Investigating risk contagion initiated by endogenous liquidity shocks: evidence from the US and eurozone interbank market

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Abstract

This paper investigates liquidity spillovers between the US and European interbank market during turbulent and tranquil periods. We show that an endogenous model with time-varying transition probabilities is effective in describing the propagation of liquidity shocks within the interbank market, while predicting liquidity crashes characterised by changed dynamics. We show that liquidity shocks, originating from movements of the spread between the Asset Backed Commercial Paper and T-bill, drive regime changes in the euro fixed-float OIS swap rate. Our results support the idea of endogenous contagion from the US money market to the eurozone money market during the global financial crisis.

Keywords: Endogenous risk, Financial crisis, Interbank market, Liquidity shocks, Regime switching
JEL classification: C11, F37, G01

1. Introduction

This paper investigates the origins of fluctuations in interbank rates and spreads, as well as the propagation of liquidity shocks within the short-term interbank market. The aim is to yield predictive distributions for benchmark money market spreads and interest rates, and at the same time analyse the effects of liquidity shocks on the interbank market overall.

Financial crises and their destabilising effect on economies and the functionality of the financial system have been the focus of recent research (Cardarelli et al., 2011; Apostolakis and Papadopoulos, 2015; Dungey et al., 2015). However, as yet there is no financial model which is able to describe the propagation of liquidity shocks in the interbank market or to predict liquidity crashes. Linear models cannot describe financial crises accurately, since drastic changes in price levels or interest rates that last for prolonged periods are fundamentally regime changes or structural breaks. Besides, endogenous dis-equilibrating forces or shocks are due to the interconnectedness of financial markets (Daníelsson, 2011) and linkages between short-term interbank rates and spreads enable us to understand how liquidity risk/shocks propagate in times of financial crises (Minsky, 1992). Yet, the majority of models described in the financial risk literature assume that risk itself is exogenous, arising from shocks which originate outside the system being modelled. Thus, variations in asset prices and interest rates are external to the influence of market players.[1]

In reality, both exogenous and endogenous risk affects the smooth functioning of financial markets; however, the later has a more pronounced and at times devastating effect. Daníelsson (2011) and Brunnermeier and Oehmke (2012), among others, argue that financial crises are primarily the result of endogenous financial risk, owing to the fact that endogenous risk is harder to model. If risk models do not incorporate endogenous risk, these are flawed and consequently unreliable from financial stability point of view.[2]

The first shock paving the way to the financial crisis of 2007-08 was felt in February 2007, when the Federal Home Loan Mortgage Corporation revealed that it would no longer purchase asset-backed securities known as collateral-

[1]Such external forces, which are fundamental in the development of bubbles, are for example market expectations, innovations in technology, market participants dropping out, etc. (Allen and Gale, 2000a).

[2]Daníelsson and Saltoğlu (2003) suggest the term 'endogenous risk' as being the one generated and intensified from inside the financial system. To further clarify the terminology, in our setup endogeneity does not imply that some independent variable is correlated with the error term. To visualise endogenous risk, consider an institution, which reacts to a liquidity shock and adjusts its position by selling a large amount of assets whose value dropped. Immediately, the rest of the agents and institutions react and adjust their positions accordingly; the majority of large institutions liquidate their positions of complex assets. Such coordinated movement may cause turmoil in the interbank market, creating a standstill in interbank dealings. The resulting feedback loop is fed either by exogenous or endogenous liquidity shocks, or by both. This ultimately may lead to insolvency and bankruptcy among the liquidity affected market players.

ized debt obligations.[3] The crisis in the interbank market was self-sustaining as a result of institutions responding to the initial liquidity shocks originating from the asset-backed securities market. On the 9th of August 2007, BNP Paribas bank announced that it had suspended trading its complex assets as they could not be valued. Even though the initial shock from February 2007 had passed, the reactions of financial institutions continued to rock the financial system. This is a perfect illustration of a force which is produced and intensified inside of the system; in essence, this is an endogenous response.

To address the issues discussed above, our study proposes a new endogenous liquidity risk contagion model. There are several advantages of using an endogenous and at the same time a dynamic regime switching model. We assume that the rules which govern the changes from one state of the economy to another are not independent from the rest of the system. By using an endogenous model, one is able to obtain more efficient estimates via extra information contained within the endogenous system. In our model the Markov chain is affected by the shocks or innovations of the system, and not only by the previous state.To make our setup more realistic, the transition from one state to another is assumed stochastic over time. By using a binary indicator, our models detect a finite number of structural changes in the time series. Also, the two identified states will have different dynamics. The new models show that shifts in the mean and variance are different for the two regimes. Lastly, we assume that shocks originating from asset-backed securities along with the dynamic transition probabilities drive the evolution of turbulent and tranquil periods.

Empirically, our study estimates the parameters of an endogenous liquidity risk contagion model, in which the daily euro fixed-float OIS swap (EUSWEC) depends on the VIX index, on the spread between the Asset Backed Commercial Paper and T-bill (ABCP-Tbill), on the US-German bond spread (USGer3M) and on the US LIBOR-OIS spread (USLIBOIS). The study investigates 10 years of daily data, including the recent financial crisis, thus it covers the period 1st January 2002 to 30th December 2011.[4] The short-term interbank spreads and rates used in this analysis are representative of the

[3]The Federal Reserve Bank of St. Louis provides a full timeline of the events related to the global financial crisis, available at https://www.stlouisfed.org/financial-crisis/full-timeline.

[4]To avoid our results being contaminated by the eurozone crisis, our sample period concludes on 30th December 2011.

interbank market and capture well its dynamics.

The models presented in this study complement the empirical liquidity and contagion models as well as providing a theoretical explanation of the self-fulfilling behaviour of liquidity shocks and liquidity risk propagation within the short-term interbank market. We make three important contributions. First, the main limitation of classical econometric models applied in the finance literature are that they cannot jointly estimate the parameters of the model and the duration of states. Our multivariate endogenous non-parametric model estimates with precision the parameters when dealing with time series which evolve over turbulent times. Thus, our regime switching Markov models with time-varying transition probabilities presented below provide a framework to implementing inferences about fundamental financial crisis occurrences. Second, the finance literature does not discuss the endogenous nature of liquidity shocks and their propagation within the short-term interbank market. This study fills the gap by showing that liquidity shocks originate from within the banking system, and not only from external sources, as the majority of financial crisis literature assumes. Both these risks contribute to the development of financial crises, however endogenous shocks magnify within the system increasing the overall effect of the shocks. Third, we trace the dynamics of liquidity shocks over a longer period of time and at higher frequency (as opposed to the previous literature in which weekly or monthly data is used), and subsequently better understand interbank liquidity risk and its effect on the whole financial system.

The remainder of this paper is organised as follows. The literature review is presented in Section 2. The data and methodology is revealed in Section 3. Empirical results are shown in Section 4 and Section 5 concludes.

2. Literature Review

Before discussing the relevant literature, we lay down our theoretical explanation of endogenous shocks and their spillover. We then proceed to discuss the literature on financial crises and contagion.

2.1. Theoretical design of endogenous liquidity risk contagion

Figure 1 displays the fundamental feedback-loop of a liquidity shock hitting the interbank market. The figure visualises how single shocks (external or internal) to the system intensify and result in extreme market behaviour, which ultimately lead to turmoil in the interbank market. The turmoil of the financial market is a self-sustaining process as a result of agents' responses to an initial liquidity shock. Even after the initial shock has dissipated, the process continues to intensify due to an 'energy' that is produced and magnified within the financial system. As a perfect analogy to the financial crisis of 2008-2010, an initial decrease in the value of assets - as outcomes of market players' responses to the Federal Home Loan Mortgage Corporation's and credit rating agencies' actions - further triggered actions within the interbank market, while at the same time the initial liquidity shocks continued to magnify.

