Switching VAR (trivariate) model. They find that US stock returns Granger cause a joint combination of UK stock returns and UK Industrial Production. The results are in agreement with Canova and De Nicolo, (1995) and show that the addition of the US stock market in the model strengthens the role of UK lagged real stock returns in explaining UK future growth rate. It also provides evidence of transmission channels and consumption interdependencies between the two countries. Kanas and Ioannidis (2010) explain that it is possible that US stock returns hold significant information about the UK stock market which is then transmitted to the relationship of UK stock returns and industrial production. The results show that the causal relationship between the variables is not regime dependent, and causality is statistically significant in both regimes.

Milani (2011) studied the influence of large foreign stock markets on relatively smaller open economies, using Bayesian methods. The results show that US and UK stock market volatility cause changes in the Irish output growth rates and similarly US and Germany stock market fluctuations affect Austrian output growth rates. He attributes such causality due to the international wealth effect and maintains that foreign stock price fluctuations play a significant role in affecting domestic expectations about future output gaps.

Espinoza *et al.* (2012) built on literature on the spill-over effect of business cycles, looking at the influence one country's business cycle casts on another country's business cycle. They included financial variables as explanatory variables in the hope of forecasting business cycles more effectively both domestically and internationally. The study is based on three economic regions, the US, the Euro area and the rest of the world, for the time period 1970:Q1 to 2007:Q4. The Euro area comprises of Germany, France, Italy, Spain, Belgium and the Netherlands. The rest of world includes a weighted average of Australia, Canada, Denmark, Norway, New Zealand, Sweden and Switzerland. The real activity is measured by GDP and the financial variables comprise of stock market indices, dividend yields and yields (3 months, 10 years). The results show that financial variables do not improve the forecasts of business cycles across countries. However, the research is based on linear models and frameworks and the authors suggest that using non-linear frameworks may bring different results.

Another recent paper that studies the link between these variables across borders is by Chen and Wu (2013). Using a simple Bayesian dynamic factor model on a group of 34 countries, from 1995 to 2009, they found that the global factors (including maro-economic shocks) account for significant portions of an individual country's stock market volatility and its macroeconomic fluctuations. Their results suggest that cross-country macroeconomic risks may be a cause of the co-movement of stock markets in an increasingly integrated global economy.

Becker *et al.* (1995) and Nikkinen *et al.* (2006) also point out the link between cross-country spill-over of the stock market and business cycle relationship. From the literature discussed above, it is clear that there is some evidence of possible cross-country relationships between stock market and macroeconomic variables, especially industrial production. However, to our knowledge no research has looked at the causality of stock volatility in one country on the industrial production/level of economic activity of the other country, or the changes in a business cycle in one country influencing the changes in stock market volatility in a non-linear multivariate setting, which forms our second hypothesis.

3.7 SMV- BC Relationship during Financial Crisis

Recessions are intrinsically different, both in terms of what causes them and how the initial shocks spread across the economy (Di Mauro *et al.*, 2011). Stock return/volatility and the business cycle relationship may be influenced by rare or unusual events, such as unexpected shocks, or major events like a financial crisis. The recent financial crisis of 2007-2011 has had a severe impact on stock market prices and return volatility in 2007-2008. It has also had a long-run influence on the industrial production growth and economic state of countries around the globe. We now look at the literature that has studied macro-financial relationships considering financial crises of the past and present.

Bernanke (1983b), in his study of the Great Depression, reported that financial crises cause financial losses that exacerbate recession in the economy. Schwert

(1990a), mentioned earlier in the chapter, studied the relationship between business cycles, stock market volatility (risk) and financial crises in the US (1834 to 1987) and reports that an exogenous volatility shock in the stock market could increase the probability of financial crisis, but stock volatility cannot be blamed for the crisis. He showed that the stock market is very sensitive to a crisis, as the stock market volatility rises during the financial crisis. He used dummy variables to capture the effect of a crisis period. The results, based on the linear AR model and a variation of the non-linear Markov Switching model, indicate that stock volatility was considerably higher on average during and after episodes of crisis and the Great Depression. Furthermore, the periods of high volatility are shorter than the duration for which low volatility persisted, which provides evidence that business cycles are asymmetric.

Cappiello *et al.* (2006) found that correlations between the US, Europe, the EMU and Australian stock return volatility significantly increased during times of financial turmoil, such as the crash of '87, the beginning of the Gulf war and the Asian Financial crisis. They used the Asymmetric DCC model to show that when bad news arrives in a financial market, the conditional correlation between regional equity markets rises, making diversification ineffective. Mun and Brooks (2012) looked at the changing nature of correlations between world financial markets (developed and developing) during the current financial crisis. They found evidence of de-coupling (increase in correlations) as the news of the crisis evolves in the early stages. Also, the analysis shows that changes in correlations are due more to the changing volatilities and less as a cause of the news.

Chinzara (2011) based his research on South Africa over the period August 1995 - June 2009. He examined the systematic risk arising from the macro-economy that is reflected in stock market volatility. The analysis is based on the univariate GARCH for estimating volatility and the multivariate VAR model to determine the inter-relationships. Volatility transmission was found to be bi-directional between the two sets of variables. Stock market volatility causes volatility in the macro-economy. The results indicate that for the entire sample only 25% of the volatility in the stock market is explained by volatility in macroeconomic factors (combinations of several variables). However, when the structural breaks in volatility are taken into account during the period of crisis, the results change significantly. Macroeconomic volatility then causes around 80% volatility in stock prices, although industrial production is not found to be one of the major macroeconomic variables causing uncertainty. It is an interesting finding that both financial and macroeconomic volatility increase significantly during financial crises and undergo structural breaks, making the influence of macroeconomic volatility more pronounced on stock market volatility. Thus, if the element of the financial crisis is not taken into account, an error of misspecification can incur, resulting in understated causality among the said variables.

A slightly different angle for looking at the impact of financial contraction and expansion on the real economy has been adopted by Aizenman *et al.* (2011). They analysed the factors that cause the rare events in the financial sector, and their impact on the real economy (sectors of economy). Their analysis is based on data covering from 1947 through to 2005 (annual data) for 28 countries, including the US, for 10 broad economic sectors. Financial contractions (especially abrupt ones) lead to rapid declines in value added to the real economy, whereas financial expansion doesn't show much impact. The effect of these financial contractions gets magnified if the economy has characteristics of financial openness, and is mitigated if the economy carries foreign reserves (they act as a financial buffer in times of crises). They used a Probit estimation methodology to identify the determinants of the financial contraction and found that abrupt financial collapse is mostly preceded by accelerated (immediate) growth in the financial sector. With time, the different aspects of the recent financial crisis are unfolding and rapid additions to the financial crisis literature are taking place. However, we have yet to see any work on the SMV-BC relationship that discusses the recent financial crisis in much depth. Thus, our third hypothesis of research focuses on these dynamic relations.

3.8 Contribution to the Literature

In order to identify the gap in the literature that we try to fill with this research, we will now reiterate a few significant key points from the earlier discussions. The literature review shows that there is evidence of a linear correlation, cointegration and/or causal relationship between the stock market (returns and volatility) and macroeconomic activity – output (measured in terms of GDP, GNP or Industrial Production). The findings on the direction of the causality, however, are not definitive and do vary on different data sets.

Our research significantly adds to the current body of knowledge in the following ways. We test non-linear bi-directional causality between changes in stock market volatility and changes in the business cycle, which may explain the causal relationship much better than the existing linear studies. This seems likely considering the evidence that stock returns/volatility bear non-linear characteristics. Thus, using a model that can explain the non-linear causal relationship between stock volatility and business cycles (proxied by the industrial growth rate) will give us the base to extend into the multivariate setting.

The second contribution of our research is looking at the cross-country causal relationship between stock volatility and the business cycle. There is a strand of research that has previously hinted at, and partially examined, this relationship across borders. There is also evidence of cross-country relationships between stock markets and macro-economic variables shown in the limited research in this area, mainly: 1) macro-economic variables of the US, such as industrial production or GDP, having an impact on stock markets of other countries (the UK and Europe); 2) including stock returns of the US, alongside domestic stock returns, for predicting domestic production growth improves the forecast; and 3) while using the business cycle of one country to forecast another country's business cycle, the inclusion of financial variables doesn't improve the forecast. However, these papers are limited in scope. The basic premise of these papers is to give consideration to variables from the US in addition to the domestic variables for predicting stock returns or the future macro-economy, to improve forecasts. There is still a need to look at the cross-country macro-financial relationship in a non-linear multivariate setting. In an attempt to find a non-linear causal relationship between domestic stock market volatility and domestic business cycles, we include international stock volatility and business cycles. We test the causal influence that stock volatility (of domestic and international markets) exerts on industrial production growth, and vice-versa.

The third important element in this research is acknowledging the financial crisis when evaluating these complex relationships. Previous research has not generally looked at the stock volatility and business cycle relationship during the current financial crisis, especially using non-linear framework. Thus, we analyse the relationships in the pre-crisis time frame and then see how these relationships vary during the troubled period of global financial crisis. The financial crisis is not treated as a mere event, but rather we acknowledge the fact that it has changed the dynamics of the economy and financial markets (domestically and around the globe).

Chapter 4: Data and Methodology

The chapter describes the data set used in the research and the methodology used for testing the hypotheses. The second section discusses the stationarity tests of the data. The third section in the chapter explains the volatility estimation using the Threshold GARCH model. The fourth section details the causality testing (bivariate and multivariate) according to the hypotheses. It also explains how the financial crisis changes the results of the causality tests when included. The fifth section is committed to explaining the framework of non-linear causality (bivariate and multivariate) and hypothesis testing.

4.1 Stationarity and Unit Root Tests

One of the key assumptions in financial modelling is that the underlying time series are random/stochastic. A stochastic process is considered stable (stationary) over a period of time if the mean, variance and auto-covariance of the series are constant over time (Brooks, 2002; Gujarati, 2003b). Any time series with this property is said to be ergodic or stationary. A random time series, Y_t with these properties will have:

1. Mean: $E(Y_t) = \mu$
2. Variance: $Var(Y_t) = E(Y_t - \mu)^2 = \sigma^2$
3. Covariance: $\gamma(Y_t,Y_{t+k}) = E[(Y_t - \mu)\ (Y_{t+k} - \mu)]$

Properties (1) and (2) above, describe the first and second moments for time series Y_t (i.e. mean and variance) and should be constant over time, and the third requirement states that the covariance (or auto-covariance) is the covariance between two values of a series at different points in time. For instance, the above $\gamma(Y_t,Y_{t+k})$ is the covariance between two values of Y at k periods apart (at lag k). k can take different values, if k=0 the covariance becomes the variance of Y values, if k=1 the covariance would be between two adjacent values of Y (lagged at the 1 period). The value of the covariance between the two time periods depends only on the distance (or lag) between the two time periods and not the actual time at which the covariance is computed, i.e. covariance will remain the same at whatever time is measured at a certain number k (Gujarati, 2003a). Stationary time series have a characteristic of mean reversion (a tendency to return to their mean) and the variance (fluctuations around the mean) will have broadly constant amplitude

(Cuthbertson *et al.*, 1992). On the other hand, if the series is non-stationary, its mean and/or variance will vary over time. Also, if the series is non-stationary, the results based on a specific time period cannot be generalized for other time sets.

In finance, non-stationary time series (random walk) are often found. According to efficient market hypothesis, stock prices are believed to follow random walk, i.e. today's stock prices are yesterday's prices plus a random shock, leaving no chance of speculation. There are two classes of stationary series described in the literature on the subject, i) weak or covariance stationary; and ii) strong or strict stationarity. Weak or covariance stationary series are characterized by the above three properties, whereas a strong or strictly stationary series requires that the joint distribution of any n items is independent of the time they occur, or alternatively, joint distributions of (Y_1, Y_2.... Y_n) and (Y_{1+k}, Y_{2+k},..., Y_{n+k}) respectively are the same for all values of n and k. Furthermore, this condition requires that all the moments, including mean and variance, are independent of time.

In the literature, various tests for stationarity and unit root are cited e.g. Dickey-Fuller, Augmented Dickey-Fuller, KPSS and Philip-Perron etc. In this research, the Augmented Dickey-Fuller and KPSS methods are used for unit root and stationarity testing.

$$Y_t = \rho Y_{t-1} + u_t \quad (-1 \leq p \leq 1) \tag{1}$$

Y_t has been regressed on its lagged term (first difference) Y_{t-1}, u_t is the white noise error term. If the estimated p is equal to 1, it is the case of the unit root, random walk model without drift, which is a non-stationery stochastic process. For theoretical reasons, the above equation can be modified by subtracting Y_{t-1} on both sides as in eq. 2 and replacing $\Delta Y_t = Y_t - Y_{t-1}$, where Δ is the first difference operator, in eq. 3 and $\delta = (p - 1)$ as in eq. 4.

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + u_t \tag{2}$$

$$\Delta Y_t = (\rho - 1)\, Y_{t-1} + u_t \tag{3}$$

$$\Delta Y_t = \delta\, Y_{t-1} + u_t \tag{4}$$

Thus, equation 1 is used to test for unit root (stationarity), the null hypothesis is H_o: δ=0. In the case of non-stationary time series, the estimated slope coefficient 'δ' will not be different to 0 (i.e. ρ=1). Thus, the first term δY_{t-1} becomes equal to 0 and drops out of the equation (1), which then becomes equation 4. Although Y_t may be non-stationary, its first difference is stationary. The resultant error term is stationary and the first difference of the random walk time series is stationary. If 'δ' is a negative number, then Y_t is a stationary time series.

$$\Delta Y_t = Y_t - Y_{t-1} = u_t \qquad (5)$$

The t-statistic cannot be used here as under the null hypothesis the t value of the estimated coefficient, δ, does not have asymptotic normal distribution, in other words it does not follow t-distribution. Thus we use the Dickey and Fuller (1979) test (Tau test). The DF test is run in three different forms to test three null hypotheses of H_o: δ=0, i.e. the time series is non-stationary, it has a unit root or it follows random walk.

Random walk with no drift (no intercept/ constant),

$$\Delta Y_t = \delta Y_{t-1} + u_t \qquad (6)$$

random walk with drift (constant term is present) and

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + u_t \qquad (7)$$

random walk with drift around stochastic trends.

$$\Delta Y_t = \beta_1 + \beta_{2t} + \delta Y_{t-1} + u_t \qquad (8)$$

In all three equations above, if δ is negative, the null hypothesis will be rejected and the time series Y_t will be found to be stationary, with zero mean in equation 6, non-zero mean in equation 7 and stationary around the deterministic trend in equation 8.

The Tau statistic is computed as 'δ' (the estimated coefficient of Y_{t-1}) divided by each standard error. The resultant absolute value is compared with DF or MacKinnon critical tau values, if it exceeds the critical value, the null hypothesis H_o: δ=0 is rejected, i.e. the time series is stationary. Whereas, if the absolute value is less than or equal to the critical Tau value, the time series will be non-stationary. In the previous equations the error term was assumed to be uncorrelated. For cases where error terms are correlated, there is another test known as the Augmented Dickey Fuller test.

4.1.1 Augmented Dickey Fuller Test

This test is an augmented version of the simple Dickey Fuller test, as it adds lagged values of the dependent variable ΔY_{t-1} to the regression equation (Dickey and Fuller, 1979). The regression equation with the additional lagged terms becomes:

$$\Delta Y_t = \beta_1 + \beta_{2t} + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \qquad (9)$$

The lagged difference terms can be $\Delta Y_{t-1} = (\Delta Y_{t-1} - \Delta Y_{t-2})$, $\Delta Y_{t-2} = (\Delta Y_{t-2} - \Delta Y_{t-3})$ and so on, till the error term ε_t becomes a serially uncorrelated pure white noise term. The null hypothesis is the same as in the Dickey Fuller test, $\delta=0$.

4.1.2 Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

KPSS is one of the econometric models used to assess the stochastic structure (presence of drift and/or trend) of variables. KPSS, proposed by Kwiatkowski *et al.* (1992), tests the null hypothesis of stationarity of the underlying variable. KPSS type tests are meant to complement unit root tests such as the Dickey-Fuller and the ADF. This test is conducted using the following procedure:

$$Y_t = \alpha + \beta t + \varepsilon_t \qquad (10)$$

In the above equation Y_t is an observed variable whereas α and β are the intercept and coefficient of the trend variable (t), respectively. ε_t represents residuals obtained from the above regression. These residuals are further used in equation 11 to test the null hypothesis of trend-stationarity (i.e. Y_t is stationary around its own trend) under the KPSS method.

$$\eta_t(q) = T^{-2} \sum_{t=1}^{T} \frac{s_{\varepsilon_t}{}^2}{\sigma_\varepsilon^2(q)} \qquad (11)$$

Where η_t is the KPSS test statistic based on the first q number of lags. T is the total number of observations and s^2 is the sum of the squared residual (ε^2_t) estimated in equation 10, whereas σ^2_ε is the variance of error term (ε) and it is estimated using the Newey-West method. The Newey-West method adopts the Bartlett windows approach and uses the first q number of lags for sample auto-covariance. Hence q is a truncation parameter above. In simple words, the KPSS test for any given variable is based on its residuals obtained from a linear regression estimated with an intercept and a trend variable. In the case of $\beta=0$, the null hypothesis is level-stationarity (i.e. Y_t is level stationary and thus it is stable over time).

4.2 Volatility Estimation

According to Taylor (2011), volatility is a measure of stock price variation over some specific time period. It is generally described as the standard deviation of stock returns. It is also considered 'a crude measure' of total risk in financial assets. However, in the context of volatility estimation and forecasting literature, a large number of contributions have been made proposing various methods and models to estimate volatility in both ex-post and ex-ante settings (Brooks, 2002). There are the ARCH and GARCH family of models, Stochastic Volatility models, EWMA and realized volatility models (Brooks, 2002; Taylor, 2011). However, in recent years the GARCH models have been heavily cited for stock market volatility estimation (Taylor, 2011)

For the purpose of this research, volatility is estimated using stock market returns, and thus univariate models suffice for this purpose. Volatility or standard deviation estimation based on returns alone has been vastly evidenced in the literature, including Schwert (1990c).

4.2.1 Generalized Autoregressive Conditional Heteroskedastic (GARCH) Models

GARCH (Bollerslev, 1986) and ARCH (Engle, 1982) models are much celebrated in the financial econometric world as these solved dealing with heteroskedasticity, volatility clustering and leptokurtosis (peaked and fat tail distributions) in the data. For financial time series, the variance of errors is unlikely to be constant over time, i.e. errors have heteroskedasticity,[23] and also most of the financial asset return

[23] The Classical Linear Regression Model assumes that variance of errors is constant, i.e. homoscedastic, whereas in real life financial time series the variance of errors varies over time.

series bear characteristics of unpredictability, fat tails (large number of extreme values) and volatility clustering[24] (Engle, 2004). The ARCH model has been designed around these characteristics. It describes how the variance of errors evolves. The ARCH model uses weighted averages of lagged squared forecast errors, with greater weights (and influence) for recent information than the distant past. The following equation presents the ARCH model in its general form. The conditional variance depends on the q lags of squared errors. The conditional variance, h_t is a positive value. $\alpha_i \geq 0$

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \cdots + u_t \qquad u_t \sim N(0, \sigma_t^2) \tag{12}$$

$$\sigma_t^2 = h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 \tag{13}$$

The GARCH model came as a successor to the ARCH model, to overcome the limitations of the ARCH model and also account for volatility clustering and leptokurtosis. In this model, the conditional variance is dependent upon previous own lags, as given in the following equation, known as GARCH (p,q) as conditional variance is dependent on lags of the squared error (ARCH effect) and additionally on its own lags of one period.

$$\sigma_t^2 = h_t = \alpha_0 + \Sigma_{i=1}^{q} \alpha_i u_{t-i}^2 + \Sigma_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{14}$$

In GARCH (p,q), the conditional variance (σ^2_t) would depend upon q lags of the squared error (u^2_{t-i}) and p lags of the conditional variance (σ^2_{t-j}). A famous simplification of the GARCH (p,q) model is GARCH (1,1) where conditional variance at time '*t*' is modelled on the basis of one lag of each squared error and conditional variance.

$$\sigma_t^2 = h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{15}$$

GARCH (p,q) enforces that volatility changes symmetrically to positive and negative shocks, whereas in recent years it has been observed that volatility rises more in magnitude as a consequence of negative shock than it falls as a result of positive shock (Tsay, 2010). Many extensions and modifications of GARCH models have

[24] Volatility clustering is a feature whereby volatility may have a positive correlation with the immediately preceding volatility over time, i.e. large (small) positive or negative changes in asset prices are followed by large (small) changes.

been made, encompassing the asymmetric effect (leverage effect), since the original Bollerslev (1982) model was presented. However, GARCH (1-1) still stays as a preferred model, and is usually deemed sufficient and a good starting point for academic finance.

The limitation of GARCH (1,1) has been corrected by the GARCH GJR model, which corrects for the leverage effect. The leverage effect is caused by asymmetric characteristics of volatility, i.e. a greater change in volatility after a negative event as compared to the change in volatility following a positive event. The model is named after its presenters Glosten *et al.* (1993). An additional term has been added to the original GARCH model to capture the effect of possible asymmetries present in the data. In the equation below, where φu^2_{t-1} is for asymmetry, the value of $I_{t-1}=1$ if $u_{t-1}< 0$ (and $I_{t-1}= 0$ otherwise).

$$\sigma_t^2 = h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \qquad (16)$$

The leverage effect is significant when $\gamma > 0$, which implies that γ captures the asymmetric changes in the volatility for all negative events over the sample time period. Lastly, to impose a non-negativity condition, the model requires α_0 and $\alpha_1 > 0$, $\beta \geq 0$ and $\alpha_1 + \gamma \geq 0$. This Threshold GARCH model is known to be the best forecasting model across different volatility regimes (Brownlees *et al.*, 2009).

4.3 Causality Testing

This section describes the Granger causality test (Granger, 1969b) between time series of changes in stock market volatility and industrial production growth, using linear and non-linear causality in bivariate and multivariate settings. Causality has three generally accepted conditions to hold for any variable Y to cause X or vice versa:

- Time precedence - Y must occur before X in time
- Relationship - Functional relationship between variables, i.e. cause and effect
- Non-spuriousness - Causal relationship between Y and X should not hold only due to another variable, Z, which when controlled stops Y from causing X

Causality was first explicitly specified and tested in an econometric setting by Granger (1969a). He adapted Weiner's (1956) definition of causality into practical formulations. Granger's definition of causality is based on the time precedence condition mentioned above, i.e. cause occurs before the effect. Y_t would "Granger cause" X_{t+1} if: (a) Y_t precedes X_{t+1} in time or, more generally, Y_t explains changes in X_{t+k} (subscript refers to time with k>0); and (b) it contains information useful in forecasting X_{t+k} that is not found in a group of other appropriate variables.

4.3.1 Linear Causality

For testing linear causality, the widely accepted Granger (1969) causality test is employed. This test detects the causality between time series in terms of time precedence. For instance x Granger causes y, if lags of x can explain changes in current y. The simplest form of writing the linear causality function is a two-equation model:

$$x_t = \varphi_1 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_{1t} \tag{17}$$

$$y_t = \varphi_2 + \sum_{i=1}^{n} \gamma_i x_{t-i} + \sum_{i=1}^{n} \delta_i y_{t-i} + \varepsilon_{2t} \tag{18}$$

The model assumes that both the variables x and y are stationary and ε_1 and ε_2 are the residuals satisfying the Classical Linear Regression Model assumptions. The coefficients α_i, β_i, δ_i and γ_i in the above equations are in linear form, presenting the linear relationship between variables x and y. n is the optimal lag in the system determined on the basis of information criteria including AIC, BC and HQ methods. The variable y_t does not Granger cause x_t if $\beta_i = 0$. In other words, the past values of y_t do not provide any additional information on the performance of x_t. Similarly x_t does not Granger cause y_t in the case of $\gamma_i=0$.

4.3.2 Granger Causality Test between Stock Volatility and Business Cycles

This section explains the Granger causality test used in this study in bivariate and multivariate settings. In this study, the relationship between two time series, stock market volatility and the business cycle, is to be tested according to the following hypotheses. To test for the Granger causality, a standard VAR model is used. The

VAR model assumes that all the variables are stationary. In the context of VAR, the significance of variables is not evaluated by individual coefficient estimates but rather they are analysed based on all the lags of a particular variable as a joint test using the F-statistic.

Hypothesis 1a*: There is a linear causal relationship between Stock Market volatility and Business Cycles.*

Hypothesis '1a' is aimed at testing the linear Granger causality between the two variables, within the same country. For each country, monthly stock volatility has been estimated using asymmetric GARCH (1,1) discussed earlier. To test this assumption, the linear Granger causality test has been employed using the following VAR model:

$$\begin{pmatrix} SV_{c,t} \\ BC_{c,t} \end{pmatrix} = \begin{pmatrix} \alpha_{10} \\ \alpha_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \begin{pmatrix} SV_{c,t-1} \\ BC_{c,t-1} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix} \begin{pmatrix} SV_{c,t-2} \\ BC_{c,t-2} \end{pmatrix} + \\ \dots\dots \begin{pmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{pmatrix} \begin{pmatrix} SV_{c,t-n} \\ BC_{c,t-n} \end{pmatrix} + \begin{pmatrix} \varepsilon_{SV,t} \\ \varepsilon_{BC,t} \end{pmatrix} \tag{19}$$

The above vector autoregression may be described for both the variables as under:

$$SMV_{c,t} = \alpha_{10} + \beta_{11}SV_{c,t-1} + \beta_{12}BC_{c,t-1} + \gamma_{11}SV_{c,t-2} + \gamma_{12}BC_{c,t-2} + \cdots \\ + \varphi_{11}SV_{c,t-n} + \varphi_{12}BC_{c,t-n} + \varepsilon_{SV,t} \tag{20}$$

$$BC_{c,t} = \alpha_{20} + \beta_{21}SV_{c,t-1} + \beta_{22}BC_{c,t-1} + \gamma_{21}SV_{c,t-2} + \gamma_{22}BC_{c,t-2} + \cdots \\ + \varphi_{21}SV_{c,t-n} + \varphi_{22}BC_{c,t-n} + \varepsilon_{BC,t} \tag{21}$$

Where *SMV* is the changes in stock market volatility and *BC* denotes the changes in the business cycle at time *t*. β, γ and φ are (nxn) parameter matrices whereas α (intercept) and ε (residuals) are (nx1) vectors. Subscript *c* above describes the country of analysis.

Hypothesis 2a*: A linear causal relationship exists between the stock market volatility of country A and the business cycle of country B.*

Hypothesis 2a differs from Hypothesis 1a in that the variables are now compared across economies. The aim is to analyse whether the causal relationship established between stock volatility and the business cycle within a country (say country 'A') in Hypothesis-1a spills across borders. Thus, the business cycle of country B is assumed to bear a causal relationship with the volatility of its own stock market 'B' and that of another country's stock market 'A'. Country 'A' in all cases is the US, as it is the biggest economy that has economic and political influence on countries around the globe. To test hypothesis 2a, the following multivariate VAR model is used for testing Granger causality.

$$\begin{pmatrix} SV_t \\ BC_t \end{pmatrix} = \begin{pmatrix} A_{SV[n_1\times 1]} \\ A_{BC[n_2\times 1]} \end{pmatrix} + \begin{pmatrix} A_{SV_1,SV_2}(L)_{[n_1\times n_1]} & A_{SV_1,BC_2}(L)_{[n_1\times n_2]} \\ A_{BC_1,SV_2}(L)_{[n_2\times n_1]} & A_{BC_1,BC_2}(L)_{[n_2\times n_2]} \end{pmatrix} \begin{pmatrix} SV_{t-1} \\ BC_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{SV} \\ \varepsilon_{BC} \end{pmatrix}$$

$$\begin{pmatrix} SV_{c1,t} \\ BC_{c1,t} \\ SV_{c2,t} \\ BC_{c2,t} \end{pmatrix} = \begin{pmatrix} \alpha_{10} \\ \alpha_{20} \\ \alpha_{30} \\ \alpha_{40} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{pmatrix} \begin{pmatrix} SV_{c1,t-1} \\ BC_{c1,t-1} \\ SV_{c2,t-1} \\ BC_{c2,t-1} \end{pmatrix} \tag{22}$$

$$+ \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{pmatrix} \begin{pmatrix} SV_{c1,t-2} \\ BC_{c1,t-2} \\ SV_{c2,t-2} \\ BC_{c2,t-2} \end{pmatrix}$$

$$+ \cdots \begin{pmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} & \varphi_{14} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \varphi_{24} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} & \varphi_{34} \\ \varphi_{41} & \varphi_{42} & \varphi_{43} & \varphi_{44} \end{pmatrix} \begin{pmatrix} SV_{c1,t-n} \\ BC_{c1,t-n} \\ SV_{c2,t-n} \\ BC_{c2,t-n} \end{pmatrix} + \begin{pmatrix} \varepsilon_{SV_{c1},t} \\ \varepsilon_{BC_{c1},t} \\ \varepsilon_{SV_{c2},t} \\ \varepsilon_{BC_{c2},t} \end{pmatrix}$$

L is the lag operator and is used to denote the lags of stock market volatility (SMV) and the business cycle (BC) for the different countries.

Where *SMV* is the change in stock market volatility and *BC* denotes the changes in business cycles for the two countries c1 and c2 at time *t*. β, γ and φ are (nxn) parameter matrices whereas α (intercept) and ε (residuals) are (nx1) vectors. Subscript *c* above describes the country of analysis. ε_i is the vector of residuals, which are assumed to be asymptotically distributed as $N(0,\sigma^2)$. Lags are decided for each equation according to information criteria such as Akaike's Information Criterion (AIC), Schwarz Criterion (SC) and HQ. Wherever these criteria give conflicting lags, the number of lags suggested by two of the three criteria is selected. In order to test hypothesis 2a, the standard F-statistic is used. Further post estimation diagnostics include serial correlation, heteroskedasticity and specification (RESET) tests.

Hypothesis 3*: The current financial crisis (2007-2011) has an effect on hypotheses 1 and 2.*

The financial crisis became visible in July 2007. The literature, however, reports different dates for the start of the financial crisis on the time-line of events and for when the crisis became amenable. The US economy went into recession in Dec 2007 (NBER). To examine the effect of the financial crisis on the causal relationships established by testing hypotheses 1 and 2, the two hypotheses are run on two datasets. The first dataset runs from January 1990 to June 2007. The second dataset covers this time period and also includes the period of financial crisis, thus comprises of data from January 1990 to December 2011. The two sample periods are termed as 'Before the Financial Crisis' and 'Including the Financial Crisis'. The results of tests from both data sets are then compared to see if there is any change in the causal relationships between variables during the period of crisis. The equations used for hypothesis 2a apply here again, with the sample time running differently.

Hypothesis 4*: The linear causal relationship between the stock market volatility of developed country A and the business cycle of developed country B is stronger compared to the relationship between the stock market volatility of developed country A and the business cycle of developing country C.*

This hypothesis is an extension of hypothesis 2a and does not require running causality tests again. To test this hypothesis, the results of hypothesis 2a are segregated and compared in terms of developed countries (the UK, Japan and Canada) and developing countries (Malaysia, Brazil, Turkey and China). The analysis will reveal whether the Granger causality is stronger between variables of the US and the developed countries or the US and the developing countries, based on F-tests.

4.3.3 Non-Linear Causality

The previous section explained the tests on the four hypotheses (1a- 4) in a linear framework. In this section, the part b's of the same hypotheses are tested in a non-linear setting. According to Granger (1989), the real world is almost certainly non-linear and he argued that univariate and multivariate non-linear models represent the proper way to model this real world. Non-linear causality has received great recognition in the past few years as researchers have tested non-linear causal relationships among a variety of variables.

In the past the nonlinear features in financial and macroeconomic time series has been supported by various studies including Keynes, 1936; Kahneman and Tversky, 1979; Scheinkman and LeBaron, 1989; Hsieh, 1991; Shiller, 1993; Barnett et al., 1997; Barnett and Serletis, 2000; Shiller, 2005; and most recently Shin et al., 2013.

