Contagion in sovereign debt and commodities markets

Contagion in Sovereign Debt and Commodities Markets

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Declaration

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Abstract

This thesis introduces the notions of good contagion, bad contagion and reverse contagion. It focuses on addressing five research questions relating to the empirical literature on contagion, the 2010 EMU sovereign debt crisis, and the commodities markets crisis of 2008.

The first research question asks whether contagion is only associated with extreme negative events i.e. bad contagion. Using non-linear simultaneous equations, this thesis shows that both bad and good contagion (associated with extreme positive shocks beyond what fundamentals can explain) occurred in the EMU sovereign debt crisis.

The second research question probes the EMU sovereign debt crisis of 2010 to ascertain whether Greece is the only source of the crisis. Non-linear simultaneous equations are used to investigate, with all periphery markets acting as potential crisis source countries. Greece is found not to be the only source of contagion, Ireland and Portugal also acted as sources.

The third research question queries whether contagion effects resulting from extreme negative shocks can be propagated as extreme positive shocks and vice versa. Non-linear simultaneous equations are applied to the 2008 commodities crisis. From the results, reverse contagion is captured i.e crisis triggered flight to quality effects captured through counter intuitive but statistically significant contagion indicators which fundamentals cannot explain.

The fourth research question requests insight on the tail event patterns of vulnerability to contagion within the exchange traded commodities complex. This thesis applies non-linear simultaneous equations to the 2008 commodities crisis. Industrial metals and energy markets are found to be the most systemically important sources of contagion.

The fifth research question requests insight on the patterns of contagion vulnerability to commodities markets from conventional financial markets. This thesis uses a coexeedance approach to explore commodities markets. Results indicate that energy markets are the most vulnerable to bad contagion from conventional financial markets.

Dedication

To Diekolola, Daniel, Samuel and Esther.

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Chapter 1

Introduction

1.1 Introduction

The reoccurrence of financial market crises and the contagion episodes which usually follow brought to the fore the idea that unrestricted capital flows have side effects that could be costly and disruptive. Reoccurring episodes of financial market contagion have clearly proven that higher market integration brought about by increased capital flows between two markets might be beneficial in normal economic or financial market conditions but could also be detrimental in periods of financial crisis or extreme events, (Eichengreen, 2004). This makes highly connected/integrated markets vulnerable to each other if a market crash occurs in one of them. The shock transmission mechanism between the two markets which allows events in one market to be mirrored in the other in normal times is broken in periods of turmoil to an extent that fundamentals cannot predict or explain. This is applicable whether the extreme shocks transmission is positive or negative.

The spread of crises from market to market has been established empirically. For example, King and Wadhwani (1990) show the spread of crisis from Hong Kong to markets in Europe and America in 1987, Pesaran and Pick (2007) show the spread of the ERM crisis of 1992 to relevant markets around Europe, Arghyrou and Kontonikas (2012) also show evidence that the European Monetary Union (EMU) sovereign debt crisis of 2010 spread from Greece to other euro zone economies.

In the empirical literature, the spread of crisis (extreme negative shocks) from market to market was considered a result of either contagion or interdependence; this classification divide is the foundation of the empirical debate on financial contagion.

While this thesis defines interdependence as the level of integration between markets both in crisis and non-crisis times due to real and financial linkages, contagion is considered to be a phenomenon that occurs when there is an extreme departure from the interdependence regime of shock transmission between two or more markets beyond what fundamentals can explain or predict. Interdependence is different from contagion in the following ways: interdependence exists both in crisis and non-crisis times. During crises, interdependence involves an insignificant change in levels of market integration which usually can be explained or predicted by fundamentals while contagion is a phenomenon associated with crises, and manifests in anomalous increase in market correlation which is statistically significant and which observable economic fundamentals cannot explain or predict (Forbes and Rigobon, 2002). Spillovers occur when crisis from one country affects the other

through links such as trade while monsoon effects have to do with crises in one country seemingly spreading to another because of macroeconomic similarities (Masson, 1999). Monsoon effects are different from interdependence in that whilst interdependence refers to shock transmission patterns between any two markets, monsoonal effects refer to the impact of changes to an external common factor which could impact several markets at the same time.

In the contemporary global financial system, contagion remains a reoccurring feature, e.g stock market contagion of 1987 (King and Wadhwani, 1990), East Asian currency contagion of 1998 (Forbes and Rigobon, 2002 and Corsetti et al, 2005), banking contagion of 2008 (Pais and Stork, 2011) and EMU sovereign debt contagion of 2010 (Arghyrou and Kontonikas, 2012 and Caceres et al, 2010). It is therefore not surprising that the contagion phenomenon has generated sustained interest and remains a topical issue in the empirical literature.

The empirical debate on contagion has advanced from tackling issues such as the contagion interdependence divide, to debating the effect of using conditional versus unconditional volatility in empirical estimations (Forbes and Rigobon, 2002), to empirically acknowledging or incorporating the fact that shocks have a common and idiosyncratic component as well as acknowledging that both contagion and interdependence effects can be observed at the same time during a crisis (Corsetti et al, 2005), to the endogenization of crisis identification (Pesaran and Pick, 2007).

In financial services, financial market participants (such as analysts, traders, portfolio managers etc) dealing with different financial instruments/markets want to know about the vulnerability to contagious crises of markets they are involved in or financial instruments they hold, as this will inform their hedging and portfolio construction decisions. They also want to know more about contagion resulting from extreme positive shocks and if it has any implications for the markets/instruments of interest to them.

This thesis contributes to the empirical literature in the following ways: firstly, the notion of good and bad contagion is introduced, secondly the notion of reverse contagion is highlighted. Thirdly, the fact that contagion effects can be identified within exchange traded commodities markets, which are not structured along the lines of national sovereignty is highlighted. The vulnerability of exchange traded commodities markets to contagion from conventional markets is also highlighted. This thesis ultimately demonstrates the possibility that the following phenomenon can be empirically identified in a market crisis episode: interdependence, monsoonal effects, good contagion, bad contagion and reverse contagion.

This thesis is a compendium of closely related studies which addresses the following research questions:

1. Is contagion only associated with negative disturbances, negative crises, and extreme negative events?
2. In the EMU sovereign debt crisis of 2010, is Greece the empirically established source of the crisis? if so, was Greece the only source of the crisis?
3. Can contagion effects resulting from extreme negative shocks be propagated as extreme positive shocks and vice versa?
4. What are the patterns of vulnerability to contagion within the exchange traded commodities complex?
5. What are the patterns of contagion vulnerability to commodities markets from conventional financial asset markets?

Chapter 2 presents a survey of the empirical literature on financial contagion. Chapter 3 addresses research questions 1and 2 and introduces the notion of good contagion which is associated with the propagation of extreme positive shocks beyond what fundamentals can explain or predict. The contagion literature has traditionally focused on the contagion resulting from extreme negative shocks, i.e. bad contagion. Chapter 3 shows that both bad contagion and good contagion can be present and need not come from the same sources or affect the same markets. Results suggest that, indeed, both good and bad contagion have occurred in the EMU sovereign debt crisis. Controlling for interdependence and monsoonal effects, the periphery (Greece, Italy, Ireland, Portugal and Spain) countries were found to be most exposed to bad contagion. Notably, core countries such as Belgium were also exposed to significant bad contagion originating from periphery countries. It is also noteworthy that Spain caused significant good contagion to almost the entire Eurozone. This finding is not only interesting per se, but also has important policy implications. For example, policy makers could potentially ameliorate the impact of a contagious market crisis by deploying relief in one systemically important market which could spread relief to other affected markets.

In tackling research questions 3 and 4, chapter 4 investigates contagion within the exchange traded commodities complex with respect to the 2008 commodities market crash using a system of non-linear simultaneous equations which considers both bad and good contagion. The chapter 4 methodology also enables the endogenization of crisis periods and investigates contagion to and from multiple sources, as such there is no need to make assumptions about systemically important commodities. Two main sets of estimations are carried out. The first set of estimations look broadly at contagion effects between the index returns for the 5 major commodity groups whilst the second

set of estimations consider contagion effects between the returns for 18 individual exchange traded commodities. Controlling for interdependence and monsoon effects, industrial metals and energy are found to be the most systemically important sources of contagion. “Reverse” contagion effects are also captured i.e crisis triggered flight to quality effects captured through counter intuitive but statistically significant bad and good contagion indicators which fundamentals cannot explain or predict. This demonstrates that contagion effects resulting from extreme negative shocks can be propagated as extreme positive shocks and vice versa.