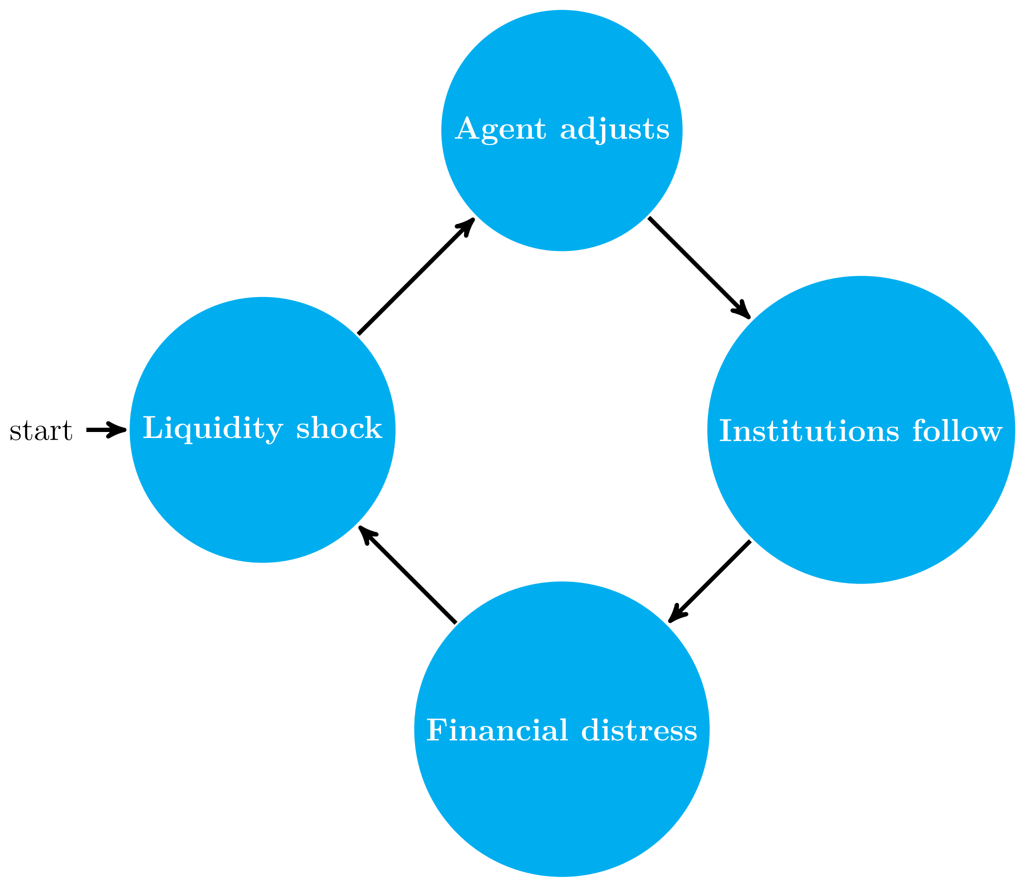

Figure 1: Feedback loop of a self-fulfilling liquidity crisis: from liquidity shock (which can be exogenous and/or endogenous) to liquidity crisis and ultimately financial crisis. In the first stage of the spillover process, shocks propagate between financial institutions, then latter in a second stage contagion occurs between financial markets which involves shocks spreading across regional borders.

There are two types of effects originating from exogenous shocks or innovations. The first one is 'direct effects' which are typical impacts of shocks which arise when market players place zero probability on a state change. The second type of effects is the 'expectation formation effects' when it is assumed that market players' rational expectations of potential state change prompts them to revise their expectation functions (Davig and Leeper, 2006). When shocks are exogenous, the analysis cannot identify whether these produce asymmetric effects or not; moreover, the investigation cannot yield quantitatively significant results, nor one can formulate policy responses or advise policy makers (Kim, 2004). In an exogenous scenario, a stochastic process drives the dynamics of the system in which both rules and instruments are state dependent, however the Markov chain which drives the transition from one state to another evolves independently from the other parts of the system (Kaufmann, 2011). The only thing that matters in deciding the future state is the present state, therefore the decision process is not influenced by the realisations (or innovations) of the time series which enter the regression equation. This view is rather unrealistic considering that in most financial and economic processes it is something from within the system that defines future states, and not factors external to it.

Pritsker (2001) identifies the interbank market as one spillover channel, and accordingly the activities of financial institutions operating internationally permit initial domestic shocks to overflow across regions, provoking market reactions beyond borders.[5] It is well documented in the literature that the US and EU markets are interdependent, primarily due strong presence on the global market, same market structure and strong trade and financial links between each other. If the US and EU markets move together, the likelihood of contagion increases and consequently international risk management and policy transmission outlook advances to an utmost significance.

In an endogenous scenario, the coefficients driving the level of adjustment of the daily euro fixed-float OIS swap rate for example, to financial interbank variables, are themselves a function of the state. Besides, the dynamics of the transition from one state to the other is influenced by both the realisation of the time series of the model, and also by past and current states. This is

[5] We use the definition of contagion as provided by Karolyi and Stulz (1996): "Contagion effects result when enthusiasm for stocks in one market brings about enthusiasm for stocks in other markets, regardless of the evolution of market fundamentals".

in sharp contrast to exogenous models, where only the past state influences the transition dynamics. Due to the fact that extra information goes into the estimation process, the estimates and transition probabilities are more precise and valid as endogeneity is accounted for (Daníelsson, 2011).

2.2. Empirical literature on financial crises and contagion

Fratzscher (2003) argues that financial crises are outcomes of either weak economic fundamentals, exogenous changes in agents' beliefs, or contagion. Linear models, such as the ARIMA and GARCH are known to be unreliable when approximating asymmetric shocks.[6] Hamilton and Susmel (1994) and Henneke et al. (2011) develop regime changing GARCH models and Zhou and He (2012) develop an MCMC estimated financial risk contagion model. However, volatility models (such as GARCH models) and exogenous regime-switching models with constant transition probabilities (Dahlquist and Gray, 2000; Fratzscher, 2003; Bussiere and Fratzscher, 2006; Ang and Timmermann, 2011; Guo et al., 2011) do not consider the time-varying nature of parameter estimates in turbulent times, and thus do not provide reliable recommendations.

Some studies assess interbank contagion by the way banks are linked with each other (Allen and Gale, 2000b; Freixas et al., 2000; Allen et al., 2010; Makarov and Plantin, 2013) or by looking at balance sheet data and implementing simulation techniques (Mistrulli, 2011; Upper, 2011). Others analyse the behaviour and effects of market fundamentals in periods of financial turmoil (Kaminsky and Reinhart, 2000). Market microstructure models attempt to describe the role of information and its relationship to price discovery during financial crises (Hartmann et al., 2001; Daníelsson and Saltoğlu, 2003), whereas spillover effects are primarily investigated via correlation techniques (Baba et al., 2008; Frank et al., 2008; Gorton and Metrick, 2012). The weakness of these models is that these do not explain what exactly drives volatile time periods, neither how liquidity risk propagates within the interbank market.

A string of financial crises since the start of the millennium prompted the development and assessment of early warning indicators and systems. The majority of the banking crisis literature is based on either signal extraction

[6]Non-linear GARCH models do exist, for example the NGARCH of Engle and Ng (1993).

models (which assess single variables crossing an arbitrarily set threshold), a logit/probit estimation or both. The crises identified by the models are compared to World Bank and IMF bank crisis databases (Caprio et al., 2012; Laeven and Valencia, 2012). Drehmann and Juselius (2014) argue that early warning indicators can be efficient if signals arrive one and a half year in advance and policy actions can be adjusted accordingly. Abiad (2003) and Berg et al. (2005) note that in most cases early warning systems (EWS) perform better in forecasting financial crises than credit ratings, bond spreads, and estimates of credit and liquidity risk (which are measures of financial vulnerability) did in the past. Abiad (2003) identifies several problems associated with EWSs. The main issues are related to knowing *a priori* the timing of the crises, the determination of sample-dependent threshold levels (which are set arbitrarily, and vary from $1.5 \times \sigma$ to $3 \times \sigma$), the selection of 'exclusion windows' (which are set arbitrarily and may vary between 3 -18 months) and issues associated with the transformation of continuous variables into binary ones (in which case important dynamics are removed from the variables). To avoid all these pitfalls, Abiad (2003) proposes a Markov switching model with time-varying transition probabilities which he argues is an improvement to threshold dating methods based on binary signals, such as the classic indicator variable model. Besides, EWSs are prone to documenting false crisis occurrences and do not describe the starting and ending dates, nor the severity of crisis periods (Demirgüç-Kunt and Detragiache, 1998; Kaminsky et al., 1998; Kaminsky and Reinhart, 1999; Goldstein et al., 2000; Demirgüç-Kunt and Detragiache, 2005; Berg et al., 2005; Bussiere and Fratzscher, 2006; Bauer et al., 2007; Davis and Karim, 2008; Karim et al., 2013; Lang and Schmidt, 2016).