Hiemstra and Jones (1994), developed a non-linear and nonparametric Granger causality test based on the work of Baek and Brock (1992). They tested the relationship between stock returns and volume with this model and found significant bidirectional causality. In more recent years, Diks and Panchenko (2006) identified some limitations in Hiemstra and Jones' nonlinear causality test and proposed a modification of it.[25] Non-linear causality framework has then been extended to other variables of interest, such as Bekiros and Diks (2008) who used the model for examining the non-linear causality between crude oil spot and future prices. Bai *et al.* (2010) extended nonlinear causality in a multivariate setting using the Hiemstra and Jones (1994) model.

Next, the non-linear causality hypotheses to be tested are listed and then the non-linear bivariate and non-linear multivariate models are explained along with the test statistics.

***Hypothesis 1b**: There is a non-linear causal relationship between Stock Market volatility and Business Cycles within a country.*

This hypothesis requires testing the presence of bivariate non-linear causality between the variables within the same country. To test the non-linear bivariate causality hypothesis, we follow Hiemstra and Jones (1994) and Diks and Panchenko (2006). The first pair of authors has defined non-linear causality in the following equation.

$$\begin{aligned} Pr\left(\|X_t^m - X_s^m\| < \varepsilon \middle| \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < \varepsilon\right) \\ = Pr\left(\|X_t^m - X_s^m\| < \varepsilon \middle| \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon\right) \end{aligned} \tag{23}$$

[25] Dr. Valentine Panchenko has kindly made available the nonlinear causality programme codes for Hiemstra and Jones (1994) and Diks and Panchenko (2006) on his website.

In this equation, Pr ·|·denotes conditional probability and ||·|| denotes the maximum norm. The left hand side of the equation is the conditional probability that the distance between two arbitrary m-length lead vectors X_t and X_s is less than 'ε', given that the distance between corresponding Lx-Length lag vectors of X_t and Ly-Length lag vectors of Y_t are less than 'ε' as well. The right hand side of the equation is the conditional probability that any two m-length lead vectors of X_t are within a distance of 'ε' of each other, given that their corresponding Lx-length lag vectors are within a distance 'e' of each other. According to which the null hypothesis is that stock market volatility, $SMV_t = X_t$ does not Granger cause business cycles $BC_t = Y_t$ and vice versa. If the above equation holds true, it implies that Y_t does not strictly Granger cause X_t in nonlinear terms.

Hiemstra and Jones (1994) expressed the conditional probabilities (in equation 23), as ratios of joint probabilities (equations 25-28). They developed a test statistic (equation 24) for testing the non-linear causality. The test statistic requires values of correlation integrals (C1-C4) that are theoretically explained in equations 25-28 through joint probabilities, and are empirically estimated through equations 29-32 The concept of correlation integrals was first proposed by Grassberger and Procaccia (1983). Correlation integrals explain the probability that two points in space are within a distance from one another. After the estimation of correlation integrals, the test statistic for nonlinear Granger causality in a bivariate setting, is given by:

$$\sqrt{n}\left(\frac{C1(m+Lx,Ly,e,n)}{C2(Lx,Ly,e,n)} - \frac{C3(m+Lx,e,n)}{C4(Lx,e,n)}\right) \tag{24}$$

$$C1(m+Lx,Ly,e,n) \equiv \Pr\left(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < e\right) \tag{25}$$

$$C2(Lx,Ly,e,n) \equiv \Pr\left(\left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < e\right) \tag{26}$$

$$C3(m+Lx,e,n) \equiv \Pr\left(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < e\right) \tag{27}$$

$$C4(Lx,Ly,e,n) \equiv \Pr\left(\left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e\right) \tag{28}$$

The two points in space for this research are t and s, between which the variations in variables are measured. 'e' is a threshold value that defines a band within which we allow values of X_t and Y_t to deviate in different formations of lead and lag of variables. This threshold value is interpreted as the standard deviation multiplier, i.e. any observation deviating beyond the 'e' time of the standard deviation[26] of the underlying variable is considered invalid or outlier for causality testing. The threshold value can be any value between 0.5 and 1.5 (Diks and Panchenko, 2005; Diks and Panchenko, 2006). The number of observations is represented by 'n'.

Where t, s = max (Lx, LY) +1, … ,T – m +1 and
n = T+1 – m – max (Lx, Ly)

C1, C2, C3 and C4 are correlational integrals, C1 for lead vector of X_t^m and lag vector of y_{t-Ly}^{Ly} , C2 for lag vector of $x_{t-L_x}^{Lx}$and lag vector of $y_{t-L_y}^{Ly}$, C3 for lead vector of X_t^m and C4 for lag vector of $x_{t-L_x}^{Lx}$. The four correlation integrals are defined in notation:

$$C1\ (mx+Lx,Ly,e,n) \equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(x_{t-L_x}^{m_x+L_x}, x_{s-L_x}^{m_x+L_x}, e).\, I(y_{t-L_y}^{L_y}, y_{s-L_y}^{L_y}, e) \tag{29}$$

$$C2\ (Lx,Ly,e,n) \equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(x_{t-L_x}^{L_x}, x_{s-L_x}^{L_x}, e).\, I(y_{t-L_y}^{L_y}, y_{s-L_y}^{L_y}, e) \tag{30}$$

$$C3\ (mx+Lx,e,n) \equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(x_{t-L_x}^{m_x+L_x}, x_{s-L_x}^{m_x+L_x}, e) \tag{31}$$

$$C4\ (Lx,e,n) \equiv \frac{2}{n(n-1)}\sum_{t<s}\sum I(x_{t-L_x}^{L_x}, x_{s-L_x}^{L_x}, e) \tag{32}$$

$$I(x,y,e) = \begin{Bmatrix} 0, if\ \|x-y\| > e \\ 1, if \|x-y\| \le e \end{Bmatrix}$$

Diks and Panchenko (2006) proposed a test statistic to test the above defined non-linear Granger causality, which was an improvement of the test statistic proposed by Hiemstra and Jones, (1994). According to Diks and Panchenko (2005), the Hiemstra-Jones test is subject to over-rejection bias on the null hypothesis of Granger causality, i.e. it may wrongly accept the alternate hypothesis and show

[26] Standard deviation in this case is 1, due to standard normal assumptions of this method.

causality between variables when there is no or very little causality. The test statistic can be estimated using the following model.

$$Tn\ (\varepsilon) = \frac{(2\varepsilon)^{-dx-2dy-dz}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} I_{ik}^{XYZ} I_{ij}^{Y} - I_{ik}^{XY} I_{ij}^{YZ} \right] \tag{33}$$

Where $I_{ij}^{W} = I(\|W_i - W_j\| < \varepsilon)$ and the terms within brackets are the correlation integrals (I_{ik}^{XYZ} I_{ij}^{Y} I_{ik}^{XY} I_{ij}^{YZ}) of vectors representing, 1) series X_t, Y_t and $Z=Y_{t+k}$,2) series Y_t, 3) series X_t and Y_t and 4) series Y_t and $Z=Y_{t+k}$. *k* and *j* denote the length of lags and these can have equal values. *n* is the number of observations and *d* is a constant. 'ε' is the threshold value, which Diks and Panchenko (2006) define as $0 \leq \varepsilon \leq 1.5$. Tn(ε) if it is significantly different than zero, would signify that variable X_t holds information which can explain changes in Y_{t+k}, i.e. X_t is Granger causing Y_{t+k}.

For the above nonlinear causality tests, of Hiemstra and Jones (1994) and Diks and Panchenko (2006), programme codes have been written and estimated in RATS (Version 7.0).[27]

***Hypothesis 2b**: A non-linear causal relationship exists between the stock market volatility of country A and the business cycle of country B.*

Bai *et al.* (2010), extended the bivariate non-linear Granger causality model of Hiemstra and Jones to multivariate settings for analysing the causal relationships between more than two variables. For the multivariate setting, there are a total of four variables: business cycle of country A, business cycle of country B, stock market volatility of country A and stock market volatility of country B. The aim is to analyse whether the non-linear causal relationship established between stock market volatility and business cycles within a country (say country 'A') in Hypothesis-1b spills across borders. Thus, the business cycle of country B is assumed to bear a causal relationship with the volatility of its own stock market 'B' and that of another country 'A'. Country 'A' in all cases is the US, as it is the biggest economy which has economic and political influence on countries around the globe. To determine the direction of causality, the multivariate causality is run four times for each pair of countries. The dependent variables are denoted by X_t and Y_t is the independent variables. After running the linear causality (in the multivariate

[27] See Appendix-1 for the details of the programme codes converted from C++ and rewritten in RATS.

setting), the residuals from the causality equation are recorded as series X_t and Y_t. X_t is not a single variable, rather a vector of variables. In this research a vector Y_t consists of three independent variables (of a total of four variables) in multivariate regression equations, and X_t represents the residual series for the fourth variable.

Lead vector of size m_{xi} for $X_{i,t}$ can be defined as $X_{i,t}^{m_{x_i}} = (X_{i,t},\ X_{i,t+1}, \dots, X_{i,m_{x_i}-1})$. Lag vector of length L_{xi} for $X_{i,t}$ can be defined as: $X_{i,t-L_{x,i}}^{L_{x_i}} = \left(X_{i,t-L_{x_i}}, X_{i,t-L_{x_i}+1}, \dots, X_{i,t-1}\right)$. Similarly, the m_{yi}-length lead vector $Y^{myi}_{i,t}$, lag vector $Y^{Lyi}_{I,t-Lyi}$ based on vector $Y_{i,t}$ can be so defined.

However, as here there is only one dependent variable, $X_{i,t}$ becomes X_t. Also, the size of the lead vector $m_{x,I}$ and the lag vector L_{xi} are both set to 1, following Hiemstra and Jones (1994) and Diks and Panchenko (2006). Although here vector X_t consists of only one variable and there is one value for each length of lead and lag vectors, if there were more than one variable within vector X_t, and there were different lead and lag structures for the variables $X_{t,}$ for instance $M_x = (m_{x1},.., m_{xn1})$ and $L_x=(L_{x1},...,L_{xn1})$, in that case the maximum lead vector and lag vector values would be selected and applied across vectors such as $m_x=\max(m_{x1},\dots,m_{xn1})$ and $l_x= \mathrm{Max}\ (L_{x1},\dots, L_{xn1})$.

The test statistic proposed by Bai *et al.* (2010) to test multivariate causality is based on correlation integrals:

$$\sqrt{n}\left(\frac{C1\ (Mx+Lx, Ly, e, n)}{C2\ (Lx, Ly, e, n)} - \frac{C3\ (Mx+Lx, e, n)}{C4\ (Lx, e, n)}\right) \tag{34}$$

Where 'e' is a threshold value that defines a band within which we allow values of X_t and Y_t to deviate in different formations of lead and lag of variables. 'n' is the number of observations. C1, C2, C3 and C4 are correlational integrals, C1 for lead vector of $X_{i,t}^{m_{x_i}}$ and lag vector of $y_{i,t-L_{yi}}^{L_{yi}}$, C2 for lag vector of $x_{i,t-L_{xi}}^{L_{xi}}$and lag vector of $y_{i,t-L_{yi}}^{L_{yi}}$, C3 for lead vector of $X_{i,t}^{m_{x_i}}$ and C4 for lag vector of $x_{i,t-L_{xi}}^{L_{xi}}$. The four correlation integrals are defined in the following notations.

$$C1\ (Mx+Lx, Ly, e, n) \equiv \frac{2}{n(n-1)}\sum_{t<s}\sum\prod_{i=1}^{n1} I(x_{i,t-L_{xi}}^{m_{xi}+L_{xi}}, x_{i,s-L_x}^{m_{xi}+L_{xi}}, e).\prod_{i=1}^{n2} I(y_{i,t-L_{yi}}^{L_{yi}}, y_{i,s-L_{yi}}^{L_{yi}}, e) \tag{35}$$

$$C2\,(Lx, Ly, e, n) \equiv \frac{2}{n(n-1)} \sum\nolimits_{t<s} \sum \prod_{i=1}^{n1} I(x_{i,t-L_{xi}}^{L_{xi}}, x_{i,s-L_x}^{L_{xi}}, e). \prod_{i=1}^{n2} I(y_{i,t-L_{yi}}^{L_{yi}}, y_{i,s-L_{yi}}^{L_{yi}}, e) \tag{36}$$

$$C3\,(Mx + Lx, e, n) \equiv \frac{2}{n(n-1)} \sum\nolimits_{t<s} \sum \prod_{i=1}^{n1} I(x_{i,t-L_{xi}}^{m_{xi}+L_{xi}}, x_{i,s-L_x}^{m_{xi}+L_{xi}}, e) \tag{37}$$

$$C4\,(Lx, e, n) \equiv \frac{2}{n(n-1)} \sum\nolimits_{t<s} \sum \prod_{i=1}^{n1} I(x_{i,t-L_{xi}}^{L_{xi}}, x_{i,s-L_x}^{L_{xi}}, e) \tag{38}$$

$$I(x, y, e) = \begin{Bmatrix} 0, if\ \|x-y\| > e \\ 1, if \|x-y\| \leq e \end{Bmatrix}$$

The test statistic given in equation 34 above is the difference of correlation integral ratios between C1/C2 and C3/C4, standardized by the square root of the number of observations. The first ratio explains the changes in dependent variable X_t with respect to changes in independent variable Y_t and lags of X_t, whereas the second ratio gives the extent of changes in X_t with respect to its own lags. If the difference of the two ratios is zero, it means that the independent variable Y_t does not contain any significant information to explain changes in X_t. In other words, zero difference between the ratios implies acceptance of the null hypothesis that Y_t does not Granger cause X_t.

More specifically about the variables of interest in this research, the two sets of variables, stock market volatility and the business cycle, become four as another country is introduced in this hypothesis. The four variables are SMV_A, BC_A, SMV_B and BC_B. All countries in the sample are tested for nonlinear multivariate causality against the US stock volatility and business cycle. This test is repeated N number of times for identifying the various possible directions of multivariate nonlinear causality, where n refers to the number of variables (i.e. 4 in this case).

Hypothesis 3*: The current financial crisis (2007-2011) has an effect on hypotheses 1and 2.*

To examine whether the causality relationships established as a result of testing hypotheses 1b and 2b are affected by the financial crisis in the recent years, the tests are also run on a shorter time period (July 2007 to Dec 2011) marked by the financial crisis for the same countries. The results of this data set are compared with regular sample running for the whole length of time. This hypothesis analyses the impact of the financial crisis on the causal relationships between stock markets and business cycles within countries and across borders.

***Hypothesis 4b**: The non-linear causal relationship between the stock market volatility of developed country A and the business cycle of developed country B is stronger compared to the relationship between the stock market volatility of developed country A and the business cycle of developing country C.*

Hypothesis 4b does not require running a model-based test. Similar to the technique used for Hypothesis 4a, here the results of hypothesis 2b shall be compared for the developed and developing countries. Non-linear causality test statistics for each of the two groups of countries (developed and developing) are evaluated to see if the causality is stronger for one of the two groups.

4.4 Data

The two sets of time series required for the research are the stock market index and the industrial production index. The stock market index gives the total market value of the underlying equity, which is used to calculate returns (first difference) and conditional stock market volatility (based on various estimation models). The final dataset includes eight countries, namely the US, UK, Japan, Canada, Malaysia, Turkey, Brazil and China. The first four of these countries are characterised as developed and the latter as developing countries[28] for two of the hypotheses[29]. The

[28] Among the developing countries, Brazil, Russia, India, China (BRIC) and Malaysia, Indonesia, Nigeria and Turkey (MINT) were first chosen as a sample. The reason for incorporating these countries into the sample was as follows. These countries represent emerging economies from a wide geographic and economic region and have been widely used by researchers focusing on developing countries. However, in the case of most of these and other developing countries, data regarding the underlying variables was either not available for the full time period, or on a monthly basis, or both. For instance, the index of production data for India, Russia, Nigeria and Indonesia is available for a short time period only. In the case of Brazil, China, and Turkey, the required data was available for the full time period, hence only these countries were included in this research. Thus, this research tests all the hypotheses for four developing countries.

[29] According to the World Bank, economies are divided according to GNI per capita of 2012, calculated using the World Bank Atlas method. The groups are: low income, $1,035 or less; lower middle income, $1,036 - $4,085; upper middle income, $4,086 - $12,615; and high income,$12,616 or more. Low-income and middle-income economies are sometimes referred to as emerging economies. In this research the same convention has been used to select developed and emerging economies. The 'Emerging economies' term was coined by economists at the International Finance Corporation (IFC) in 1981. Since then, 'developing economies' or developing countries' have been used interchangeably.

data runs for the period Jan 1990 to Dec 2011 with monthly frequency for both the stock market index and the industrial production index.

The data source is Datastream. Datastream provides end of the month figures for stock market index, whereas macroeconomic figures are given in the middle (15th) of the month. For each country, the stock market index picked is the benchmark index for that country. These indices are the S&P 500 Composite index (the US), the FTSE All Shares index (the UK), the Nikkei 225 Stock average index (Japan), the S&P/TSX Composite index (Canada), the Brazil Bovespa index (Brazil), the Istanbul Stock Exchange index (Turkey), and FTSE Bursa Malaysia Index and Shinghai Stock Echange A share index (China). The Industrial Production index (total) for each of these countries has been obtained for the same length of time. Data obtained is already seasonally adjusted.

The stock market indices are then used to estimate continuously compounded stock returns on a monthly basis. The following equation shows that returns R_t are a natural log of the ratio of stock prices P_t at time t, and stock prices P_{t-1} at a previous time period (Brooks, 2002). The index of production series and stock return series are both converted in log series.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{39}$$

4.4.1 Descriptive Statistics

Descriptive statistics are generally the initial point in most financial time series research. This is also referred to in the literature as descriptive analysis and it helps to identify and understand some of the key features of the underlying data concerning asymptotic distribution and stochastic properties. Some of the major aspects analysed in this regard are the first four moments, i.e. mean, variance, skewness and kurtosis. It also includes the Jarque-Bera test, which essentially is based on the skewness and excess kurtosis measures, for testing the null hypothesis of normal distribution.

This section describes the descriptive statistics (Table 4.1) and graphic presentation (Figures 4.1-4.4) of the variables in log level and first difference forms. Figure 4.1 shows the Index of Production for all the sample countries and shows a general upward trend over the sample period signifying economic growth in these countries, with the exception of Japan and the UK. For Japan, the index of production shows upward and downward movements with no clear trend. In the case of the UK, the index shows an upward trend up until the financial crisis and shows a huge decline afterwards, signifying the recession due to the current financial crisis.

Similarly, Figure 4.2 presents the log stock market indices for the sample countries. The figure shows a general upward trend for most of the countries, however, a steep drop in stock market indices shows the financial crisis incidence. A few other important observations: i) in the case of Malaysia, a drop can be seen around 1997-98, which coincides with the Asian Financial Crisis; ii) the Japanese stock market show a declining trend over the sample period, indicating a possible negative average return over the sample period; iii) stock market indices for Brazil, Malaysia and Turkey show a relatively lesser response to the financial crisis during 2007-2011. Figures 4.3 and 4.4 describe the growth rates of the production index and stock market returns, respectively. Stock market returns are seen to be volatile for all the countries with large positive and negative spikes, signifying positive and negative returns over the sample period.

In order to assess the impact of the financial crisis, descriptive analysis has been conducted based on two sample lengths, i.e. before the financial crisis (Jan-1990 to Jun-2007) and then using the whole sample period which includes the financial crisis (Jan-1990 to Dec-2011).

Before the Financial Crisis (January 1990 to June 2007)

Table-4.1 (Panel-I) shows the descriptive analysis of the main variables in levels as well as in first difference terms. The average industrial production growth rate is positive for all the sample countries, with Malaysia having the highest growth rate of 0.59% per annum over the sample period, followed by Turkey (0.35%), the US (0.23%), Canada (0.18%), Brazil (0.16%), and 0.05% for both Japan and the UK. Similarly, the average stock market returns for almost all the countries are positive, except for Japan, with -0.37% average stock market returns over the sample period. Among the sample countries, Brazil and Turkey offer the highest average return, i.e. 7.41% and 3.66% respectively for the period January 1990 to June 2007.

Including the Financial Crisis (January 1990 to December 2011)

In this context, the mean of the first difference of these variables for most of the countries are positive, which implies that both the index of production growth rates and the stock market returns are positive. However, monthly average production index growth rates for Japan and the US are zero and -.01% for the sample time period, i.e. January 1990 to December 2011. Malaysia, the UK and Brazil have relatively higher growth rates among the rest of the sample countries, i.e. 0.49%, 0.17% and 0.15% per month, respectively. Similarly, average monthly stock market returns for most of the countries are positive, except for Japan where the average monthly return is -0.57% over the sample period. Among the remaining countries, Brazil and Turkey have the highest monthly average returns, i.e. 5.92% and 2.96%, respectively.

Comparing the average growth rates for the industrial production index and stock market returns for both sample lengths, a general decline is observed for almost all the cases (Table 4.1). This reflects the role of the financial crisis in the global economic down turn, as shown by the decline in average productivity and stock market growth rates. In the US, for instance, the average production growth rate has reduced from 0.23% to -0.01%.

Besides the central tendency of the level and first difference variables, normal distribution assessment is the other key element of descriptive analysis. As earlier mentioned, skewness and kurtosis, along with the Jarque-Bera test, are used for this analysis. Financial Time series are often cited for exhibiting non-normal distribution attributes, i.e. data is skewed, either positive or negative, as well as being characterised by tall peaks and fat tails (leptokurtosis) (Brooks, 1998; Taylor, 2011). Therefore, as expected, the null hypothesis of normal distribution is rejected at the 1% or 5% significance levels for most of the level and first difference variables, as shown in Table 4.1. Exceptions in this regard are the Japanese and Malaysian stock market index (log) variables, which are normally distributed.

Table 4.1: Descriptive Statistics for Level and First Difference Variables

Panel-I: Before the Financial Crisis (Jan-1990 to Jun-2007)

Countries	Series	Mean	Variance	Skewness	Kurtosis	JB-Stat
Brazil	IOP (Log)	4.5258	0.0186	-0.0385	-0.4899	2.15
	Δ IOP	0.0016	0.0011	-1.7606	34.3109	10359 ***
	SM Index (Log)	7.1354	19.6326	-1.5545	0.9548	92.55 ***
	SM Returns	0.0741	0.0397	0.3781	3.2084	94.62 ***
Canada	IOP (Log)	4.4369	0.0230	-0.3885	-1.3859	22.09 ***
	Δ IOP	0.0018	0.0001	0.1850	0.8767	7.89 **
	SM Index (Log)	8.7241	0.1718	0.0101	-1.1262	11.10 ***
	SM Returns	0.0061	0.0019	-0.9005	3.8995	160.6 ***
Japan	IOP (Log)	4.5700	0.0021	0.0660	-0.6093	3.40
	Δ IOP	0.0005	0.0002	-0.2937	0.9119	10.25 ***
	SM Index (Log)	9.6949	0.0968	-0.1109	-0.0863	0.50
	SM Returns	-0.0037	0.0042	-0.2317	0.6236	5.26 *
Malaysia	IOP (Log)	4.1485	0.1398	-0.3538	-0.9925	13.00 ***
	Δ IOP	0.0059	0.0027	0.1414	0.4614	2.55
	SM Index (Log)	6.6504	0.0785	-0.3316	0.0734	3.90
	SM Returns	0.0042	0.0070	-0.3133	4.2818	163.0 ***
UK	IOP (Log)	4.5977	0.0030	-0.8760	-0.6081	30.09 ***
	Δ IOP	0.0005	0.0001	-1.0773	5.3296	287.7 ***
	SM Index (Log)	7.6082	0.1164	-0.3892	-1.0452	14.86 ***
	SM Returns	0.0051	0.0017	-0.5801	1.2870	26.15 ***
US	IOP (Log)	4.3816	0.0267	-0.4193	-1.3713	22.61 ***
	Δ IOP	0.0023	0.0000	-0.2017	1.2279	14.55 ***
	SM Index (Log)	6.6729	0.2454	-0.4188	-1.3761	22.71 ***
	SM Returns	0.0070	0.0015	-0.3855	0.7427	9.98 ***
Turkey	IOP (Log)	4.3313	0.0390	0.2866	-0.7159	7.36 **
	Δ IOP	0.0035	0.0028	-0.0861	1.4505	18.58 ***
	SM Index (Log)	7.4743	6.0821	-0.3895	-1.3232	20.63 ***
	SM Returns	0.0366	0.0252	0.2831	2.6210	62.61 ***

***,**,* denote significance level at 1%, 5%, and 10% respectively.

Panel-II: Including the Financial Crisis (Jan-1990 to Dec-2011

Countries	Series	Mean	Variance	Skewness	Kurtosis	JB-Stat	
Brazil	IOP (Log)	4.5868	0.0300	0.0315	-0.9100	9.1	**
	Δ IOP	0.0015	0.0010	-1.8871	33.3227	12324	***
	SM Index (Log)	7.9215	18.0207	-1.8136	2.0098	189.1	***
	SM Returns	0.0592	0.0336	0.5661	4.0744	195.9	***
Canada	IOP (Log)	4.4502	0.0196	-0.6202	-0.9870	27.6	***
	Δ IOP	0.0012	0.0001	-0.3515	1.8019	40.9	***
	SM Index (Log)	8.8620	0.2157	-0.1942	-1.2000	17.5	***
	SM Returns	0.0042	0.0023	-0.9487	3.4778	171.9	***
Japan	IOP (Log)	4.5648	0.0043	-0.8662	2.7840	118.2	***
	Δ IOP	0.0000	0.0004	-3.0759	21.1271	5305.9	***
	SM Index (Log)	9.6112	0.1143	0.0544	-0.5658	3.6	
	SM Returns	-0.0057	0.0044	-0.3957	1.1412	21.1	***
Malaysia	IOP (Log)	4.2543	0.1554	-0.5895	-0.8689	23.5	***
	Δ IOP	0.0049	0.0026	0.1792	0.5492	4.71	*
	SM Index (Log)	6.7519	0.1085	-0.1921	-0.3708	3.1	
	SM Returns	0.0037	0.0059	-0.3132	5.0169	280.1	***
UK	IOP (Log)	4.4109	0.0252	-0.7032	-0.9617	31.9	***
	Δ IOP	0.0017	0.0000	-1.6655	8.0643	834.2	***
	SM Index (Log)	6.7529	0.2267	-0.7062	-0.9773	32.4	***
	SM Returns	0.0048	0.0021	-0.7219	2.1646	74.1	***
US	IOP (Log)	4.5882	0.0032	-0.4939	-1.2929	29.1	***
	Δ IOP	-0.0001	0.0001	-0.9703	4.1213	227.4	***
	SM Index (Log)	7.6722	0.1129	-0.6441	-0.7502	24.4	***
	SM Returns	0.0032	0.0020	-0.5304	0.7868	19.1	***
Turkey	IOP (Log)	4.4153	0.0601	0.1481	-1.1008	14.3	***
	Δ IOP	0.0034	0.0028	-0.2127	1.6909	33.3	***
	SM Index (Log)	8.1483	6.6243	-0.6376	-1.0471	29.9	***
	SM Returns	0.0296	0.0223	0.3392	2.9176	98.3	***

***,**,* denote significance level at 1%, 5%, and 10% respectively.

Figure 4.1: Index of Production (Log)

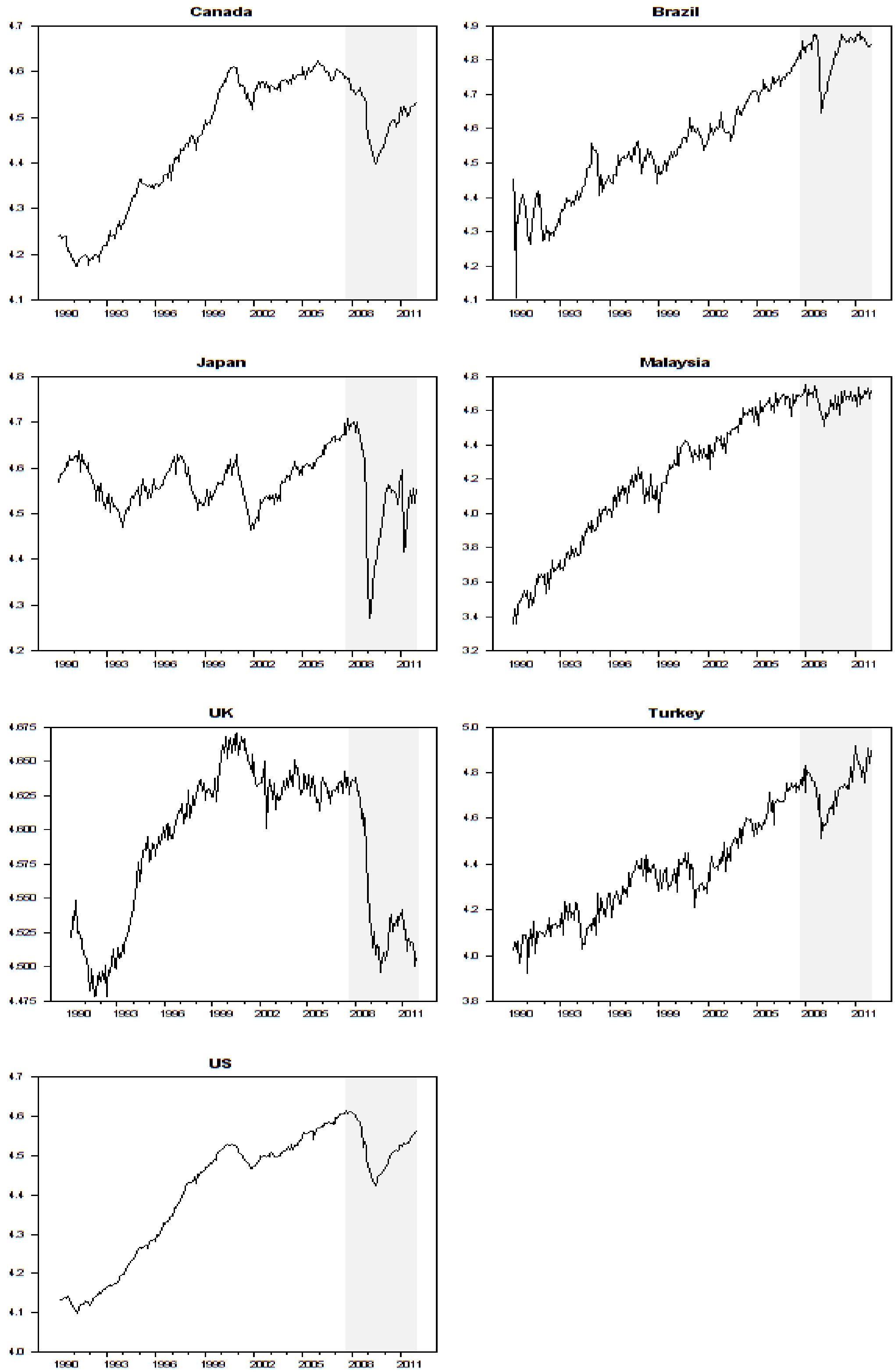


Figure 4.2: Stock Market Index (Log)

Figure 4.3: Changes in Index of Production (Log First Difference)