Chapter 5 empirically explores research question 5 by investigating the vulnerability of exchange traded commodities markets such as copper, corn, Brent crude and gold to contagion from conventional asset markets such as equities. A coexeedance/quantile regressions methodology is used as the empirical framework, it gives more insight into tail dependence structures relative to other methodologies. Results indicate that exchange traded energy commodities appear most vulnerable to suffering bad contagion from conventional asset markets. Industrial metals and precious metals appear to benefit from reverse contagion and good contagion respectively. Chapter 5 also empirically corroborates the fact that commodities markets have been financialized.

Chapter 6 summarises the findings of this thesis and concludes.

Chapter 2

A Review of the Empirical Literature on Financial Contagion

2.1 Introduction

The term contagion is widely used across different disciplines. It generally refers to the transmission of a predicament or state from one entity to another. In psychology, it refers to the transmission of emotions or a state of mind from one person to another, in medicine it refers to the transmission of a disease from an infected person to an uninfected person, in finance and economics, it usually refers to the transmission of economic and/or financial crises or prosperity from one market/economy to another. As far as this study is concerned, contagion will be considered in the context of economics and finance.

The term contagion became a fairly common feature in the empirical literature in the early 1990's shortly after the U.S stock market crash of 1987. Earlier papers such as Sharpe (1964), Grubel and Fadner (1971) have simply focused on investigating channels through which negative shocks were propagated while papers like King and Wadhwani (1990), Engle, Ito and Lin (1990), and Bekaert and Hodrick (1992) pioneered the more contemporary empirical debate/literature on contagion. The more contemporary debate on contagion focuses on empirically identifying the contagion phenomenon whilst investigating crises episodes.

Since the early nineties, an extensive volume of work has been done on contagion. This has resulted in the presentation of numerous definitions, as well as methodologies to the body of knowledge on the subject. Incidentally, the volume of work has not resulted in consensus among researchers on the concept of contagion (Bae et al, 2003) also share this view); rather different groups exist in the literature. Each of the groups hold similar but differentiated views on issues such as the definition of contagion, the most empirically expedient approach to identifying contagion, and inference on outcomes of empirical investigations.

The burgeoning empirical literature has been reviewed extensively by survey papers like Dornbusch et al (2001), Pericoli and Sbracia (2003) and Dungey et al. (2005). These papers have identified patterns and trends in the body of knowledge on contagion as such, they have been used as a guide to the very vast literature.

Chronologically, the empirical literature on contagion has evolved through four major stages. Regardless of the numerous views, definitions, and methodologies that characterize the literature on

contagion, major contributions have been made as the body of knowledge moved from one generation to the next.

The first generation of works on contagion contributed to the body of knowledge by laying the foundation for capturing the phenomenon called contagion empirically (e.g King and Wadhwani (1990)). They did this by demonstrating contagion in terms of discontinuities in shock transmission regimes. The first generation of papers also contributed by empirically differentiating interdependence from contagion.

The second generation of empirical works on contagion made the estimation of contagion more statistically valid, by shedding light on the need to take into account the fact that observed shocks have both a common and idiosyncratic component (Corsetti et al, 2005). The third generation of research works on contagion demonstrated how arbitrary selection of crisis and non-crisis periods potentially introduce sample selection bias into estimation, and proffered different means to endogenize crisis identification in the empirical estimation of contagion (e.g. Pesaran and Pick, 2007).

The fourth and evolving generation of research works on contagion is more policy oriented and seems to focus more on efficient ways to understand patterns of vulnerability to contagious spread of crises. Another salient contribution of this generation of research on contagion is demonstrating that contagion and interdependence effects can be found in a given market at the same time, this is contrary to the idea implied by previous generations of contagion research which simply test for contagion or interdependence in a given market (e.g. Pesaran and Pick, 2007 and Markwat et al, 2009).

Sbracia (2003) reports that contagious financial crises can be of three forms. These are currency crises, banking crises and stock market crises. Stock market crises generally manifest with a substantial decline in the stock market index, or a large change in market volatility level. A common example is the US stock market crash of 1987. As for currency crises, the key feature is that of major currency devaluations especially for managed exchange rate regimes. A prominent example of a currency crisis is the East Asian crisis of 1998. Banking crises describe a scenario of widespread illiquidity and a rise in non-performing assets, relative to performing ones. A good example of a banking crisis is the subprime mortgage crisis of 2007.

A fourth type of contagious financial crisis which is less prominent in the empirical literature is the sovereign debt crisis. A sovereign debt crisis occurs when a government defaults or is likely to default on its sovereign bonds (debt instruments issued by a national government usually

denominated in a foreign currency) payments/obligations when they are due. Information about a default or a likely default then causes the price of the bonds to drop sharply while the yields on the bonds rise sharply (as investors demand a high premium for holding a highly risky debt instrument) thereby increasing the cost at which an affected sovereign can borrow. A recent example of a sovereign debt crisis is the EMU crisis of 2010. A fifth type of potentially contagious crises is commodities market crisis/crash such as the commodities market crash of 2008.

2.2 Definition of Contagion

There is no one single universally agreed definition or description of what contagion is. In the vast empirical literature, different papers have used financial theory or empirical evidence to coin a definition for contagion. However, there are three broad groups of definitions of contagion that have been identified in the literature.

2.2.1 Contagion Described as the Spread of Crisis

The first broad group of definitions of contagion is driven by on-the-surface observation of the outcome of crisis periods, in which turmoil in one market affects another market and reflects in it. This definition is less subscribed to in the empirical literature but widely subscribed to in the financial media. In their second definition (their first definition being that contagion refers to a significant increase in cross market linkages after a shock to one or more markets), Dornbusch et al. (2000) consider contagion simply as a spread of negative market disturbances. Dungey et al. (2009) offer similar definitions, their definition first is that contagion occurs when financial crises spread turmoil into foreign markets, whilst their second definition is that contagion is the impact of crisis in one market on another non-crisis market. The above definitions are similar as they see contagion in the light of the transmission of negative shocks from the markets where they originated to other markets. Compared to other definitions contributed to the debate on contagion, these definitions look at contagion in a simple way. They imply that once crises in one country spills over into another, there is contagion. In the empirical literature, a spread of turmoil from one market to another is regarded as a necessary but not sufficient condition for the occurrence of contagion to be validated.

Based on the perspective of contagion held in the wider literature, and the assertions of Masson (1999), this group of definitions is less technical and lacks clarity as it might also be describing interdependence in a situation where the level of correlation during a crisis can be predicted by macroeconomic fundamentals. In the light of the other definitions contributed to the literature, this

group of definitions is therefore problematic as it does not incorporate the separation of contagion and interdependence effects which is very salient in the empirical debate on contagion.

2.2.2 Contagion Described in Terms of Regime Switches

The second group of definitions is motivated by empirical evidence relating to the spread of shocks between markets during or after a crisis. In this group of definitions, contagion is generally seen in the light of a significant departure from the interdependence regime of shock transmission between two or more markets, or break/discontinuities in shock transmission mechanisms between two or more markets. Though this group of definitions is based on empirical evidence from correlations based tests which were pioneered by King and Wadwhani (1990) (where contagion was established in the spread of negative shocks relating to the U.S stock markets crash of 1987), Masson (1999) is one of the first papers to coin a definition describing contagion in terms of regime switches. They describe contagion as a scenario where a market jumps from a good equilibrium to a bad one after suffering from the impact of shocks from another market in crisis.

Dornbusch et al. (2000) define contagion as a significant increase in cross market linkages after a shock to one or more markets. Forbes and Rigobon (2002) also offer a similar but differentiated definition: they refer to contagion as a significant increase in cross market comovement after a shock to one country, they also contrast contagion to interdependence in a crisis situation which they refer to as insignificant increase in market comovement. The Dornbusch et al (2000)/Forbes and Rigobon (2002) definition is widely subscribed to in the empirical literature. In most cases, it is adopted by papers employing correlation-based tests but is also widely subscribed by papers using other methodologies. Pesaran and Pick (2007) see contagion as a jump between equilibria and a largely unpredictable higher correlation between markets during crises times compared to normal times. According to Pais and Stork (2011), contagion is observed when markets or asset prices move together after a shock in a way that fundamentals cannot explain.

Similarly, Markwat et al. (2009) considers contagion as dependence that still exists after correcting for interdependence between markets. Mink and Mierau (2009) refer to contagion as a sudden strengthening of shock transmission between financial markets. All the above definitions invariably describe a switch in shock transmission regime but in different parlance. Seemingly new and different definitions have been added to the literature, they in fact turn out to portray the contagion phenomenon as described by previously coined definitions. Baur and Schulze (2005) describe contagion as a structural break in international shock propagation mechanism during a crisis while they describe interdependence in contrast as a stable data generating process with constant or increased variances.