Davig and Leeper (2006) show that exogenous switching causes the disproportionate propagation of shocks (meaning that some symmetric impulse responses will have an asymmetric influence) as well as the expectation formation effects which govern the impact of monetary policy and ultimately cause the distribution of the parameters to be skewed. On the other hand, Branch and Evans (2007) argue that regime changes in volatility may arise endogenously due to model uncertainty, estimates of underparameterised models or dynamic forecasting model choices.

3. Methodology

We first present the data sets used in this study, then move on to outline the endogenous multivariate regime switching model with time-varying transition probabilities.

3.1. Data

We use the spread between the US LIBOR and overnight indexed swap (OIS) rate (USLIBOIS), the US-German bond spread (USGer3M), the euro fixed-float OIS swap rate (EUSWEC), the VIX® Index (VIX) and the spread between the Asset Backed Commercial Paper rate and T-bill (ABCP-TBill). All the time series are computed using 3-month daily closing rates. In order to document significant events since the turning of the millennium, our data spans from 1st January 2002 to 30th December 2011. We do not want to document the eurozone crises that followed, as we assume that is this event can not be described by our variables and models. The time series used in this study are fundamental money market rates and spreads; their long-term dynamics describe primarily credit risk and liquidity risk. Data was obtained from Bloomberg and the Federal Reserve Bank of St. Louis data-bank.

The London Interbank Offer Rate (LIBOR) is used as a reference rate in financial agreements around the world and is the rate at which banks and financial institutions of equal size decide to lend each other. Rises in LIBOR rates can be attributed to banks calling for better compensation in case of default risk on their loans. The Overnight Interest Swap (OIS) rate is the rate of the derivative contract on the federal funds rate, and in usual market circumstances is generally below the LIBOR rate. During financial market turmoil, the LIBOR-OIS spread is a suitable measure of risk premiums owing to credit and funding liquidity risk. The term LIBOR-OIS spread evaluates the health of banks, as it reflects the risk associated with lending to other banks. The daily VIX Index is a fundamental gauge of market expectations of near-term volatility conveyed by the prices of S&P 500 stock index option, computed by the Chicago Board Options Exchange. Moreover, the index is the world's trusted chief indicator of investor sentiment and market volatility. The third variable is the spread between the Asset Backed Commercial Paper rate (ABCP) and US T-bill. The ABCP rate is the rate on the AA ranked asset backed commercial paper issued by banks or financial institutions in need for working capital with the aim to reduce risk. The ABCP-TBill spread expresses compensation for credit, liquidity and insolvency risk arising from counterparty, "rolling over" or structural matters. The fourth variable is the spread between the three-month US and German government bond rate. Changes between the US and German government bond rate reflect changing future economic development and interest-rate outlook for the two largest economies in the world. Essentially, varying economic and monetary policies between the two biggest economies determine the broadening or tightening of the spread. Thus, US and eurozone country specific debt and job market views impact US-German bond spread variations. The US and German Government bonds bear no risk as they are considered the two safest assets in the world.

Our dependent variable is the euro fixed-float OIS swap (EUSWEC) in which the floating leg is based on the euro Over-night Index Average rate (EONIA), which is calculated as the weighted average interest rate at which a group of highly active European banks provide unsecured, euro denominated loans to one another. The rate, seen as the overnight Euribor rate, is the benchmark rate for the euro short-term money market. Essentially, the rate indicates the stance of the ECB's monetary policy and movements in the EONIA rate can be attributed primarily to liquidity conditions, market expectations of policy decisions and calendar effects. Some argue that there is a positive correlation between the overnight interbank rate and the structural liquidity deficit. The nominal amount agreed upon is euro denominated, however only interest cash flows are exchanged at maturity. Due to tight spreads and high volume trades, this is the most liquid segment of the European money market.

In times of financial distress, all variables employed in this study are suitable measures of risk premiums as a consequence of credit-, funding liquidity-, default-, forex-, and ultimately, systemic risk. The benchmark spreads and rates mirror changes in interest rates on both the eurozone and US market markets disturbed by the subprime crisis and they will help detect where liquidity crises start in the short-term interbank market and follow their spillover beyond regional borders.

3.2. Model specification

Our analysis is driven by the following research question: What drives liquidity crashes and risk spillovers from the US to the EU interbank market? What do tranquil and turbulent episodes tell us, considering that the literature acknowledges that risk contagion occurs when market volatility is excessive. Last, is the propagation of liquidity shocks endogenous (i.e., something from within the system drives the dynamics of contagion from one region to the other)?

The models outlined below are applied to the system consisting of the interaction between the five short-term interbank spreads and rates. In the example below all variables (more specifically their mean) are allowed to change states as well as the variance.

$$y_t = \beta_{1,S_t}\, x_{1,t} + \beta_{2,S_t}\, x_{2,t} + \beta_{3,S_t}\, x_{3,t} + \beta_{4,S_t}\, x_{4,t} + \epsilon_t \tag{1}$$

$$\epsilon_t \sim N(0, \sigma^2_{S_t}) \tag{2}$$

where $x_{i,t}$ are the input variables as follows: the VIX index, the ABCP-TBill spread, the US LIBOR-OIS spread and the US-German bond spread. S_t is the state variable at time t. ϵ_t is the vector of residuals, which follows a normal distribution. $\sigma^2_{S_t}$ is the variance of the vector of innovations at state S_t. β_{i,S_t} is the beta coefficient for explanatory variable i at state S_t. The target variable y_t is represented by the euro fixed-float OIS swap rate (EUSWEC).

The binary variable S_t follows a first-order two-state autoregressive Markov regime switching process, and can take the following values:

$$S_t = \begin{cases} 1, & \text{if there is tranquility in the interbank market;} \\ 2, & \text{if there is turbulence in the interbank market.} \end{cases} \tag{3}$$

To make the time-varying transition probabilities endogenous, one either correlates the variables that are expected to drive the transition from one state to another to the approximated state probabilities, or explicitly incorporates the assumed influencing variables in the transition probabilities. In both scenarios, the independent variable that drives the dynamics of the transition, implicitly via the state dependent β_{S_t} influences the impact of both input and output variables (Kaufmann, 2011).Thus, we're interested in revealing whether shocks coming from the ABCP-TBill (the endogenous variable in our setup) drive the dynamics of the system as a whole. Due to the fact that the credit boom and subsequent emergence of asset-backed securities originated in the US market, we expect that contagion materialised via interbank channels from the US onto the European market.

To save space, the methods by which the posterior distribution infers the coefficients of the system, the estimation of the likelihood function and transition probabilities are presented in the Appendices.