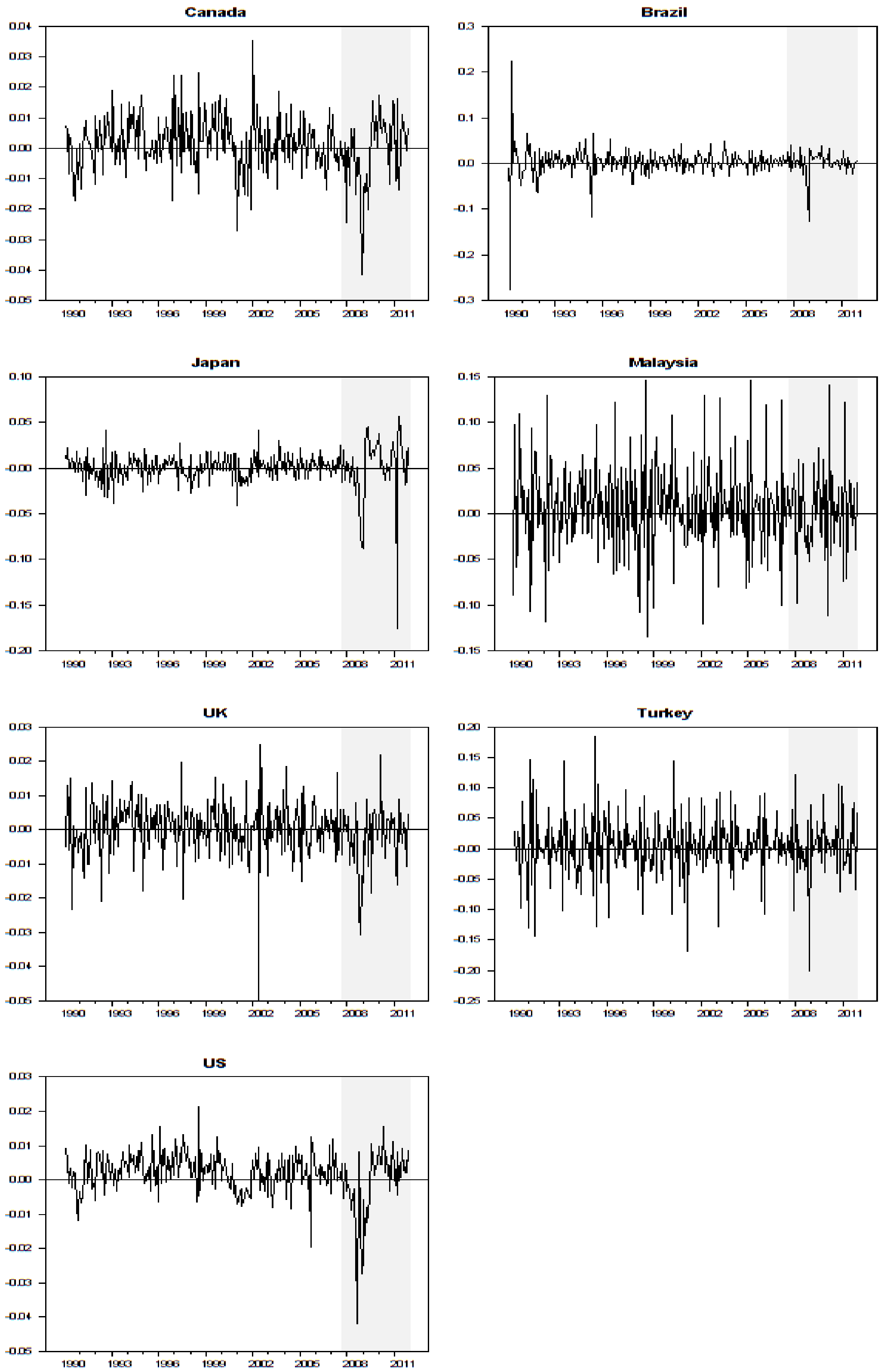
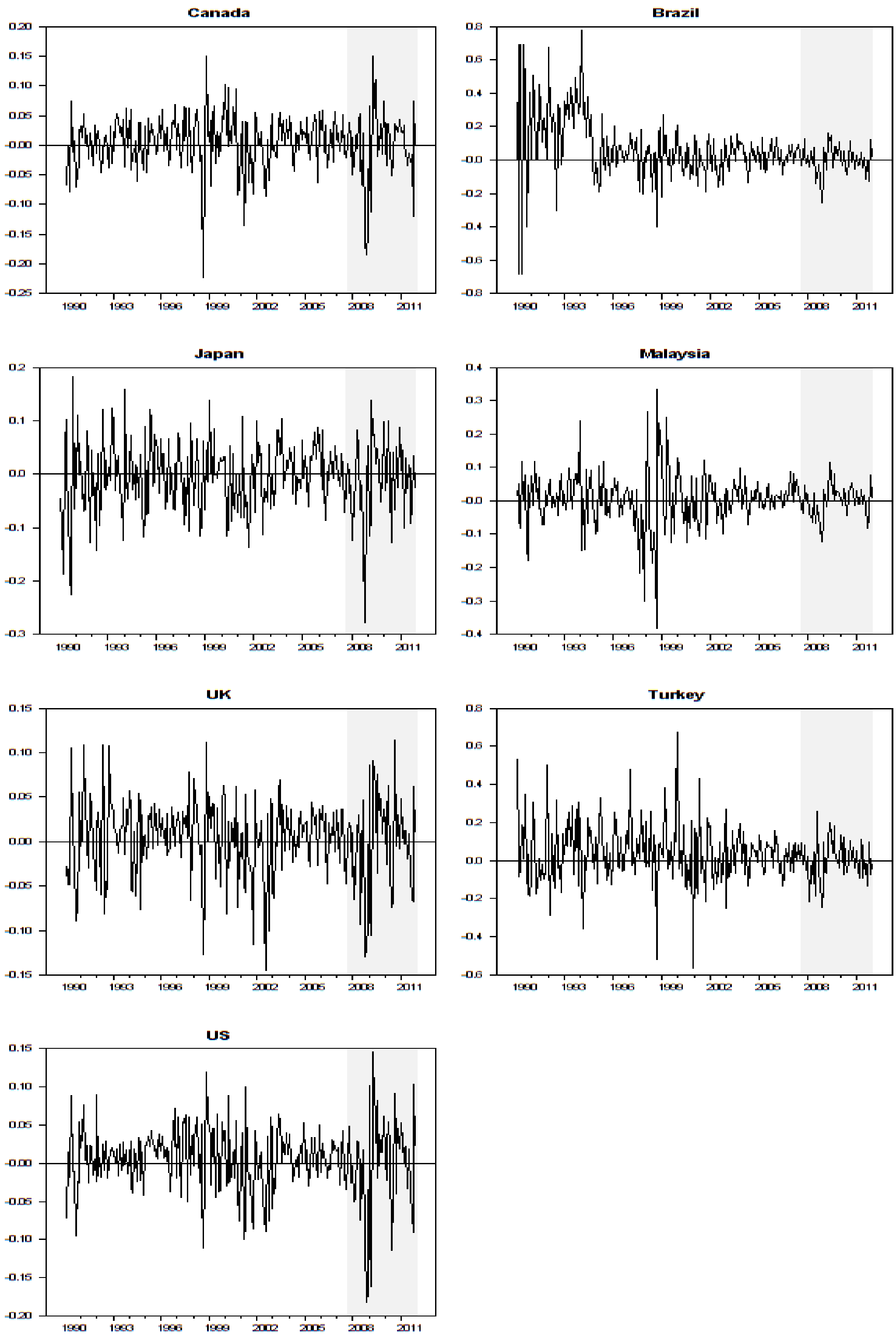


Figure 4.4: Stock Market Returns



4.4.2 Unit Root/Stationarity Tests

As described in section 4.1, this research employs the Augmented Dickey Fuller (Dickey and Fuller, 1979) and KPSS (Kwiatkowski *et al.*, 1992) tests for unit roots and stationarity. Table 4.2 presents the unit root/stationary analysis of the underlying data series. These results generally show that level variables are mostly nonstationary under KPSS and have at least one root under ADF, whereas all first difference variables are stationary. This conforms with the widely cited evidence that financial time series often exhibit nonstationary attributes at level and are stationary at first difference or I(1) (Hol, 2003; Taylor, 2011). Details of these tests for each series are provided below:

4.4.2.1 Index of Production (Log)

The index of production for Canada, Malaysia, the UK, the US and Turkey are reported to have at least one root under ADF and are nonstationary under the KPSS test with and without trend (Table 4.2). These results are in line with standard econometric evidence, where most of the economic series are reported to be nonstationary at levels (Brooks, 2002).

Some conflicting results, however, are also documented in the cases of Brazil and Japan. The Brazilian index of production (log) are found to be stationary with drift and trend at the 1% significance level, although it is found to be nonstationary in the rest of the tests. Similarly, the Japanese production index has shown stationarity with drift, with both drift and trend under the ADF test, and with trend stationary under KPSS as well. These conflicting results are reported but do not pose any challenge for the empirical methodologies adopted in this research.

4.4.2.2 Index of Production (First Difference)

According to the norm, changes in the index of production are reported to be stationary under both the tests for almost all developed and developing countries. In case of the UK and the US, there is some weak evidence of non-stationarity under KPSS, but as these series are stationary according to the rest of the tests, these findings do not bear any implications for this research.

4.4.2.3 Stock Market Indices (Log)

Stock market indices (log series) for all the countries are reported to be non-stationary, which is in line with the existing literature on the subject. The only exception in this regard is the Brazilian stock market index, where the null hypothesis of the unit root is rejected at the 1-5% levels for unit root with drift and also with drift and trend under the ADF test. This finding again may be ignored, as the rest of the tests confirm this series to be non-stationary.

4.4.2.4 Stock Market Returns

Continuously compounded stock market returns for all countries are found to be stationary under all the tests, with the only exception of Brazil, where stock returns are stationary under all ADF tests, but non-stationary under the KPSS test. As these returns are still confirmed by one of the tests, however, it is expected that this conflicting result will not pose any implications for the rest of the empirical analysis in this research.

Table 4.2: Unit Root Test for Level and First Difference Variables

Countries	Series	ADF	ADF (Int & Trend)	ADF (Intercept)	KPSS w/o Trend	KPSS Trend
Brazil	IOP (Log)	1.584	-4.2 ***	-0.735	5.06 ***	0.14 **
	Δ IOP	-8.423 ***	-8.591 ***	-8.603 ***	0.05	0.03
	SM Index (Log)	-0.193	-3.983 **	-4.946 ***	3.47 ***	0.94 ***
	SM Returns	-3.219 ***	-4.337 ***	-3.555 ***	1.89 ***	0.34 ***
Canada	IOP (Log)	1.017	-1.323	-1.485	3.84 ***	1.14 ***
	Δ IOP	-4.44 ***	-4.613 ***	-4.551 ***	0.33	0.11
	SM Index (Log)	1.309	-2.789	-1.130	4.85 ***	0.32 ***
	SM Returns	-6.653 ***	-6.821 ***	-6.827 ***	0.04	0.04
Japan	IOP (Log)	-0.139	-3.624 **	-3.631 ***	0.15	0.16 **
	Δ IOP	-5.896 ***	-5.873 ***	-5.885 ***	0.02	0.02
	SM Index (Log)	-1.219	-3.26 *	-2.261	3.49 ***	0.25 ***
	SM Returns	-6.836 ***	-6.967 ***	-6.963 ***	0.09	0.05
Malaysia	IOP (Log)	2.626	-2.082	-2.305	5.07 ***	1.00 ***
	Δ IOP	-6.787 ***	-7.771 ***	-7.532 ***	0.19	0.01
	SM Index (Log)	0.663	-2.36	-1.720	2.01 ***	0.41 ***
	SM Returns	-7.554 ***	-7.585 ***	-7.594 ***	0.04	0.04
UK	IOP (Log)	-0.346	-0.463	-0.890	1.42 ***	1.13 ***
	Δ IOP	-5.319 ***	-5.608 ***	-5.311 ***	0.54 **	0.08
	SM Index (Log)	0.961	-2.004	-1.853	3.59 ***	0.74 ***
	SM Returns	-6.146 ***	-6.297 ***	-6.244 ***	0.11	0.05
US	IOP (Log)	1.342	-1.857	-1.473	4.44 ***	1.08 ***
	Δ IOP	-3.465 ***	-3.802 **	-3.744 ***	0.41 *	0.11
	SM Index (Log)	1.158	-1.537	-1.705	3.91 ***	0.98 ***
	SM Returns	-6.146 ***	-6.429 ***	-6.325 ***	0.22	0.06
Turkey	IOP (Log)	2.285	-2.856	-0.339	5.08 ***	0.18 **
	Δ IOP	-7.084 ***	-7.474 ***	-7.486 ***	0.02	0.02
	SM Index (Log)	2.317	-0.779	-1.700	5.00 ***	1.13 ***
	SM Returns	-6.218 ***	-7.16 ***	-6.972 ***	0.34	0.04

Notes:

1. ADF: Augmented Dickey Fuller Test
2. ***,**,* denote significance level at 1%, 5%, and 10% respectively.

4.4.3 Stock Market Volatility Analyses

This section provides the analysis of stock market volatility estimates based on the Threshold GARCH model. Figure 4.5 provides the graphical presentation of the stock market volatilities for the sample countries. The shaded areas in figure 4.5 represent the financial crisis period, i.e. July 2007 to December 2011. The developed countries are stacked on the left side of the figure whereas the developing countries are on the right hand side. One visible difference to be observed is that the stock market volatilities for the developed countries are relatively more volatile than the developing economies, especially during the financial crisis; the stock market volatilities for Canada, Japan, the UK and the US show far more turbulence than the developing markets.

Table 4.3 presents the parameter estimates for the mean return and conditional volatility of the sample countries. This section also covers the descriptive analysis and unit-root tests of the stock market volatility estimates of the sample countries. The average return (M) for most of the countries is significantly positive, except for Japan, with a negative mean return of -0.09%. In addition, volatility parameters, i.e. long term average volatility (α_0), past volatility effect (α_i), lagged conditional variance (β) and asymmetric sensitivity of past volatility (γ), are found to be significantly positive for almost all the countries. The only exceptions in this regard were: i) the UK, where the past volatility effect parameter (β_1) was insignificant, and ii) Japan, where a significant negative ARCH effect is reported.

These results also confirm the asymmetric response of the volatility estimates which imply a varying reaction of the conditional stock market volatility to positive and negative information shocks across all the countries included in the sample. Moreover, this asymmetric effect is observed to be greater among the developed countries compared to the developing countries, which highlights the asymmetric impact of stock market uncertainty in the developed countries.

Country specific analysis of the ARCH effects shows that all the parameters are significant except for the UK. Japan, Brazil and Malaysia have the highest ARCH effects (α_1) 0.1683, -0.203 and 0.183, respectively. In contrast, the lagged GARCH parameters are highly significant and positive for all the countries. Turkey, the US, Japan and Brazil have the largest effect in this regard with coefficients (β) of 0.926, 0.755, 0.849 and 0.799 respectively.

Besides the above, the standardized and squared standardized residuals of the conditional volatility equation are tested for the possibility of high order autocorrelation using Ljung and Box (1978) Q-statistics up to 12 lags. However, the null hypothesis of 'no autocorrelation' cannot be rejected for any of the sample countries. This test also justifies the use of p and q to first levels only (Giannopoulos, 1995; Taylor, 2011).

Descriptive analysis of the stock market volatility estimates (Table 4.4) for the sample countries also reveals some important insights. For instance, mean conditional volatility level series for most of the developed countries are relatively lower before the financial crisis sample, with an increase in the mean conditional volatility observed when the sample period is extended to include the financial crisis period. Non-normal attributes of the volatility series for all the countries have been seen for both the sample lengths, showing a consistent characteristic of stock market volatility across all the countries.

Unit root/stationarity test results for the Augmented Dickey Fuller and KPSS tests are presented in Table 4.5. As expected, both volatility and changes in volatility (i.e. level and first difference) variables are reported to be level-stationary under both the methods. This provides evidence of the stochastic stability of the underlying volatility variables and their first difference transformation, and justifies further econometric estimations for hypotheses testing.

Figure 4.5: Stock Market Volatility - Threshold GARCH(1,1)

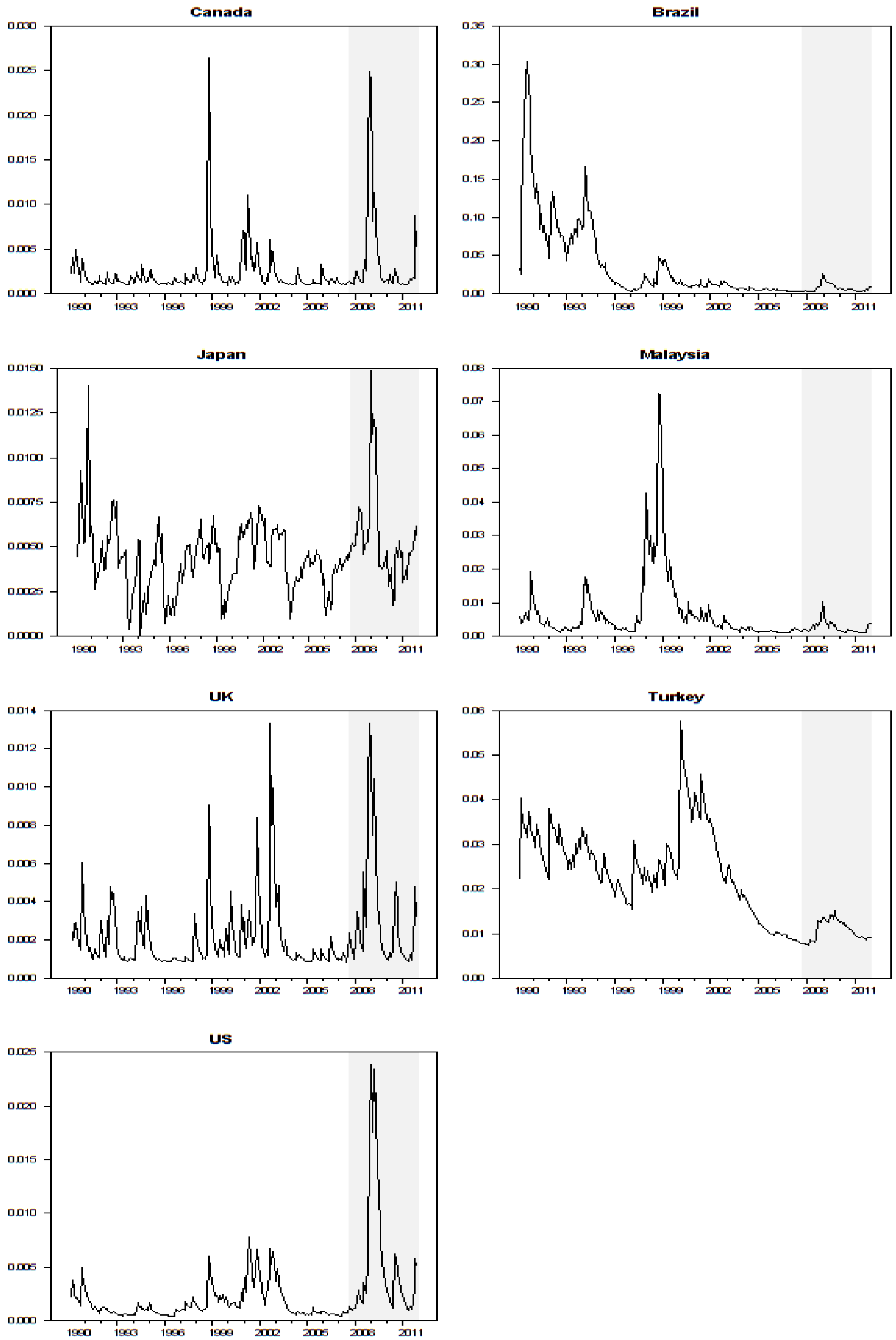


Table 4.3: Threshold GARCH(1,1) Results for Stock Market Volatility

Parameters	Brazil	Canada	Japan	Malaysia	UK	US	Turkey
M	0.0201***	0.0067***	-0.009***	0.0063*	0.0053**	0.006***	0.027***
α_0	0.0003*	0.0005***	0.0009***	0.0002***	0.0004***	0.0001***	0.0004***
α_1	0.1683***	0.0797**	-0.203***	0.1873***	0.0309	0.0635***	0.0778**
Β	0.799***	0.5089***	0.8497***	0.7075***	0.5665***	0.7556***	0.9265***
Γ	0.0387	0.3742***	0.3397***	0.1427***	0.4155***	0.2894***	-0.0545
L	171.67	457.13	359.17	368.5	465.2	482.99	140.34
Std. Resids (Q-Stat,12)	14.63	9.09	12.87	18.96	7.51	10.71	6.04
Sq.Std.Resids (Q-Stat,12)	4.15	13.56	5.9	9.56	6.18	5.63	7.77

Notes:

1. ***,**,* denote significance level at 1%, 5%, and 10% respectively.
2. M: Mean Stock Market Return; α0: Contemporaneous Conditional Variance; α1: ARCH effect; β: GARCH effect; γ: Asymmetric effect; L: Log Likelihood; Std, Resids: Standardised Residuals; Sq.Std.Resids: Squared Standardised Residuals; (Q-Stat, 12): Ljung-Box Autocorrelation Test up to 12 lags.

Table 4.4: Descriptive Statistics for Stock Market Volatility (Level and First Difference)

Panel-I: Before the Financial Crisis (Jan-1990 to Jun-2007)

Countries	Series	Mean	Variance	Skewness	Kurtosis	JB-Stat
Brazil	Stock Volatility	0.0399	0.003	2.3772	6.5189	566.9***
	Δ Stock Volatility	-0.0001	0.0002	2.6846	14.5061	2073.5***
Canada	Stock Volatility	0.0021	0	6.5747	57.8698	30669.2***
	Δ Stock Volatility	0	0	5.3577	69.6701	43062.4***
Japan	Stock Volatility	0.0042	0	0.6712	3.2305	106.6***
	Δ Stock Volatility	0	0	-1.898	12.3309	1442.7***
Malaysia	Stock Volatility	0.0071	0.0001	3.6813	16.7123	2904.3***
	Δ Stock Volatility	0	0	4.4178	38.8123	13732***
UK	Stock Volatility	0.002	0	3.2747	14.1131	2108.1***
	Δ Stock Volatility	0	0	2.487	15.9228	2411.7***
US	Stock Volatility	0.0016	0	1.8219	2.8798	187.8***
	Δ Stock Volatility	0	0	2.9042	14.5674	2131.6***
Turkey	Stock Volatility	0.0249	0.0001	0.3494	0.2416	4.8*
	Δ Stock Volatility	-0.0001	0	5.199	35.3015	11737.4***

Panel-II: Including the Financial Crisis (Jan-1990 to Dec-2011)

Countries	Series	Mean	Variance	Skewness	Kurtosis	JB-Stat
Brazil	Stock Volatility	0.0333	0.0025	2.7298	8.714	1158.76***
	Δ Stock Volatility	-0.0001	0.0002	2.97	18.607	4164.77***
Canada	Stock Volatility	0.0024	0	5.0657	30.4134	11261.03***
	Δ Stock Volatility	0	0	3.6726	42.1166	19953.08***
Japan	Stock Volatility	0.0045	0	1.4328	5.4589	416.54***
	Δ Stock Volatility	0	0	-0.6461	13.309	1951.89***
Malaysia	Stock Volatility	0.0062	0.0001	4.12	21.1555	5648.47***
	Δ Stock Volatility	0	0	4.8698	48.2737	26475.16***
UK	Stock Volatility	0.0022	0	2.9783	10.3941	1572.7***
	Δ Stock Volatility	0	0	2.0407	11.9805	1748.74***
US	Stock Volatility	0.0024	0	4.0838	19.6713	4971.49***
	Δ Stock Volatility	0	0	3.2651	25.6721	7660.2***
Turkey	Stock Volatility	0.0219	0.0001	0.5169	-0.171	12.03***
	Δ Stock Volatility	0	0	5.7229	43.8545	22425.22***

***,**,* denote significance level at 1%, 5%, and 10% respectively.

Table 4.5: Unit Root Test for Stock Market Volatility

Panel-I Before the Financial Crisis (Jan-1990 to Jun-2007)

Countries	Series	ADF	ADF (Int & Trend)	ADF (Intercept)	KPSS w/o Trend	KPSS Trend
Brazil	Stock Volatility	-4.8 ***	-5.19 ***	-4.87 ***	0.24	0.04
	Δ Stock Vol.	-9.71 ***	-10.3 ***	-9.94 ***	0.04	0.04
Canada	Stock Volatility	-2.66 ***	-4.33 ***	-4.33 ***	0.18	0.18 *
	Δ Stock Vol.	-8.24 ***	-8.2 ***	-8.23 ***	0.01	0.01
Japan	Stock Volatility	-1.41	-4.02 ***	-4.03 ***	0.21	0.18 *
	Δ Stock Vol.	-6.96 ***	-6.93 ***	-6.95 ***	0.02	0.02
Malaysia	Stock Volatility	-2.1 **	-2.63	-2.59 *	0.04 *	0.05
	Δ Stock Vol.	-7.59 ***	-7.56 ***	-7.57 ***	0.03	0.03
UK	Stock Volatility	-2.25 **	-4.23 ***	-4.23 ***	0.16	0.016
	Δ Stock Vol.	-8.05 ***	-8.01 ***	-8.03 ***	0.01	0.01
US	Stock Volatility	-1.77 *	-2.59	-2.59 *	0.42 *	0.036
	Δ Stock Vol.	-7.21 ***	-7.18 ***	-7.2 ***	0.03	0.03
Turkey	Stock Volatility	-2.22 **	-3.92 **	-3.44 **	0.13	0.046
	Δ Stock Vol.	-7.08 ***	-7.11 ***	-7.11 ***	0.09	0.03

Panel-II Including the Financial Crisis (Jan-1990 to Dec-2011)

Countries	Series	ADF	ADF (Int & Trend)	ADF (Intercept)	KPSS w/o Trend	KPSS Trend
Brazil	Stock Volatility	-5.39 ***	-5.63 ***	-5.52 ***	0.27	0.061
	Δ Stock Vol.	-10.9 ***	-11.5 ***	-11.1 ***	0.03	0.03
Canada	Stock Volatility	-3.38 ***	-5.16 ***	-5.05 ***	0.19	0.06
	Δ Stock Vol.	-8.51 ***	-8.47 ***	-8.49 ***	0.01	0.01
Japan	Stock Volatility	-1.55	-4.7 ***	-4.65 ***	0.19	0.13 *
	Δ Stock Vol.	-8.55 ***	-8.52 ***	-8.53 ***	0.01	0.01
Malaysia	Stock Volatility	-2.35 **	-2.99	-2.88 **	0.06	0.03
	Δ Stock Vol.	-8.54 ***	-8.51 ***	-8.53 ***	0.02	0.02
UK	Stock Volatility	-2.82 ***	-5.15 ***	-5.06 ***	0.21	0.07
	Δ Stock Vol.	-8.41 ***	-8.38 ***	-8.4 ***	0.01	0.01
US	Stock Volatility	-3.39 ***	-4.97 ***	-4.55 ***	0.08	0.1
	Δ Stock Vol.	-7.12 ***	-7.09 ***	-7.11 ***	0.02	0.02
Turkey	Stock Volatility	-1.34	-2.29	-1.59	0.89	0.044
	Δ Stock Vol.	-7.94 ***	-7.95 ***	-7.97 ***	0.06	0.03

Notes:

1. ADF: Augmented Dickey Fuller Test
2. ***,**,* denote significance level at 1%, 5%, and 10% respectively.

4.5 Conclusion

To conclude, this chapter details the methodology used for the research. It explicates the research questions and four hypotheses that are to be tested to answer the questions. It shows the data selection and transformation and discusses its characteristics based on the descriptive statistics. Data comprises of: 1) major national stock indices, and 2) Index of production, of eight countries from January 1990 to December 2011 (at monthly intervals). The countries are the US, the UK, Canada, Japan, Brazil, Malaysia, Turkey and China. The latter three countries are used as the developing countries for hypothesis no. 4. For the cross-country causality (in hypothesis 2), the US has been used as the major influential external economy.

The chapter further explains the estimation of stock market volatility from the national indices by means of the Threshold GARCH(1,1) model proposed by Glosten *et al.* (1993). The modelling has also been explained at length for linear and non-linear settings for causality testing on the estimated variables. Results in this regard are quite standard and in line with the existing literature. Asymmetry terms for all countries are significant and justify the adoption of the Threshold GARCH model. Stock market volatilities for the developed countries show relatively higher sensitivity to the financial crisis compared to the developing countries. The index of production is used as an estimate of the business cycles for the respective countries, based on logic and evidence from relevant literature.

Hypotheses tests are mainly based on Granger causality tests in bivariate linear, bivariate non-linear (Hiemstra and Jones, 1994; Diks and Panchenko, 2006), multivariate linear and multivariate non-linear settings (Bai *et al.*, 2010). Descriptive statistics and unit root/stationarity tests have also been discussed in this chapter, results of which are reported at the end of the chapter (Tables 4.1 to 4.5). All variables are found to be non-stationary at all levels, with the exception of the stock market volatilities where the 1st difference series of both variables are stationary for all countries.

"Analysis – Developed Countries" is the next chapter which contains results and discussion of the hypotheses tests for the Developed Countries, along with comparisons with available evidence in the literature.

Chapter 5: Analysis – Developed Countries

5.1 Introduction

This chapter presents the estimations and results of all four hypotheses for the developed countries under study, and analyses the findings of the research at length. From the discussion in the previous chapters it has already been established that the theme of this research is to study the relationship between stock market volatility and business cycles within a country and across countries. This chapter includes a discussion of the empirical results with respect to the relationship between variations in stock market volatility and changes in business cycles for the developed countries only, i.e. Canada, Japan, the UK and the US. For cross-country analysis, variables of interest for Canada, Japan and the UK are compared against the US to identify the direction of causality between the variables. These results will have significant implications in terms of theory and practice for investment, policy making and risk management.

The analytical framework builds upon research looking at how the recent global economic down-turn has affected the relationship between stock market volatility and business cycles both intra and across countries. For this purpose, all hypotheses are tested and compared on the basis of two samples: i) the pre-crisis period (January 1990 to June 2007); and ii) including the financial crisis period (January 1990 to December 2011). The comparison of results aims to identify the differences and/or similarities between the results in order to highlight the role of the financial crisis in this context.

This thesis will explore the incidence of Granger causality between the variables of interest within each country and across countries included in the sample. Furthermore, the Granger causality is tested both in the linear and nonlinear settings, to provide an extensive insight into the nature and extent of interaction between these variables and thereby contribute to the knowledge base in this area.

From a methodological aspect, as detailed in Section 2.6 (Theoretical Framework), this research employs the Granger causality framework in different settings in terms of the variables and parametric distributions. In terms of the variables, the bivariate Granger causality test is used for within country analysis and the multivariate Granger test is adopted for cross-country analysis.

This thesis also explores the bivariate and multivariate nonlinear dimensions of the Granger causality between the variables of interest and aims to contribute significantly to the current literature. To the best of our knowledge, there is no existing academic evidence on this particular subject. Bivariate nonlinear Granger causality is assessed based on test statistics suggested by Hiemstra and Jones (1994), Diks and Panchenko (2006) and Bai et al (2010) and framework is employed for multivariate nonlinear Granger causality.

5.2 Bivariate Linear Causality

The causal relationship between changes in stock market volatility and changes in the business cycle within the country is tested in hypothesis 1. Hypothesis 1a tests the linear Granger causality between the said variables on a sample period of January 1990 to June 2007 (termed as the period before the crisis). Table 5.1 shows the results from this causality test. Furthermore, we take into account the recent financial crisis and evaluate whether the crisis has had any impact on the strength of causality between stock market volatility and the business cycle in Hypothesis 3.1a.

The financial crisis started in the US and rapidly spread globally in the summer of 2007, indicating a rise in the financial market volatility across the major markets around the globe (Kamin and DeMarco, 2012). The conditional stock market volatility in the developed countries, including Canada, Japan, the UK and the US, increased after June 2007, as shown in Figure 4.5. Therefore, this research runs each causality test for two sample lengths, i.e. 1990:01 to 2007:06, before the recent financial crisis period; and then 1990:01 to 2011:12 for the time period including the recent financial crisis. The differences between the results from both sample lengths indicate the impact that the recent financial crisis may have had on the causal relationship between the variables. Results for hypotheses 1a and 3.1a are presented in Tables 5.1 and 5.2, respectively.

5.2.1 Before the Financial Crisis (Jan-1990 to June 2007)

The results based on the linear causality test (Table 5.1) for before the financial crisis time period (January 1990 to June 2007) show that a Granger causal relationship exists between the variables. However the strength and direction of causality varies for different countries. Detailed country specific analysis is provided below:

5.2.1.1 Canada

The business cycle and stock market volatility for Canada exhibits significant strong feedback effects, as seen in Table 5.1. Thus, the null hypothesis 1a for Canada cannot be accepted; both variables are mutually dependent on each other at the 1% or 5% significance levels. This result is theoretically in line with Binswanger (2001).