The second group of definitions introduces more clarity to the empirical literature on the contagion phenomenon in the sense that they improve upon the first group by classifying the transmission of negative shocks (which is synonymous with market crashes or crises) into interdependence and contagion components. By doing this, they make it clear that in order to fulfill the criteria of what constitutes contagion, not only must there have been a spread of negative shocks, but such shock transmission must have breached the interdependence shock transmission threshold which (based on historical observation) was in force. The knowledge of dividing shocks into different components would help policy makers decipher whether the spread of negative shocks, is as a result of interdependence due to real and financial linkages, or certain vulnerabilities that are inherent in their markets. This knowledge would aid appropriate policy response to mitigate and avoid the effects of the spread of such negative shock in the current, medium, and long term. Contagion as defined by this group has been branded shift-contagion by Forbes and Rigobon (2001) to distinguish it from other groups of definitions of contagion.

2.2.3 Contagion as Vulnerability to Impending Crisis

The third broad group of definitions depicts contagion in terms of the vulnerability/exposure of a market to external crises based on the possibility of crisis occurring in another market. While the first groups of definitions approach contagion in an ex-post way, this second group looks at possible contagion ex-ante. This group of definitions is usually related to tests of contagion based on conditional probability, for example logit models, probit models and leading indicator models. This group of definitions is also related to the empirical literature on early warnings systems for financial crisis and contagion risk which are distinct sub-strands of the wider empirical literature on financial crisis and financial contagion, respectively. Eichengreen et al. (1996) imply that contagion occurs when the probability of crisis in a country at a point in time is correlated with the incidence of crisis in other countries at the same time, after controlling for the effects of political and economic fundamentals. Cipollini and Kapetanios (2009) imply that contagion is vulnerability to external crises represented by quantities like the ratio of external debt to external reserve and the ratio of short-term external debts to the stock of foreign reserves. Likewise, Ait-Sahalia et al. (2010) refer to contagion as cross-region transmission of shocks and an increase in the likelihood of successive shocks in the countries affected after an initial shock. This group of definitions look at contagion in the light of the probability of being affected by external crises based on the size and frequency of shocks transmitted during crisis, as well as the resilience of the affected market to withstand it.

2.2.4 Summary on Contagion Definitions

Even though the earlier discussed groups of definitions are presented to look different, they refer to the same phenomenon. In the context of financial/economic crises, contagion is described as a

situation in which an anomalous level of interdependence is experienced in the aftermath of a crisis originating in another market.

Pesaran and Pick (2007) also present a description of contagion which is a hybrid of the perspectives of the second and third groups of descriptions respectively; they opine that contagion occurs when crisis in one market increases the likelihood of crisis in another, over and above what would be implied by pre-crisis levels of interdependence.

This thesis subscribes to the second group of definitions, as such it defines contagion as an extreme departure from the interdependence regime of shock transmission between two or more markets which fundamentals cannot explain or predict, while interdependence is defined as the phenomenon that generally describes the level of integration between markets in crisis and non-crisis times, due to real and financial linkages. Interdependence is different from contagion in the following ways: interdependence exists both in crisis and non-crisis times. During crisis, interdependence involves an insignificant change in levels of market integration which usually can be explained or predicted by fundamentals while contagion is a phenomenon associated with crises, and manifests in anomalous increase in market correlation which is statistically significant and which observable economic fundamentals cannot explain or predict (Forbes and Rigobon, 2002).

Spillovers occur when crisis from one country affects the other through links such as trade, while monsoon effects have to do with crisis in one country seemingly spreading to another because of macroeconomic similarities (Masson (1999)).

2.3 Estimation of Contagion

A crucial part of the empirical literature on contagion is the debate on the most effective means to test for contagion. In the empirical literature on contagion, different techniques of testing for contagion have been suggested, and it is likely that more will be introduced. There are five major types of estimation techniques that have been identified in the empirical literature on contagion. These include the correlation based tests, tests based on conditional probabilities (logit models and probit models), tests based on ARCH/GARCH models, tests based on Markov switching models, and tests based on simultaneous equations; each shall be examined in turn.

2.3.1 Correlation Based Tests

Traditionally, correlation-based tests check to see if there was a significant increase in cross market correlation by comparing correlation in a specified pre-crisis period to a crisis period. Early

correlation-based tests were popularized by King and Wadwahni (1990) which was among the first papers that presented models meant to detect contagious crisis. In their study, contagion was captured using the model:

$$\Delta S = (I + B)\eta \tag{2.1}$$

Where ΔS is a $J \times 1$ vector of price changes, J is the number of markets, I is an identity matrix and η is a $J \times 1$ vector of news term. B is the matrix of contagion coefficient. When B is statistically significant, then there is evidence of contagion, and when B is not statistically significant, then it is assumed that the spread of crisis between markets was as a result of interdependence. The study found empirical evidence of stock market contagion from Hong Kong to markets in Europe and America in 1987.

The traditional correlation-based test was challenged by Forbes and Rigobon (2002) which introduced the adjusted correlation-based test. The adjusted correlation-based test was supposed to correct for the bias introduced into the estimation of contagion by the simple correlation-based test described earlier. Whilst Forbes and Rigobon (2002) generally agree with the intuition of the earlier correlation tests, they discovered that cross market correlation was being estimated based on conditional instead of unconditional volatility. This possibly introduced an upward bias in the cross-market correlation coefficient of previous research works. Hence, Forbes and Rigobon (2002) advocated the need to adjust cross-market correlation for heteroscedasticity. However, to use their adjusted correlation tests, Forbes and Rigobon (2002) make the following assumptions: First, there are no omitted variables. Second, there is no endogeneity between markets considered. Forbes and Rigobon (2002) agree that the implications of the restrictions are that the adjusted correlation test is valid under the conditions that there are no exogenous global shocks and no feedback from the crisis market to the affected foreign market. Forbes and Rigobon (2002) estimate the model below using data related to the Asian crisis of 1997, the Mexican crisis of 1994, and US. Stock market crash of 1987:

$$X_t = \emptyset(L)X_t + \Phi(\mathrm{L})\mathrm{I_t} + \eta_t \tag{2.2}$$

Where X_t stands for transposed vector of returns in the same two stock markets. $\emptyset(L)$ and $\Phi(L)$ are vectors of lags of short-term interest rates for the crisis country and another country which the crisis was transmitted to, respectively. η_t is a vector of reduced form disturbances

$$X_t \equiv \{x_t^c, x_t^j\} \tag{2.3}$$

x_t^c represents stock market returns in the crisis country, x_t^j represents stock market returns in another country.

$$I_t \equiv \{i_t^c, i_t^{us}, i_t^j\} \tag{2.4}$$

The variables i_t^c, i_t^{us}, i_t^j represent short term interest rates for the crisis country, the united states, and market j

The parameter ρ represents correlation between x_t^c and x_t^j during the full period (non-crisis period), while ρ_t^h represents correlation between x_t^c and x_t^j during a high volatility period (crisis period). Forbes and Rigobon (2002) test the following null hypothesis $H_0: \rho > \rho_t^h$ against an alternative: $H_0: \rho \leq \rho_t^h$. In this empirical study, there is evidence of contagion if the null hypothesis is rejected.

In Forbes and Rigobon (2002), the empirical position is that unconditional volatility in the crises periods considered was unchanged, but there was soaring market co-movement. Forbes and Rigobon (2002) therefore assert that there was interdependence but no contagion. Dungey et al. (2005) however considers their estimation as being too conservative on the grounds that they did not find evidence of contagion in all of the crisis periods they investigated.

Corsetti et al. (2005) argue that adjusted correlation tests like Forbes and Rigobon (2002) ignored the fact that increases in cross market correlation could be a function of both common and idiosyncratic shocks. They opine that by adjusting cross-market correlation coefficient for heteroscedasticity, the adjusted correlation based tests implicitly make the unrealistic assumption that the variance of stock returns in the market were crisis originates is the same as the volatility of the common factor affecting all markets. According to Corsetti et al. (2005), this introduces an upward bias to correlation-based tests of contagion. To remedy the problem, they present a test that looks at relative changes in idiosyncratic shocks pre and post crises. They therefore estimate the model presented below:

$$r_i = \alpha_i + \gamma_i f + \varepsilon_i$$
(2.5)

$$r_j = \alpha_j + \gamma_j f + \varepsilon_j$$

were r_i *is the* stock market returns in country i, r_j is the stock market returns in country j . γ_i and γ_j are country specific factor loadings for countries i and j respectively. $\propto_i$ and $\propto_j$ are constants. f is a common factor, ε_i and ε_j represent the idiosyncratic factors for countries i and j

respectively. f , ε_i and ε_j are mutually independent random variables with finite variance. In testing for contagion, the terms λ_j^{C} and λ_j^{T} represent variance ratios $(var\frac{\varepsilon_j}{\gamma_j f})_t$ and $(var\frac{\varepsilon_j}{\gamma_j f})_c$ of the idiosyncratic factors and common factors scaled by the factor loading γ_j for the tranquil (non-crisis) and crisis periods respectively. The intuition of the above model is such that when $\lambda_j^{\mathrm{C}} > \lambda_j^{\mathrm{T}}$ there is contagion, and when $\lambda_j^{\mathrm{C}} < \lambda_j^{\mathrm{T}}$ there is evidence of interdependence. In their estimation, Corsetti et al. (2005) employed factor analysis and used data similar to Forbes and Rigobon (2002).