For comparison purposes, the following three models are presented. For all three models, the ABCP-TBill spread is set to be endogenous, i.e the ABCP-TBill spread is incorporated into the transition matrix.[7]

Model 1: it is assumed that the state dependent coefficients β_{1,S_t} and β_{2,S_t} are allowed to switch states. The changes therefore occur in the mean of the VIX rate and the ABCP-TBill spread. Moreover, it is expected that the vector of innovations is switching states too.

$$EUSWEC_t = \beta_{1,S_t} VIX_t + \beta_{2,S_t} ABCP - TBill_t + \beta_3 USLIBOIS_t + \beta_4 USGer3M_t + \epsilon_{t,S_t} \tag{4}$$

Model 2: changes occur only in the mean of the ABCP-TBill spread (β_{1,S_t}).

$$EUSWEC_t = \beta_1 VIX_t + \beta_{2,S_t} ABCP - TBill_t + \beta_3 USLIBOIS_t + \beta_4 USGer3M_t + \epsilon_t \tag{5}$$

Model 3: none of the coefficients of the independent variables change regimes, only the variance.

$$EUSWEC_t = \beta_1 VIX_t + \beta_2 ABCP - TBill_t + \beta_3 USLIBOIS_t + \beta_4 USGer3M_t + \epsilon_{t,S_t} \tag{6}$$

As a result of dealing with two states, for all three models two equations have to be solved, that is one for state 1 and one for state 2 (more precisely one for the tranquil and one for the turbulent state). Consequently, there are two variance terms with two different dynamics, such that in the tranquil state the error term evolves according to $\epsilon_t \sim N(0, \sigma_1^2)$ and in the turbulent

[7]Media coverage and prominent financial analyses (aired by The Economist, FT and alike) all acknowledge that the recent financial crisis was primarily caused by the repackaging of mortgage obligations into assets backed by US commercial papers and reselling of these to other geographical markets. Yet, to the best of our knowledge, no academic research proves empirically the process by which endogenous crisis contagion occurred.

state $\epsilon_t \sim N(0, \sigma_2^2)$, respectively. The higher the uncertainty in the model, the higher the variance will be; thus, it is more likely that inter-regional contagion occurs.

3.3. Model comparison and model selection criteria

The measures critical to model outcomes are primarily based on hypothesis testing and the p-values (at 5% significance level) of the parameters under scrutiny. Under the null hypothesis, for all regression equations, the values of the parameters are assumed to be zero. The ML estimation is well known to yield robust and consistent standard errors when the sample size is large, as it is in our case. In terms of model selection, if the number of estimated parameters would be similar for the three models, the model with greater log-likelihood value would be considered best. However, the estimated parameter numbers vary for the three models, and such the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) values are paramount in deciding which model fits best. Both criteria are centred on the likelihood function; the former assesses how each extra parameter added to the model improves on the log-likelihood function, whereas for the latter, model improvement depends on the sample size and the more parameters are added to the model, the higher the penalty.

Other criteria for model strength are the transition probability values (the probability of being in a turbulent state if the previous state was a turbulent one, for example). The diagonal values of the transition probability matrix should be fairly similar and close to unity, i.e. the $P_{11,t}$ and $P_{22,t}$), which are the probabilities assuming that the tranquil state is followed by a tranquil one and the crisis state is followed by a crisis one. Similarly, the off-diagonal values representing the $P_{12,t}$ (transition from a tranquil state to a crisis one) and $P_{21,t}$ (transition from a crisis state to a tranquil one) should yield similar values; overall, this ensures that the estimation of the transition matrix is precise. The expected duration of regimes (in terms of days) should match real life events: crisis periods should reflect liquidity risk induced turbulent financial events.

Thus, the true model explains well the phenomena under investigation, whether the coefficients of the model are significant and whether the persistence of states (in terms of expected duration of turbulent and tranquil days) matches (past) real financial events. Fundamentally, at the core of these financial events are endogenous liquidity shocks propagating within the interbank market.

4. Results

The section below presents the summary statistics and the parameter estimates. Table 1 presents the summary statistics for the five variables. The LIBOR-OIS spread presents the highest variability in the data, followed by the VIX index, with a standard deviation of 40.65 and 10.11 respectively; observations vary between the interval [1.91,364.43] and [9.89, 80.86].

Table 1: Summary statistics of the VIX, ABCP-Tbill, USLIBOIS, USGer3M and EUSWEC spreads.

Variable	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
VIX	21.85	10.11	9.89	80.86	1.84	7.84
ABCP-TBill	0.45	0.58	0.05	4.39	3.15	14.59
USLIBOIS	28.50	40.65	1.91	364.43	3.80	22.32
USGer3M	-0.27	1.23	-4.01	2.29	0.35	2.44
EUSWEC	2.25	1.23	0.35	4.35	-0.006	1.83

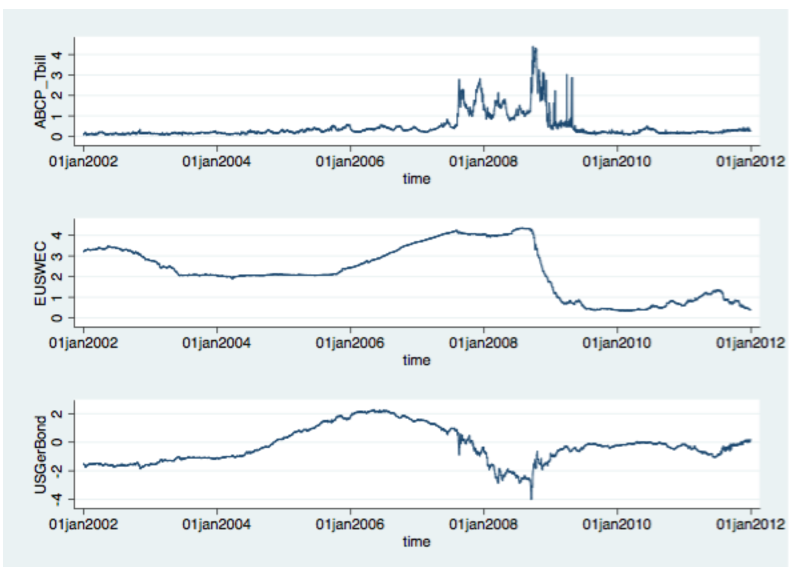

Figure 2: Behaviour of the ABCP-Tbill, EUSWEC and US-German Bond spreads for the period 1st January 2002 to 30th December 2011.

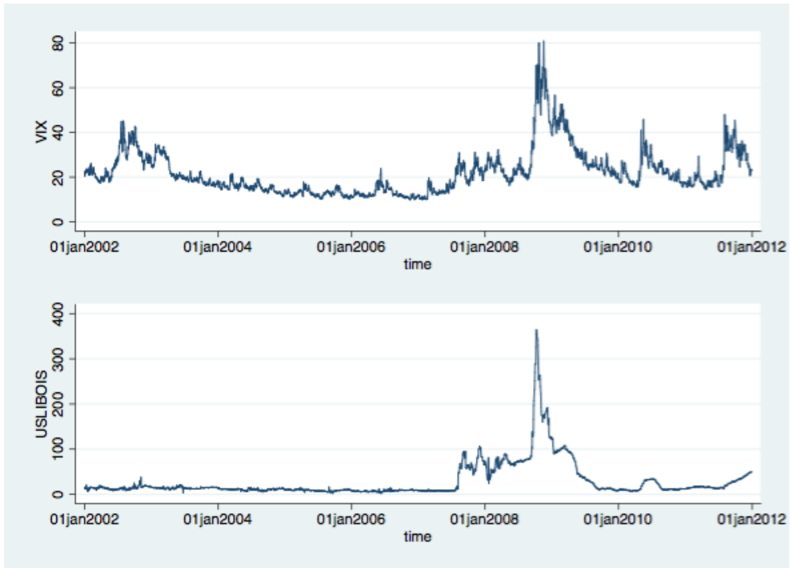

Figure 3: Behaviour of the VIX index and US LIBOR-OIS spread for the period 1st January 2002 to 30th December 2011.

The mean values of the ABCP-TBill, USGer3M and EUSWEC spreads are close to zero, and the standard deviation is around one; their minimum and maximum values are within much narrower intervals. Figures 2 and 3 depict the changing behaviour of the five time series over the 10 years period. The patterns suggest structural breaks characterised by persistence. Out of the five, the ABCP-TBill spread, the VIX index and the LIBOR-OIS spread exhibit the most dramatic behaviour implying that structural shocks do not temporarily affect the series, but these are significant and sustained over a prolonged period of time.

The estimated parameters for the three models are presented in Table 2. Fundamentally, the sequence of regimes is determined by the sequence of liquidity shocks - which may originate from the ABCP-TBill spread - affecting the interbank market, and also by the correlation of the liquidity shocks with some of the covariates. Thus, the ABCP-TBill spread is the endogenous variable which is presumed to aid the propagation of liquidity shocks within the system, leading to the widening of spreads and wild fluctuation of interest rates. When the ABCP-TBill spread crosses some threshold, liquidity risk spreads within the system of covariates via domino effects while triggering regime changes within the EUSWEC spread. In other words, the US variable

ABCP-TBill spread - as the source of spillovers - predicts the switch to a turbulent regime for the European market represented by the EUSWEC spread.