5.2.1.2 Japan

Japanese variables are found to be independent of each other in the pre-crisis scenario as no statistical evidence of causation is found in either direction (Table 5.1). Thus, the null hypothesis 1a cannot be rejected in the case of Japan. These results are similar to Ahn and Lee (2006), who found no relationship, and Binswanger (2001), who found that the relationship between the Japanese stock returns and real activity has broken down since the 1980s. In the literature, where the relationship between these variables has been analysed specifically to forecast or predict the business cycle, the models have not performed well on Japanese data (Fornari and Lemke, 2010). One of the reasons for these distinct results in the case of Japan may be the extended periods of recession in the country. The Japanese economy has been in recession for almost fifty percent of the sample time and these recessions have been clustered and longer in duration than the expansionary phases, very different to the other developed countries. Another possible reason could be that the causal relationship between Japanese variables may not be linear in nature, and thus the nonlinear framework may show some relationship between stock volatility and the business cycle for Japan.

5.2.1.3 United Kingdom

Relatively weak evidence of a linear feedback effect (at the 10% significance level) is shown for the UK stock market volatility and business cycle. The results are slightly better than the findings of Errunza and Hogan (1998) and Morelli (2002) for the UK, who found no significant causal relationship between macroeconomic factors and stock market volatility. However, results in Morelli (2002) are based on the conditional volatility of macroeconomic factors, rather than the growth rates of these macroeconomic variables. Thus, the results imply that the null hypothesis 1a cannot be accepted in the case of the UK as well, but only at the 10% significance level

5.2.1.4 United States

For the US, unidirectional causality has been found as its stock market Granger causes the business cycle at 1% significance (Table 5.1), but no evidence is found for reverse causality. These findings are in line with Schwert's (1989) findings for the US, indicating that stock market volatility predicts volatility in industrial production but not vice versa. Our findings are also consistent with Errunza and Hogan (1998) who reported that macroeconomic volatility cannot explain time variations in stock market volatility. Also, Chen and Wu (2013) found that US domestic macroeconomic shocks account for a very small portion of variations in stock market returns in comparison to other global and international factors. Hence, the null hypothesis 1a cannot be accepted in the case of the US as well. There are a number of studies which have reported similar findings for the US using different data samples and empirical settings (Lee, 1992; Campbell *et al.*, 2001; Ahn and Lee, 2006; Bloom *et al.*, 2009; Fornari and Mele, 2009; Rahman, 2009).

5.2.1.5 Findings from Hypothesis 1a

To summarize, the null hypothesis (1a) of no Granger linear causality between the business cycle and stock market volatility cannot be accepted in the pre-crisis period for most of the developed countries, with the exception of Japan. The main findings in this section are that: i) a strong linear feedback effect is only reported for Canada, only a weak feedback relationship is found for the UK; and ii) stock market volatility is shown to Granger cause business cycles in the US. These results imply that the overall economic performance (changes in business cycle) and stock market (changes in volatility) are inter-dependent and hence mirror each other in the case of Canada. Stock market volatility shifts significantly preceding business cycle changes, hence showing a greater reliance of the US economy on its stock market volatility. For Japan and the UK, such dependence either does not exist or is very weak.

5.2.2 Including the Financial Crisis (Jan-1990 to Dec-2011)

The results for the bivariate (within country) linear causality between the variables for the full sample comprising of before the crisis and during the crisis time period are presented in Table **5.2**. Country specific hypothesis tests and analyses are as follows:

5.2.2.1 Canada

In the case of Canada, a strong feedback effect is reported between stock market volatility and the business cycle in Table 5.2. Thus, the null hypothesis (3.1a) cannot be accepted at the 5% significance level. Stock market volatility and the business cycle in Canada show a strong and stable mutual dependence on each other for both time periods (see section 5.2.1.1 above). The evidence in the case of Canada adds to the existing literature showing mutual linear dependence between the underlying variables.

5.2.2.2 Japan

However, in the case of Japan, relatively weak unidirectional Granger causality is observed between business cycles and stock market volatility with a significance level of only 10% (Table 5.2). Hence, stock market volatility in Japan shows minimal linear dependence on the business cycle after inclusion of the recent financial crisis. It is interesting to see that in Japan, stock market volatility and the business cycle had shown no relationship before the financial crisis however, after including the financial crisis time span, changes in the business cycle are having some influence on its stock volatility, even though the impact is found to have only weak statistical significance.

5.2.2.3 United Kingdom

After inclusion of the financial crisis period, the feedback effect strengthens between stock market volatility and the business cycle of the UK at the 1% or 5% significance level (Table 5.2). This causal relationship was only significant at the 10% level for the pre-crisis time period (see 5.2.1.3 above). Thus, the null hypothesis 3.1a in the case of the UK cannot be accepted as well, implying the significant ability of both variables to cause and also predict each other to a certain extent.

5.2.2.4 United States

With the inclusion of the recent financial crisis period, strong linear bidirectional causality, or feedback effect, is reported for the US (Table 5.2). Thus, the null hypothesis 3.1a cannot be accepted at the 1% or 5% significance level. These results can be explained by looking at a few past studies, for example, Bernanke's (1983b) study of the Great Depression reported that a financial crisis causes financial losses that intensify recession in the economy. Schwert (1990a) found that the stock market is very sensitive to financial crisis and stock market volatility rises during a financial crisis. Campbell *et al.* (2001) found that the stock market volatility significantly increases during economic downturns and leads recession. (Hamilton and Lin, 1996)

5.2.2.5 Comparison of results for Pre and during the Financial Crisis Period

A comparison of results for both sample lengths reveal that the results have significantly changed for the UK and the US after including the financial crisis period. Stock market volatility and the business cycle show relatively stronger mutual linear dependence for most of the countries, except for Japan. In the case of Japan, after inclusion of the crisis period, weaker causality is reported for business cycles causing stock market volatility at the 10% significance level. Thus, this thesis offers fresh evidence of stock market volatility causing business cycles and vice versa, after inclusion of the recent financial crisis. The stronger causality results for the full sample including the financial crisis time period may be due to a number of reasons. The stock volatility increases with the increasing uncertainty during recessions and periods of crisis; the nature of risk premia is counter-cyclical whereby investors require relatively higher returns during bad times implying larger changes in risk premia or stock market volatility. This could lead to enhanced associations with a worsening economic situation (business cycle). Chauvet *et al.* (2011) reports that financial volatility[30] consistently leads business cycle peaks and performs well in anticipating the recession caused by the recent financial crisis.

5.3 Diagnostic Tests

Tables 5.1 and 5.2, in addition to the hypothesis test results, also provide standard diagnostic test results, such as the Jarque-Berra, Ljung-Box for autocorrelation, RESET for misspecification and White's heteroskedasticity tests. The results

[30] Realized volatility estimates based on the market and industry portfolios from stock and bond markets.

discussed above comply with these assumptions and no violations of the standard assumptions/diagnostics are observed.

5.4 Bivariate Nonlinear Causality

After analysing the intra country linear Granger causality between respective changes in stock market volatility and business cycles, an attempt has been made to explore the possibility of nonlinear Granger causality between the underlying variables. Nonlinear models suggested by Diks and Panchenko (2006) and Hiemstra and Jones (1994) employ normalized residuals series obtained from linear causality tests, to further explore nonlinear causality among the underlying variables. These methods are based on the test statistics based on correlation integral ratios between the variables. They employ conditional joint probabilities of co-movement between the lags and lead vectors of the two variables within a given range in terms of standard deviation (variation threshold), as explained in Methodology (see section 4.3.3). The null hypothesis of no Granger causality is rejected if the test statistic is significantly different than zero.

Hypothesis 1b in this context tests the null hypothesis of no nonlinear dependence between the lags of changes in stock market volatility and changes in the business cycles of the respective countries. The same hypothesis is further tested for possible effects of the financial crisis on the relationship in 3.1b. These hypotheses, as discussed in the Theoretical Background (section 2.7), are aimed at testing the Granger causality between the variables within the country in a non-linear framework.

Results for hypotheses 1b and 3.1b are shown in Tables 5.3 and 5.4, representing both samples, i.e. before and including the financial crisis, respectively. These hypotheses test the incidence of nonlinear Granger causality using the different approaches proposed by Diks and Panchenko (2006) and Hiemstra and Jones (1994). The results for both methods are reported in Panel-I and Panel-II, respectively.

5.4.1 Bivariate Nonlinear Causality - Diks and Panchenko (2006) Method

Diks and Panchenko's (2006) method is used in addition to that of Hiemstra and Jones (1994) for nonlinear causality. The results for this approach are presented in

Tables 5.3 and 5.4 (Panel-I) for both samples, i.e. before the financial crisis and including the financial crisis. The variation threshold for these results is 1.5 as suggested by Diks and Panchenko (2006) on the basis of their extensive Monte Carlo simulations.

5.4.1.1 Canada

In the case of Canada, the presence of nonlinear causality is reported where stock market volatility is causing the business cycle with a 5% significance level in the pre-crisis period (Tables 5.3 and 5.4). However, no evidence of causality in the reverse direction is found. This implies that changes in stock market volatility (nonlinear) precede the changes in the business cycle in Canada. Similar results are reported for the time period including the financial crisis, where stock market volatility is again causing the business cycle in Canada. Hence, the null hypotheses 1b and 3.1b cannot be accepted at the 5% significance level.

5.4.1.2 Japan

A nonlinear causal relationship is reported for the Japanese business cycle towards its stock markets before the financial crisis (Tables 5.3 and 5.4). Therefore, the null hypothesis 1b cannot be accepted at the 5% significance level for Japan. After inclusion of the recent financial crisis period, the direction of the causality is altered, i.e. Japanese stock market volatility precedes its business cycle at the 1% significance level. This shows the impact of the current financial crisis on the real economy through stock market volatility. Hence, the null hypothesis 3.1b is also rejected at the 1% significance level.

5.4.1.3 United Kingdom

In the case of the UK, nonlinear independence is observed between the two variables before the financial crisis (Tables 5.3 and 5.4). This implies that the Diks and Panchenko (2006) method could not find any information in nonlinear settings which could explain the variations in the underlying variable. Thus, the null hypothesis 1b for the UK cannot be rejected. However, after extending the sample to include the financial crisis period, stock market volatility is seen to Granger cause the business cycle in the UK at the 10% significance level.

5.4.1.4 United States

The US business cycle is reported to precede its stock market volatility according to Diks and Panchenko's (2006) test statistic, implying that the null hypothesis 1b cannot be accepted at the 5% significance level before the financial crisis (Table 5.3). However, this relationship does not hold for the full sample length (Jan-1990 to Dec-2011), where no evidence of nonlinear Granger causality is found. This means that the null hypothesis 3.1b cannot be rejected even at the 10% significance level (Table 5.4).

5.4.1.5 Summary of findings for hypothesis 1b (Diks and Panchenko, 2006)

These results suggest that the joint conditional probabilities of co-movement between stock market volatility and business cycles are significant and highlight nonlinear dependence between the underlying variables of each country. Thus, this method captures the nonlinear association between the variables in addition to the linear framework, as discussed in section 5.2, which helps in understanding the stochastic behaviour of the underlying variables.

After including the financial crisis period, the nonlinear causality results change significantly. Business cycles cause stock market volatility in Canada and the US, whereas in the case of Japan the causality flows from stock market volatility to the business cycle (5% significance level in both cases). UK stock market volatility shows weaker causality towards its business cycle with a 10% significant level.

5.4.2 Bivariate Nonlinear Causality - Hiemstra and Jones (1994) Method

This section present nonlinear Granger causality results using the Hiemstra and Jones (1994) method. Detailed results for this test are shown in Panel-II of Tables 5.3 and 5.4. Country specific discussion of the results is provided below:

5.4.2.1 Canada

Using Hiemstra and Jones' (1994) nonlinear Granger causality test, stock market volatility in Canada precedes the business cycle before the financial crisis period (Table 5.3). This leads to rejection of the null hypothesis 1b at the 5% significance level for Canada. After inclusion of the financial crisis period, the direction of causality changes and the feedback effect, or bidirectional causality, is observed between the two variables (Table 5.4). This shows the association of the two variables during the recent financial crisis. Hence, the null hypothesis 3.1b cannot be accepted at the 5% significance level.

5.4.2.2 Japan

In the case of Japan, the null hypothesis 1b of no nonlinear Granger causality can only be rejected at the 10% significance level (Table 5.3). This shows relatively weak support for the existence of a nonlinear causal relationship between stock market volatility and the business cycle in Japan before the financial crisis. However, results do show evidence of the business cycle leading stock market volatility in Japan after including the financial crisis period (Table 5.4). Therefore, the null hypothesis 3.1b for Japan can be rejected at the 5% significance level.

5.4.2.3 United Kingdom

Stock market volatility and the business cycle for the UK show weaker nonlinear mutual dependence or feedback effect before the financial crisis (Table 5.3). This means that the null hypothesis 1b cannot be accepted for the UK only at the 10% significance level. This result holds even after the recent financial crisis period is included in the analysis, showing structural stability. Thus, the null hypothesis 3.1b cannot be accepted at the 10% significance level either (Table 5.4).

5.4.2.4 United States

Stock market volatility leads the business cycle in the US under the Hiemstra and Jones (1994) method, for the sample covering before the financial crisis period. This results in rejection of the null hypothesis at the 5% significance level. However, this causal association fades away after inclusion of the financial crisis period, as no evidence of nonlinear causality is noted for this period. Hence, the null hypothesis 4.1b cannot be rejected at any threshold significance levels (1%-10%)

5.4.2.5 Summary of Findings for Hypothesis 1b – Hiemstra and Jones (1996) Method

Using the Hiemstra and Jones (1994) approach, nonlinear causality statistics show significant nonlinear causality for Canada and the US, as the stock market volatility causes the business cycle at the 5% significance level. Evidence for Japan and the UK in the same context is relatively weaker, and the null hypothesis can only be rejected at the 10% significance level. Comparing the results for the pre-crisis and including the crisis periods, the nonlinear causality direction has altered after including the crisis period. Business cycles and stock market volatility now show a feedback effect for Canada as well, whereas for the UK the feedback effect remains unchanged. The Japanese business cycle is observed to drive the stock market volatility significantly at the 5% level, which reinforces the impact of prolonged economic crisis leading to increased systemic and market risks and hence resulting in stock market volatility.

5.4.3 Comparison of Results for Nonlinear Granger Causality Tests based on the two methods

Comparison between the above two methods, reveal that the null hypotheses of no nonlinear causality are accepted in 10/16 cases under the Diks and Panchenko (2006) framework, whereas in the case of Hiemstra and Jones (1994) only 6 out of 16 null hypotheses are accepted. According to Diks and Panchenko (2006) this may be due to over-rejection bias, i.e. rejection of the null hypothesis when it is true. They also show that Hiemstra and Jones' (1994) statistic is insensitive to conditional variations in the underlying variables, which may be present under the null hypothesis. Canada and Japan consistently show strong associations, based on Diks and Panchenko's (2006) approach, between their respective stock market volatilities and business cycles for both sample lengths. However, the US shows such nonlinear dependence in the pre-crisis period only. In the case of the UK, only nonlinear independence or weak evidence is reported in this respect. Using the Hiemstra and Jones (1994) model, Canada shows significant causality between both variables across both sample periods. However, relatively stronger nonlinear dependence in the case of Japan is shown in the pre-crisis period, whereas for the US such a relationship is reported only after inclusion of the financial crisis period. Stock market volatility and the business cycle of the UK show no, or only weak, nonlinear dependence for both sample periods.

5.5 Comparison of Bivariate Linear and Nonlinear Causality Results- Hypotheses 1a and 1b

This research combines both traditional linear Granger causality tests and nonparametric nonlinear models to understand the relationship between stock market volatility and the business cycle. Nonlinear models are based on the argument that variables may still contain useful information after linear effects are removed from the data. Hence, any evidence of causality found shows the inability of linear models to explain fully the variations in variables. This research shows strong evidence of nonlinear relationships in many cases where the nonlinear causality exists beyond what can be inferred by linear combinations. Country specific comparisons of bivariate causality results between linear and nonlinear models are given below:

5.5.1 Canada

Linear causality tests show a significant feedback effect between stock market volatility and the business cycle for both the pre-crisis and including the crisis periods. After removing the linear effects, the Diks and Panchenko (2006) statistic shows the business cycle causing stock market volatility for both sample lengths, whereas mixed results are shown under Hiemstra and Jones (1994), i.e. changes in stock market volatility precede corresponding changes in the business cycle in the pre-crisis sample period, and the feedback effect is reported between the two variables when the crisis period is included.

5.5.2 Japan

Mixed results are reported for Japan under the linear causality test. Stock market volatility and the business cycle are shown to be statistically independent of each other. However, nonlinear causality runs from the business cycle to the stock market in the pre-crisis period and this direction switches after the inclusion of the crisis period, meaning stock market volatility becomes a significant predictor of business cycles under the Diks and Panchenko (2006) method. In the case of Hiemstra and Jones (1994), relatively weaker causality is reported where the stock market causes the business cycle, with a significance level of 10% before the financial crisis. After extending the sample, reverse causality is reported, i.e. Japanese changes to the business cycle causes variations in stock market volatility.

5.5.3 United Kingdom

Stock market volatility and the business cycle show a relatively weak (10%) linear feedback effect before the financial crisis, and this linear relationship grows statistically stronger at a significance level of 1-5% after inclusion of the financial crisis period. However, nonlinear models offer relatively weak evidence in this context at a significance level of 10%. Under the Diks & Panchenko (2006) method, stock volatility causes the business cycle for the full sample, whereas both variables are statistically independent in the pre-crisis period. The Hiemstra and Jones (1994) statistic reports stock volatility affecting the business cycle in the pre-crisis period, and even after inclusion of the financial crisis period.

5.5.4 United States

Linear Granger causality results reveal that the business cycle is caused by stock market volatility in the pre-crisis sample; however, both variables seem to affect each other after inclusion of the crisis period. Hence a significant feedback effect, or bidirectional causality, is reported with a significance level of 1-5%. After filtering the data for linear causality, the Diks and Panchenko (2006) model shows that some important information is contained by the variables, i.e. stock market volatility precedes the business cycle significantly in the pre-crisis period (5%). Similarly, the Hiemstra and Jones (1994) statistic shows stock market volatility causing the business cycle for the same sample length. However, both methods fail to detect any evidence of nonlinear causality after inclusion of the financial crisis.

5.6 Multivariate Linear Causality

In this section, hypotheses 2a and 3.2a are tested using the multivariate linear causality method as discussed and detailed in Section 2.6. These hypotheses mainly test the linear Granger causality between the stock market volatility of country A and the business cycle of country B, and vice versa. As explained in section 2.3, for all these hypotheses the countries in the sample have been compared with the US as it is the largest economy. Thus, the main aim is to identify the possibility of spill-over among the variables of interest between the US and the rest of the countries in the sample, i.e. Canada, Japan and the UK. The analysis has been done based on two sample lengths, i.e. before the financial crisis (Jan-1990 to June-2007) and including the financial crisis (Jan-1990 to Dec-2011). Tables 5.5 and 5.6 show the results for the hypotheses 2a and 3.2a. Besides the main hypotheses results, evidence relating to stock market volatility spill-overs and business cycle spill-overs across the sample countries are also described and discussed in this section.

In addition to F-statistics, corresponding lags of each regressor, adjusted R squares, standard errors of estimates, sum of squares of residuals, Ramsey's misspecification test, White's heteroskedasticity test, Ljung-Box autocorrelation test and Jarque-Berra test results are also presented to test the reliability and consistency of the estimates.

5.6.1 Cross-country Spill-over (Stock Volatility against the Business Cycle)

5.6.1.1 Before the Financial Crisis (Jan-1990 to June 2007)

This section explains the empirical results for analysis of the linear spill-over effect between stock market volatility and the business cycle across the developed countries (Table 5.5). The hypotheses in this context are set out in section 2.7.2. For cross-country analysis, all of the developed countries included in the sample are compared against the US because the US is the largest economy among the rest of the developed countries and there is sufficient evidence in the literature that the US was at the epicentre of the recent financial crisis. Country specific analysis of these hypotheses is provided in the following sub-sections:

5.6.1.1.1 Canada

In the pre-crisis time period, a significant feed-back effect between Canadian stock market volatility and the US business cycle has been observed, i.e. both the variables are mutually dependent on each other at a significance level of 5% in both cases (Table 5.5). Similarly, the Canadian business cycle is observed to be a significant predictor of US stock market volatility at the 5% significance level. However, no significant evidence is reported for the US stock market volatility causing the Canadian business cycle.

5.6.1.1.2 Japan

A mutual interdependence is revealed for all four variables in the case of Japan and the US, i.e. Japanese stock market volatility and business cycle and the US stock market volatility and business cycle, with varying significance levels of 1% to 5% (Table 5.5). This cross-country linear relationship between Japanese and US variables demonstrates the mutual dependence between the two countries. This implies that any endogenous or exogenous shock to any one of the variables will be affecting the rest of the variables in both countries. It is interesting to observe that the Japanese stock market and business cycle bear weak causality within the country, but these variables are strongly influenced and bear influence on cross-country (US) variables. It could be due to the integration between the equity markets and business cycles of the US and Japan. In the literature, the stock markets of the US and Japan have been found to be interdependent and volatility spill-overs are evidenced across these markets (Hamao *et al.*, 1990, Koutmos and Booth, 1995). These volatility spill-overs are known to be asymmetric, i.e. shocks due to bad news transmit more than those due to good news. Similarly, Lombardi *et al.* (2011) found a strong relationship between the US and Japanese business cycles where real economic shocks transmit from the US to Japan.

5.6.1.1.3 United Kingdom

UK stock market volatility and the US business cycle show a significant (10%) but weak feedback effect between each other, indicating a feeble mutual interdependence. Additionally, the UK business cycle also significantly causes the US stock market volatility with a 5% significance level, but the linear causality in the opposite direction is only significant at 10% before the financial crisis. If we try to relate this result to that of Kanas and Ioannidis (2010), where they add US stock returns (cross-country variable) to the regression of UK stock returns to improve the forecast of UK growth rates, we find a causal relationship between the US variable and the UK variables, as in Table 5.5. However, the inclusion of the US variable does not strengthen the relationship between UK variables, as suggested by Kanas and Ioannidis (2010), because the significance of causality is 10% in both bivariate (Section 5.2.1.3) and multivariate settings.

Chen and Wu (2013) found that more than 80% of the total stock market volatility in the UK is contributed to by global macroeconomic facts (output), which supports our results. As discussed in the literature review earlier, Espinoza *et al.* (2012) has also studied the cross-country relationships between financial and macroeconomic variables. They found that financial variables (including stock market indices) do not improve the forecast of business cycles across economies in a linear setting. However, their study was based on regions rather than individual countries. Similarly, Milani (2011) studying the impact of large foreign stock markets on small open economies found that fluctuations in the former cause changes in the output growth rates. But his sample of markets and time length is different to this study, hence comparing our results to Espinoza *et al.* (2012) and Milani (2011) may not be completely appropriate. Nevertheless, it is still interesting to see that the results from this section of multivariate linear causality bear some similarities with their findings. Espinoza *et al.* (2012) suggested that financial variables may have a nonlinear impact on macroeconomic variables, which needs to be researched further.

5.6.1.2 Including the Financial Crisis (Jan-1990 to Dec-2011)

5.6.1.2.1 Canada

In the post financial crisis scenario, the feedback effect between Canadian stock market volatility and the US business cycle remains unchanged and slightly strengthens at significance levels varying between 1% and 5% (Table 5.6). The Canadian business cycle shows serious dependence on the US stock market volatility, with a 5% significance level, which is in contrast to earlier results where it was shown to be insignificant for the pre-crisis time period, implying US stock market volatility affects the Canadian economy.

5.6.1.2.2 Japan

In the case of Japan, most of the relationships found in the pre-crisis sample hold, except one, i.e. the US business cycle does not cause stock market volatility in Japan when we include the financial crisis period (Table 5.6). The rest of the relationships reported above for Japan and the US remain unchanged. These results show a strong linear relationship between the Japanese and US economies and stock markets. This has important implications both for investors, financial managers, and policy makers. The results show that changes in any one of the underlying variables also affects the rest.

5.6.1.2.3 United Kingdom

The linear dependence between the UK and the US variables grows stronger after inclusion of the crisis period (Table 5.6). The cross-country feedback effect between the UK business cycle and US stock market volatility is reported to be significant at the 5% level. Moreover, the US business cycle is shown to cause UK stock market volatility with a significance level of 5%, but reverse causality is significant only at 10%, it means the feedback effect in this case is weaker compared to the earlier instances between the UK business cycle and US stock market volatility. This implies that the UK economy is more affected by US stock market volatility compared to the US economy being affected by UK stock market volatility.

5.6.1.3 Findings for Hypothesis 2a

This section summarises the linear causality results between stock market volatility and business cycles across countries in the pre-crisis scenario. The US stock market volatility and business cycle show bidirectional linear causality with the stock market volatility and business cycles of Canada, Japan and the UK for the pre-crisis period. However, incidents of bidirectional causality (feedback effect) is reported in only a few cases for the full sample length. For instance, significant feedback effects between US stock volatility and the business cycles of Japan and the UK are reported, whereas for the US business cycle and stock market volatilities of Canada, Japan and the UK mixed results are documented.

5.6.2 Stock Market Volatility Spill-overs Across Countries

In addition to the above, our results also show some important findings in the context of stock market volatility spill-overs across countries in a linear setting. As discussed in the theoretical background chapter, there is a strand of literature that looks at the relationship (co-movement or Granger causality) between stock markets across countries. Here we test linear Granger causality for a possible linear dependence between US stock market volatility and the stock market volatility of the rest of the countries in the sample. The analysis describes how the results have possibly changed with the financial crisis.

Table 5.5 shows statistically significant bidirectional causality between Canadian and US stock market volatilities (1% to 5% levels) before the Financial Crisis (Jan-1990 to June 2007). The results for the UK are very similar to those of Canada, and stock market volatility for both the UK and the US exhibits mutual interdependence (1% to 5% significance levels). These results conform to Hamao *et al.* (1990), Arshanapalli and Doukas (1993) and Koutmos and Booth (1995). Moreover, Japanese stock market volatility has been reported as a significant predictor of US stock market volatility, with a 1% significance level, but the US stock market does not seem to have any impact on the Japanese stock market before the crisis erupted. No volatility spill-over from the US to Japan was also reported by Arshanapalli and Doukas (1993).

The full sample including the financial crisis (Jan-1990 to Dec 2011) shows somewhat similar results. Stock market volatilities for Canada and the UK indicate a strong feedback effect against US stock market volatility with 5% and 1% significance levels, respectively (Table 5.6). These results are consistent for both the sample periods, implying a stable interdependence between stock market volatilities in these countries before and during the financial crisis. The results for Japan are also similar to those reported for the short sample period, whereby the Japanese stock market volatility Granger causes US stock market volatility with a 1% significance level. The financial crisis does not seem to have had much impact on stock volatility spill-over across these countries.

5.6.3 Business Cycle Spill-overs Across Countries

Linear Granger causality tests are further applied for assessing the evidence of business cycle spill-overs across the sample countries, i.e. analysing whether changes in the business cycle of one country cause changes in the business cycle of another country. The results for testing the null of no Granger causality between the business cycles of the sample countries are presented in Tables 5.5 and 5.6. The business cycle of each country is compared with respect to changes in the business cycle of the US and vice versa. The following paragraphs show the causal relationship between business cycles across the countries based on the time before the financial crisis and during the financial crisis.

Based on the sample before the financial crisis (Jan-1990 to June 2007), it is interesting to see that both Canadian and UK business cycles have strong feedback effects (at a significance level of 1%) against US business cycles. However, only unidirectional spill-over is documented in the case of Japan, i.e. the Japanese business cycle affecting the US economy with a 1% significance level. The Japanese business cycle seems to be indifferent to the changes in the US business cycle before the 2007 crisis engulfed the world (Table 5.5).

The results for the full sample (Jan 1990 to Dec 2011), including the period of financial crisis, for the UK and Canada show similar results to the earlier findings before the crisis started. The business cycles of the UK and Canada show strong Granger causality with the US business cycle. The relationship remains significant for Canada and the UK at 1% after adding the sample marked by the financial crisis into the full sample, whereas the results for the Japanese business cycle relationship with the US business cycle seem to change when the financial crisis time is taken into account. Including the crisis period into the analysis, changes in the US business cycle Granger cause the Japanese business cycle at the 1% significance level, but the Japanese business cycle has a weak impact (at only 10% significance level) on the US business cycle (Table 5.6).

5.7 Multivariate Nonlinear Causality

This section describes the multivariate nonlinear Granger causality results between the variables, based on the test statistic proposed by Bai *et al.* (2010). Their approach essentially follows Hiemstra and Jones' (1994) framework for testing nonlinear Granger causality by estimating the correlation integrals ratio, or joint probability, of the underlying independent variables Granger causing the dependent variable (for more details see section 4.3.3 above). This statistic tests the null hypothesis of joint independence between the independent variables and a dependent variable based on correlation integrals in a multivariate framework. The results are shown in Tables 5.7 and 5.8. Following the same theme, firstly country specific results for the sample containing the period before the financial crisis are presented through Table 5.7 and later results pertaining to the full sample period are described via Table 5.8.

5.7.1 Before the Financial Crisis (Jan-1990 to June-2007)

5.7.1.1 Four Variables

This section explores the multivariate nonlinear causality across countries between the stock market volatility for Country A and the business cycle for Country B, while controlling for the business cycle of Country A and the stock market volatility of Country B. As the nonlinear measure proposed by Bai *et al.* (2010) tests the joint causality, for each case this is tested by taking each of four variables as the dependent variable and taking the rest of the three as independent variables.

5.7.1.1.1 Canada

In the case of Canada, relatively weak joint causality is reported at the 10% significance level (Table 5.7). The joint causality test models stock market volatility in Canada as a dependent variable and the independent variables are US stock volatility, the US business cycle and the Canadian business cycle. It implies that the latter three variables jointly cause Canadian stock market volatility in the pre-crisis period. It provides evidence of US stock market volatility and business cycle spill-over affecting Canadian stock market volatility. Besides this, no other evidence of joint nonlinear causality has been reported between Canada and the US, based on other combinations of joint causality tests taking the other three variables as the dependent variable in the equation.

5.7.1.1.2 Japan

Japanese stock market volatility and the Japanese business cycle have been found jointly significant along with US stock market volatility to cause changes in the US business cycle at the 5% significance level (Table 5.7). This offers seminal evidence of nonlinear associations or spill-over of Japanese stock market volatility and business cycles affecting US stock market volatility before the financial crisis.

5.7.1.1.3 United Kingdom

US stock market volatility is jointly caused by the UK business cycle and UK stock market volatility in addition to the US' own business cycle at the 1% significance level (Table 5.7). As shown in the case of Japan, UK stock market volatility and business cycle are also reported to jointly cause US stock market volatility. Moreover, relatively weak evidence is reported for US business cycles and US stock market volatility causing UK business cycles and stock market volatility, respectively, significant at the 10% confidence level.

5.7.1.2 Three Variables

This section explains the multivariate nonlinear causality where joint causality between the stock market volatility or business cycle of country A is tested against the stock market volatility and business cycle of country B. Thus, three variable are analysed in each test with each of Country A, i.e. both stock market volatility and the business cycle are separately modelled as the dependent variables with the remaining two variables of country B taken as the independent variables. The reason for doing these three-variable causality tests in addition to the all four-variables are: i) to exclude the impact of domestic variables as an independent variable and check whether only foreign variables cause the dependent variable; and ii) it also helps when comparing if the change of variables affects the earlier results of joint causality. Country specific results in this respect for the pre-crisis period are discussed below:

5.7.1.2.1 Canada

US stock market volatility and business cycles cause Canadian stock market volatility and these two US variables also cause business cycles, with a 10% significance level in each test. However, no nonlinear causality is reported in the reverse direction, i.e. US variables are observed to be empirically independent of their Canadian counterparts.

5.7.1.2.2 Japan

In the case of Japan, variables of both countries are shown to be statistically independent of each other in the pre-crisis sample (Table 5.7). This result is in contrast to the one reported in Section 5.7.1.1.2 above, where Japanese variables together with US stock market volatility are reported as the key drivers of US business cycles. Thus, it shows that by dropping the US stock market volatility from the equation, the Japanese stock market and business cycle do not continue to influence the US business cycles. The reason for this could be that in the four variable model the relationship was holding mainly due to the US stock market volatility that also causes the US business cycle in the bivariate non-linear model as well.