While the traditional contagion tests generally find evidence of contagion effects for example in the stock market crash of 1987, the adjusted correlation test (Forbes and Rigobon, 2002), found evidence of no contagion effects. The Corsetti et al. (2005) paper, which considers relative changes in common and idiosyncratic factors, found mixed results, i.e. evidence of contagion in some cases and no contagion in others.

The effectiveness of correlation-based tests in capturing the contagion phenomenon has been questioned on three major grounds. Firstly, a significant increase in correlation cannot be sufficient proof of contagion because if markets are contemporaneously related, during crisis periods which are usually synonymous with high volatility, shock transmission mechanisms will be strengthened, and therefore there would be a significant increase correlation.

Secondly, in order to overcome the challenge of crisis period identification, correlation-based tests have introduced sample selection bias implicitly, by arbitrarily specifying crisis and non-crisis periods (Pesaran and Pick, 2007).

Thirdly, Mink and Mierau (2009) show that the correlation coefficients as used in many contagion research works employing correlation based tests (especially those using stock returns data), are like weights based on standardized instead of actual returns. They argue that standardized returns cannot give information on the actual magnitude of returns, but only give information on the magnitude of return relative to each other. This implies that finding an extreme standardized return does not automatically imply an extreme actual return as well. Mink and Mierau (2009) also argue that for standardization to be done, actual returns must be de-meaned and scaled using population means and standard deviation. In their view standardization is less appropriate during crises periods because estimation of correlation cannot be carried out due to non-stationarity of stock market returns.

2.3.2 Tests based on Conditional Probabilities

Eichengreen et al. (1996) answers the question of whether trade linkages or macroeconomic similarities make countries more exposed to contagion. In doing this, they employ conditional probabilities to test for contagion, making it one of the first papers to apply conditional probabilities to the study of contagion. Employing thirty years of panel data for twenty industrialized countries, they estimate the probability of crisis spreading for one country to another based on interdependence and other factors. They used a probit model similar to the one presented below to establish the occurrence of a crisis:

$$EMP_{i,t} \equiv \left[\left(\propto \%\Delta e_{i,t}\right) + \left(\beta\Delta\left(i_{i,t} - i_{i,t} - i_{G.t}\right)\right) - \left(\gamma\left(\%\Delta r_{i,t} - \%\Delta r_{G,t}\right)\right)\right] \quad (2.6)$$

Where EMP is the index of exchange rate market pressure, $e_{i,t}$ is the price of a DM in *i*'s currency at time *t*; i_G denotes the short-term German interest rates; *r* stands for the ratio of international reserves; and *α, β* and γ are weights.

They also set out a model of estimating contagion:

$$\text{Crisis}_{i,t} = \omega \text{D}\left(\text{Crisis}_{j,t}\right) + \lambda \text{I(L)}_{j,t} + \varepsilon_{i,t} \quad (2.7)$$

where $\text{D}\left(\text{Crisis}_{j,t}\right) = 1$ if $\left(\text{Crisis}_{j,t}\right) = 1$, for any $j \neq i$,otherwise, $\text{D}\left(\text{Crisis}_{j,t}\right) = 0$. In the above model contagion effects are said to be evident if ω is statistically significant.

Eichengreen et al. (1996) find that there is an eight percent probability of speculative attack in other countries conditioned on the occurrence of crises in one country. They also discovered that countries are more susceptible to contagion brought about by trade linkages than contagion brought about by macroeconomic similarities.

Van Rijckeghem and Weder (2003) answer another question crucial to the literature, the question of whether common lending channels are valid causes of banking contagion. Using cross-sectional data for 118 industrial and developing countries in 1994, 1996, 1997 which covered the Asian , Mexican , and Russian crises, they developed and used indicators of competition for funds to show that shocks relating to earlier mentioned crisis periods started from Thailand, Mexico, and Russia and spread mainly through common lending channels.

Conditional probabilities based tests have also been used to espouse new orientation on contagion. Markwat et al. (2009) used an ordered probit model to describe contagion as a domino effect which starts locally and then goes regional before going global. In doing this, they use stock returns data for 6 East Asian countries, 6 Latin American countries, Europe, US, regional indices for Asia and Latin

America and (01/07/1996 - 30/07/2007) alongside covariates which they use to differentiate between contagious domino effect and interdependence. Their findings indicate that less severe crashes tend to be followed by more severe ones, the likelihood of global and regional crises increase when there is a local crash. Markwat et al (2009) also claim that out of sample forecast obtained from a logit model, perform better than those obtained from a standard binomial model.

2.3.3 Tests Based on Coexceedances

Baur and Schulze (2005) investigate contagion effects between 11 Asian stock markets and between 4 regional markets (Asia, Latin America, Europe and United States) by using a quantile regression framework (Koenker and Basset;1978) to analyse extreme coexceedances between them. Baur and Schulze (2005) considers coexceedance as the value of tail movement shared by two markets, they define a bivariate coexceedance, Φ_t of a pair of returns r_{1t}, r_{2t} is defined such that:

$$\Phi_t(r1,\ r2) = \begin{cases} \min(r_{1t},\ r_{2t}) \text{ if } r_{1t} > 0 \wedge r_{2t} > 0 \\ \max(r_{1t},\ r_{2t}) \text{ if } r_{1t} < 0 \wedge r_{2t} < 0 \\ \quad 0 \text{ otherwise} \end{cases} \tag{2.8}$$

Baur and Schulze (2005) employ two quantile regression models. The first is a simple model set out as follows:

$$Q_{COEX_t}(\tau|\boldsymbol{X}) = \boldsymbol{X}\beta(\tau) \tag{2.9}$$

where $\boldsymbol{COEX_t}$ denotes the $(n \times 1)$ vector of the coexceedances, $\boldsymbol{X}$ is a $(n \times k)$ matrix of k exogenous variables, $\beta(\tau)$ represents a $(k \times 1)$

Baur and Schulze (2005) also use a full model which controls for the influence of regional or global markets and persistence of coexceedances such that:

$$Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis} + \beta_2(\tau)\, r_{Mt} + \beta_3(\tau)\, \hat{h}_{Mt} + \beta_4(\tau)\, COEX_{t-1} \tag{2.10}$$

Where r_{Mt} is the return of a global or regional market index, $\hat{h}_{Mt}$ is the estimated conditional variance for r_{Mt}, $COEX_{t-1}$ is the lagged coexceedance, which controls for persistence of coexceedances. They find mixed results of contagion and interdependence within regions and across regions, however they did not find evidence of contagion to the United States.

Ultimately, Baur and Schulze (2005) empirical framework makes it feasible to consider any values of the lowest or highest coexceedances without specifying a priori any distribution or threshold. It also means the degree of the coexceedance can be ascertained unlike the case of a multinomial logistic regression.

2.3.4 Tests Based on GARCH Models

GARCH models have also been employed in the empirical literature on contagion; they are generally used to capture contagion effects by analyzing shock transmission across markets. Transmission of volatility from market to market is considered as evidence of contagion. Research papers like Hamao et al. (1990) employed GARCH in the analysis of volatility transmission relating to the stock market crash of 1987, Engle et al. (1990) also used GARCH to investigate the cause(s) behind the intra-day volatility of the yen/dollar exchange rate.

Dungey et al. (2010) employed a variant of GARCH, identified structural GARCH. Their multivariate estimation framework is not only able to distinguish between contagion effects and what they refer to as hypersensitivity (interdependence in a crisis period), but through variance decomposition is able to decipher the direction from where shocks affecting a particular market have originated. Using daily data for four East Asian countries: Returns as residuals from VAR (1) on the log changes in market indices (US Dollars) and 3-month US treasury bill rate (2/1/1992-9/1/2007), they estimate the following model:

$$y_{it} = \sum_{j=1,j\neq 1}^{k} b_{ij} y_{ij} + \sum_{j=1,j\neq 1}^{k} b_{c,ij} D_{jt} y_{jt} + \sum_{j=1,j\neq 1}^{k} b_{s,ij} D_{it} y_{jt} + u_{it} \qquad (2.11)$$

where y_{it} and y_{jt} stands for asset return of markets i and j respectively in period t, b_{ij} and b_{ij} represents non-crisis linkages, D_{it} and D_{jt} are indicator variables that identify crisis periods, $b_{c,ij}$ and $b_{s,ij}$ are the coefficients of contagion and hypersensitivity respectively between markets i and j, u_{it} stands for idiosyncratic shocks. The occurrence of contagion and hypersensitivity are validated if the parameters $b_{c,ij}$ and $b_{s,ij}$ respectively are statistically significant. In the event that there is no contagion or hypersensitivity, $b_{c,ij} = b_{s,ij} = 0$ for all i, j . Dungey et al. (2009) find evidence of both contagion and hypersensitivity.