At the 5% significance level, all coefficients of Model 1, 2 and 3 are significant, denoting that there is a significant relationship between the VIX index, the ABCP-TBill spread, the US-German bond spread, the LIBOR-OIS and the EUSWEC spread. Consequently, for all models, the spillover of liquidity shocks is experienced during both turbulent and tranquil periods.

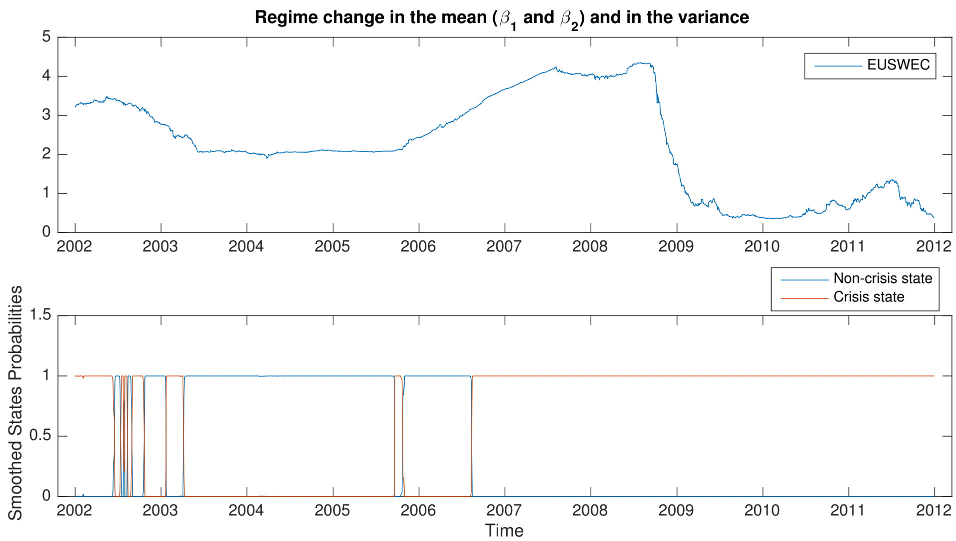

Figure 4: Model 1 - Estimation of turbulent and tranquil regimes in the EUSWEC spread. The multivariate endogenous model with time-varying transition probabilities switches in the coefficients of the VIX rate, the ABCP-TBill spread and in the variance.

The matrices with the transition probabilities and duration (measured in days as units) of states is shown in Table 3.[8] The persistence of the states for Model 1 are 78 days in average for tranquil periods and 315 days for tur-

[8]The transition probabilities are unrestricted between 0 and 1. Having a (near) unit probability of a stable/crisis state being followed by a stable/crisis state means that unless a regime change or structural break occurs, the state continues to remain in a stable/crisis state. On the other hand, the probability of switching from tranquil to crisis state is extremely low, unless a shift occurs in the mean or volatility of variables (Goldfeld and Quandt, 1973). In other words, during tranquil periods, the probability of an intensified liquidity crisis emerging within the money market is extremely low (however it does occur

Table 2: Coeff.estimates of the endogenous regime switching models.

	Model 1	Model 2	Model 3
Non-switching parameters			
VIX			
Mean		0.0632*	0.1098*
Standard error		0.0012	0.0008
ABCP-TBill			
Mean			3.0710*
Standard error			0.0881
USLIBOIS			
Mean	-0.0246*	-0.0312*	-0.0464*
Standard error	0.0014	0.0008	0.0015
USGer3M			
Mean	0.1733*	-0.0728*	0.1211*
Standard error	0.0104	0.0153	0.0128
Variance			
Value		0.9427*	
Standard error		0.0235	
Switching parameters			
VIX			
Tranquil State			
Mean	0.1214*		
Standard error	0.0012		
Turbulent state			
Mean	0.0598*		
Standard error	0.0024		
ABCP-TBill			
Tranquil State			
Mean	2.2685*	5.7672*	
Standard error	0.0895	0.0611	
Turbulent state			
Mean	2.5028*	2.3218*	
Standard error	0.0892	0.0438	
USLIBOIS			
Tranquil State			
Mean			
Standard error			
Turbulent State			
Mean			
Standard error			
USGer3M			
Tranquil State			
Mean			
Standard error			
Turbulent State			
Mean			
Standard error			
Variance			
Tranquil State			
Model Variance	0.0690*		0.1818*
Standard error	0.0031		0.0096
Turbulent State			
Model Variance	2.2810*		3.2088*
Standard error	0.0998		0.1445
AIC	6388.7	7614	7195.8
BIC	6447.4	7660.9	7242.8

* indicates significance at 5% level

Table 3: Time-varying transition probability matrices and expected duration of regimes.

	Model 1	**Model 2**	**Model 3**
Transition probabilities			
	$\begin{bmatrix} 1.00 & 0.00 \\ 0.00 & 1.00 \end{bmatrix}$	$\begin{bmatrix} 1.00 & 0.00 \\ 0.00 & 1.00 \end{bmatrix}$	$\begin{bmatrix} 1.00 & 0.00 \\ 0.00 & 1.00 \end{bmatrix}$
Expected duration (days)			
Tranquil State	78.43	14.22	171.28
Turbulent State	315.27	14.94	248.04

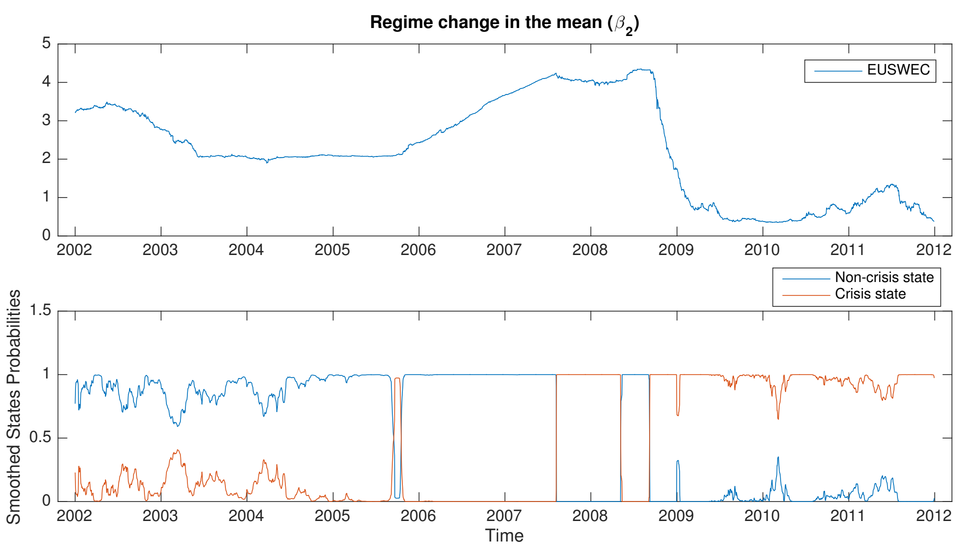

Figure 5: Model 2 - Estimation of turbulent and tranquil regimes in the EUSWEC spread. The multivariate endogenous model with time-varying transition probabilities switches only in in the coefficient of the ABCP-TBill spread (β_2).