5.7.1.2.3 United Kingdom

In the case of the UK, US variables cause changes in the UK business cycle, whereas UK variables cause changes in US stock market volatility, both at 10% significance levels (Table 5.7). This shows relatively weak evidence of a spill-over effect between the stated variables. After dropping the domestic variable from the equation, the US variables cause the UK business cycle and the UK variables cause the US stock market volatility as before. However, the dependence of the UK stock market volatility over the other variables diminishes as the UK's business cycle is dropped, This indicates that the UK business cycle was playing a stronger role in the comovement among the variables. Therefore, when it is dropped the relationship of the US variables with UK stock market volatility diminishes.

5.7.2 Including the Financial Crisis (Jan-1990 to Dec-2011)

5.7.2.1 Four Variables

5.7.2.1.1 Canada

Multivariate nonlinear causality results for the full sample including the financial crisis are presented in Table 5.8. The results for Canada against the US show strong mutual interdependence between all variables at 1% or 5%, except for the US business cycle, which is caused by joint variables at only 10% significance level. This shows strong mutual dependence between the underlying variables for Canada and the US.

5.7.2.1.2 Japan

The joint variables of Japan and the US cause changes in Japanese stock market volatility and its business cycle in separate equations at the 1% significance level (Table 5.8). Similarly, Japanese variables and the US business cycle jointly cause US stock market volatility at the 1% significance level. The US business cycle is the only variable which is independent. Hence, similar to the linear cross-country results, the Japanese stock market and economy seem to be more influenced by the US both before and after the financial crisis. Furthermore, after including the period of financial crisis into the sample, the nonlinear causality between Japanese and US variables has strengthened.

5.7.2.1.3 United Kingdom

The UK business cycle shows joint dependence over the US stock market volatility and business cycle after controlling for the UK stock market volatility at the 1% significance level (Table 5.8). This evidence shows the nonlinear dependence of the UK's economy on the US economy and stock market volatility, implying a strong influence of the US business cycle and stock market volatility on the UK's economic outlook.

5.7.2.2 Three Variables

5.7.2.2.1 Canada

Canadian stock market volatility shows strong dependence over the US variables at the 1% significance level (Table 5.8), but Canadian stock market volatility and business cycle do not cause changes in US variables. This shows a significant macro-financial spill-over effect from the US to Canadian stock market volatility. After dropping the domestic variables, the number of cross-country causal relationships reduces. This may show that the spill-over effect is stronger when the domestic variables are taken into account.

5.7.2.2.2 Japan

The Japanese business cycle is mutually caused by the US stock market volatility and business cycles at the 10% significance level (Table 5.8). In addition, US stock market volatility is caused by Japanese stock market volatility and business cycles. These results are in line with the earlier evidence reported in section 5.7.2.1.2 above. These results show a stable nonlinear association between the underlying variables, suggesting a significant spill-over across Japan and the US after inclusion of the financial crisis period. It is worth noting that even after dropping the US business cycle, Japanese variables alone cause changes in US stock market volatility.

5.7.2.2.3 United Kingdom

In comparison to Canada and Japan, the UK shows relatively less evidence of cross-country causality in a nonlinear setting. The UK business cycle is jointly caused by US business cycles and stock market volatility at the 10% significance level (Table 5.8). Thus, no strong evidence of the spill-over effect is reported for the UK after inclusion of the financial crisis. Comparison with the four-variable case indicates that the direction of causality remains the same, even after dropping the domestic variables. However, the strength of the result grows weaker.

5.8 Conclusion and Implications

The chapter analyses the linear and nonlinear causality between stock market volatility and business cycles within and across countries. It further analyses the impact of the recent global financial crisis on these variables. The causality between the variables within a country is analysed using bivariate models. The results show that before the financial crisis, bivariate linear causality is strongly bidirectional in Canada, weakly bidirectional in the UK, and unidirectional for the US from stock volatility to the business cycle. These relationships have grown stronger after inclusion of the financial crisis period, for instance, the US, the UK and Canada have strong bidirectional causality, and the earlier finding of no relationship in Japan changed into a weak causal relationship from the business cycle to stock market volatility. Bivariate nonlinear causality between these variables is then tested to explore any nonlinearities that could not be captured in the linear model. The results using two different methods show some presence of nonlinear causality between the variables in all countries before the financial crisis, whereas for the full sample period the US does not bear any relationship between its stock market volatility and business cycle. Also, in some instances the strength or direction of causality has changed over the two sample lengths.

The analysis on cross-country causality is carried out using multivariate linear and nonlinear models before the financial crisis and including the crisis period. The results indicate strong cross-country spill-over from the US to the developed countries, and vice versa. After inclusion of the financial crisis, the results do not significantly change for the linear causality. In the nonlinear framework, US variables have an influence on the business cycle of the UK and Canada and the stock market volatility of Canada, and the UK variables cause changes in US stock market volatility. After inclusion of the financial crisis, US variables cause changes in the business cycle of Japan, and Japanese variables influence the volatility of the US stock market, whereas the rest of the relationships remain unchanged. Based on all these results, it can be concluded that stock market volatility and business cycles bear a causal relationship not only within a country but also with spill-over effects across borders. In addition, linear causality is not sufficient to explain the relationship in full; therefore, it is extremely important to take into account the nonlinear causal relationships for these variables.

These findings are of significance to the investors, market participants and portfolio managers to help them in making wise investment decisions, devising diversification strategies and managing their portfolios effectively. The knowledge of these causal dependencies within and across countries is also relevant for policy makers, as they need to have this knowledge for effective policy making and implementation. Lastly, stock market volatility is used as a leading business cycle indicator in the US, the UK and other major countries. At present, for business cycle prediction, only the country's own stock volatility is included, but the results of this research suggest that cross-country stock volatility can also be a major business cycle indicator. Thus, inclusion of cross-country stock volatility may further enhance the predictive capability of these indicators regarding business cycle turning points.

Table 5.1: Bivariate Linear Causality between Stock Market Volatility (GARCH) and Business Cycles (Before the Financial Crisis Jan-1990 to June-2007)

Countries	Business Cycle → Stock Market Volatility				Stock Market Volatility → Business Cycle			
	Canada	**Japan**	**UK**	**US**	**Canada**	**Japan**	**UK**	**US**
Lags BC-SMV	11-8	6-11	11-7	12-4	4-9	6-2	9-8	12-1
F-Stat	**2.06****	0.9	**1.82***	0.539	**2.004****	1.342	**1.93***	**13.96*****
Adj. R^2	0.163	0.07	0.1855	0.047	0.06349	0.1744	0.15999	0.1246
SSE	0.000	0.00	0.000002	0.0000	0.00007	0.0001	0.00006	0.000025
RSS	0.001	0.00	0.0003	0.00008	0.01366	0.0283	0.01088	0.00457
RESET	1.133	1.20	1.4487	3.3595	3.65692	1.7019	2.03796	0.3158
White	197.000	182.17	193.3520	187.9149	120.58	56.35	173.18	98.923
LB	2.942	12.84	5.7382	0.9356	8.8972	14.623	1.72863	2.908
JB	2.950	10.75	1.9225	2.7870	2.00631	3.1206	5.51756	2.5041

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 5.2: Bivariate Linear Causality between Stock Market Volatility (GARCH) and Business Cycles (Including the Financial Crisis Jan-1990 to Dec-2011)

Countries	Business Cycle → Stock Market Volatility				Stock Market Volatility → Business Cycle			
	Canada	Japan	UK	US	Canada	Japan	UK	US
Lags BC-SMV	10-10	7-11	11-10	7-12	9-9	3-9	5-9	11-11
F-Stat	**2.193****	**1.693***	**2.7067*****	**2.0556****	**3.117*****	1.3903	**2.08****	**2.8*****
Adj. R^2	0.1106	0.1313	0.1307	0.3311	0.17109	0.0346	0.05	0.2492
SSE	0.0005	0.0001	0.0002	0.0001	0.0077	0.0045	0.01	0.0034
RSS	0.0012	0.0003	0.0004	0.0003	0.01796	0.1073	0.02	0.008
RESET	1.7809	5.9827	1.7903	87.0837	1.03917	5.3900	2.06	3.929
White	245.9	208.2	251.3	235.5	210.5	188.1	135.70	260.97
LB	2.50	8.06	5.46	6.22	2.35	9.12	12.56	0.767
JB	2.58	14.40	1.71	5.88	3.37	5.85	2.52	9.240

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 5.3: Bivariate Nonlinear Causality between Stock Market Volatility (GARCH) and Business Cycles (Before the Financial Crisis Jan-1990 to June-2007)

Panel-I Diks and Panchenko (2006)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Canada	-0.85982	**1.8886****
Japan	0.9655	**1.64183****
UK	-1.3998	-1.46704
US	1.031	**1.69175****

Panel-II Hiemstra and Jones (1996)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Canada	**1.7979****	-1.12378
Japan	**1.59125***	1.12803
UK	**-1.33233***	**-1.36057***
US	**-2.11689****	-0.71874

Table 5.4: Bivariate Nonlinear Causality between Stock Market Volatility (GARCH) and Business Cycles (Including the Financial Crisis Jan-1990 to Dec-2011)

Panel-I Diks and Panchenko (2006)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Canada	-2.37044	**1.81664****
Japan	**2.50286*****	0.87706
UK	**1.30777***	-1.50774
US	0.59158	-0.07696

Panel-II Hiemstra and Jones (1996)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Canada	**1.80051****	**-2.01078****
Japan	1.02277	**2.59402****
UK	**-1.56752***	**1.42886***
US	0.04628	0.5875

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Table 5.5: Multivariate Linear Causality between Stock Market Volatility (GARCH) and Business Cycles (Before the Financial Crisis Jan-1990 to June-2007)

Country	CANADA							UNITED STATES						
Dependent Variable	**Stock Market Volatility (GARCH)**							**Stock Market Volatility (GARCH)**						
Independent Variables	**BC_{CAN}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**BC_{US}**	**SV_{CAN}**	**BC_{CAN}**	**Diagnostics**			
Lags	5	2	4	Adj-R^2	0.19073	RESET	2.6	1	11	2	Adj-R^2	0.18866	RESET	4.7
				SEE	0.00004	White	246				SEE	0.00008	White	203.37
F-Stat	2.246**	3.436**	2.514**	RSS	0.00107	LB	4.6	3.93**	2.87**	3.46**	RSS	0.01758	LB	12.98
				-	-	JB	2.7				-	-	JB	4.19
Dependent Variable	**Business Cycle**							**Business Cycle**						
Independent Variables	**SV_{CAN}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**SV_{US}**	**SV_{CAN}**	**BC_{CAN}**	**Diagnostics**			
Lags	9	5	1	**Adj-R^2**	0.00008	**RESET**	3.2	5	7	3	**Adj-R^2**	0.28418	**RESET**	2.48
				SEE	0.00058	**White**	231				**SEE**	0.00003	**White**	214.07
F-Stat	2.37**	0.96	11.3***	**RSS**	0.00230	**LB**	3.9	3.95***	3.2**	4.3***	**RSS**	0.00761	**LB**	2.92
				-	-	**JB**	4.07				-	-	**JB**	2.27

Table-5.5 (Contd.)

Country	JAPAN							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{JP}	SV_{US}	BC_{US}	Diagnostics				BC_{JP}	SV_{JP}	BC_{US}	Diagnostics			
Lags	2	1	6	Adj-R^2	0.1565	RESET	3.46	6	3	2	Adj-R^2	0.37056	RESET	2.62
				SEE	0.0001	White	222.89				SEE	0.00001	White	241.8
F-Stat	3.02**	0.268	2.81**	RSS	0.0025	LB	6.34	2.343**	4.5***	2.37**	RSS	0.00026	LB	7.04
						JB	3.45						JB	3.89
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{JP}	SV_{US}	BC_{US}	Diagnostics				SV_{JP}	SV_{US}	BC_{JP}	Diagnostics			
Lags	9	10	5	Adj-R^2	0.1693	RESET	3.059	3	11	1	Adj-R^2	0.16164	RESET	5.30
				SEE	0.0003	White	253.6				SEE	0.00004	White	174.0
F-Stat	2.3**	4.76***	1.985*	RSS	0.0872	LB	7.780	3.81**	2.01*	11.01***	RSS	0.00899	LB	4.73
						JB	3.97						JB	3.46

Table-5.5 (Contd.)

Country	UNITED KINGDOM							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BCUK	SV_{US}	BC_{US}	Diagnostics				BCUK	SV_{US}	BC_{US}	Diagnostics			
Lags	5	11	6	Adj-R^2	0.1284	RESET	4.92	6	3	4	Adj-R^2	0.41730	RESET	4.07
				SEE	0.0001	White	270.24				SEE	0.00001	White	252.6
F-Stat	2.27**	2.45**	2.08*	RSS	0.0004	LB	15.92	2.64**	7.27***	3.27**	RSS	0.00024	LB	6.55
						JB	1.53						JB	2.971
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SVUK	SV_{US}	BC_{US}	Diagnostics				SVUK	SV_{US}	BC_{US}	Diagnostics			
Lags	7	10	3	Adj-R^2	0.1268	RESET	1.74	9	1	4	Adj-R^2	0.29141	RESET	4.46
				SEE	0.0007	White	251.6				SEE	0.00003	White	221.9
F-Stat	2.03*	1.99*	5.745***	RSS	0.015	LB	15.36	1.99*	3.74**	4.23***	RSS	0.00758	LB	3.327
				-	-	JB	1.65				-	-	JB	2.56

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 5.6: Multivariate Linear Causality between Stock Market Volatility (GARCH) and Business Cycles (Including the Financial Crisis Jan-1990 to Dec-2011)

Country	CANADA							UNITED STATES						
Dependent Variable	**Stock Market Volatility (GARCH)**							**Stock Market Volatility (GARCH)**						
Independent Variables	**BC_{CAN}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**BC_{US}**	**SV_{CAN}**	**BC_{CAN}**	**Diagnostics**			
Lags	5	2	4	**Adj-R^2**	0.19	**RESET**	2.70	1	11	2	**Adj-R^2**	0.238	**RESET**	5.862
				SEE	0.01	**White**	246				**SEE**	0.001	**White**	251
F-Stat	**2.246****	**3.43****	**2.51****	**RSS**	0.011	**LB**	4.58	**3.93****	**1.8745****	1.73	**RSS**	0.003	**LB**	5.46
				-	-	**JB**	2.74						**JB**	3.62
Dependent Variable	**Business Cycle**							**Business Cycle**						
Independent Variables	**SV_{CAN}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**SV_{US}**	**SV_{CAN}**	**BC_{CAN}**	**Diagnostics**			
Lags	12	1	4	**Adj-R^2**	0.200	**RESET**	2.17	1	11	2	**Adj-R^2**	0.284	**RESET**	2.475
				SEE	0.001	**White**	250.3				**SEE**	0.0003	**White**	214.0
F-Stat	**1.67***	**2.9****	**3.5*****	**RSS**	0.0167	**LB**	7.23	**3.95*****	**3.39*****	**6.4*****	**RSS**	0.007	**LB**	2.92
						JB	3.34						**JB**	1.29

Table-5.6 (Contd.)

Country	JAPAN							UNITED STATES						
Dependent Variable	**Stock Market Volatility (GARCH)**							**Stock Market Volatility (GARCH)**						
Independent Variables	**BC_{JP}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**BC_{us}**	**SV_{JP}**	**BC_{JP}**	**Diagnostics**			
Lags	6	3	1	**Adj-R^2**	0.1176	**White**	235.62	6	1	2	**Adj-R^2**	0.3730	**RESET**	4.36
				SEE	0.0001	**LB**	6.69				**SEE**	0.0002	**White**	233.04
F-Stat	**1.945***	0.889	0.0634	**RSS**	0.0003	**JB**	3.57	**2.287****	**6.099*****	**2.44****	**RSS**	0.0003	**LB**	7.25
				RESET	3.95								**JB**	3.86
Dependent Variable	**Business Cycle**							**Business Cycle**						
Independent Variables	**SV_{JP}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**SV_{US}**	**SV_{JP}**	**BC_{JP}**	**Diagnostics**			
Lags	1	10	3	**Adj-R^2**	0.1877	**RESET**	5.3350	4	1	6	**Adj-R^2**	0.2624	**RESET**	3.0227
				SEE	0.0004	**White**	231.17				**SEE**	0.0003	**White**	190.93
F-Stat	**4.058****	**4.414*****	**3.242****	**RSS**	0.0876	**LB**	6.74	**3.23****	1.753	**2.064***	**RSS**	0.0081	**LB**	4.18
				-	-	**JB**	3.89				-	-	**JB**	6.31

Table-5.6 (Contd.)

Country	UNITED KINGDOM							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{UK}	SV_{US}	BC_{US}	Diagnostics				BC_{US}	SV_{UK}	BC_{UK}	Diagnostics			
Lags	5	3	6	Adj-R^2	0.1656	RESET	2.99	6	3	4	Adj-R^2	0.4173	RESET	4.99
				SEE	0.0002	White	257.15				SEE	0.0001	White	252.64
F-Stat	**2.27****	**5.29*****	**2.33****	RSS	0.0004	LB	4.73	**2.64****	**7.27*****	**3.27****	RSS	0.0002	LB	6.55
						JB	1.64						JB	9.79
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{UK}	SV_{US}	BC_{US}	Diagnostics				SV_{US}	SV_{UK}	BC_{UK}	Diagnostics			
Lags	4	9	3	Adj-R^2	0.1371	RESET	1.276	9	1	4	Adj-R^2	**0.2914**	RESET	4.460
				SEE	0.0001	White	186.292				SEE	**0.0003**	White	221.926
F-Stat	**2.488****	**2.75****	**6.89*****	RSS	0.0151	LB	10.767	**1.9039***	**3.743***	**4.234*****	RSS	**0.0076**	LB	3.327
						JB	3.608						JB	5.47

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test

Table 5.7: Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and Business Cycles (Before the Financial Crisis Jan-1990 to June-2007)

Panel-I (Four Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Canada	**SVCAN**	**BCCAN, SVUS, BCUS**	**1.429***	**0.0765**
	BCCAN	SVCAN,SVUS,BCUS	-0.55351	0.28996
	SVUS	SVCAN,BCCAN,BCUS	1.04495	0.14802
	BCUS	SVCAN,BCCAN,SVUS	-0.63836	0.26162
Japan	SVJP	BCJP,SVUS,BCUS	0.23036	0.4089
	BCJP	SVJP,SVUS,BCUS	0.42603	0.33504
	SVUS	SVJP,BCJP,BCUS	0.24784	0.40213
	BCUS	**SVJP,BCJP,SVUS**	**-2.13209****	**0.0165**
UK	**SVUK**	**BCUK,SVUS,BCUS**	**-1.46955***	**0.07084**
	BCUK	**SVUK,SVUS,BCUS**	**-1.51473***	**0.06492**
	SVUS	**SVUK,BCUK,BCUS**	**-2.38037****	**0.00865**
	BCUS	SVUK,BCUK,SVUS	-0.7737	0.2195

Panel-II (Three Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Canada	**SVCAN**	**SVUS, BCUS**	**1.58224***	**0.0568**
	BCCAN	**SVUS,BCUS**	**-1.35315***	**0.088**
	SVUS	SVCAN,BCCAN	0.97729	0.16421
	BCUS	SVCAN,BCCAN	-0.50321	0.30741
Japan	SVJP	BCUS,SVUS	-0.61279	0.27001
	BCJP	BCUS,SVUS	-0.39077	0.34798
	SVUS	SVJP,BCJP	0.89603	0.18512
	BCUS	SVJP,BCJP	-0.94313	0.17281
UK	SVUK	BCUS,SVUS	-0.68048	0.2481
	BCUK	**BCUS,SVUS**	**-1.47667***	**0.06988**
	SVUS	**SVUK,BCUK**	**-1.5672***	**0.05853**
	BCUS	SVUK,BCUK	-0.36614	0.35713

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Table 5.8: Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and Business Cycles (Including the Financial Crisis Jan-1990 to Dec-2011)

Panel-I (Four Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Canada	**SVCAN**	**BCCAN, SVUS, BCUS**	**2.19322****	**0.0116**
	BCCAN	**SVCAN,SVUS,BCUS**	**-0.69831****	**0.0455**
	SVUS	**SVCAN,BCCAN,BCUS**	**0.31833****	**0.0418**
	BCUS	**SVCAN,BCCAN,SVUS**	**0.06839***	**0.0650**
Japan	**SVJP**	**BCJP,SVUS,BCUS**	**1.31097*****	**0.0014**
	BCJP	**SVJP,SVUS,BCUS**	**1.76767*****	**0.0016**
	SVUS	**SVJP,BCJP,BCUS**	**0.96777*****	**0.0042**
	BCUS	SVJP,BCJP,SVUS	-1.28746	0.2242
UK	SVUK	BCUK,SVUS,BCUS	-0.26232	0.0889
	BCUK	**SVUK,SVUS,BCUS**	**-2.17248*****	**0.0064**
	SVUS	SVUK,BCUK,BCUS	0.13711	0.2958
	BCUS	SVUK,BCUK,SVUS	-0.63885	0.1116

Panel-II (Three Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Canada	**SVCAN**	**SVUS, BCUS**	**2.47397*****	**0.00668**
	BCCAN	SVUS,BCUS	-1.00206	0.15816
	SVUS	SVCAN,BCCAN	0.96183	0.16807
	BCUS	SVCAN,BCCAN	-0.45287	0.32532
Japan	SVJP	BCUS,SVUS	0.18374	0.42711
	BCJP	**BCUS,SVUS**	**1.51355***	**0.06507**
	SVUS	**SVJP,BCJP**	**1.39477***	**0.08154**
	BCUS	SVJP,BCJP	-0.96451	0.1674
UK	SVUK	BCUS,SVUS	-0.39707	0.34566
	BCUK	**BCUS,SVUS**	**-1.36079***	**0.08679**
	SVUS	SVUK,BCUK	1.01013	0.15622
	BCUS	SVUK,BCUK	-0.38468	0.35024

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Chapter 6: Analysis – Developing Countries

6.1 Introduction

This chapter presents the causal analysis of the stock market volatility and business cycles of the developing countries including Brazil, China,[31]Malaysia and Turkey. Causal analysis is aimed at studying the underlying relationships both from intra-country and cross-country perspectives. For cross-country analysis, the developing countries are compared against the US to identify the possibility of spill-overs between the stock market volatility and business cycles of these countries from/onto the US[32]. The findings of the cross-country causal relationship between the stock volatility and business cycle of the US with the developing countries could have significant implications in terms of theory and practice, for investment, policy making and risk management. To the best of our knowledge, there is no current academic evidence on this subject which takes into account these various dynamics.

This research, as explained in Section 4.3, conducts Granger causal analyses on the basis of the conventional linear method as well as the nonlinear causality models suggested by Hiemstra and Jones (1994) and Diks and Panchenko (2006) for bivariate causality, and the Bai *et al.* (2010) model for nonlinear multivariate analysis. This is to provide an extensive insight into the nature of the interactions beyond just a straight-line relationship between these variables, and thereby aims to contribute to the knowledge base in this area.

The analytical framework is designed to investigate how the recent global economic crisis has affected the relationship between stock market volatility

[31] For China, complete analyses of all the hypotheses have been carried out. This includes bivariate linear and nonlinear causality tests within the country, and also multivariate linear and nonlinear causality tests in the cross country framework, with the US as the world leader and Japan as the regional leader. The analysis further includes the consideration of the pre-crisis and financial crisis periods. The results from all these empirical analyses are found to be insignificant, indicating that a causal relationship between stock market volatility and business cycles involving China is nearly non-existent. The tables comprising of results for China are given in Appendix-2.

[32] As per the examiners' suggestion, the developing countries such as Malaysia and China are also compared against Japan as their regional leader. This analysis and discussion is given in Appendix – 3.

and business cycles both intra and across these countries. Thus, there are four main hypotheses tested for the developing countries. Hypotheses 1a and 1b test the linear and nonlinear causality within each of these countries, respectively. Hypotheses 2a and 2b analyse the cross-country spill-over between the variables of the countries against the US using linear and nonlinear causality tests, respectively. Hypotheses 3.1 and 3.2 take into account the impact of the financial crisis on the within and cross-country results of the above hypotheses. For this purpose, all the above hypotheses are tested and compared on the basis of two samples: i) the pre-crisis period (January 1990 to June 2007); and ii) including the financial crisis period (January 1990 to December 2011). The comparison of results aims to identify the differences and/or similarities between the results to highlight the role of the financial crisis in this context. The fourth and last hypothesis compares the findings for the developed countries (Chapter 5) and the developing countries.

The null hypotheses in all cases state that the underlying variables do not cause each other both in linear and nonlinear settings. Threshold significance levels for testing these null hypotheses are at 1%, 5% or 10%, based on standard practice.

6.2 Bivariate Linear Causality

The relationship between stock market volatility and the business cycle intra-country using bivariate linear causality has been tested in hypothesis 1a. The same hypothesis is further tested for possible effects of the financial crisis on the relationship in 3.1a. These hypotheses, as discussed in the Theoretical Background (section 2.6), are aimed at testing the Granger causality between the variables within the same country in a linear framework.

Results for hypotheses 1a and 3.1a are presented in Tables 6.1 and 6.2, respectively. Table 6.1 shows the linear causality results between the changes in the business cycle and the changes in stock market volatility for the pre-crisis time period (January 1990 to June 2007), whereas Table 6.2 exhibits the results representing the whole sample period (January 1990 to December 2011). Both of these results are then compared to test if the results significantly differ for the two samples of different time lengths, i.e. before the financial crisis and after including the financial crisis period, to identify any possible differences arising due to the financial down-turn.

6.2.1 Before the Financial Crisis (Jan-1990 to June 2007)

Table-6.1 presents the results for testing hypothesis 1a for bivariate linear intra country causal analysis between stock market volatilities and business cycles for the pre-crisis period. The empirical model used here is defined in equation 8.01, section 4.3.1. Detailed country specific analysis is provided in the following sub-sections:

6.2.1.1 Brazil

Table 6.1 shows strong evidence of a feedback effect in the case of Brazil, where the first difference of the business cycle and stock market volatility Granger cause each other at the 1% significance level. It means that the lagged values of each of these variables contain useful information to explain current variations in the other variable. Hence, in the pre-crisis period, both stock market volatility and the business cycle for Brazil can be significant predictors of the other corresponding variable. This leads to rejection of the null hypothesis 1a of no Ganger causality between changes in stock market volatility and changes in the business cycle at 1% significance level.

6.2.1.2 Malaysia

The Malaysian stock market volatility and business cycle display similar associations as Brazil between the two variables at the 1% significance level (Table 6.1). This confirms the rejection of the null hypothesis for Malaysia in the pre-crisis time period. This result implies that both variables are mutual predictors of each other; hence each variable would be an important regressor while modelling the other corresponding variable. These results partially support the findings of Rasiah (2010) who found that volatility in the macro-economy leads to Malaysian stock market volatility, but not vice versa.

6.2.1.3 Turkey

In the case of Turkey, stock market volatility is shown to Granger cause the business cycle at the 1% significance level (Table 6.1). However, the result for possible reverse causality is only significant at the 10% level. This shows a relatively weak feedback effect in the case of the Turkish stock market volatility and business cycle, implying the strong influence of variations in stock market volatility in leading the Turkish business cycle in the pre-crisis scenario. Thus, the null hypothesis 1a is also not accepted for Turkey.

6.2.2 Findings from Hypothesis 1a

The results for hypothesis 1a of Granger linear causality between changes in stock market volatility and changes in the business cycle for developing countries are presented in Table 6.1. The null hypothesis of no causal relationship between the stated variables has not been accepted for all the developing countries including Brazil, Malaysia and Turkey before the financial crisis, implying a strong causal relationship between the respective stock market volatilities and business cycles of these countries at the first difference levels. The results suggest a strong feedback effect for Brazil and Malaysia. However, Turkish stock market volatility shows a strong impact on its business cycle but the evidence of reverse causality is only weak. In addition to the Granger causality results, Table 6.1 also provides important diagnostic test results confirming the accuracy and reliability of these findings.

6.2.3 Comparison of Findings from Hypothesis 1a for Developed and Developing Countries

The null hypothesis 1a is rejected in all three developing countries (section 6.2.2) and most of the developed countries (section 5.2.1.5) as well. One exception for the developed countries is Japan, where no causal relationship is reported. In terms of the direction of causality, a strong feedback effect is shown for Brazil and Malaysia, among the developing countries, whereas in the case of the developed countries, bidirectional causality or feedback is only reported for Canada. In the case of Turkey and the US, stock market volatility leads the business cycle in the pre-crisis period.

6.2.4 Including the Financial Crisis (Jan-1990 to Dec-2011)

One of the key contributions of this research is to analyse the impact of the recent financial crisis on the causal relationship between stock market volatility and business cycles. For this purpose, hypothesis 3.1a (for details see section

2.6.3) assesses the impact of the financial crisis on the relationships identified under hypothesis 1a in section 6.2.1 above. Results are provided in Table 6.2. The following sections provide country specific details of the tests for hypothesis 3.1a:

6.2.4.1 Brazil

The results suggest mutual linear dependence between the stock market volatility and the business cycle as both relationships are significant at the 1% or 5% level (Table 6.2). This shows that both the variables cause each other and are mutually dependent on each other in a linear framework. The strong linear causality results for Brazil hold for both sample lengths.

In addition to the recent global financial crisis, the behaviour of the stock market volatility and the business cycle relationship has also been analysed in the context of the Russian financial crisis[33]. Similar to the above results, during and after the Russian financial crisis, there was a feedback effect between Brazil's stock market volatility and its business cycle.

6.2.4.2 Malaysia

In the case of Malaysia, stock market volatility is observed to Granger cause the business cycle at the 1% significance level; however, the causality in the opposite direction is insignificant (Table 6.2). This implies a unidirectional causality running from stock market volatility to the business cycle in Malaysia for the full sample.

Malaysia is an export-oriented economy. Its exports form 100% of its GDP. The impact of the global financial crisis was transmitted mainly through a decline in Malaysian exports. In the wake of the financial crisis, Malaysia's manufacturing/industrial sector got the major shock, as 80% of the output of the industries are exported, 40% of these being destined for the G3 (the US, Japan and the European Union) alone. The companies lost foreign direct investment, foreign portfolio investment and suffered reduced demand for their output. Thus, the manufacturing sector was losing on all fronts and this

[33] The Russian financial crisis and its impact on the Brazil's stock market volatility and the business cycle has been analysed in linear and nonlinear framework at length in Appendix-5.

was reflected in the stock market. Portfolio investment outflows in 2008 were another important factor causing an increase in the stock market volatility during that time period (Khoon and Mah-Hui, 2010).

Although exports would affect the economy and business cycle in the long-run, initially the impact was only felt by the Malaysian exporting companies. Hence, the business cycle was affected through increased stock market volatility, in addition to other factors, explaining the results of the hypothesis, which shows unidirectional causality from stock market volatility to the business cycle. Other than the stated reasons, there were probably no other economic dynamics that could be predicted by the market participants in addition to the known information, which was already reflected in the stock market.

In addition to the recent global financial crisis, the behaviour of the stock market volatility and the business cycle relationship has also been analysed in the context of the Asian financial crisis[34]. It has been found that the stock market volatility Granger causes the business cycle in the post crisis period only.

6.2.4.3 Turkey

In the case of Turkey, only unidirectional Granger causality is reported from changes in stock market volatility to changes in the business cycle, significant at the 1% level (Table 6.2). However, no evidence of the business cycle causing stock market volatility is reported. These results are similar to those of the Malaysian data set including the financial crisis period, and the reasons could be similar. The global financial crisis affected Turkey mainly through its exports which fell sharply starting in October 2008. Not only did the export volume decline, but also the price of these commodities dwindled, causing a hit to the Turkish economy (Uygur, 2010).

6.2.5 Findings for Hypothesis 3.1a

A comparison of results for both sample lengths reveals that the causal relationships have significantly changed for Malaysia after including the

[34] The Asian financial crisis and its impact on the Malaysian stock market volatility and the business cycle has been analysed in linear and nonlinear framework at length in Appendix-4.

financial crisis period, as the bidirectional causality changes to unidirectional, from stock market volatility to the business cycle only. In the case of Brazil, the bi-directional causal relationship remains consistent over both sample lengths. Similarly, Turkey's unidirectional causality, running from stock market volatility to the business cycle, holds over both sample lengths, but the relatively weak reverse causality reported in the pre-crisis period has faded away with the inclusion of the crisis period.