2.3.5 Tests Based on Markov Switching Models

In the literature on contagion, Fratzcher (1999) is one of the first papers which use Markov switching models. The paper presents a model in which a set of fundamentals together with measures of both financial and trade integration (with other markets) in a certain market explain the exchange rate market pressure in that market. Fratzcher (1999) analyze scenarios of both two and three market integration regimes. His results show that it is better to estimate markov switching models without measures of both real and financial linkages with other markets, because no change in regime will be found, but it is necessary to include them when forecasting, as this would generate reliable forecasts

when compared with other prediction frameworks. Fratzcher (1999) applied their estimation framework to the Mexican and Asian Crises.

Another application of markov switching models to estimate contagion is Rodriguez (2007) which discovers that tail dependence is more pronounced during times of financial crisis. In their work, Rodriguez (2007) utilized tail dependence, a property of copulas which is useful in the study of non-linear dependence. A bivariate copula, C is such that

$$`\lim_{u\uparrow 1} \frac{1-2u+C(u,u)}{1-u} = \lambda_U \tag{2.12}$$

then C has upper tail dependence if $\lambda u \in (0,1)$ and upper tail dependence if $\lambda_U = 0$, likewise, if a bivariate copula is such that $\lim_{u\uparrow 0} \frac{C(u,u)}{u} = \lambda_L$ exists, then C has lower tail dependence if $\lambda_L \in (0,1)$, and lower tail dependence if $\lambda_L = 0$. Rodriguez (2007) treat contagion as a non-linear phenomenon and use three types of copula (the Student Copula, the Frank copula and the Gumbel–Clayton Copula) with markov switching models to estimate daily Stock Returns data (US Dollars) for 5 East Asian Countries (1/1/96-30/6/98) and 4 Latin American Countries (1/1/93-31/12/95) during the East Asian and Mexican (Currency Crises) respectively. Rodriguez (2007) applies SWARCH (Switching ARCH) which allows variance of series under study to be subject to occasional shifts in order to endogenize identification of crisis and contagion. Rodriguez (2007) shows that in times of financial turmoil, dependence increased. This is achieved by considering a univariate estimation of Latin American and Asian countries.

2.3.6 Tests Based on Simultaneous Equations

In the literature on contagion so far, few attempts have been made to estimate contagion effects using non-linear simultaneous equations. Papers using simultaneous equation generally carry out estimations using GIVE (Generalized Instrumental Variable Estimation). Favero and Giavazzi (2002) pioneer the use of simultaneous equations in the empirical literature to distinguish between contagion and interdependence. In their work they consider the case of the ERM attack of 1992. Their findings show that there is non-linearity in the propagation of devaluation expectations among seven European markets between 1998 and 1992. Their work is however faulted on the grounds that it suffers from selection bias through arbitrary categorization of crisis and non-crisis periods.

Pesaran and Pick (2007) make another attempt at estimating contagion effects with simultaneous equations. The uniqueness of Pesaran and Pick (2007) lies in its attempt to estimate both contagion and interdependence simultaneously, and not testing for contagion or interdependence like the earlier discussed papers, whose outcome is usually one of both. This is a very crucial contribution to the

empirical literature on contagion because it has shown that both the contagion and interdependence phenomenon can occur in the same crisis period, and that they can both be empirically identified.

Pesaran and Pick (2007) also stands out in the sense that it does not belong to the class of contagion tests that arbitrarily specify pre and post crises period. Pesaran and Pick (2007) assert that crisis periods must be identified endogenously, else there will be a sample selection bias. Pesaran and Pick (2007) show that ignoring endogeniety of sample selection will bias contagion and interdependence estimates, as it has been the case in previous studies. Pesaran and Pick (2007) apply a two-country variant of their model which is a system of two non-linear simultaneous equations model to European interest rate spreads data (Three month interest rate figures for seven European countries during the ERM crisis). Pesaran and Pick (2007) find evidence of clear asymmetry in contagion effects of sharp rises and falls with only the contagion effects of sharp rises having statistically significant effects.

Pesaran and Pick (2007) set a new agenda for what contemporary contagion models should be able to do. They advocate the simultaneous estimation of contagion and interdependence; they also advocate for contagion models or tests that could identify crisis periods without any arbitrary specifications. In the literature on contagion, simultaneous equations (non-linear) have not been extensively used in the empirical debate.

Research opportunities therefore exists in terms of applying the simultaneous equation framework as used by Pesaran and Pick (2007) to investigate contagion effects especially with respect to types of contagious crises that have not commonly featured in the empirical literature on financial contagion such as commodities market crises and sovereign debt crises (EMU sovereign debt crisis of 2010).

Following a critical review of the vast empirical literature on contagion and considering the merits of the numerous methodologies discussed earlier in this chapter, this thesis adopts the co exceedances and non-linear simultaneous equations methodologies, respectively.

Chapter 3

Good Contagion, Bad Contagion: Evidence from the Eurozone Sovereign Debt Crisis

3.1 Introduction

After the introduction of the EMU, the yields of the sovereign debt of the EMU countries have seen a remarkable convergence, to the point where yields were almost indistinguishable from each other, and economic fundamentals of the individual countries no longer seemed to play an important role. However, in the wake of the credit crisis the yield spreads, vis-à-vis German sovereign debt, of the riskiest countries, Greece, Italy, Ireland, Portugal and Spain (known as the periphery countries), started to rise significantly, followed by a Greek default on its sovereign debt, the first default in a developed country in a long time. Of particular concern for policy makers and market participants was the potential spread of the crisis to other member states of the EMU. The EU, assisted by the IMF and the ECB, implemented several rounds of policy measures in an attempt to sooth markets and bring the sovereign debt crisis under control.

This brings up an interesting issue: If there is evidence of bad contagion following extreme negative events then there may also be good contagion following extreme positive events. Until now empirical studies on contagion have focused mainly on the bad contagion while investigation into potential contagion as a result of unforeseen extreme positive shocks has been all but ignored.

This chapter considers the presence of good contagion, in addition to bad contagion, in the context of the EMU sovereign debt crisis. In particular, this chapter considers contagion stemming from any the periphery countries to each other and other members of the Euro Zone over the period January 2007 to June 2017. This is done using a system of non-linear simultaneous equations based on the canonical model developed in Pesaran and Pick (2007). The main contribution of this chapter is thus the introduction of the notion of “good contagion” associated with extreme positive events in the source countries. Moreover, this chapter improves upon the econometric framework of Pesaran and Pick (2007) by making allowing for a time-varying threshold for the endogenous crisis identification mechanism.

The results show that good contagion and bad contagion can both occur during a crisis episode. This chapter also shows that the source and targets of bad contagion and good contagion need not be the same. In this chapter, it is demonstrated that during the EMU crisis all periphery countries are sources of bad contagion; this bad contagion mainly affected the other periphery countries, as well as

Belgium. Spain was the main source of good contagion; extreme drops in Spanish yield spreads had significant positive effects on almost all other Eurozone countries. The results imply that policy makers could ameliorate systemic crisis by targeting policy intervention to one or more systemically important markets which could then further propagate the relief effect to other affected markets or markets at risk.

The rest of the chapter is organized as follows. Section 2 presents a review of the literature on contagion. Section 3 explains the estimation framework. Section 4 describes the data. Section 5 sets out the main results and section 6 concludes.

3.2 Literature Review

3.2.1 Contagion

As discussed in chapter 1, contagion remains a reoccurring feature in the global financial system. For example well documented cases of contagion are the spread, in 1987, of shocks from Hong Kong to markets in Europe and America (King and Wadhwani, 1990), the Asian Crisis crisis (e.g Forbes and Rigobon, 2002; Corsetti et al., .2005), and contagion during the ERM crisis (e.g. Favero and Giavazzi, .2002; Pesaran and Pick, 2007). Of more recent interest is evidence of banking contagion at the onset of the credit crisis (Pais and Stork, 2011) and contagion during the EMU sovereign debt crisis which is the focus of this chapter.