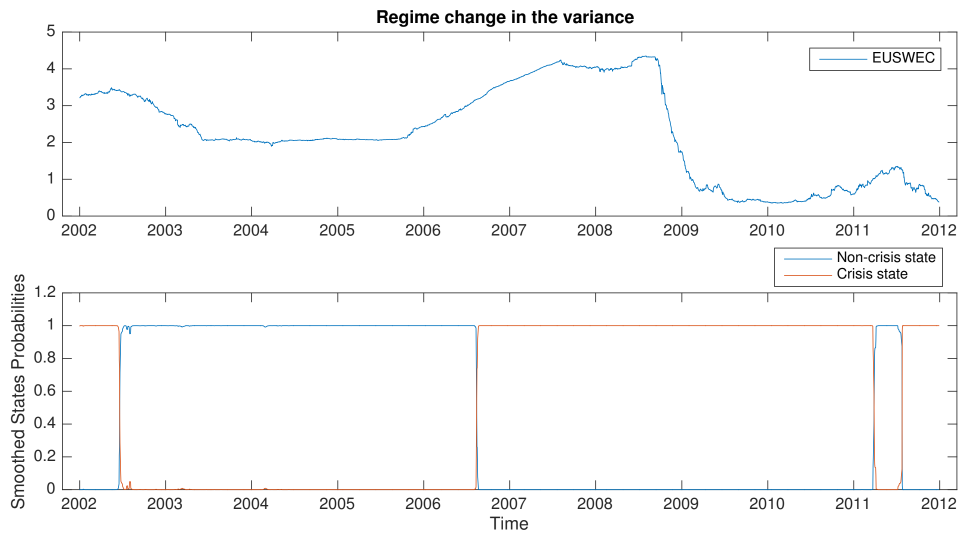

Figure 6: Model 3 - Estimation of turbulent and tranquil regimes in the EUSWEC spread. The multivariate endogenous model with time-varying transition probabilities switches only in the variance.

bulent periods. Model 1 (see Figure 4) identifies several turbulent periods, one from January 2002 to approx March 2003 with short recovery periods in between; this can be credited to the dot-com boom and the US stock market crash with markets reaching their lowest in March 2003. There is a short period of crisis around October 2005. Finally, there is a prolonged period of turbulence starting in September 2006 until December 2011. This model suggests that the recent financial crisis started much earlier than as it was widely documented, whereas the global financial crisis literature argues that the subprime crisis started around September 2007. For Model 2 the tranquil periods last on average for 14 days and the turbulent periods for 15 days. Figure 5 depicts two longer turbulent periods and one structural break around October 2005. Due to the fact that Model 2 identifies a tranquil period from May to August 2008, we're discrediting it as it does not reflect the reality. Model 3 (see Figure 6) identifies three turbulent periods: from January 2002

when the variables contain outliers); similarly, if the money market is in the midst of financial distress, the probability of swift calming is very low. This is consistent with the volatility clustering phenomena seen in time series during tranquil/turbulent time periods.

to approximately July 2002 representing the dot-com crisis, from September 2006 to approximately February 2011 representing the global financial crisis, and a crisis period starting from September 2011 which represents the eurozone crisis (specifically the issues surrounding the bail-out of Greece). This model identifies 172 days in average for tranquil periods and 248 days for the turbulent periods. For all three models the transition probabilities suggest that there is 100% chance that a tranquil phase will be followed by a tranquil state; similarly, there is 100% chance that a turbulent phase will be followed by a turbulent state. As stated earlier, contagion occurs in the high variance state, and this is confirmed for Model 1 and 3, in which the variance is allowed to change states; compared to the tranquil state variance the turbulent state variance is significantly elevated with values 2.2810 and 3.2088 correspondingly. With the lowest values of the AIC, BIC and DIC, Model 1 is set as the model with the best fit.

During turbulent periods, shocks to the US interbank market have significant impact on the eurozone interbank market.[9] Model 1 describes well the feedback-loop of self-fulfilling liquidity crisis and the transmission mechanism.[10] To validate our concept, we concentrate on the recent financial crisis. There was a liquidity shock around October-November 2005, which did not materialise into a financial crisis. It seems, internal shocks started to propagate from the US interbank market onto the eurozone market from around September 2006 when a permanent break/shift occurred, which was in fact

[9]It is imperative to distinguish between changes in correlation of asset returns during financial distress and risk contagion. The market integration literature documents that the two biggest regional markets are more correlated during market downturns. This has implications for international portfolio diversification. As for risk contagion that leads to financial crisis, the implications are for involvement of international institutions and bail-out strategies.

[10]Triggers for contagion can be various risks/shocks propagating between institutions or markets, either domestically or across regions. Contagion is more likely when a combination of various risks affects institutions or markets. In the case of the global financial crisis what started as credit risk accumulating due to a significant drop in the value of asset backed securities (or their default in some cases), it then followed by liquidity risk due to credit drying up within the interbank market; this ultimately led to insolvency risk for several systemically important banks within the USA and Europe. The primary reason that contagion occurs is the fact that financial institutions are interlinked, either by trade connections or by cross-ownership. By 2007, financial institutions and markets were heavily deregulated, and comprehensive stress tests and strict capital requirements were not in place to support financial institutions in mitigating risks and avoiding contagion.

an early warning sign. There was a significant cooling of the housing market, which can be credited to the slowdown in residential investments while housing prices stared to decline and mortgage defaults began to increase. On the other hand, US sub-prime lenders began filing for bankruptcy, while the fed funds rate increased to 5.25%. Other clear signs of a crisis looming was that at the beginning of 2006, the world's largest insurer AIG ended its selling of protection against collaterised debt, while by September Merrill Lynch, the investment company, began struggling selling credit default obligations. On the other hand, by mid 2006, the world's leading financial newspapers and magazines heralded the bursting of the sub-prime bubble.

Clearly, the initial shock originated from the banking system, which provided the avenue for the intensifying of the crisis - by over-reacting to the initial shocks - and for regional contagion. In August 2007, when PNB Paribas bank announced that it stopped dealing with mortgage backed securities and credit default swaps, the channels of interbank contagion were practically severed, yet the endogenous shocks, which originated from US, continued to magnify and cause havoc on both sides of the Atlantic. If proper policy and regulatory guidelines were in place which were able to deal with shocks detected by early warning models, the recent financial crisis and the recessions that followed could have been avoided, or its damaging consequences were less harmful.

To demonstrate the importance of shocks and their contagion to other markets, we first split the data into two periods: 1st January 2002 to 31st August 2006 and 1st September 2006 to 30th December 2011 and run the non-parametric correlation test of Kendall (1938). Table 4 presents Kendall's τ coefficients for the two time periods shown in Panel A and Panel B. It seems that some negative shock coming from the ABCP-TBill spread (as the endogenous variable) significantly changes market correlations after 1st September 2006 (Panel B).[11] Contagion from the US to the eurozone market is supported by increases in cross-market (interbank) linkages. The two correlation results are striking as all coefficients changed significantly: some changed direction and most increased significantly indicating that the turbulence - induced by liquidity shocks originating from the ABCP-TBill spread

[11] In this paper we're not intending to demonstrate how shocks propagate between markets, i.e. the transmission mechanism *per se* is not the focus of this paper, but to find out whether endogenous contagion between regional markets has occurred.

Table 4: Kendall correlation test of the VIX, ABCP-Tbill, USLIBOIS, USGer3M and EUSWEC spreads. * indicates significance at 5% level.

Panel A: Period 1/1/2002 to 31/08/2006					
	VIX	ABCP-TBill	USLIBOIS	USGer3M	EUSWEC
VIX	1.0000				
ABCP-TBill	-0.5085*	1.0000			
USLIBOIS	0.4578*	-0.3271*	1.0000		
USGer3M	-0.6511*	0.5741*	-0.5584*	1.0000	
EUSWEC	0.2177*	-0.0466*	0.0786*	-0.1441*	1.0000
Panel B: Period 1/09/2006 to 30/12/2011					
	VIX	ABCP-TBill	USLIBOIS	USGer3M	EUSWEC
VIX	1.0000				
ABCP-TBill	0.1862*	1.0000			
USLIBOIS	0.5267*	0.4487*	1.0000		
USGer3M	-0.3343*	-0.1893*	-0.4716*	1.0000	
EUSWEC	-0.1104*	0.5226*	0.1545*	-0.2347*	1.0000

and magnified through feedback mechanisms - became contagious via the interbank market. As for the period 1st September 2006 - 30th December 2011, the most noteworthy are the pairwise increases in correlations between the ABCP-TBill and the USLIBOIS and EUSWEC spreads; these correlations changed direction from negative to meaningful positive correlation. Similarly, significant increases are noted for the pairwise correlation between the USLIBOIS and the VIX and EUSWEC spreads. These increases in correlations denote that contagion between the markets occurred. Yet, the correlation coefficients are static and do not describe well the long-run changes of the co-movements of spreads; moreover, these provide an equal weight to both small and large rate/spread values and thus, we treat our correlation coefficients with caution. Next, we implement a three year forward rolling window correlation test to reveal the strength of time varying co-movements of the spreads.[12] Figure 7 presents the pair-wise time varying correlation of the spreads. We're only focusing on regional correlations, i.e. on the correlation coefficients between the US and eurozone spreads. The figure illustrates

[12]The longer the window size, the smoother the rolling window estimations are.

how dramatically correlations change over time. The correlation between the ABCP-TBill and EUSWEC spreads begins to be significant from about January 2006 and stays significant for a longer period apart from a short dip around mid 2009, then finally decreases from end of 2011, which period coincides with the onset of the eurozone crisis. This is a clear indication of contagion from the US to the eurozone interbank market. Likewise, noteworthy are the correlations between the ABCP-TBill USGer3M spreads, the VIX USGer3M spreads and the USLIBOIS and USGer3M spreads, which are meaningful denoting increased market integration during the global financial crisis.