6.2.6 Comparison of Findings from Hypothesis 3.1a for Developed and Developing Countries

Results for both the developing (section 6.2.4) and developed countries (section 5.2.2) show that the causality relationship between stock market volatility and business cycles has changed after inclusion of the financial crisis period. Furthermore, the null hypothesis of no causal relationship is rejected in all of the cases for both the developed and developing countries, showing strong evidence of a linear dependence between the two variables in all the countries included in the sample. In the case of the US and the UK, a strong feedback effect is reported. In the case of Malaysia, the causality direction has changed from a feedback effect to unidirectional causality, i.e. stock market volatility leading the business cycle. Results for Brazil, Canada and Turkey remain unchanged across both data samples. These results are supported by standard diagnostic tests where the null hypotheses under the Jarque-Berra, Ljung-Box for autocorrelation, RESET for misspecification and White's heteroskedasticity tests are accepted for all countries.

6.3 Bivariate Nonlinear Causality

The residual series obtained from the linear causal analysis in section 6.2 are further tested for nonlinear causal dependence in the underlying variables. For this purpose, the nonlinear causality tests proposed by Hiemstra and Jones (1994) and Diks and Panchenko (2006) are employed. These tests are based on correlation integrals and indicate Granger causality if the lag vector of variable X significantly precedes the lead vector of variable Y, while controlling for the lags of Y. The hypotheses testing is similar to the linear models, i.e. the null hypotheses of no nonlinear Granger causality is rejected if the test statistics are significantly different than zero and the corresponding probabilities fall within the 1%, 5% or 10% levels. This indicates the causal relationship between the underlying variables under these models.

Hypothesis 1b in this context set the null hypothesis of no nonlinear dependence between the lags of changes in stock market volatility and changes in business cycles of the respective countries. The same hypothesis is further tested for possible effects of the financial crisis on the relationship in 3.1b. These hypotheses, as discussed in the Theoretical Background (section 2.6), are aimed at testing the Granger causality between the variables within the same country in non-linear dimensions based on approaches proposed by Hiemstra and Jones (1994) and Diks and Panchenko (2006). Results for these hypotheses are presented in Tables 6.3 and 6.4.

6.3.1 Bivariate Nonlinear Causality – Diks and Panchenko (2006) Method

Tables 6.3 and 6.4 present results for the hypotheses 1b and 3.1b tests under the Diks and Panchenko (2006) method for bivariate nonlinear causality both before the financial crisis (Table 6.3) and after inclusion of the recent financial crisis period (Table 6.4). As suggested by Diks and Panchenko (2006), the variation threshold in terms of standard deviation is 1.5, as explained in section 4.3.3, to test the incidence of bivariate nonlinear causality between the underlying variables. Country specific discussion of these results is as follows:

6.3.1.1 Brazil

In the case of Brazil, no evidence of nonlinear dependence is reported between the residuals series of stock market volatility and the business cycle (Tables 6.3 and 6.4). It implies that after filtering the data using the Granger linear causality test, the data does not contain any useful information to explain/indicate any further nonlinear dependence between the variables. Thus, the null hypothesis 1b cannot be rejected even at the 10% significance level. Furthermore, these results do not change even after inclusion of the financial crisis period, leading to the inference that the recent financial crisis has no impact in the case of Brazil when testing the nonlinear causality between stock market volatility and the business cycle.

6.3.1.2 Malaysia

In contrast to Brazil, some evidence of nonlinear dependence is documented in the case of Malaysia, where a significant nonlinear causal relationship is found at the 5% level from changes in the business cycle to stock market volatility (BC →SMV). Hence, the null hypothesis 1b in the case of Malaysia cannot be accepted at the 5% level (Tables 6.3 and 6.4). Furthermore, the relationship is consistent both before and after inclusion of the financial crisis, whereby the Malaysia business cycle causes stock market volatility. This shows the stability of the relationship across both data samples.

6.3.1.3 Turkey

In the case of Turkey, no evidence of nonlinear causality is reported, implying stochastic independence between stock market volatility and the business cycle (Tables 6.3 and 6.4). Thus, the null hypothesis cannot be rejected even at the 10% level. Furthermore, inclusion of the financial crisis period does not affect the underlying results, and both variables are found to be independent of each other under the Diks and Panchenko (2006) method of nonlinear causality.

6.3.1.4 Findings from Hypothesis 1b (Diks and Panchenko, 2006)

Nonlinear bivariate causality results under Diks and Panchenko (2006) show evidence of nonlinear causality in the case of Malaysia only, where changes in stock market volatility are caused by the variations in the business cycle across both samples. No instance of nonlinear causality between the variables is reported for Brazil and Turkey, using both data lengths. The results may imply that the relationship between the variables was only linear in nature, which was evident from the results of linear causality.

6.3.1.5 Comparison of Findings from Hypothesis 1b (Diks and Panchenko, 2006) for Developed and Developing countries

Evidence of nonlinear causality is more pronounced in the developed countries compared to the developing countries, where a nonlinear causal relationship is reported for Malaysia only. In the case of the developed countries strong evidence of nonlinear causality is shown between stock market volatility and the business cycles in Canada, Japan and the US. The presence of a non-linear relationship in the developed countries may signify the complexities of a causal relationship, as there are multiple interactions through various asset classes (some of them financially engineered) and markets. Because of these complexities, relationships are not fully explained by linear models but reflect non-linear features too. However, for developing countries this phenomenon may not exist, as these countries do not have non-real assets at play in their economies. These economies put the emphasis on their manufacturing sectors and exports of their produce/output.

6.3.2 Bivariate Nonlinear Causality – Hiemstra and Jones (1994) Method

The Hiemstra and Jones (1994) test statistic is the second nonlinear causality test employed in this research to explore the causal relationship between stock market volatility and the business cycle. This section presents the results under this test (Tables 6.3 and 6.4). As explained in section 6.3.1, the variation threshold in terms of standard deviation is 1.5 to test the incidence of bivariate nonlinear causality between the underlying variables. Country specific discussion of the results follows:

6.3.2.1 Brazil

In the case of Brazil, no incident of nonlinear causality is reported (Tables 6.3 and 6.4). In other words, both stock market volatility and the business cycle show mutual nonlinear independence of each other across both data samples, hence the null hypotheses 1b and 3.1b under this approach cannot be rejected even at the 10% level.

6.3.2.2 Malaysia

Tables 6.3 and 6.4 show strong evidence of a nonlinear association between the variables, whereby changes in stock market volatility are causing variations in the business cycle in Malaysia. However, nonlinear causality in the reverse direction is relatively weak and significant only at the 10% level, implying a weak feedback effect between the two variables. These results also hold when the sample period is extended to include the financial crisis. This shows the consistency and stability of the results over the period.

6.3.2.3 Turkey

In the case of Turkey, again no evidence of nonlinear causality is found, which shows the nonlinear independence of both the variables of interest (Tables 6.3 and 6.4). These findings remain unchanged even after the sample length of the data is extended to include the financial crisis period, i.e. from Jan-1990 to Dec-2011.

6.3.2.4 Findings from Hypothesis 1b

The nonlinear bivariate causality test under Hiemstra and Jones (1994) shows evidence of nonlinear causality only in the case of Malaysia, where the business cycle is caused by stock market volatility across both samples. Furthermore, some weak evidence of reverse causality is also reported, indicating a relatively weak feedback effect between the two variables. However, no instance of nonlinear causality between the variables is reported for Brazil or Turkey using both data samples.

6.3.2.5 Comparison of Findings from Hypothesis 1b (Hiemstra and Jones, 1994) for Developed and Developing countries

As reported in section 6.3.1.5 above, the incidence of nonlinear causality is strongly reported for the developed countries. Among the developing countries, nonlinear causality is only significant for Malaysia, whereas there is strong evidence of nonlinear causality found for Canada, Japan and the US in at least one or more directions.

6.3.3 Comparison of Bivariate Linear and Nonlinear Causality Results

This section compares the results of traditional linear Granger causality tests (section 6.1) and nonparametric nonlinear models (section 6.2) to understand the relationship between stock market volatility and the business cycle. This research extends the conventional linear causality test to incorporate nonlinear causality between the variables. Hence, any evidence of causality found shows the inability of the linear models to fully explain the variations in variables. The results discussed in Sections 6.1 and 6.2 earlier show evidence of nonlinear relationships in some instances in the developing countries, where the nonlinear causality exists beyond what can be inferred by linear models. Country specific comparison of the bivariate causality results between the linear and nonlinear models is given below:

6.3.3.1 Brazil

Linear causality tests show a strong feedback effect between the stock market volatility and the business cycle for both sample periods. However, nonlinear tests show that both the variables are statistically independent of each other and thus no evidence of nonlinear causality is reported. In the context of linear causality, the Brazilian stock market volatility and business cycle affect each other consistently over both periods.

6.3.3.2 Malaysia

The Malaysian stock market and business cycle shows strong linear mutual dependence before the financial crisis period. However, unidirectional linear causality running from the stock market to the business cycle is found statistically significant at 1% including the financial crisis. Hence, reverse causality is not shown for the full sample. In contrast to this, nonlinear models show consistent and stable causal relationships for both the sample periods. According to test statistics proposed by Diks and Panchenko (2006), the Malaysian business cycle is observed to cause stock market volatility at a significance level of 5% both in the pre-crisis and including the financial crisis period as well. Hiemstra and Jones' (1994) test statistic, on the other hand, shows significant evidence of stock market volatility in Malaysia causing business cycles at a significance level of 5%. However, it also shows relatively weak evidence of reverse causality running through the business cycles on to stock market volatility for both the sample lengths, at 10% significance level only. Hence, there is reported some evidence of a possible feedback effect between the two variables under the Hiemstra and Jones (1994) method.

This explains the importance of Malaysian stock market volatility when predicting changes in the business cycle for the country. This information may also be useful for investors, risk managers and policy makers.

6.3.3.3 Turkey

In the case of Turkey, a linear causal relationship is shown for stock market volatility causing the business cycle for both sample lengths at the 1% significance level. There is, however, reverse causality shown for the pre-crisis period, but at the 10% significance level only. Hence, the linear causality model reports strong evidence of linear dependence of the Turkish business cycle over stock market volatility.

On the other hand, the nonlinear causality tests offer no significant relationship in any direction for both sample periods. Hence, the statistical independence of the Turkish stock market volatility and business cycle from each other is documented in both the pre-crisis period as well as when including the financial crisis, under the nonlinear causality models suggested by Hiemstra and Jones (1994) and Diks and Panchenko (2006). This may be due to the fact that, like Brazil, the Turkish stock market was relatively calm (Figure 4.5) compared to the developed countries such as the US, the UK and Japan.

6.4 Multivariate Linear Causality

After analysing the causal relationship between the stock market volatility and the business cycle in the intra country settings, this section explores the relationship between the two variables across countries, with the aim of identifying the spill-overs and interdependence between the variables of the developing countries and the US. The main purpose for comparing the developing markets with the US is to see how the US stock market volatility and changes in the business cycle affect these countries, and vice versa. From the methodological perspective, this analysis employs both linear and nonlinear approaches to account for detailed causal relationships and interdependencies. Similarly, to capture the impact of the recent financial crisis the analysis covers two sample periods, as already explained in the earlier sections. To better understand the underlying relationships, the set of hypotheses are tested using linear and nonlinear models. These hypotheses are explained in Section 2.3 (Chapter 2 Theoretical Framework).

Empirical results for hypotheses 2a and 3.2a, as discussed and detailed in Section 2.6, are tested using the multivariate linear causality method and a discussion of their results is provided. Tables 6.5 and 6.6 show the results for hypotheses 2a and 3.2a. Besides the main hypotheses results, evidence relating to stock market volatility spill-overs and business cycle spill-overs across the sample countries is also described and discussed in this section.

In addition to F-statistics, corresponding lags of each regressors, adjusted R squares, standard errors of estimates, sum of squares of residuals, Ramsey's misspecification test, White's heteroskedasticity test, Ljung-Box autocorrelation test and Jarque-Berra test results are also presented to test the reliability and consistency of the estimates.

6.4.1 Cross-country Spill-over (Stock Volatility against the Business Cycle)

6.4.1.1 Before the Financial Crisis (Jan-1990 to June 2007)

This section explains the hypothesis test results (Table 6.5) for analysis of the linear spill-over effect between stock market volatility and the business cycle between the US and developing countries, including Brazil, Malaysia and Turkey. The hypotheses in this context are set out in section 2.7.2. For cross-country analysis, all of the developing countries included in the sample are compared against the US because the US is the largest economy globally and there is sufficient evidence in the literature that the US was at the epicentre of the recent financial crisis. Country specific analysis of these hypotheses is provided in the following sub-sections:

6.4.1.1.1 Brazil

In the pre-crisis time period, a significant feedback effect between Brazilian stock market volatility and the US business cycle has been observed, i.e. both the variables are mutually dependent on each other with varying significance levels of 1% or 5% (Table-6.5). Similarly, US stock market volatility is shown to cause the Brazilian business cycle with a 1% significance level. Weaker evidence of reverse causality is also observed, with a significance level of 10%, hence evidence of possible feedback is relatively weak and US stock market volatility seems a dominant predictor of Brazilian business cycles. Thus, due to the existence of a significant causal relationship irrespective of the direction of causality, the null hypothesis 2a cannot be accepted at the 1% or 5% significance levels. Brazil has had a rising share of foreign investment in its stock market. According to Kaltenbrunner and Painceira (2009), the attractiveness of the Brazilian market was due to its high liquidity, caused by the willingness of the central bank to provide liquidity at any time and the very short-term nature of its financial assets. This made the Brazilian domestic economy increasingly dependent on conditions in international financial markets.

6.4.1.1.2 Malaysia

Stock market volatilities of both Malaysia and the US show a spill-over effect on each other's business cycles, at the 1% significance level (Table 6.5). This shows the impact of uncertainty in Malaysian and US stock markets affecting real economic conditions in the other country, highlighting the importance of stock markets in leading the business cycles of another country (cross-country spill-over). However, no significant evidence of cross-country feedback effect is reported for either country. These findings lead to rejection of the null hypothesis 2a for Malaysia at the 1% significance level. Chen and Wu (2013), found that Malaysian stock market volatility is only affected 20% by global factors, supporting our results that show that Malaysian stock market volatility is not being caused by the US.

6.4.1.1.3 Turkey

Similar causal relationships between Turkey and the US have also been reported, whereby stock market volatilities linearly cross-effect each other's business cycles at the 1% significance level (Table 6.5). The business cycles are shown to be dependent on each other's stock market volatility in a linear framework. This implies that the null hypothesis 2a of no cross-country causality cannot be accepted at the 1% significance level.

6.4.1.2 Findings for Hypothesis 2a

This section encompasses the linear causality between stock market volatility and the business cycle across the US and the developing countries. US stock market volatility is observed to lead the business cycles of all three developing countries, i.e. Brazil, Malaysia and Turkey, whereas stock market volatilities of these countries respectively cause the US business cycle in the pre-crisis period. Thus, hypothesis 2a is rejected for all three developing countries in the pre-crisis period.

6.4.1.3 Comparison of Findings from Hypothesis 2a for Developed and Developing Countries

Strong evidence of cross-country stock market volatility and business spill-over is presented for both the developed and developing countries against the US in the pre-crisis period, hence rejection of the null hypothesis 2a in almost all cases, with the exception of the UK where the null hypothesis is only rejected at the 10% level which implies relatively weak evidence of cross-country spill-over.

6.4.1.4 Including the Financial Crisis (Jan-1990 to Dec-2011)

6.4.1.4.1 Brazil

A significant feedback effect is reported across Brazilian and US variables after inclusion of the financial crisis period at the 5% significance level. This implies a mutual dependence between i) changes in Brazilian stock volatility and changes in the US business cycle and ii) changes in the Brazilian business cycle and changes in US stock market volatility. Thus, inclusion of the financial crisis period, i.e. July 2007 to December 2011, strengthens these relationships in comparison to the pre-crisis period.

During the financial crisis, the main cause of Brazil's vulnerability was its large exposure to short term foreign capital and the increased liquidity of its financial assets (Kaltenbrunner and Painceira, 2009). The Brazilian financial assets were increasingly used in global investment portfolios due to the high liquidity provided by the central bank. The losses made by foreign investors in other markets forced them to liquidate their investments in the Brazilian market. According to de Barros (2010), Brazil was strongly hit by the financial crisis at the end of 2008, its industry was affected and industrial production dropped by 21% in the last quarter of 2008. Thus, our findings of changes in the US stock volatility causing changes in the Brazilian economy, and vice versa, may be explained through the above channels.

6.4.1.4.2 Malaysia

Linear causal analysis shows a significant (5%) feedback effect between the Malaysian business cycle and US stock market volatility, showing the cross-country spill-over between the countries (Table 6.6). Similarly, Malaysian stock market volatility is reported as one of the significant predictors of the US business cycle, with a 1% significance level. In addition, no evidence of reverse causality between the two variables is reported for this period, implying the linear independence of Malaysian stock market volatility.

6.4.1.4.3 Turkey

In the case of Turkey, the only evidence reported under the linear causality tests is that of Turkish stock market volatility causing the US business cycle with a 1% significance level (Table 6.6). No other relationship between the variables of the two countries is found to be significant. Hence, these variables demonstrate mutual independence of each other in the linear settings, except for the US business cycle being affected by the Turkish stock market volatility.

6.4.1.5 Findings for Hypothesis 3.2a

To summarize, significant evidence of cross-country spill-over effect is reported for Brazil, Malaysia and Turkey, where at least one or more instances of spill-over are documented. However, stronger bi-directional causality or feedback is evident in the case of Brazil and Malaysia only, which shows the significance and influence of the US stock market and business cycle on the developing countries. Turkey shows the least linear dependence against the US, however its stock market volatility shows some evidence of causing the US business cycle. These findings contribute significantly towards the literature on cross-country spill-over between stock market volatility and business cycles because evidence in this context is non-existent, to the best of the author's knowledge.

6.4.1.6 Impact of Japan as a Regional Leader on the Developing Countries

The analysis of cross country causality among the variables has been extended to analyse the impact and implications of a regional leader[35] instead of the world economic leader – the US. For this purpose, Japan has been taken as the regional leader in Asia. The linear and nonlinear causal relationships have been tested between Japan and other developing countries, i.e. Malaysia and China, respectively.

The results of the hypotheses show no significant evidence of cross-country causality among the underlying variables when US is replaced by Japan as a regional leader. This implies that respective changes in stock market volatility and the business cycles of China and Malaysia are statistically independent of Japanese variables, both before and during the recent financial crisis period.

6.4.1.7 Comparison of Findings from Hypothesis 3.2a for Developed and Developing Countries

Comparison of the results for the developed and developing countries for hypothesis 3.2a reveals a strong cross-country spill-over effect between stock market volatility and business cycles of the US against the rest of the countries included in the sample. This not only validates the importance of cross-country dependence among the underlying variables but also indicates the need to include cross-country stock market volatility while forecasting business cycle turning points.

6.4.2 Stock Market Volatility Spill-overs Across Countries

In addition to the cross-country linear causal analysis of stock market volatilities and business cycles, this section describes stock market volatility to stock market volatility spill-overs across countries in linear settings. As discussed in the theoretical background, there is a strand of literature that looks at the relationship (co-movement or Granger causality) between stock markets across the countries. Here we test the linear Granger causality for a

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[35] The cross-country anlaysis involving regional leader was suggested by the examiners. Detailed results of these relationships are presented in Appendix-3.

possible linear dependence between US stock market volatility against the stock market volatility of the developing countries in the sample. The analysis also looks at the pre and including the financial crisis time periods to explore possible changes/shifts in the underlying relationships due to the financial crisis.

Table-6.5 shows statistically significant bidirectional causality between Brazilian and US stock market volatilities (5% to 10% levels) which is consistent over both sample lengths, i.e. pre-crisis and including the crisis periods. Malaysian stock market volatility shows no relationship against US stock volatilities in the pre-crisis period, however, after including the financial crisis period (Table-6.6), both variables show a feedback effect at the 5% significance level.

In the case of Turkey, there is almost no significant evidence of stock market spill-overs between the two countries, except for one instance in the pre-crisis period where US stock volatility shows a frail indication of spill-over on to the Turkish stock market, with a 10% significance level (Table 6.5).

6.4.3 Business Cycle Spill-overs Across Countries

Linear Granger causality tests are further applied for assessing the evidence of business cycle spill-overs across the sample countries, i.e. analysing whether changes in the business cycle of one country causes changes in the business cycle of another country. The results for testing the null of no Granger causality between the business cycles of the sample countries are presented in Tables 6.5 and 6.6. The business cycle of each country is compared with respect to changes in the business cycle of the US, and vice versa. The following paragraphs show the causal relationship between business cycles across the countries based on the periods before the financial crisis and including the financial crisis.

A strong bidirectional causality relationship is indicated between the Brazilian and US business cycles for both sample lengths, i.e. the pre-crisis and including the financial crisis, at the 5% significance level (Tables 6.5 and 6.6). For the pre-crisis period, similar evidence has been found by Canova (2005) where output for Brazil (among the other Latin American countries) shows a sizeable response to US demand shocks. It means that economic performance of both countries affects each other and this may be termed as integration of the business cycles of these two countries.

In the case of the Malaysian and the US business cycles, only a unidirectional causal relationship (1% significance level) is indicated for the pre-crisis period, whereby the US business cycle spills-over on to the Malaysia economy and affects its economic performance (Table 6.5). However, this relationship becomes weaker after the sample period is extended to include the financial crisis period (Table 6.6). Similarly, the Turkish business cycle only shows an incidence of spill-over on to the US business cycle at a 5% significance level before crisis and no other evidence of business cycle spill-over is reported for both sample periods.

6.5 Multivariate Nonlinear Causality

This section describes the multivariate nonlinear Granger causality results between the variables, using the test statistic proposed by Bai, Wong and Zhang (2010). This statistic tests the null hypothesis of joint independence between the independent variables and a dependent variable based on correlation integrals in a multivariate framework. The results are shown in Tables 6.7 and 6.8. Following the same theme as above, initially results for the sample containing before the financial crisis data are presented through Table-6.7 and later results pertaining to the full sample period are described via Table-6.8.

6.5.1 Before the Financial Crisis (Jan-1990 to June-2007)

6.5.1.1 Four Variables

This section analyses the multivariate nonlinear Granger causality between stock market volatility for Country A and the business cycle for Country B, while controlling for the business cycle of Country A and stock market volatility of Country B. The nonlinear measure employed in this research tests the joint causality, therefore, of each of the four variables modelled against the remaining three variables in each case. Thus, for each country nonlinear causality is tested in four possible ways. The countries in reference are the developing countries included in the sample, i.e. Brazil, Malaysia and Turkey, tested against the US for possible spill-over across the variables of interest.

6.5.1.1.1 Brazil

In the case of Brazil, none of the variables show any causal dependencies in the nonlinear settings (Table 6.7), hence, all these are regarded to be independent of each other for the pre-crisis period. It means that the null hypothesis 2b cannot be accepted in the case of Brazil, implying no cross-country spill-over of variables of interest between Brazil and the US.

6.5.1.1.2 Malaysia

However, the US business cycle shows joint dependence on the Malaysian stock volatility and business cycle and the US stock volatility at the 5% significance level (Table 6.7). This result implies that US business cycle is jointly caused by the other three variables in the pre-crisis scenario. These findings lead to a rejection of the null hypothesis 2b in the case of Malaysia.

6.5.1.1.3 Turkey

Similarly, Turkish stock market volatility is shown to be jointly caused by the Turkish business cycle in addition to US stock volatility and the US business cycle at the 10% significance level (Table 6.7). This implies relatively weak evidence of nonlinear causality between these variables. In addition, for the rest of the variables, the null hypotheses of no Granger causality cannot be rejected even at the 10% significance level.

6.5.1.2 Three Variables

6.5.1.2.1 Brazil

US stock market volatility and business cycles cause Brazilian stock market volatility with a 5% significance level (Table 6.7). However, no nonlinear causality is reported in the reverse direction, i.e. US variables are observed to be empirically independent of their Brazilian counterparts. Thus, the null hypothesis of no cross-country spill-over in this case is rejected at the 5% level. It is interesting to note that there was no nonlinear causal relationship found when all four variables were jointly tested. However, when the domestic variable of Brazil is dropped from the model, the nonlinear relationship from the US variables to the Brazilian stock market becomes apparent. If this result is looked at in light of the bivariate nonlinear findings it is confirmed that Brazilian variables do not show any nonlinear features in our model. Thus, the nonlinear causality is only channelled through the US variables.

6.5.1.2.2 Malaysia

Table 6.7 provides no evidence of any nonlinear cross-country spill-over between the US and Malaysian variables of interest. This implies that the stock market volatility and business cycles of both countries are independent of each other under the Bai *et al.* (2010) test statistic. Hence, the null hypothesis 2a cannot be rejected even at the 10% significance level in the case of Malaysia in the pre-crisis period. If the results are looked at keeping in mind the findings from the bivariate nonlinear causality for the US and Malaysia individually, as well as the multivariate nonlinear causality in the four variables case, the following observations can be made: US stock market volatility causes the US business cycle; and US stock market volatility, together with Malaysian variables, also causes the US business cycle (in the four variable setting). However, when US stock market volatility is dropped from the equation, Malaysian variables do not hold any causal relationship with the US business cycle. Thus, the causal relationship in the four variable case could have been only due to the US stock market volatility.

6.5.1.2.3 Turkey

No cross-country causal relationship is observed between the stock market volatilities and business cycles of Turkey and the US (Table 6.7). Therefore, the null hypothesis 2b of no cross-country spill-over cannot be rejected even at the 10% significance level. This implies stochastic independence between the underlying variables in the nonlinear settings proposed by Bai *et al.* (2010). In the bivariate nonlinear model, Turkey's variables do not show any causal relationship within the country. Similarly, in the cross-country nonlinear analysis, evidence of very weak causality is found where changes in Turkish stock market volatility are being jointly caused by US and Turkish variables. This relationship disappears when the domestic variable (Turkish business cycle) is dropped.

6.5.1.3 Findings for Hypothesis 2b

To summarize the hypothesis test results for 2b based on the developing countries, out of 12 null hypotheses of no Granger causality only two are rejected, for the rest of the 10 instances, the underlying variables are jointly independent of each other in the nonlinear multivariate framework suggested by Bai *et al.* (2010). These results are based on the four-variables setting. In the case of the three-variable design, significant cross-country spill-over (causality) is reported only in one instance out of 12 cases, i.e. US stock market volatility and business cycle jointly affecting Brazilian stock market volatility.

6.5.2 Including the Financial Crisis (Jan-1990 to Dec-2011)

6.5.2.1 Four Variables

6.5.2.1.1 Brazil

Table 6.8 presents the results for hypothesis test 3.2b under Bai *et al.* (2010) for multivariate nonlinear causality after including the financial crisis period. The results for Brazil show joint independence of the stock market volatility and business cycle against the US variables, as no evidence of cross-country causality in any direction is reported. Thus, the null hypothesis 3.2b for Brazil cannot be rejected even at the 10% level. The cross-country non-linear results for Brazil remain the same before the financial crisis and for the full sample including the financial crisis.

6.5.2.1.2 Malaysia

Similar to Brazil's results in section 6.5.2.1.1 above, no evidence of cross-country causality is reported for Malaysia (Table 6.8). Thus, the null hypothesis 3.2b cannot be rejected. This shows another instance of the joint independence of stock market volatility and the business cycle between the developing countries and the US.[36]

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[36] The examiners suggested that other than US as a world leader, a regional leader – Japan should be included in the cross-country spillover analysis for Malaysia. The results show no linear or non-linear causal relationship across Japan and Malaysia both before and during the financial crisis. The detailed results are provided in Appendix - 3

6.5.2.1.3 Turkey

Stock market volatility and the business cycle of the US are reported to affect the Turkish business cycle while controlling for Turkish stock market volatility at the 5% significance level (Table 6.8). This leads to the rejection of the null hypothesis 3.2b for Turkey, indicating evidence of a cross-country spill-over effect between the US and Turkey, using the nonlinear framework proposed by Bai *et al.* (2010). After inclusion of the financial crisis to the sample, the results for Turkey change significantly. The weak causality running from joint variables to the Turkish stock market volatility, changes from joint variables to just the Turkish business cycle. It may be explained as the economic and financial volatility during the financial crisis causing a slowdown in the Turkish economy.

6.5.2.2 Three Variables

6.5.2.2.1 Brazil

In the case of Brazil, the US stock market volatility and business cycle are reported to cause stock market volatility in Brazil at the 5% significance level. This shows the impact of the US economy and stock market uncertainties over the Brazilian stock market for the period including the financial crisis. Therefore, the null hypothesis 3.2b, using the three-variable setting, can be conveniently rejected. It is important to note that this relationship did not hold when the Brazilian business cycle was included in the model, in section 6.5.2.1.1 above. As Bai *et al.* (2010) is a joint causality test, inclusion of any dormant variable with other active variables may cause a false rejection of the causal relationship. Therefore, when the Brazilian business cycle is excluded, the remaining variables, i.e. the US stock market volatility and business cycle, are significant at the 5% level.

6.5.2.2.2 Malaysia

The US stock market volatility and business cycle are reported to jointly cause the Malaysian business cycle at the 5% significance levels. This leads to the rejection of the null hypothesis 3.2b for Malaysia. This result, along with the Brazilian stock market volatility's dependence over US variables, shows the importance of the US economy and spill-overs on the developing economies.

6.5.2.2.3 Turkey

Lastly, some relatively weak joint spill-overs are indicated between Turkish and US stock market volatilities and business cycles at the 10% significance levels. Therefore, the null hypothesis 3.2b can also be rejected in the case of Turkey. This contributes further to the evidence offered by this thesis regarding cross-country spill-over between developing countries and the US variables of interest.

6.5.2.3 Findings for Hypothesis 3.2b

This section summarizes the findings for hypothesis 3.2b based on the developing countries. Out of 12 null hypotheses of no Granger causality only one is rejected, for the rest of the 11 instances the underlying variables are jointly independent of each other in the nonlinear multivariate framework suggested by Bai *et al.* (2010). These results are based on the four-variables setting. In the case of the three-variable design, significant cross-country spill-over (causality) is reported in five instances out of 12, implying evidence of cross-country nonlinear spill-over between stock market volatility and business cycles across the US and these developing countries. As explained in section 3.8, these findings offer evidence on the nonlinear causality (spill-over) across the developing countries, namely Brazil, Malaysia and Turkey, and contribute to the literature as no prior evidence is available on this subject.

6.5.2.4 Impact of Japan as a Regional Leader on the Developing Countries

The analysis of cross country causality among the variables has been extended to analyse the impact and implications of a regional leader, as stated earlier. Thus, rather than the world economic leader – the US, Japan has been taken as the regional leader in Asia. The linear and nonlinear causal relationships have been tested between Japan and other developing countries, i.e. Malaysia and China, respectively.

The nonlinear multivariate model rejects incidents of causality in all cases. These results are consistent across both sample lengths, which means that even after inclusion of the recent financial crisis period, variables of Malaysia and China bear no causal relationship with the regional leader (Japan). Thus, it could be concluded that the developing countries although share financial and trade ties with the regional leader but the influence is not statistically significant in linear and nonlinear causal tests.

6.6 Comparison between Developed and Developing Countries' Results

The results from chapters 5 and 6 indicate stronger causal relationships between variables for developed countries than those of developing countries. In the multivariate setting, the linear causality results show that the US bears a strong influence on the variables of Canada, Japan and the UK. These results become even stronger after inclusion of the financial crisis period.

For developing countries, the US stock market volatility and business cycle have comparatively less influence, especially in nonlinear settings. Although the linear causality results show cross-country causality between the US and Brazil, Malaysia and Turkey, evidence of nonlinear cross-country spill-over is reported in only a very few instances for the developing countries, especially in the pre-crisis period.