Chapter 2 highlights the vastness of the contagion literature as well as the striking lack of a consensus definition of what contagion exactly constitutes. For example, Dornbusch et al. (2000) and Dungey et al. (2010) consider contagion simply as a spread of negative market disturbances. In another strain of literature, Eichengreen et al. (1996) define contagion as the probability of crisis in a country at a point in time is correlated with the incidence of crises in other countries at the same time, after controlling for the effects of political and economic fundamentals. Similarly, Ait-Sahalia et al. (2010) refer to contagion as cross-region transmission of shocks and an increase in the likelihood of successive shocks in the countries affected after an initial shock.

In line with the second group of definitions discussed in chapter 2, this chapter defines contagion as an extreme departure from the interdependence regime of shock transmission between two or more markets which fundamentals cannot explain or predict. Contagion is defined here in terms of regime switches. This chapter follows the measure of contagion proposed in Pesaran and Pick (2007); they define contagion as a jump between equilibria (shock transmission regime) causing a largely unpredictable, higher correlation between markets during crises compared to normal times. To test

for contagion, Pesaran and Pick (2007) use GIVE (Generalized Instrumental Variable Estimation) and endogenize crisis identification through a threshold mechanism. Their framework also allows for the introduction of both good and bad contagion.

In the definition of contagion used in this chapter, it is important to distinguish the contagion from the interdependence already present in normal times, and the occurrence of monsoonal effects. Interdependence is defined as the level of integration between markets present in normal times. Monsoonal effects refer to a coincidence of crisis in different markets as a result of common global shocks (Masson, 1999). The definition of contagion used in this chapter belongs to the second group of contagion definitions discussed in chapter 2.

3.2.2 The EMU Sovereign Debt Crisis

Prior to the sovereign debt crisis, markets operated a convergence trade where bonds of peripheral EMU members were bought in expectation that their yield would converge with those of Germany which was associated with the convergence of EMU sovereign yields to the point where the yields were virtually equal, implying that markets assumed that the bonds of all EMU states were as safe as German bonds (see e.g. Giordano et al., 2013). This systemic underestimation of fundamentals such as debt to GDP and mispricing of sovereign came undone at the start of the current crisis. After the sovereign crisis broke out, the wide dispersion in yield spreads might indicate an overreaction as risk premia were suddenly priced into the bonds (De Grauwe and Ji ,2012), indicating the potential for contagion in the EMU sovereign risk crisis. Arghyrou and Kontonikas (2012), Caceres et al. (2010), Caporin et al. (2013) and Mink and Haan (2013) have empirically tested for the evidence of sovereign debt contagion from Greece to other Euro Zone economies. Arghyrou and Kontonikas (2012) empirically establish contagion of the Greek Sovereign debt crisis of 2010 to most of the EMU countries investigated using and OLS based model. They find low levels of contagion in France, and high levels of contagion in Portugal, Ireland and Spain. Employing a GARCH based model, Caceres et al. (2010) also investigate sovereign debt contagion and find evidence that contagion contributed to changes in the Eurozone swap spreads they investigated. Caporin et al. (2013) which employ non-linear regression, quantile regression and bayesian quantile regression to investigate contagion based on CDS spreads data find no evidence of contagion. They found that they were no changes to shock propagation mechanisms between countries. They are of the opinion that the comovment observed in CDS spreads of Eurozone economies was a result of interdependence.

Using OLS, Mink and Haan (2013) carry out an event study on 48 European banks in 2010 to empirically establish whether any link existed between news about the Greek economic situation and a possible Greek bailout on bank stock prices. They find “no evidence of contagion” in the sense that

news about the Greek economic situation only led to abnormal returns in the stock prices of Greek banks while news about a Greek bailout had significant effect on the stock prices they investigated. They posit that the bond markets were not worried about widespread contagion and that a Greek bailout announcement was interpreted as a signal that the ECB was ready to use public funds to douse the crisis.

3.3 Methodology

To model contagion this chapter uses the canonical model

$$\Delta y_{it} = \alpha_{0i} + \boldsymbol{\alpha}_i' \boldsymbol{x}_{it} + \boldsymbol{\delta}_i' \boldsymbol{z}_t + \beta_i^{bad} C_{it}^{bad} + \beta_i^{good} C_{it}^{good} + \epsilon_{it} \tag{3.1}$$

adapted from Pesaran and Pick (2007). Here, Δy_{it} is the first difference in sovereign yield spreads for country i at time t and the dummies C_{it}^{bad} and C_{it}^{good} capture the contagion effects. The control variables are $\boldsymbol{x_{it}}$, a vector containing country specific regressors, and $\boldsymbol{z_t}$, a vector containing predetermined observed common factors. The disturbance term, ϵ_{it}, is assumed to be serially uncorrelated with conditional variances $\sigma_{i,t-1}^2$. The disturbances are allowed to have contemporaneous correlations, ρ_{ij}, which are assumed to be constant over time. The assumption of constant correlations facilitates the interpretation of ρ_{ij} as the degree of interdependence between countries i and j.

The model captures the baseline interdependence between different countries and monsoonal effects through the control variables, it also Endogenises crisis periods.

This chapter defines two sets of crises with two potentially different contagion effects. The first type of crisis, an upside crisis, is defined as a large unanticipated increase in the yield spread. Such events may be associated with significant bad news about a creditor country and this type of crisis is commonly thought about when talking about contagion. The contagion associated with this type of crisis is labelled “bad contagion”. This type of contagion signifies effects of bad news that are larger than would be expected in stable periods.

Conversely the second type of crisis, a downside crisis is defined as an episode of sudden unanticipated drops in sovereign spreads, such as may be associated with positive news about the position of a creditor country, for example the successful negotiation of a bailout package. This chapter refers to contagion effects associated with this downside crisis as “good contagion”. Significant evidence of good contagion may potentially be interpreted as positive psychological

effects that are associated with the good news about the source country, whereas bad contagion may be associated with panic.

Market participants are assumed to form one-week-ahead Value-at-Risk forecasts for both the right and the left tail of the distribution, capturing both large increases and decreases in yields. These VaR(α) forecasts are based on a 3 year rolling ARMA(1,1)-EGARCH(1,1) model with conditionally normal residuals. Model parameters were re-estimated every period and all forecasts were formed using the information available at the time of the forecast. These VaR estimates are made at the 95% or 99% confidence levels, as recommended at the time by the Basel Committee for Banking Supervision.

These VaR forecasts form a time-varying threshold for crisis identification. A period of bad contagion can thus be defined as a period in which the estimated VaR for the right tail is breached, ie. a period in which the increase of the yield spread is larger than the forecasted $VaR(\alpha)_{it}$:

$$C_{it}^{bad} = \begin{cases} 1 & \text{if} \quad \Delta y_{it} > VaR(\alpha)_{it} \\ 0 & \text{else} \end{cases} . \tag{3.2}$$

The contagion dummy can also be written as an indicator function I($\Delta y_{it} - VaR_{i,\alpha}$) which takes the value one if the VaR is breached and zero otherwise. In a similar vein, a period of good contagion is defined as a period in which the VaR forecast for the left tail is breached.

3.3.1 Multiple Sources

So far, this chapter has only discussed contagion from a single source. However, in the Eurozone sovereign debt crisis the financial markets seemed to closely follow news about all five periphery countries to infer the stability of the Eurozone, instead of focussing, say, solely on Greece as a source. This makes sense, as it has been described earlier that several of the periphery countries received loans from the Troyka. As such, a good measure for crisis periods in the Eurozone crisis should incorporate this multi-country nature of the crisis. The statistical model used can easily accommodate such a setup in which there are multiple source target countries of contagion. In an alternative definition, crises periods are defined by

$$\tilde{C}_{it}^{bad} = I\left(\sum_{j=1, j\neq i}^{P} I(\Delta y_{it} - VaR_{i,\alpha})\right) \tag{3.3}$$

and

$$\tilde{C}_{it}^{good} = I\left(\sum_{j=1,j\neq i}^{P} I(-\Delta y_{it} - VaR_{i,\alpha})\right) \tag{3.4}$$

In this case, a period is identified as a crisis whenever one of the sources countries is experiencing a crisis, as defined by (4) and (5). Here the source countries include all periphery countries and are indexed from $i \in \{1, \dots, P\}$. The core countries (Austria, Belgium, Finland, France and Netherland) are indexed from $i \in \{(P+1), \dots, N\}$. In the case where the target country is itself a source country, it is excluded from the crisis definition. For the example of, say, Greece a crisis is said to occur if any of the other source countries, excluding Greece itself, is experiencing a crisis.

3.3.2 Control Variables

Several control variables are included to capture potential monsoonal effects. The first two lags of the dependent variable are included as country specific variables. The inclusion of the lagged dependent variables allows for momentum in the yield spreads, potentially created through overreaction/underreaction of the markets to news on the yield spreads. Interaction with other yield spreads in the system is restricted to contemporaneous effects, which is imposed as an identification restriction (see e.g. Favero and Giavazzi, 2002). As the frequency of the data is weekly, a period in which information can be reasonably expected to be incorporated in the respective yield spreads, this identification restriction seems reasonable.