Due to the fact that the ABCP-TBill spread is set to be endogenous within the regime switching models and also representative of the US money market, we can confidently argue that spillover occurred from the US onto the eurozone market, which is represented by the euro fixed-float OIS rate. Thanks to the feedback loop, single shocks intensified and the bubble continued to amplify due to an energy that is created and magnified within the mortgage backed securities market; the process concluded with the burst of the mortgage backed securities bubble in September 2007 indicating the beginning of the global financial crisis.

In our econometric models, the conditional distribution of money market rates were allowed to vary in line with the state of the economy. The results indicate that short-term interest rates and spreads fully reveal regime switching information. If transition probabilities are state and time dependent, regime changes will be a function of the level of the ABCP-TBill spread. Moreover, changes in the variance of Model 1 have a drastic and everlasting effect on the short-term interbank time series; one can conclude that a change to the high-volatility state might be driven by an increased level of the ABCP-TBill spread. In other words, liquidity shocks originating from movements of the ABCP-TBill spread, which represents the health of the US debt market, drive regime changes in the euro fixed-float OIS swap rate.

The results show that extreme market behaviour fed on endogenous shocks - which intensify through a feedback-loop - ultimately leads to financial crises. Thus, the propagation of liquidity shocks and persistence of turbulent periods are fostered by an ‘energy’ which is produced and magnified from within the financial system. If the shocks are endogenous (such as those originating from the ABCP-TBill spread), the model identifies the asymmetric effects of such shocks.

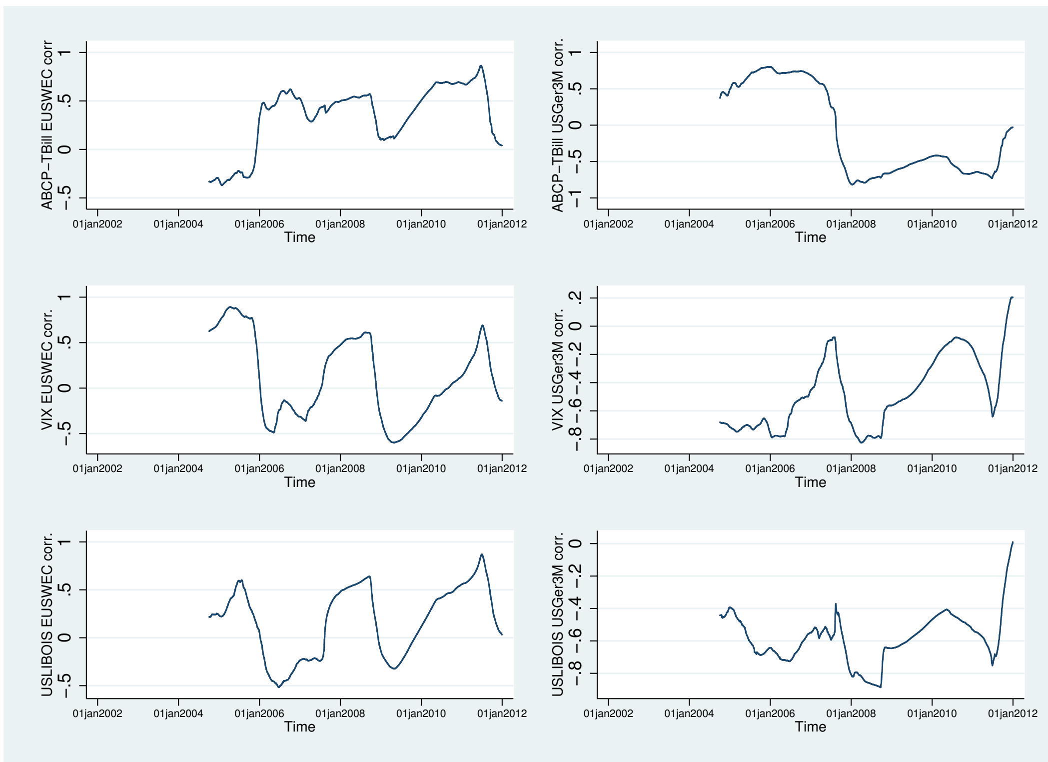

Figure 7: Graphs of the pair-wise three year rolling window correlation of the US and eurozone spreads.

5. Conclusions

Our study introduces the idea of endogenous regime switching in the short-term interbank market, which was non-existent in the finance and banking literature. Fundamentally, financial crises go hand in hand with amplified interest rates and elevated spread levels, whereas increased volatility provides the avenue for inter-regional contagion. Our models are powerful extensions to signal and logit based models, such as those implemented by Demirgüç-Kunt and Detragiache (1998), Kaminsky et al. (1998), Kaminsky and Reinhart (1999), Goldstein et al. (2000), Kaminsky and Reinhart (2000), Demirgüç-Kunt and Detragiache (2005) and Lang and Schmidt (2016). The assumptions of these models hypothesise on exogenous processes that affect financial behaviour and do not describe the peristence of turbulent and tranquil periods, neither they explain the characteristics of estimated coefficients, since important observations are excluded from the investigations. Furthermore, our models surpass two- and multinomial-regime models (Dahlquist and Gray, 2000; Fratzscher, 2003; Bussiere and Fratzscher, 2006) as well as volatility models (the family of GARCH models, for example) where the estimated parameters indicate explosive variances which are constant over time, and these cannot capture the true dynamics of money market rates and spreads. In such cases, studies cannot propose practical policy advice. On the other hand, recent investigations in the field of macroeconomic policy acknowledge that policy change behaviours (such as shocks) are in fact endogenous, such that these respond methodically to variations in the macroeconomic environment (Davig and Leeper, 2006; Kaufmann, 2011).

However, increased variation in rates does not necessarily lead to a financial crisis. Policy decisions do disturb rates and asset prices, however the market generally quickly stabilises. What is specific to turbulent periods is that they gather impetus from endogenous reactions of market participants (Daníelsson, 2011). Consequently, this will be reflected in volatile rates and spreads. The financial crisis of 2008-10 is a perfect example of a self-fulfilling feedback mechanism that feeds on endogenous liquidity risk. In other words, liquidity shocks are meaningful and the state of the economy reacts to such endogenous behaviour. Our study reveals a specific characteristic of endogenous liquidity risk, namely that small liquidity shocks through contagion induce large variation in market rates and asset prices. Our models aggregate the information provided by the VIX index, the ABCP-TBill spread, the US LIBOR-OIS spread, the US-German bond rate and the euro fixed-float OIS swap rate in a multivariate endogenous system by quantifying fragility and spillover effects in the interbank market, and this is where our main contribution lies. We show that new information arriving into the market is smoothly incorporated into the realisation of shocks via a non-linear framework.[13] This framework proved optimal compared to exogenous regime switching models and therefore the implications for Basel III are significant[14]. Thus, the uncertainty that drives liquidity dynamics in turbulent periods is better explained as being endogenous rather than exogenous.