This may be explained by the different stock market volatility patterns for developed and developing countries, as shown in Figure 4.5. Changes in stock market volatility are much larger in size for developed countries compared to those of developing countries. Furthermore, during the financial crisis period, represented by the shaded area, developing countries are relatively much calmer compared to the developed countries, where major disruptions can be observed. Another important factor is the extent of economic and financial dependence which drives the intensity of the spill-over across countries. Developing countries are often observed to be more sensitive due to economic and financial ties with other countries of a similar size and economic status. In a different stream of research on the convergence and divergence of global business cycles, a recent study by Kose et al. (2012) found that there is an emergence of group specific cycles. They found substantial convergence between the business cycles of developed/industrial economies and similarly among developing economies but the two groups diverge from each other. Evidence offered by this thesis, where developed countries show greater linear and nonlinear cross-country spill-over effects compared to developing countries, is thus in line with the above argument. However, the above study has not addressed the issue of financial crisis except to hint that a financial crisis may go against the assumption of reduced importance of global factors. In this research, we find that during the financial crisis the influence of the US variables on the developing countries has been greater than prior to the financial crisis.

6.7 Conclusion and Implications

This chapter presents the results for the developing countries, i.e. Brazil, Malaysia, Turkey and China[37]. Major findings of the causality results show strong evidence of bivariate linear causality between stock market volatility and the business cycles for all the developing countries except China. There is some indication of feedback effect, especially for Brazil where bidirectional causality is found for both sample lengths. In the context of the recent financial crisis, the causal relationships for Brazil and Turkey were consistent over both periods, whereas in the case of Malaysia, the relationship changed from a strong feedback effect to only unidirectional causality running from stock market volatility to the business cycle.

Nonlinear Bivariate causality results using the Diks and Panchenko (2006) and Hiemstra and Jones (1994) methods reveal some evidence of nonlinear causality as Malaysian stock market volatility is caused by the business cycle across both samples. However, no instance of nonlinear causality between the variables is reported for Brazil, Turkey or China using both data samples.

This thesis contributes significantly to the literature by offering evidence regarding cross-country linear spill-overs between stock market volatility and the business cycles of the US and the developing countries included in the sample, i.e. Brazil, Malaysia, Turkey and China. However, evidence of cross-country spill-over under the nonlinear framework proposed by Bai *et al.* (2010) is relatively limited. Furthermore, nonlinear spill-overs are more evident after inclusion of the financial crisis period compared to the pre-crisis period.

[37] The results and discussion for China are given in the Appendix 2

Considering the fact that both business cycles and stock market volatility are important macro-financial indicators of the economic outlook of a country, the above findings have important implications for a much wider audience including economic policy makers, investors/portfolio managers and academics. This research bridges the causal gap between these two economic yard-sticks by offering fresh evidence pertaining to their relationship both within one country and then more importantly across other countries. For example, both Malaysia and Brazil show strong feedback effects between underlying variables against the US. This implies that any policy or strategy aimed at the business cycles and/or stock markets of developing countries must consider the impact of both the US business cycle and stock market uncertainties for increasing the success possibility of these policies. These findings have important implications for estimating/forecasting domestic business cycle turning points where stock market volatility of foreign countries can be an important determinant.

Table 6.1 Bivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Countries	Business Cycle → Stock Market Volatility			Stock Market Volatility → Business Cycle		
	Brazil	Malaysia	Turkey	Brazil	Malaysia	Turkey
Lags BC-SMV	6-11	7-1	1-9	4-12	12-3	3-12
F-Stat	5.1***	4.2***	1.83*	4.1***	3.89***	2.49***
Adj. R^2	0.059	0.1947	0.0023	0.078	0.546	0.342
SSE	0.0013	0.0002	0.00001	0.004	0.0012	0.00176
RSS	0.0184	0.0012	0.00205	0.073	0.217	0.317
RESET	0.84	0.7025	0.8035	2.824	0.547	1.103
White	193.13	144.71	156.594	166.30	151.48	152.2
LB	15.02	10.329	13.373	11.51	4.085	18.21
JB	3.78	4.65	1.39	2.46	2.89	4.04

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 6.2 Bivariate Linear Causality Between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Countries	Business Cycle → Stock Market Volatility			Stock Market Volatility → Business Cycle		
	Brazil	Malaysia	Turkey	Brazil	Malaysia	Turkey
Lags BC-SMV	8-12	12-8	10-10	7-12	12-5	2-12
F-Stat	2.05**	0.97	1.28	2.52***	2.87***	2.19***
Adj. R^2	0.060	0.2247	0.02217	0.048	0.5496	0.32485
SSE	0.0008	0.00001	0.00001	0.0005	0.00115	0.0018
RSS	0.018	0.0031	0.00196	0.1077	0.26804	0.43467
RESET	2.8456	4.4059	3.3923	3.0556	1.3551	0.99464
White	247.84	247.92	246.409	221.57	188.709	129.628
LB	13.96	1.2028	2.2547	9.4086	3.840	17.8639
JB	1.87	1.02	3.2	3.35	1.603	0.90

Notes:
1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 6.3 Bivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Panel-I Diks and Panchenko (2006)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Brazil	0.9313	0.68321
Malaysia	1.071	**1.686****
Turkey	0.217	0.392

Panel-II Hiemstra and Jones (1996)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Brazil	-0.31990	-0.63071
Malaysia	**1.65924****	**1.05919***
Turkey	0.31748	-0.12823

Table 6.4 Bivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Panel-I Diks and Panchenko (2006)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Brazil	0.5194	0.1625
Malaysia	1.2022	**1.7064****
Turkey	0.0618	0.888

Panel-II Hiemstra and Jones (1996)

Countries	Stock Volatility → Business Cycle	Business Cycle → Stock Volatility
	Test-Stat	Test-Stat
Brazil	0.15603	0.58412
Malaysia	**1.64917****	**1.24385***
Turkey	0.76914	0.02638

Note:
1) ***, ** and * denote 1%, 5% and 10% significance levels

Table 6.5 Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Country	BRAZIL						
Dependent Variable	Stock Market Volatility (GARCH)						
Independent Variables	BC_{BZ}	SV_{US}	BC_{US}	Diagnostics			
Lags	5	12	3	Adj-R^2	0.207	RESET	1.317
				SEE	0.0001	White	198.6
F-Stat	0.848	1.62*	2.68**	RSS	0.0172	LB	6.50
				-	-	JB	0.038
Dependent Variable	Business Cycle						
Independent Variables	SV_{BZ}	SV_{US}	BC_{US}	Diagnostics			
Lags	12	1	1	**Adj-R^2**	0.02115	**RESET**	0.1187
				SEE	0.00004	**White**	201.1
F-Stat	3.13***	4.51**	5.07**	**RSS**	0.00075	**LB**	0.9484
				-	-	**JB**	0.3149

Country	UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)						
Independent Variables	BC_{US}	SV_{BZ}	BC_{BZ}	Diagnostics			
Lags	1	3	6	Adj-R^2		RESET	
				SEE		White	
F-Stat	0.65	2.7**	1.81*	RSS		LB	
				-	-	JB	
Dependent Variable	Business Cycle						
Independent Variables	SV_{US}	SV_{BZ}	BC_{BZ}	Diagnostics			
Lags	9	4	2	**Adj-R^2**	0.109	**RESET**	0.53275
				SEE	0.000025	**White**	199
F-Stat	3.346***	4.33***	3.03**	**RSS**	0.00455	**LB**	18.301
				-	-	**JB**	0.53

Table-6.5 (Contd.)

Country	Malaysia							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{MAL}	SV_{US}	BC_{US}	Diagnostics				BC_{MAL}	SV_{US}	BC_{US}	Diagnostics			
Lags	1	6	2	Adj-R^2	0.228	RESET	0.811	2	9	1	Adj-R^2	0.072	RESET	3.518
				SEE	0.00002	White	198.87				SEE	0.000001	White	193.20
F-Stat	3.96**	0.9656	1.351	RSS	0.00305	LB	2.93	1.09	0.65	0.018	RSS	0.000074	LB	12.24
				-	-	JB	0.685				-	-	JB	0.1678
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{MAL}	SV_{US}	BC_{US}	Diagnostics				SV_{MAL}	SV_{US}	BC_{MAL}	Diagnostics			
Lags	8	11	3	Adj-R^2	0.421	RESET	3.095	1	10	1	Adj-R^2	0.098	RESET	0.40084
				SEE	0.00153	White	198.17				SEE	0.00003	White	136.369
F-Stat	4.80***	2.54***	3.83***	RSS	0.264	LB	7.86	6.99***	2.80***	1.13	RSS	0.00465	LB	17.9159
				-	-	JB	0.614				-	-	JB	1.67

Table-6.5 (Contd.)

Country	Turkey							UNITED STATES						
Dependent Variable	**Stock Market Volatility (GARCH)**							**Stock Market Volatility (GARCH)**						
Independent Variables	BC_{Tky}	SV_{US}	BC_{US}	**Diagnostics**				BC_{Tky}	SV_{US}	BC_{US}	**Diagnostics**			
Lags	4	11	1	Adj-R^2	0.025	RESET	4.04	1	2	5	Adj-R^2	0.0481	RESET	4.39
				SEE	0.00001	White	199.09				SEE	0.00004	White	197
F-Stat	0.98	1.58*	0.2	RSS	0.0019	LB	6.56	0.514	0.678	2.23**	RSS	0.0007	LB	1.14
				-	-	JB	0.679				-	-	JB	0.5178
Dependent Variable	**Business Cycle**							**Business Cycle**						
Independent Variables	SV_{Tky}	SV_{US}	BC_{US}	**Diagnostics**				SV_{Tky}	SV_{US}	BC_{Tky}	**Diagnostics**			
Lags	6	3	1	Adj-R^2	0.374	RESET	0.1068	9	3	2	Adj-R^2	0.121	RESET	2.90
				SEE	0.00177	White	153.21				SEE	0.00003	White	179.06
F-Stat	2.37**	6.87***	0.21	RSS	0.329	LB	12.05	3.057***	2.93**	3.82**	RSS	0.00453	LB	11.11
				-	-	JB	0.395				-	-	JB	0.4587

Notes:
1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 6.6 Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Country	BRAZIL							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{BZ}	SV_{US}	BC_{US}	Diagnostics				BC_{US}	SV_{BZ}	BC_{BZ}	Diagnostics			
Lags	2	4	6	Adj-R^2	0.0701	RESET	3.79	6	7	5	Adj-R^2	0.3207	RESET	6.988
				SEE	0.00008	White	257.4				SEE	0.000001	White	254.49
F-Stat	0.586	2.29*	2.41**	RSS	0.01852	LB	15.07	2.86***	2.071**	2.406**	RSS	0.00028	LB	16.300
				-	-	JB	1.55				-	-	JB	2.92
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{BZ}	SV_{US}	BC_{US}	Diagnostics				SV_{US}	SV_{BZ}	BC_{BZ}	Diagnostics			
Lags	8	12	1	Adj-R^2	0.00501	RESET	1.65	11	7	3	Adj-R^2	0.2701	RESET	3.41165
				SEE	0.0005	White	243.5				SEE	0.00003	White	269.29
F-Stat	1.79*	2.79**	4.0**	RSS	0.1091	LB	10.19	2.63***	4.45***	2.62**	RSS	0.00746	LB	3.002
				-	-	JB	2.44				-	-	JB	0.75

Table-6.6 (Contd.)

Country	Malaysia							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{MAL}	SV_{US}	BC_{US}	Diagnostics				BC_{MAL}	SV_{US}	BC_{US}	Diagnostics			
Lags	1	3	5	Adj-R^2	0.2198	RESET	2.39	6	8	3	Adj-R^2	0.269	RESET	1.957
				SEE	0.0005	White	254.72				SEE	.00001	White	246.8
F-Stat	4.40**	2.17*	1.16	RSS	0.003	LB	1.743	2.944**	1.975**	0.822	RSS	0..003	LB	15.38
				-	-	JB	0.67				-	-	JB	0.882
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{MAL}	SV_{US}	BC_{US}	Diagnostics				SV_{MAL}	SV_{US}	BC_{US}	Diagnostics			
Lags	3	6	6	Adj-R^2	0.394	RESET	3.55	12	5	2	Adj-R^2	0.2443	RESET	4.1878
				SEE	0.0015	White	183.53				SEE	0.0003	White	250
F-Stat	3.47**	2.17**	6.31***	RSS	0.362	LB	8.08	2.51***	2.03*	0.42	RSS	0.0781	LB	2.514
				-	-	JB	1.76				-	-	JB	0.5921

.**Table-6.6 (Contd.)**

Country	Turkey							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{TKY}	SV_{US}	BC_{US}	Diagnostics				BC_{TKY}	SV_{US}	BC_{US}	Diagnostics			
Lags	1	5	4	Adj-R^2	0.00214	RESET	4.067	6	9	4	Adj-R^2	0.331	RESET	3.4
				SEE	0.00009	White	250.36				SEE	0.00001	White	256.06
F-Stat	0.088	1.29	0.442	RSS	0.002	LB	1.283	2.57	2.105	4.27	RSS	0.00027	LB	9.02
				-	-	JB	1.59				-	-	JB	1.97
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{TKY}	SV_{US}	BC_{US}	Diagnostics				SV_{TKY}	SV_{US}	BC_{US}	Diagnostics			
Lags	12	2	5	Adj-R^2	0.342	RESET	1.35801	2	12	3	Adj-R^2	0.247	RESET	4.05
				SEE	0.0018	White	250.61				SEE	0.000034	White	251
F-Stat	2.156	3.26	1.85	RSS	0.41056	LB	17.71	5.79***	1.37	2.617	RSS	0.0079	LB	5.48
				-	-	JB	1.34				-	-	JB	2.96

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test

Table 6.7 Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Panel-I (Four Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Brazil	SV_{BZ}	BC_{BZ}, SV_{US}, BC_{US}	-0.396	0.346
	BC_{BZ}	SV_{BZ},SV_{US},BC_{US}	1.055	0.146
	SV_{US}	SV_{BZ},BC_{BZ},BC_{US}	-0.366	0.357
	BC_{US}	SV_{BZ},BC_{BZ},SV_{US}	-1.031	0.151
Malaysia	SV_{MA}	BC_{MA}, SV_{US}, BC_{US}	-0.795	0.213
	BC_{MA}	SV_{MA},SV_{US},BC_{US}	-0.022	0.491
	SV_{US}	SV_{MA},BC_{MA},BC_{US}	0.648	0.258
	BC_{US}	**SV_{MA},BC_{MA},SV_{US}**	**-1.658****	**0.049**
Turkey	**SV_{TK}**	**BC_{TK}, SV_{US}, BC_{US}**	**1.487***	**0.068**
	BC_{TK}	SV_{TK},SV_{US},BC_{US}	1.092	0.137
	SV_{US}	SV_{TK},BC_{TK},BC_{US}	1.034	0.151
	BC_{US}	SV_{TK},BC_{TK},SV_{US}	-0.754	0.225

Panel-II (Three Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Brazil	**SV_{BZ}**	**SV_{US}, BC_{US}**	**-1.771****	**0.038**
	BC_{BZ}	SV_{US},BC_{US}	0.665	0.253
	SV_{US}	SV_{BZ},BC_{BZ}	0.235	0.407
	BC_{US}	SV_{BZ},BC_{BZ}	-0.55	0.291
Malaysia	SV_{MA}	SV_{US}, BC_{US}	-0.535	0.296
	BC_{MA}	SV_{US},BC_{US}	-0.176	0.43
	SV_{US}	SV_{MA},BC_{MA}	0.249	0.402
	BC_{US}	SV_{MA},BC_{MA}	-0.66	0.255
Turkey	SV_{TK}	SV_{US}, BC_{US}	0.331	0.37
	BC_{TK}	SV_{US},BC_{US}	0.612	0.27
	SV_{US}	SV_{TK},BC_{TK}	1.124	0.13
	BC_{US}	SV_{TK},BC_{TK}	-0.259	0.398

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Table 6.8 Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Panel-I (Four Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Brazil	SV_{BZ}	BC_{BZ}, SV_{US}, BC_{US}	-0.77	0.221
	BC_{BZ}	SV_{BZ},SV_{US},BC_{US}	0.855	0.196
	SV_{US}	SV_{BZ},BC_{BZ},BC_{US}	0.116	0.454
	BC_{US}	SV_{BZ},BC_{BZ},SV_{US}	-0.249	0.402
Malaysia	SV_{MA}	BC_{MA}, SV_{US}, BC_{US}	-0.158	0.437
	BC_{MA}	SV_{MA},SV_{US},BC_{US}	-0.936	0.175
	SV_{US}	SV_{MA},BC_{MA},BC_{US}	0.496	0.31
	BC_{US}	SV_{MA},BC_{MA},SV_{US}	1.231	0.109
Turkey	SV_{TK}	BC_{TK}, SV_{US}, BC_{US}	-0.637	0.262
	BC_{TK}	**SV_{TK},SV_{US},BC_{US}**	**1.841****	**0.033**
	SV_{US}	SV_{TK},BC_{TK},BC_{US}	0.876	0.191
	BC_{US}	SV_{TK},BC_{TK},SV_{US}	-0.295	0.384

Panel-II (Three Variables)

Country	Dependent Variable	Independent Variables	Test Statistic	Prob.
Brazil	**SV_{BZ}**	**SV_{US}, BC_{US}**	**-2.235****	**0.013**
	BC_{BZ}	SV_{US},BC_{US}	-0.98	0.163
	SV_{US}	SV_{BZ},BC_{BZ}	0.181	0.428
	BC_{US}	SV_{BZ},BC_{BZ}	-0.724	0.235
Malaysia	SV_{MA}	SV_{US}, BC_{US}	0.035	0.486
	BC_{MA}	**SV_{US},BC_{US}**	**-1.718****	**0.043**
	SV_{US}	SV_{MA},BC_{MA}	0.256	0.399
	BC_{US}	SV_{MA},BC_{MA}	0.936	0.175
Turkey	SV_{TK}	SV_{US}, BC_{US}	-1.202	0.115
	BC_{TK}	**SV_{US},BC_{US}**	**1.522***	**0.064**
	SV_{US}	**SV_{TK},BC_{TK}**	**1.289***	**0.099**
	BC_{US}	**SV_{TK},BC_{TK}**	**-1.431***	**0.076**

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Chapter 7: Conclusion

7.1 The Stock Market Volatility (SMV) and Business cycle (BC) Relationship

The stock market depicts the health of the financial world, and the business cycle shows the ups and downs in the economy. The business cycle and the stock market are connected and researchers have been attempting to explain this relationship between the macro-economy and finance in a variety of ways. There is agreement in the literature on the presence of a relationship between stock market prices/returns and the business cycle. However, there are different views on the strength, direction and reasons behind this relationship. The different explanations as to why this relationship may exist are discussed at length in this thesis. An increase in volatility in the stock market will affect the investors' decisions and the capital available to companies, which further leads to delays in new projects/investment plans. This in turn affects employment and aggregate consumption/demand for goods, which translates into a sluggish economy (Bloom *et al.*, 2009). In the real/practical world, the stock market is used as an important lead indicator for business cycle turning points in countries such as the US and the UK. On the other hand, investors base their decisions on future economic outlook and expected cash flows, and these expectations are reflected in the share prices and returns. Any increase in economic uncertainty causes a surge in the stock volatility (Fama, 1990; Schwert, 1990a; Engle *et al.*, 2006; Giannellis *et al.*, 2010). This signifies the importance of the relationship between stock market volatility and the business cycle, as any change in one of these variables leads to changes in the other.

The global financial crisis (2007-2011) was the worst financial crisis of recent times. It emanated in the US but spread around the globe through various channels. The crisis had a severe impact on the financial markets and global economy. This thesis looks at how the industrial production and stock market volatility relationship responded to the global financial crisis. The relationships between stock volatility and the business cycle described and researched until now have heavily relied on linear methods. However, in this research, we expand the existing literature by exploring the nonlinear relationships in these macro-financial variables. This research looks at the strong influence of these interactions across countries and discusses the differences in the impacts on developed and developing countries.

7.2 Research Questions

The research tries to answer four questions. 1) Is there a linear and nonlinear causal relationship between stock market volatility and business cycles? 2) Do changes in the stock market volatility of one country Granger cause changes in the business cycle of other countries, and vice versa? 3) Has the recent financial crisis affected the causal relationship between the variables within and across countries? 4) Does the spill-over effect of the stock market volatility and business cycle relationship vary between developed and developing countries?

The answers to all these questions should fill the gap in the existing literature and will enhance the understanding of the intricate relationships between these variables.

7.3 Data and Methodology

The data for this thesis includes eight countries, the US, the UK, Canada, Japan, Brazil, Malaysia, Turkey and China, for the time period 1990 to 2011. These countries have been chosen from different regions in the world based on their importance and economy. The diversity in the sample favours the study in two ways. It makes it possible to obtain findings that are generalizable, and also findings that are more specific to the country, based on its financial markets and economy. For the analysis of the impact of the recent financial crisis on the relationship of the variables, the data has been divided based on time period into two sample lengths, before the financial crisis (Jan 1990 - June 2007) and including the financial crisis (Jan 1990 - Dec 2011).

Cross-country analysis is carried out in a multivariate setting using four variables, namely: the business cycle of country A, the business cycle of country B, the stock market volatility of country A and the stock market volatility of country B. This setting helps when analysing cross-country causality between the variables using both linear and nonlinear causality methods. For cross-country causality, US variables have been taken for hypothesis testing against the rest of the sample countries, as it is known to be economically and politically the most influential country in the world. The sample countries have been classified as developed (the US, UK, Canada and Japan) and developing (Brazil, Malaysia, Turkey and China) countries to compare cross-country causality results.

The methodology used for the thesis is causality testing between changes in stock market volatility and changes in business cycles in linear and nonlinear frameworks. The linear causality test is based on Granger (1969b) and the non-linear bivariate causality tests proposed by Diks and Panchenko (2006) and Hiemstra and Jones (1994) are employed. For multivariate non-linear causality, the Bai *et al.* (2010) methodology has been used. These nonlinear methods, as explained in section 4.3.3, suggest different test statistics based on correlation integral ratios. These test statistics provide probabilistic estimates of the co-movement between lag vectors of the independent variable(s) and the lead vector of the dependent variable.

7.4 Major Findings

The summary of the key results provides the following answers to the questions posed.

7.4.1 Stock Market Volatility (SMV) and the Business Cycle (BC) within a country:

Within the country context, this research reports strong linear causality between the variables for Canada, the UK and the US for both sample lengths. Similarly, strong linear dependence between the underlying variables for Brazil, Malaysia and Turkey is also shown. There is strong evidence of stock market volatility Granger causing the business cycle for the US, the UK, Canada and Japan, according to the Hiemstra and Jones (1994) methodology; and the business cycle causing stock volatility using the Dicks and Panchenko (2006) tests. The bivariate non-linear analysis of the developing countries shows some evidence of a causal relationship between stock market volatility and the business cycle. For instance, the Malaysian business cycle causes stock market volatility for both sample lengths under the Diks and Panchenko (2006) method, while under the Hiemstra and Jones (1994) test a weaker indication of the feedback effect is reported.

7.4.2 SMV and BC spill-over across countries:

In a multivariate setting, where cross-country spill-over is analysed, the linear results show bi-directional causality between the US and the rest of the developed countries, i.e. the UK, Japan and Canada. The non-linear results indicate that the US variables (SMV and BC) Granger cause the stock volatility of the UK, Japan and Canada.

For developing countries, mixed causality results are reported with respect to the US. US variables bear bi-directional causality with the Brazilian stock market volatility and business cycle. US variables Granger cause the Malaysian business cycle, whereas only US stock volatility causes the Turkish business cycle. In the non-linear setting, the evidence of spill-over is relatively weaker for the developing economies. This could indicate that the causal features of the developing countries do not bear nonlinear features as in the case of the developed countries.

7.4.3 Comparison of Spill-over effect between Developed and Developing Countries with respect to the US:

In both linear and non-linear settings, the causal relationship between the US variables (SMV and BC) with the developed countries is much stronger compared to the developing countries. Thus, we see more SMV-BC spill-over between the US and the developed countries. In the analysis of the individual countries, the reason for the difference of the impact could be due to the strong integration between developed countries, i.e. the stronger economic, financial and trade ties that the US has with the developed countries.

7.4.4 Impact of the Recent Financial Crisis on the SMV-BC Causal Relationships:

The impact of the recent financial crisis was tested and the Granger causal relationship between the variables is found to become stronger during the financial crisis. In the case of the developed countries, the Hiemstra and Jones (1994) method provides more evidence of business cycles causing stock volatility during the complete sample period and less of volatility causing business cycles. The Diks and Panchenko (2006) approach provides contrasting evidence in this context. For the developing economies, the recent financial crisis does not seem to significantly affect the underlying relationship between the variables.

Results for the spill-over effects under the multivariate linear settings are stable over both periods, especially in the case of the developed countries. The impact of the US stock market volatility also magnifies during the financial crisis period on other countries. Multivariate non-linear tests show stronger results in the case of Canada and Japan. These tests indicate ample evidence of business cycles being caused by stock market volatility in the case of the developed countries. Among the developing economies, US stock market volatility and business cycles jointly Granger cause the Turkish business cycle. This indicates increased interdependencies between these variables after inclusion of the financial crisis.

In addition to the recent financial crisis, Asian financial crisis and Russian financial crisis have also been taken into account for Malaysia and Brazil respectively. In the period (1991-01 to 1997-06) prior to the Asian financial crisis, no causal relationship between the variables exists, however in the post crisis period (1997-07 to 2004-12), Malaysia’s stock market volatility precedes its business cycle under both linear and nonlinear frameworks. In Brazil, before the Russian financial crisis (1993-01 to 1998-06), stock market volatility granger caused business cycle but after the crisis (1998-07 to 2003-12) there is strong feedback effect between the variables.

7.5 Research Contribution

The contributions by this thesis are threefold. Firstly, the research has explored the causal relationship between stock volatility and business cycles in a non-linear framework using the bivariate tests proposed by Hiemstra and Jones (1994) and Diks and Panchenko (2006). Secondly, it has looked at how the stock volatility or business cycle of another country (e.g. the US) Granger causes the variables within a country (e.g. the UK) by using non-linear multivariate causality as suggested by Bai *et al.* (2010). Thirdly, the research has been carried out at a time when a recent financial crisis had engulfed the world, so it takes into account how the causal relationships among the variables are affected by the global financial crisis.

7.6 Implications

This research, considering its nature and content, is aimed at serving a broad range of people but especially investors, traders, portfolio managers, policy makers, macroeconomists and researchers. Stock markets and business cycles are considered to be barometers of an economy for indicating both current health as well as future outlook for any economy or region. Analysing their causal relationship bridges up the causation gap and provides very significant insights about how the two variables are related within a country and across economies around the globe. This may serve a broad range of objectives for various groups such as stock market participants, policy makers, researchers and many more.

7.6.1 Investors and Portfolio Managers

For investors and portfolio managers, the future economic outlook is a very important strategic element as their investment decisions are based on this information. The interdependencies identified in this research between the stock market volatility and business cycles within a country and across borders can help Investors and portfolio managers to make informed investment decisions. The findings of the direction of causality between the two variables can be an important insight for forecasting future market dynamics. This information can be vital for devising diversification strategies and dealing with uncertainty in the market. The understanding of the results of causal interactions between developed and developing markets can enable international investors and asset management companies to manage their global portfolios more effectively (Ahn and Lee, 2006).

7.6.2 Policy Makers

The findings of international causal relationships between the variables are relevant for policy makers because it signifies that the policy makers do not only have to safeguard their domestic markets from domestic shocks but also have to devise policies to effectively deal with the cross-country spill-overs influencing the domestic financial markets and economy. The economic policy makers may need to insulate the real activity against the instability shocks from stock market volatility originating from domestic or international markets. The increased level of stock market volatility is detrimental for output growth not only during the financial crisis period, but during normal conditions as well (Vu, 2014). The real activity could be safe guarded, for example, through implementing a monetary policy framework with flexible inflation targeting and adjusting interest rates (Giannellis *et al.*, 2010).

7.6.3 Business Cycle Indicators

Stock market prices/returns are used as a leading business cycle indicator in the US, the UK, Japan, Brazil and other major countries (The Conference Board, 2014)[38]. At present for business cycle prediction, only the country's own stock volatility is included, but the results of this research suggest that cross-country stock volatility can also be a major business cycle indicator. For instance, the UK business cycle forecasting includes the stock market volatility of the UK as an indicator. This research proposes that in addition to the UK, US stock market volatility must also be considered while predicting the business cycle of the UK. This is because the business cycle of the UK is not only caused by its own stock volatility but also the stock volatility of the US with whom it shares economic and financial ties. This phenomenon has become even more

[38] The latest business cycle indicators can be found at the Conference Board's website. http://www.conference-board.org/data/bci.cfm

important during the recent financial crisis, when the spill-over effect has become more pronounced. Thus, inclusion of cross-country stock volatility may further enhance the predictive capability of these indicators regarding business cycle turning points.

7.7 Limitations and Future Research

There is only so much you can do in one thesis. While carrying out this research lots of aspects came up on which further research can be done. We plan to build on these findings and the model to expand it into other dimensions. The financial crisis and its impact can be captured using the financial stress index as a control variable for analysis. Thus, this could be an alternative technique for capturing the impact of the financial crisis that we have done here by comparing two sample lengths of before the crisis and including the crisis time periods.

Future research from our perspective could have the following two angles. One is building on the existing findings and exploring other aspects of this research area. The stock volatility and business cycle relationship could be explored in other countries and regions of the world, for instance, the European countries, seeing if the cross-country causality results are consistent to the Euro zone, especially as they share not only financial and economic ties but also the same currency. This research has been carried out when the financial crisis was prevalent. Therefore the research compared the time period prior to the financial crisis and the time length including the financial crisis, it would be interesting to analyse the non-linear causal relationship between these variables once the recent financial crisis is completely over.

As mentioned earlier, the findings from this thesis signal the possibility of improving business cycle leading indicators by the inclusion of cross-country stock market indicators. Further research could be done using developed forecasting techniques to analyse whether business cycle turning points can be better predicted if, for instance, the US stock market indicator is used as a leading indicator for the UK business cycle.

The second angle is to use this novel methodology of non-linear framework in other research areas in finance. Non-linear causality is a relatively recent concept in the field of finance and economics, especially its use in the multivariate setting, which is something that hasn't been explored on many macroeconomic or financial variables. The model and the methodology can thus be moulded according to other research problems.

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Appendix – 1: Issues in converting code from C++ to WinRats

We are grateful to Dr. Valentine Panchenko for making available the codes for the Hiemstra and Jones (1994) and Diks and Panchenko (2006) bivariate non-linear causality tests in C++ on his website. For this research these codes were re-written for RATS (version 7). The choice of RATS for the conversions was due to several reasons. RATS (Regression Analysis of Time Series), is a comprehensive econometrics and time series analysis software package. Its command driven language feature allows us to handle complex tasks such as user definable procedures, looping and programme controlled instructions. In addition to its programming capabilities, it handles large data and empirical analysis efficiently.

RATS can deal with a large number of variables with ease, whereas the C++ code for running causality tests is inconvenient as each variable has to be in a separate file, which in the case of many series becomes cumbersome. All empirical estimations, such as descriptive and unit roots analyses, volatility estimations and linear causality tests, were done in RATS. Therefore, in view of the above and to maintain the consistency, the C++ code was rewritten in RATS.

Syntax: As the program structure and syntax of both pieces of software is significantly different, the C++ code was compared with the original articles to understand the estimation procedures both manually and when using the code. In the conversion process, the C++ code was distributed in various blocks and accordingly rewritten in RATS. This enabled us to compare the results at different stages within the test and correct the code wherever required.

Convergence: The distribution of codes in various blocks, and comparing the results in a step-wise manner, ensured the consistency of results across various data types and lengths. Upon completion, both of the codes, i.e. both the original code written in C++ and the RATS version, were used on different data sets and the same results were attained by both versions in all cases.

Appendix – 2: Hypotheses Tests Results for China

This appendix details the analysis carried out for the Chinese market. The analysis is based on the results of the four research hypothesis. These include: 1) bivariate linear and non-linear granger causality between changes in the Chinese business cycle and Chinese stock market volatility, 2) multivariate linear and nonlinear granger causality among the four variables, the business cycle and stock market volatility of China and the business cycle and stock market volatility of the US, to test the cross country causality between China and the US and, 3) the impact of the recent financial crisis on the above relationships.