3.3.3 Estimation

The system is estimated country by country using the generalized instrumental variables estimation (GIVE) procedure to consistently estimate the contagion parameters β_i. The crisis indicators C_{it}^{bad} and C_{it}^{good} are instrumented with the lags of the yield spreads. Power series of up to the sixth power are also included to improve the strength of the instruments (see e.g. Pesaran and Pick, 2007). The set of instruments for C_{it}^{bad} and C_{it}^{good} of country $i \in P$ is thus,

$$\boldsymbol{W}_{i,t} = \left[\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t}, \dots, \boldsymbol{w}_{i-1,t}, \boldsymbol{w}_{i+1,t}, \dots, \boldsymbol{w}_{P,t}\right], \tag{3.5}$$

with

$$\boldsymbol{w}_{j,t} = \left[\Delta y_{j,t-1}, \left(\Delta y_{j,t-1}\right)^2, \dots, \left(\Delta y_{j,t-1}\right)^6, \Delta y_{j,t-2}, \left(\Delta y_{j,t-2}\right)^2, \dots, \left(\Delta y_{j,t-2}\right)^6\right]. \tag{3.6}$$

3.4 Data

The centre of the investigation is the weekly 10-year government bond redemption yield spread relative to Germany. Figures 3.1 and 3.2 plot the yield spreads over the sample period. At the beginning of the sample, the spreads are close to zero which is in line with the then prevailing belief that the Eurozone countries were converging and effectively shared the same sovereign risk. Since the start of the crisis, yield spreads have increased significantly with the largest increases seen in the periphery countries (figure 3.1). In the middle of 2011 spreads rose to above 4% for all periphery. Particularly, the spread of Greece demands attention as it has partially risen to level above 40%, a magnitude larger than any of the other spreads in the sample. Figure 3.1 shows that the spreads of the northern countries in the Eurozone were less pronounced than those of the periphery but that there is still substantial variation that was not present before the crisis. The figure also reveals the different stages of the crisis. After an initial spike around 2009, spreads seemed to decrease again, possibly in response to the policy interventions of the EU. However, around the time of the Greece default in 2011 spreads increased significantly and have remained volatile throughout the rest of the sample. A visual inspection of the figure suggests that there may be considerable co-movements between the spreads of different countries, both when yields are dropping and when they are rising, which is suggestive of potential contagion, both good and bad.

Table 3.1 Summary **Statistics.**

	AU	BG	FN	FR	GR	IR	IT	NL	PT	SP	VSTOXX
Mean	0.000	0.001	0.000	0.001	0.009	0.001	0.003	0.000	0.004	0.002	24.602
Median	-0.001	0.000	-0.001	0.000	0.006	-0.001	0.003	0.000	-0.001	0.000	22.425
Maximum	0.477	0.784	0.242	0.359	7.091	1.577	0.759	0.180	2.103	0.713	81.030
Minimum	-0.492	-1.103	-0.259	-0.401	-28.198	-1.919	-1.006	-0.175	-1.730	-1.208	11.160
Std. Dev.	0.066	0.108	0.040	0.063	1.451	0.241	0.163	0.040	0.347	0.180	9.326
Skewness	0.508	-1.059	0.108	-0.077	-13.045	-0.397	-0.342	0.394	0.126	-0.919	2.258
Kurtosis	18.497	28.939	10.840	10.226	263.206	19.536	9.970	6.762	11.334	11.472	10.712

This table reports summary statistics for VSTOXX and the first difference of weekly sovereign bond yield spreads relative to Germany for Austria, Belgium, Finland, France, Greece, Ireland, Italy, Netherlands, Portugal and Spain over the period 05/01/2007 - 30/06/2017.

Figure 3.1 Sovereign Spreads Weekly sovereign bond yield spreads relative to Germany over the period 01/01/2007 to 30/06/2017. Portugal, Ireland, Italy, Greece and Spain (Periphery countries). The Spreads of Greece are on the right hand side scale. Source: DataStream.

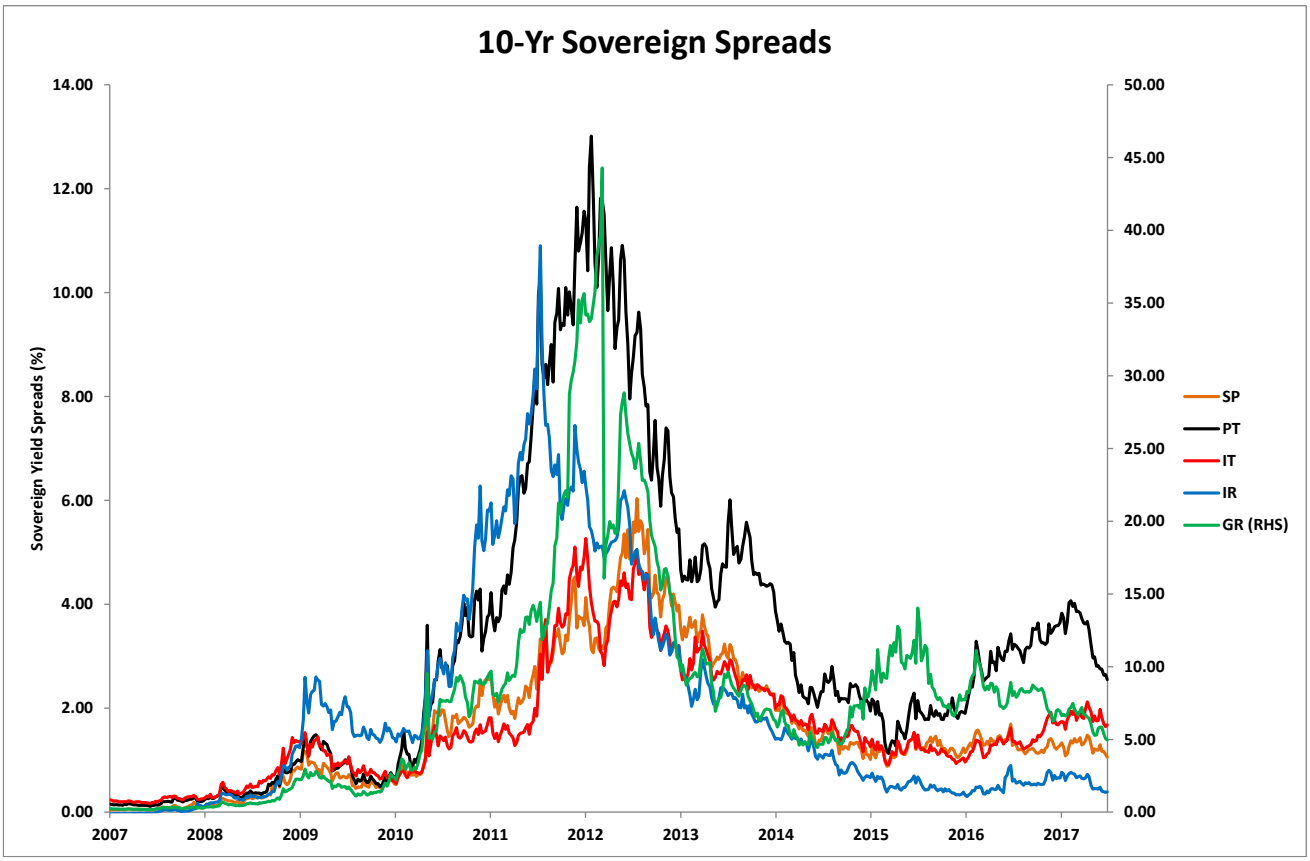
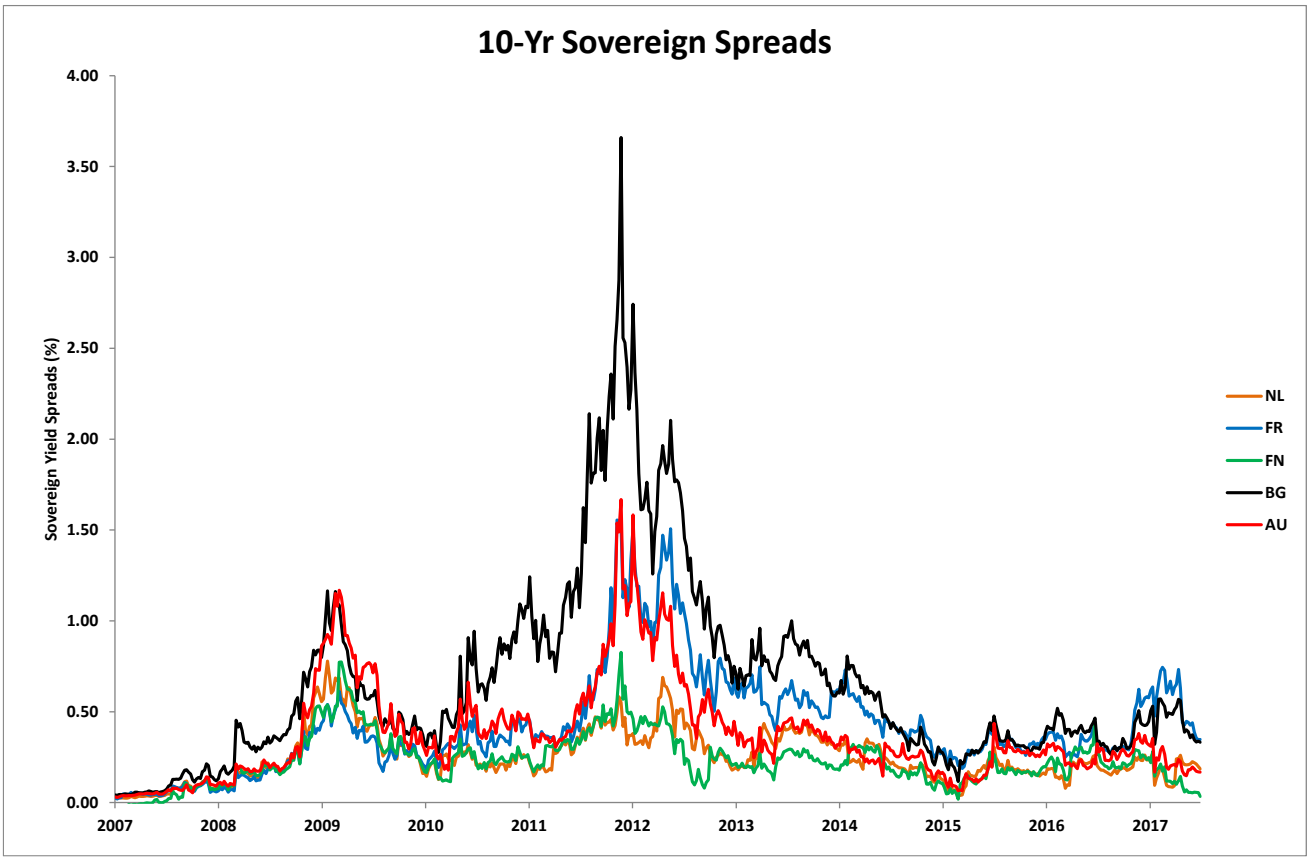