Endogenous time-varying regime switching represents a new method by which the development of market expectations matters, specifically in regulating and managing the impacts of interbank liquidity shocks. Implications of our results are threefold and directly relevant for the following aspects of the Basel III accord.[15] First, while the Basel III directive is concerned with advising on risk weights for various asset classes, the accord does not provide guidance to dealing with money market interest rate volatility. In case of a sudden drop in the value of AAA+ asset backed securities for example, the interest rate will go up and consequently the spread between affected interest rates will widen. This in turn will have a market-wide effect. Second, credit risk mitigation techniques suggested in Basel III are known to increase residual risk such as the transmission of liquidity risk, yet such scenarios - when externalities occur - are not considered. The stress tests that must be run by the Internal Rating Based banks assess market downturns, market risk events and liquidity conditions specific to the banks under scrutiny. The accord specifically stipulates that banks operating in various markets do not

[13]This contrasts the view of Fratzscher (2003) who argues that regime-switching models do not perform well when contagion is accounted for, or more precisely contagion may explain regime changes which cannot be accounted for by market fundamentals such as exchange rates, for example.

[14]Daníelsson (2011) stresses that the Basel Accords regulations do not aid the smooth functioning of the financial markets, but rather contribute to the accumulation of endogenous risk.

[15]The Basel III accord contains regulatory objectives of prudential regulation with the ultimate aim of increasing the banking sector's resilience and capacity to absorb shocks as a result of amplified uncertainty surfacing within financial markets, consequently diminishing the risk of spillover from the banking sector to the rest of the economy. As the BIS's response to the global financial crisis claims, it is work in progress in terms of how systemically important banks should have loss absorbing capacity in light of financial and economic stress.

have to design stress tests to animate the circumstances of the jurisdictions it operates within, but assess the portfolios which holds the vast majority of its total exposure. Moreover, there is no recommendation on how to manage risk concentration built up among interrelated institutions or risk concentration affecting regions. Current stress tests are solely firm-wide, meaning that market wide built-up pressure and risk spillover between institutions and markets is not assessed. Yet, at the core of interbank risk spillover is the propagation of shocks outside national borders/jurisdictions. Third, the accord does not consider the idea of endogenous risk and does not recognise that financial crises are primarily the result of endogenous risk, which is harder to model.

As an improvement, the model could have included autoregressive components for an improved tuning of regime estimates. Moreover, a possible extension of the present study would be to determine thresholds with various intensities, so that when predetermined financial variables cross some limit, interbank policy rules would adjust and subsequently aid the uninterrupted functioning of the financial market.

Appendices

The section below presents the methods of inferring the posterior distribution of the coefficients, estimating the likelihood function and the transition probabilities.

The models presented in this study use the so-called centered parametrisation, where there are no rules for thresholds. However, this would not obstruct the identification of the time-changing effect of the endogenous covariate. The Hamilton filter (1989) estimates the transition probabilities, while the maximum likelihood (ML) estimation infers the parameters of the models. All the covariates used in this study, as well as the error terms are regarded as random variables and processes, which is fundamental in regime-switching Markov processes. The time-varying transition probabilities are estimated using the logit function, which provides the base for the two-state Markov regime switching model. The state space consists of two states: a turbulent and a tranquil state.

If ψ_t represents new information available at some time t, then it can be assumed that the probability of the system being in either turbulent or tranquil state is 50%, therefore $Pr(S_0 = j) = 0.5$ where $j = 1, 2$.

Thus, at time $t = 1$, the state probability for both states up to time $t-1$ is given by:

$$p(S_t = j|\psi_{t-1}) = \sum_{i=1}^{2} p_{ji}\ \left(Pr\left(S_{t-1} = i|\psi_{t-1}\right)\right) \tag{7}$$

As new information arrives at time t, the coefficients of the model are being updated along with the transition probabilities. Fundamentally, this is the Hamilton filter (Hamilton, 1989). The updating process runs through all observations of the model, from t to T using the formula:

$$p(S_t = j|\psi_t) = \frac{f(y_t|S_t = j, \psi_{t-1})\ p(S_t = j, \psi_{t-1})}{\sum_{j=1}^{2} f(y_t|S_t = j, \psi_{t-1})\ p(S_t = j, \psi_{t-1})} \tag{8}$$

The benefit of using the Hamilton filter is that it allows approximation as well as hypothesis testing concerning the coefficients of the system. The filter uses two recursive equations (prediction and updating) when estimating the distribution of the state variable. Fundamentally, the filter calculates $f(\mathbf{y}|\Theta, y_{-r+1}, \ldots, y_0)$ and maximises with respect to Θ, which is the parameter vector. Probabilistic inference about the unobserved state variable is achieved by passing of the maximum likelihood of $\hat{\Theta}$ through the filter.

The likelihood function is determined by:

$$f(y_t|S_t = j, \Theta) \tag{9}$$

where $j = 1, 2$.

As $t \to \infty$, the ML estimate $\hat{\theta}$, also called the sufficient statistic, provides all available information about θ (which is the uncertainty parameter) attainable from the data. If the length of t is short, $\hat{\theta}$ is inefficient.

For the two states, the model is estimated by maximising the following equation with respect to all coefficients contained in Θ. It is assumed that the distribution inputted in the ML estimation is normal.

$$ln\, L = \sum_{t=1}^{T}\ ln\ \sum_{j=1}^{2}\ \left(f(y_t|S_t = j, \Theta)\ p(S_t = j|\psi_t)\right) \tag{10}$$

The transition probabilities are estimated by filtering the probabilities through the turbulent and tranquil states. Thus, the filtered probabilities are the probabilities of $S_t = j$ conditional on ψ_t (which is the information at time t).

In this setup the transition process may be driven by any of the covariates of the model. In fact, the state variables which influence the transition probabilities can be different for every probability.

In the case of time-varying transition probabilities, the transition matrix calculated at each time t can be estimated by a logit specification, and is written as follows:

$$p(S_t = s_t \,|\, S_{t-1} = s_{t-1}, z_t) \tag{11}$$

where Φ is the cumulative density function. For the turbulent and tranquil states, the probability elements which will be approximated are represented by matrix $\mathbf{Q}$.

$$Q_t = \begin{pmatrix} q_{11,t}(z_t) & q_{21,t}(z_t) \\ q_{12,t}(z_t) & q_{22,t}(z_t) \end{pmatrix} \tag{12}$$

where the dynamics of the latent state variable S_t^* will depend on variations of the information contained in crisis-indicator vector z_t and on the past prevailing state. The probability function (which is not the ultimate probability) can be generated by:

$$q_{ij,t} = \Phi(\mathbf{z}_{ij,t}\ \boldsymbol{\gamma}_z) \tag{13}$$

The state variable is described by the following equation:

$$S_t^* = \gamma_0 + \gamma_z^T \mathbf{z}_t + \gamma_1 s_{t-1} + \boldsymbol{\epsilon}_t \tag{14}$$

where γ_z is a vector of parameters to be estimated, $\mathbf{z}_t$ contains the covariate which is expected to influence the transition from one state to another and $\epsilon_t \sim^{iid} N(0, \sigma^2)$. Considering the fact that the level of the ABCP-TBill spread is a benchmark for evaluating the interbank market, we allow the spread to drive the transition from one state to another. Next, an ancillary matrix grounded on Q_t is created, as follows:

$$R_t = \begin{pmatrix} 1 & 1 \\ 1 - q_{11,t} & 1 - q_{12,t} \end{pmatrix} \tag{15}$$

Finally, the transition probability matrix is constructed, as follows:[16]

$$P_t = Q_t \bullet R_t = \begin{pmatrix} p_{11,t} & p_{21t} \\ p_{12,t} & p_{22,t} \end{pmatrix} \tag{16}$$

The time-varying transition probabilities guarantee that the influence of an increase in the ABCP-Tbill spread is to reduce the probability of remaining in the tranquil state, and subsequently to increase the probability of staying in the turbulent state (Perez-Quiros and Timmermann, 2000).

The codes to estimate the coefficients of the models and transition probabilities were provided by Perlin (2012) and Ding (2012).

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[16] The Hadamart product of two matrices is constructed by element-wise multiplication. To identify the product, the two matrices must have the same dimension. Every column must sum up to 1.

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