Before the financial crisis, Chinese economy displayed a low degree of synchronization with the developed countries, in spite of its significant trade ties with the developed countries. The financial crisis spreading from the US affected both the developed and the Asian emerging economies (Fidrmuc and Korhonen, 2010). The domestic situation in China made it more vulnerable to the global financial crisis and was thus widely affected. There was a combination of appreciation Chinese Yuan, rising inflation and market-based wages (Overholt, 2010), when the global picture dramatically changed. Labour costs were already increasing with the new labour law taking effect from January 1, 2008 which did not help when the external demand and consumer consumption were declining. This led to a fall in the Chinese exports for the first time in seven years. Also, the funds that were flowing into China to take benefit of the appreciating currency started gradually reversing (McNally, 2008).

A survey by Hong Kong Federation of Industries (HKFI, 2008) reported that 20% of their member firms were either closed or being phased out and only in the toy manufacturing industry, 53% of all toy companies had collapsed by October, 2008. According to an estimate more than 20 million workers were laid off during the crisis period (Overholt, 2010). Liu (2009) tried to quantify the impact of the global financial crisis on China by using Structural VAR. He reported that 1% decline in economic growth in the US, the EU and Japan is likely to lead to a 0.73% decrease in the Chinese growth.

The volatility increased manifold during the recent financial crisis, with volatility 3-4 times higher than its normal levels of 10-12 percent. Thus when the stock market volatility is so high, the causal relationship between stock market volatility and the business cycle may be affected by this rise. Therefore, taking the recent financial crisis as the test period allows us to analyse whether the causal relationships that exist in a stable economy and normal markets change when the volatility is surging. In this section, the causal relationship stated above is tested for two sample periods, i.e. 1) before the financial crisis, January 1990 to June 2007; and 2) including the financial crisis, January 1990 to December 2011. This allows us to analyse the impact of the global financial crisis on the various causal relationships analysed in this research.

Empirical results for China show no significant causal relationship between changes in the Chinese business cycle and stock market volatility. These results are in line with Wang (2010) who found that the Chinese stock market index could not be considered a leading indicator of future economic activity. They believed it could be because the Chinese financial structure, compared to more developed markets, is relatively weak, in spite of it being the world's second largest economy. The dominant commercial banking industry, with a greater emphasis on state-owned commercial banks, could be partly responsible for China's stock market not playing a significant role in its real economic growth. In our multivariate cross country causality analysis, no significant evidence of the spill over effect was found against the US. Moreover, including the financial crisis time period to the sample did not change the results. In other words, we find no effect of the financial crisis on the results.

Table 2-1: Bivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle – China

China	Before Financial Crisis		Including Financial Crisis	
	BC → SMV	SMV→ BC	BC → SMV	SMV→ BC
Lags BC-SMV	1-1	1-3	1-1	1-3
F-Stat	2.285	0.164	2.05	0.125
Adj. R^2	0.01543	0.36	0.012	0.32
SSE	0.00024	.00114	0.00019	0.00097
RSS	0.0449	0.213	0.041	0.2357
RESET	2.91	1.35	3.1	4.14
White	6.711	5.901	6.13	3.187
LB	10.18	7.331	9.851	3.008
JB	2.07	1.42	1.97	2.107

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 2-2: Bivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle – China

Panel-I **Diks and Panchenko (2006)**

Before Financial Crisis		Including Financial Crisis	
SMV → BC	BC → SMV	SMV → BC	BC → SMV
1.05	1.13	1.01	0.93

Panel-II **Hiemstra and Jones (1996)**

Before Financial Crisis		Including Financial Crisis	
SMV → BC	BC → SMV	SMV → BC	BC → SMV
1.15	0.62	0.64	0.59

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Table 2-3: Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Country	CHINA							UNITED STATES						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{CH}	SV_{US}	BC_{US}	Diagnostics				BC_{US}	SV_{CH}	BC_{CH}	Diagnostics			
Lags	1	1	1	Adj-R^2	0.0116	RESET	3.40	6	1	1	Adj-R^2	0.279	RESET	3.0501
				SEE	0.0001	White	6.04				SEE	0.0032	White	2.8357
F-Stat	1.854	0.0137	0.1096	RSS	0.0445	LB	10.9	13.02**	0.4384	0.0003	RSS	0.0177	LB	3.5803
				-	-	JB	1.06				-	-	JB	2.0376
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{CH}	SV_{US}	BC_{US}	Diagnostics				SV_{US}	SV_{CH}	BC_{CH}	Diagnostics			
Lags	1	1	1	Adj-R^2	0.311	RESET	4.25	1	1	1	Adj-R^2	0.2533	RESET	0.984
				SEE	0.0009	White	5.06				SEE	0.0003	White	4.063
F-Stat	0.1159	0.2283	1.4156	RSS	0.232	LB	3.73	16.41**	0.5388	0.0019	RSS	0.0079	LB	3.303
				-	-	JB	2.07				-	-	JB	1.744

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 2-4: Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Country	**CHINA**							**UNITED STATES**						
Dependent Variable	**Stock Market Volatility (GARCH)**							**Stock Market Volatility (GARCH)**						
Independent Variables	**BC_{CH}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**BC_{US}**	**SV_{CH}**	**BC_{CH}**	**Diagnostics**			
Lags	1	1	1	Adj-R^2	0.012	RESET	3.49	6	1	1	Adj-R^2	0.287	RESET	3.13
				SEE	0.0001	White	6.2				SEE	0.00334	White	2.91
F-Stat	2.03	0.015	0.12	RSS	0.0457	LB	11.2	14.28**	0.48	0.0004	RSS	0.0182	LB	3.674
				-	-	JB	1.09				-	-	JB	2.091
Dependent Variable	**Business Cycle**							**Business Cycle**						
Independent Variables	**SV_{CH}**	**SV_{US}**	**BC_{US}**	**Diagnostics**				**SV_{US}**	**SV_{CH}**	**BC_{CH}**	**Diagnostics**			
Lags	1	1	1	Adj-R^2	0.32	RESET	4.37	1	1	1	Adj-R^2	0.26	RESET	1.01
				SEE	0.0009	White	5.2				SEE	0.00034	White	4.17
F-Stat	0.127	0.25	1.55	RSS	0.239	LB	3.83	17.9***	0.59	0.0021	RSS	0.0082	LB	3.39
				-	-	JB	2.13				-	-	JB	1.79

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 2-5: Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle

(Before the Financial Crisis Jan-1990 to June-2007)

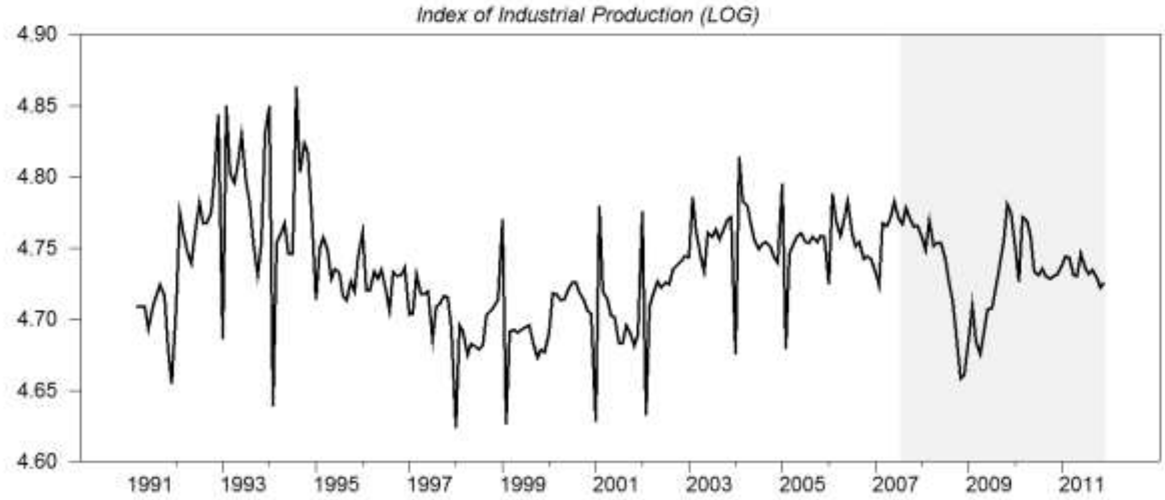
Dependent Variable	Independent Variables	Test Statistic	Prob.
SV_{CH}	BC_{CH}, SV_{US}, BC_{US}	0.99	0.1607
BC_{CH}	SV_{CH},SV_{US},BC_{US}	0.415	0.338
SV_{US}	SV_{CH},BC_{CH},BC_{US}	0.164	0.434
BC_{US}	SV_{CH},BC_{CH},SV_{US}	0.266	0.394

(Including the Financial Crisis Jan-1990 to Dec-2011)

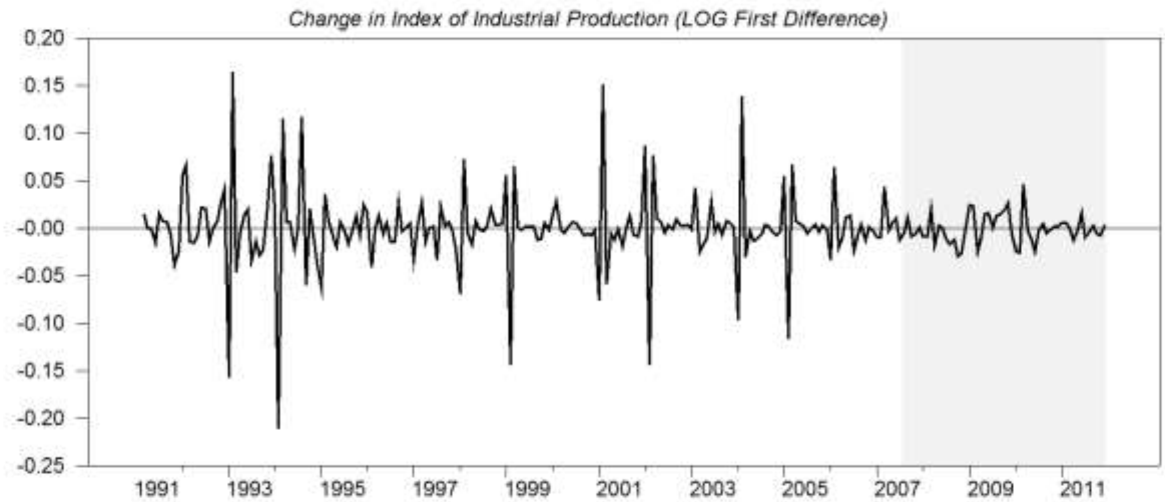
Dependent Variable	Independent Variables	Test Statistic	Prob.
SV_{CH}	BC_{CH}, SV_{US}, BC_{US}	0.54	0.292
BC_{CH}	SV_{CH},SV_{US},BC_{US}	0.78	0.215
SV_{US}	SV_{CH},BC_{CH},BC_{US}	1.14	0.152
BC_{US}	SV_{CH},BC_{CH},SV_{US}	0.24	0.402

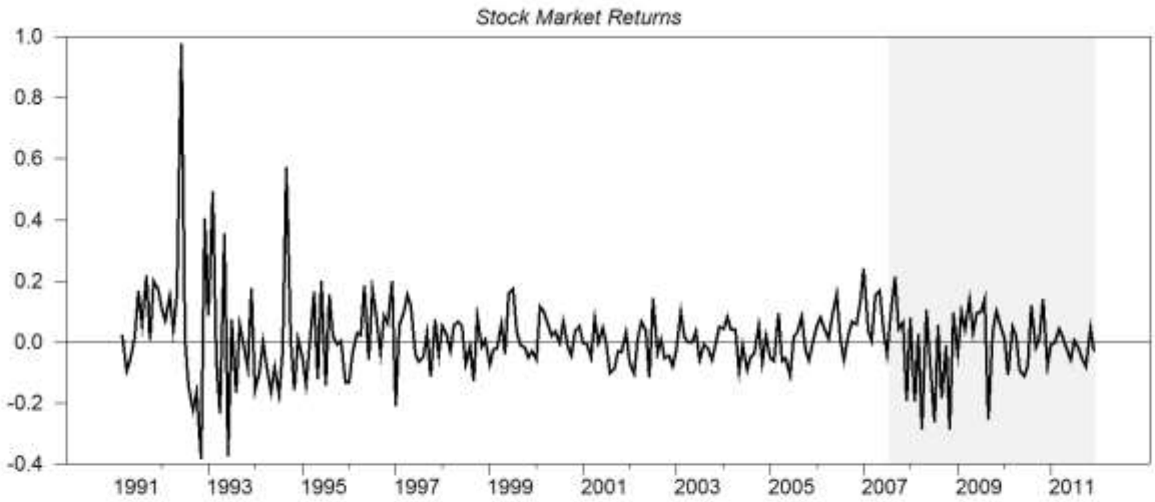
Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels

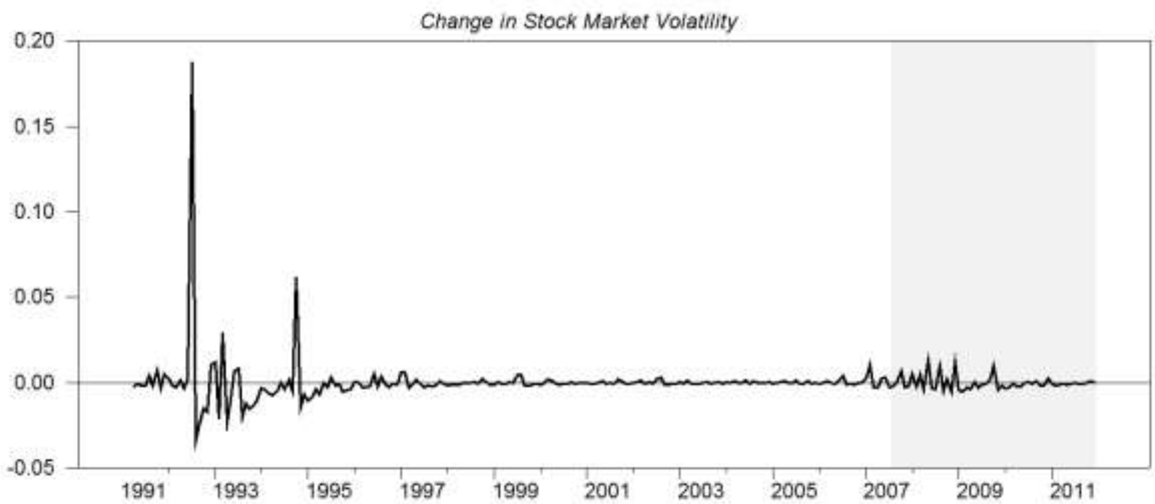

Index of Industrial Production (LOG)
4.90
4.85
4.80
4.75
4.70
4.65
4.60
1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011


Stock Market Index (LOG)
9.0
8.5
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011


Change in Index of Industrial Production (LOG First Difference)
0.20
0.15
0.10
0.05
-0.00
-0.05
-0.10
-0.15
-0.20
-0.25
1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011


Stock Market Returns
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011


Stock Market Volatility - GARCH (1,1)
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011


Change in Stock Market Volatility
0.20
0.15
0.10
0.05
0.00
-0.05
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011

Appendix – 3: Cross Country Analysis with Japan being the Regional Leader

In the thesis, research hypotheses 2a and 2b test the causal (linear and non-linear) relationship between changes in stock market volatility of country A and changes in the business cycle of country B. For these hypotheses, the US has been taken as the country B when changes in the business cycle and stock market volatility of all countries (A) are tested for presence of causality against the US (country B) variables, to determine if there is any presence of spill-over from/to the US. Moreover, hypothesis 3 tests whether these causal relationships have been affected during the recent financial crisis.

In this section, the analysis is extended to consider that for developing countries, if the US was replaced by a regional leader, how it would impact the findings of the hypotheses. Therefore, we take Japan as the regional leader and study the causal relationships with two countries, Malaysia and China, in that region, based on hypotheses 2a, 2b and 3. This was suggested by the examiners

Stock market volatility has been estimated using the Asymmetric GARCH, based on the stock indices of each country: the FTSE Jakarta for Malaysia, the Nikkie 225 for Japan and the Shanghai Composite Stock Index for China. The impact of the global financial crisis is checked by comparing the results for before the financial crisis (Jan 1990- June 2007) and the full sample including the crisis period (Jan 1990- Dec 2011).

The results of the hypotheses show no significant evidence of cross-country causality among the underlying variables, i.e. for Japan and China or Japan and Malaysia. This implies that respective changes in stock market volatility and the business cycles of China and Malaysia are statistically independent of Japanese variables. The nonlinear multivariate model also rejects incidents of causality in all cases. These results are consistent across both sample lengths, which means that even after inclusion of the recent financial crisis period, variables stay independent of any cross-border variables.

Table 3-1: Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Country	CHINA							JAPAN						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{CH}	SV_{JP}	BC_{JP}	Diagnostics				BC_{JP}	SV_{CH}	BC_{CH}	Diagnostics			
Lags	1	2	1	Adj-R^2	0.056	RESET	4.24	1	1	1	Adj-R^2	0.061	RESET	0.803
				SEE	0.0002	White	6.04				SEE	0.0009	White	5.174
F-Stat	2.63	1.65	1.39	RSS	0.0423	LB	10.4	0.744	0.659	0.743	RSS	0.0018	LB	12.11
				-	-	JB	1.29				-	-	JB	1.076
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{CH}	SV_{JP}	BC_{JP}	Diagnostics				SV_{JP}	SV_{CH}	BC_{CH}	Diagnostics			
Lags	1	3	1	Adj-R^2	0.035	RESET	1.30	1	3	1	Adj-R^2	0.026	RESET	0.541
				SEE	0.0011	White	3.17				SEE	0.00130	White	4.15
F-Stat	0.161	0.0117	0.0076	RSS	0.213	LB	1.73	0.0461	0.622	0.361	RSS	0.0239	LB	7.40
				-	-	JB	0.49				-	-	JB	0.98

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 3-2: Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Country	**CHINA**								**JAPAN**						
Dependent Variable	**Stock Market Volatility (GARCH)**								**Stock Market Volatility (GARCH)**						
Independent Variables	**BC_{CH}**	**SV_{JP}**	**BC_{JP}**	**Diagnostics**					**BC_{JP}**	**SV_{CH}**	**BC_{CH}**	**Diagnostics**			
Lags	1	1	1	Adj-R^2	0.02	RESET	2.61		1	1	1	Adj-R^2	0.051	RESET	0.523
				SEE	0.0001	White	6.29					SEE	0.0016	White	4.69
F-Stat	2.07	1.02	1.04	RSS	0.045	LB	11.8		0.153	2.48	1.63	RSS	0.035	LB	2.14
				-	-	JB	1.37					-	-	JB	1.288
Dependent Variable	**Business Cycle**								**Business Cycle**						
Independent Variables	**SV_{CH}**	**SV_{JP}**	**BC_{JP}**	**Diagnostics**					**SV_{JP}**	**SV_{CH}**	**BC_{CH}**	**Diagnostics**			
Lags	1	1	1	Adj-R^2	0.032	RESET	3.62		1	1	2	Adj-R^2	0.0383	RESET	1.065
				SEE	0.0009	White	4.02					SEE	0.0004	White	4.9
F-Stat	0.21	0.39	0.65	RSS	0.23	LB	3.86		2.03	0.362	1.467	RSS	0.1097	LB	4.80
				-	-	JB	2.01					-	-	JB	0.83

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 3-3: Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle

(Before the Financial Crisis Jan-1990 to June-2007)

Dependent Variable	**Independent Variables**	**Test Statistic**	**Prob.**
SV_{CH}	BC_{CH}, SV_{JP}, BC_{JP}	0.3757	0.3533
BC_{CH}	SV_{CH},SV_{JP},BC_{JP}	0.5921	0.2769
SV_{JP}	SV_{CH},BC_{CH},BC_{JP}	0.5972	0.2751
BC_{JP}	SV_{CH},BC_{CH},SV_{JP}	0.63	0.2531

(Including the Financial Crisis Jan-1990 to Dec-2011)

Dependent Variable	**Independent Variables**	**Test Statistic**	**Prob.**
SV_{CH}	BC_{CH}, SV_{JP}, BC_{JP}	0.5232	0.30
BC_{CH}	SV_{CH},SV_{JP},BC_{JP}	0.2178	0.497
SV_{JP}	SV_{CH},BC_{CH},BC_{JP}	0.2613	0.3969
BC_{JP}	SV_{CH},BC_{CH},SV_{JP}	1.09	0.135

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Table 3-4: Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Before the Financial Crisis Jan-1990 to June-2007)

Country	**MALAYSIA**							**JAPAN**						
Dependent Variable	**Stock Market Volatility (GARCH)**							**Stock Market Volatility (GARCH)**						
Independent Variables	**BC_{MAL}**	**SV_{JP}**	**BC_{JP}**	**Diagnostics**				**BC_{JP}**	**SV_{MAL}**	**BC_{MAL}**	**Diagnostics**			
Lags	1	1	1	$Adj\text{-}R^2$	0.19	RESET	3.41	1	1	1	$Adj\text{-}R^2$	0.15	RESET	0.63
				SEE	0.00001	White	1.94				SEE	0.0007	White	1.93
F-Stat	5.08**	1.047	0.1127	RSS	0.00331	LB	11.7	0.76	2.55	2.01	RSS	0.0018	LB	13.9
				-	-	JB	1.97				-	-	JB	0.295
Dependent Variable	**Business Cycle**							**Business Cycle**						
Independent Variables	**SV_{MAL}**	**SV_{JP}**	**BC_{JP}**	**Diagnostics**				**SV_{JP}**	**SV_{MAL}**	**BC_{MAL}**	**Diagnostics**			
Lags	6	1	1	$Adj\text{-}R^2$	0.391	RESET	3.79	1	1	1	$Adj\text{-}R^2$	0.121	RESET	0.897
				SEE	0.00155	White	3.49				SEE	0.00014	White	0.86
F-Stat	21.5	1.23	2.05	RSS	0.276	LB	5.07	0.12	1.33	0.0123	RSS	0.027	LB	5.49
				-	-	JB	0.37				-	-	JB	1.089

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 3-5: Multivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle (Including the Financial Crisis Jan-1990 to Dec-2011)

Country	MALAYSIA							JAPAN						
Dependent Variable	Stock Market Volatility (GARCH)							Stock Market Volatility (GARCH)						
Independent Variables	BC_{MAL}	SV_{JP}	BC_{JP}	Diagnostics				BC_{JP}	SV_{MAL}	BC_{MAL}	Diagnostics			
Lags	2	1	1	Adj-R^2	0.233	RESET	3.29	5	1	1	Adj-R^2	0.124	RESET	1.35
				SEE	0.00013	White	0.99				SEE	0.0006	White	2.66
F-Stat	5.41***	0.0525	0.137	RSS	0.00315	LB	1.91	8.85***	0.121	0.672	RSS	0.0032	LB	3.89
				-	-	JB	0.34				-	-	JB	0.87
Dependent Variable	Business Cycle							Business Cycle						
Independent Variables	SV_{MAL}	SV_{JP}	BC_{JP}	Diagnostics				SV_{JP}	SV_{MAL}	BC_{MAL}	Diagnostics			
Lags	1	1	1	Adj-R^2	0.17	RESET	4.14	1	1	2	Adj-R^2	0.029	RESET	0.474
				SEE	0.00178	White	3.44				SEE	0.0005	White	2.19
F-Stat	4.15**	1.84	1.56	RSS	0.431	LB	2.77	4.18**	0.328	1.315	RSS	0.118	LB	5.67
				-	-	JB	1.09				-	-	JB	0.742

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 3-6: Multivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle

(Before the Financial Crisis Jan-1990 to June-2007)

Dependent Variable	Independent Variables	Test Statistic	Prob.
SV_{MAL}	BC_{MAL}, SV_{JP}, BC_{JP}	0.69335	0.2445
BC_{MAL}	SV_{MAL},SV_{JP},BC_{JP}	0.9173	0.1743
SV_{JP}	SV_{MAL},BC_{MAL},BC_{JP}	0.6279	0.2661
BC_{JP}	SV_{MAL},BC_{MAL},SV_{JP}	0.8732	0.1912

(Including the Financial Crisis Jan-1990 to Dec-2011)

Dependent Variable	Independent Variables	Test Statistic	Prob.
SV_{MAL}	BC_{MAL}, SV_{JP}, BC_{JP}	0.8112195	0.2086
BC_{MAL}	SV_{MAL},SV_{JP},BC_{JP}	0.9360225	0.1746
SV_{JP}	SV_{MAL},BC_{MAL},BC_{JP}	0.88152727	0.1890
BC_{JP}	SV_{MAL},BC_{MAL},SV_{JP}	1.143892	0.1263

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Appendix – 4: The Asian Financial Crisis and Its Impact on Malaysia

This section describes the impact of the Asian financial crisis on the causal relationship between stock market volatility and the business cycle of Malaysia.

Hypothesis 3 tests the possible changes in the causality between stock market volatility and the business cycle brought about due to the recent global financial crisis, 2007-2011. During this crisis the volatility increased four times its normal level of 10-12%, so studying the crisis period enabled us to see whether the causal relationship between variables has strengthened, or vice versa. The examiners suggested that it could be interesting to test the impact of the prior Asian Financial Crisis on Malaysia and the Russian Financial Crisis on Brazil, as both occurred during the sample period of the research.

The Asian Financial Crisis started in July 1997 and lasted for only a few months. Malaysia along with other East Asian countries was characterised by very high saving rate i.e. marginally below 30% until 1993. However, current account deficits started widening between 1993 and 1995. Further there was an upsurge in public spending in 1995 by 25%. On the other hand, high level of interest rates offered attractive investment opportunity for the international investors. There was also a major shift of lending from manufacturing sector to equity purchases. These figures clearly showed signs of overheating of the Malaysian economy. Malaysian ringgit depreciated by 40% by December 1997. Banks Negara's first reaction was to hold back and not to increase the interest rates. As this would have been detrimental for highly leveraged financial institutions and corporations in Malaysia. Later Malaysia introduced strict capital controls as policy response to the spiral currency depreciations raising further the financial uncertainty in the region (Corsetti, Pesenti and Roubini, 1999).

The causal relationship (linear and nonlinear) between the variables is tested for two sub-samples, i.e. before the Asian financial crisis (1991-01 to 1997-06) and post the Asian financial crisis (1997-07 to 2004-12).

The results given in Table 4-1 show no linear causal relationship between changes in the business cycle and changes in the stock market volatility in

Malaysia before the Asian financial crisis. However, the stock market volatility is found to cause the business cycle after the Asian financial crisis (1997-07 to 2004-12). Similarly, no evidence of nonlinear causality is reported before the Asian financial crisis in Table 4-2. However, stock market volatility is found to Granger cause the business cycle in the post Asian financial crisis period, using both the Hiemstra and Jones (1994) and Diks and Panchenko (2006) methods. These results imply that after the Asian Financial Crisis, Malaysia's stock market volatility precedes the business cycle both under linear and nonlinear frameworks. The findings from this section highlight two points made earlier in the thesis. 1) Financial crisis has an impact on the causality between stock market volatility and business cycle, which has strengthened in all episodes of financial crisis according to our results. 2) Linear Granger causality is not sufficient to explain the complete underlying relationship between variables, thus the non-linear causality has been found in the results in addition to the linear relationships

Table 4-1: Bivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle

Malaysia	Before Asian Financial Crisis 1990-01 to 1997-06		After Asian Financial Crisis 1997-07 to 2004-12	
	BC → SMV	SMV→ BC	BC → SMV	SMV→ BC
F-Stat	0.395	0.848	1.108	**4.15*** **
Adj. R^2	0.012	0.288	0.01	0.256
SSE	0.0013	0.0012	0.0017	0.0019
RSS	0.036	0.17	0.033	0.189
RESET	2.328	1.08	2.48	3.312
White	5.369	4.721	4.904	2.55
LB	8.144	5.865	7.881	2.406
JB	1.656	1.136	1.576	1.686

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 4-2: Bivariate Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle

Panel-I Diks and Panchenko (2006)

Before Asian Financial Crisis		After Asian Financial Crisis	
SMV → BC	BC → SMV	SMV → BC	BC → SMV
0.85	1.21	**1.56***	0.53

Panel-II Hiemstra and Jones (1996)

Before Asian Financial Crisis		After Asian Financial Crisis	
SMV → BC	BC → SMV	SMV → BC	BC → SMV
0.77	0.52	**1.64****	0.93

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels

Appendix – 5: The Russian Financial Crisis and Its Impact on Brazil

According to the World Economic Outlook (IMF, 1999) the Russian crisis originated due to the very large fiscal deficit and the related increase in the investment in the Russian government bonds by foreign and domestic investors. It then escalated by the devaluation of the rouble and default by the Russian government on its internal debt. The crisis then spilled over to other emerging markets particularly to Brazil that experienced a $28 billion loss in reserves. Overvalued exchange rates, rising fiscal deficits and massive capital outflows were common phenomena in Russian and Brazilian crisis (Montes and Popov, 1999).

Table 5-1 describes the linear causality between the Brazilian stock market volatility and business cycle in the context of the Russian financial crisis (1998). Earlier studies such as Baig and Goldfain (2000), have noted, the Russian financial crisis had an extraordinary impact on Brazil. Therefore, the causal relationship between the two variables is explored for two samples, i.e. before the Russian financial crisis (1993-01 to 1998-06) and including the Russian financial crisis (1998-07 to 2003-12). The comparison of the results for the two samples, enable us to assess the impact of the Russian financial crisis on the underlying causal relationship between the two variables, both in linear and nonlinear terms. Before the Russian financial crisis, only unidirectional causality from stock market volatility to business cycle at 5% significance level is reported, as shown in Table 5-1. This indicates that the Brazilian stock market volatility leads its business cycle. However post crisis, linear dependence strengthens as the causality between Brazil's stock market volatility and the business cycle becomes bi-directional at 1% significance level.

Table 5-2 provides the nonlinear causality results using the Hiemstra and Jones (1994) and Diks and Panchenko (2006) methods. The results show that besides the linear dependence, Brazilian variables also demonstrate a nonlinear causal relationship as well. Under both non-linear methods, stock market volatility causes the business cycle before the Russian financial crisis, but a bidirectional causal relationship (feedback effect) is reported for the post crisis sample.

Although the Russian financial crisis was not of the same length or intensity as the recent global financial crisis, but the results involving this crisis in this section strengthen the argument and reinforce the conclusion of the thesis. The stock market volatility (which increases during financial crisis) and the business cycle causal relationship during and post financial crisis periods strengthens.

Table 5-1: Bivariate Linear Causality between Stock Market Volatility (GARCH) and the Business Cycle

Russia	Before Russian Financial Crisis 1993-01 to 1998-06		After Russian Financial Crisis 1998-07 to 2003-12	
	BC → SMV	SMV→ BC	BC → SMV	SMV→ BC
F-Stat	1.112	2.219**	5.593***	3.85***
Adj. R^2	0.12	0.097	0.234	0.312
SSE	0.003	0.001	0.007	0.009
RSS	0.056	0.23	0.312	0.123
RESET	1.746	0.81	1.86	2.484
White	4.027	3.541	3.678	1.913
LB	6.108	4.399	5.911	1.805
JB	1.242	0.852	1.182	1.265

Notes:

1) ***, ** and * denote 1%, 5% and 10% significance levels
2) SSE: Standard Error of Estimate Squared; RSS: Residual sum of squares; Reset: Ramsey's Specification Test; White: White's Heteroskedasticity Test; LB: Ljung-Box Test for Autocorrelation up to 12 Lags; JB: Jarque-Berra Normality of Residuals Test.

Table 5-2: Bivaraite Nonlinear Causality between Stock Market Volatility (GARCH) and the Business Cycle

Panel-I Diks and Panchenko (2006)

Before Russian Financial Crisis 1993-01 to 1998-06		After Russian Financial Crisis 1998-07 to 2003-12	
SMV → BC	BC → SMV	SMV → BC	BC → SMV
2.05**	1.21	**1.96****	**1.53***

Panel-II Hiemstra and Jones (1994)

Before Russian Financial Crisis 1993-01 to 1998-06		After Russian Financial Crisis 1998-07 to 2003-12	
SMV → BC	BC → SMV	SMV → BC	BC → SMV
2.27**	0.52	**2.14****	**1.85****

Note:

1) ***, ** and * denote 1%, 5% and 10% significance levels