Figure 3.2 Sovereign Spreads Weekly sovereign bond yield spreads relative to Germany over the period 01/01/2007 to 30/06/2017. Austria, Belgium, Finland, France and Netherland (core countries). Source: DataStream.



The Volatility Index (VSTOXX) from the EUREX Exchange, a measure of implied volatility of the Euro Stoxx 50 index options, acts in this study as a control for potential monsoonal effects. This measure, which is used interchangeably with VIX, (they are about 90% correlated) is commonly used in the literature as a proxy for international risk in studies on Euro Area sovereign bond spreads (see e.g. Arghyrou and Kontonikas, 2012). The sample period runs from January 2007 to June 2017. This period starts the year before the bankruptcy of Lehman Brothers and includes the first large emergency loan provided by the ECB in August 2007 in response to initial interbank pressures, thus providing a conservative window covering the sovereign debt crisis. The sample includes 10 Eurozone countries: Austria, Belgium, Finland, France, Greece, Ireland, Italy, the Netherlands, Spain and Ireland. This sample comprises of all original Eurozone countries with the exceptions of Luxembourg and Germany; Luxembourg is excluded from the sample because of data availability, while Germany acts as the benchmark country. All data has been downloaded from DataStream. Table 3.1 contains the summary statistics.

3.5 Results

Consider first the specification

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_{\mathrm{i}} VSTOXX_{i,t} + \beta_i^{\mathrm{bad}} C_{it}^{\mathrm{bad}} + \beta_i^{\mathrm{good}} C_{it}^{\mathrm{good}} + \epsilon_{it}. \qquad (3.7)$$

Where the contagion dummies C_{it}^{bad} and C_{it}^{good} capture crises periods in any of the source countries as defined by equations (3.3) and (3.4), the lags of the dependent variables are included as control variables and the VSTOXX index captures observed common factors (monsoonal effects). The VSTOXX is a commonly used proxy for European risk aversion (often used interchangeably with the VIX a measure of global risk aversion), one of the most important common factors determining yield spreads.

Positive and statistically significant values of $\beta_{\mathrm{i}}^{\mathrm{bad}}$ are indicative of bad contagion, i.e. an originally non-crisis country being on the receiving end of the propagation of extreme negative shocks or duplication of crisis, after another country with which it might have substantial financial and economic linkages, has suffered an extreme negative shock episode: i.e. the sovereign yields of non-crisis countries are adversely affected, which leads to a sudden spike in their yields, making it more expensive to service their debt obligations and more likely to default.

Negative and statistically significant values of $\beta_{\mathrm{i}}^{\mathrm{bad}}$ can be interpreted as flight to quality. In the case of flight to quality, market participants move their money out of markets in crisis countries/markets into what they perceive to be safe haven markets, thus significantly reducing the yields of these safe havens during crisis periods. This would lead to a negative coefficient for the bad contagion variable. Theoretically a similar phenomenon could happen during good contagion periods, where market participants put their money back into the perceived risky countries upon seeing good news about those countries (i.e a reversal of flight to quality or a reduction of the risk premium the market ascribes to hitherto risky countries which reflects by way of relatively lower sovereign debt redemption yields. This makes it cheaper for the beneficiary countries to service their debt and reduces the likelihood of sovereign default where it has not already occurred), which would lead to positive coefficients for the good contagion variable. Negative values for $\beta_{\mathrm{i}}^{\mathrm{good}}$, on the other hand, are indicative of the presence of good contagion. Positive and significant values for $\delta_{\mathrm{i}} VSTOXX_{i,t}$ demonstrate that monsoonal effects have been captured.

Table 3.2 Contagion (Joint Periphery Countries as Source, 5% VaR)

	AU		BG		FN		FR		NL		GR		IR		IT		PT		SP	
$VSTOXX$	0.006	***	0.015	***	0.003	***	0.008	***	0.005	***	0.014		0.033	***	0.030	***	0.035	***	0.025	***
	(0.002)		(0.003)		(0.001)		(0.002)		(0.001)		(0.050)		(0.009)		(0.006)		(0.011)		(0.006)	
C^{bad}	0.014		0.080	*	0.006		-0.002		-0.002		-0.434		0.004		-0.206	**	0.184		-0.089	
	(0.028)		(0.046)		(0.017)		(0.026)		(0.017)		(1.024)		(0.132)		(0.100)		(0.187)		(0.092)	
C^{good}	-0.070	***	-0.111	***	-0.023	**	-0.063	***	-0.017		-1.261	***	-0.229	***	-0.151	***	-0.265	***	-0.266	***
	(0.017)		(0.029)		(0.010)		(0.016)		(0.011)		(0.454)		(0.078)		(0.056)		(0.096)		(0.052)	
g	0.702		0.686		0.677		0.699		0.683		0.384		0.616		0.550		0.511		0.679	

This table reports the GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i VSTOXX_{i,t} + \beta_i^{\text{bad}} C_{it}^{\text{bad}} + \beta_i^{\text{good}} C_{it}^{\text{good}} + \epsilon_{it}$. The dependent variables are the sovereign yield spreads of Austria, Belgium, Finland, France, Ireland, Italy, Netherlands, Portugal and Spain over the period 05/01/2007 - 30/06/2017. *VSTOXX* is a measure of European risk aversion. C_{it}^{bad} indicates upwards (bad) contagion, C_{it}^{good} downwards (good) contagion. All periphery countries are included as source countries. Standard errors are reported in brackets under the coefficient estimates. g is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

∗ Similar results are obtained when VSTOXX is replaced with VIX as control variable for monsoonal effects.

Table 3.3 Contagion (Joint Periphery Countries as Source, 5% VaR) Split Sample

January 2007 - June 2012

	AU		BG		FN		FR		NL		GR		IR		IT		PT		SP	
$VSTOXX$	0.008	***	0.023	***	0.004	***	0.010	***	0.004	***	0.124	*	0.032	***	0.027	***	0.009		0.028	***
	(0.003)		(0.005)		(0.001)		(0.002)		(0.001)		(0.066)		(0.010)		(0.006)		(0.013)		(0.006)	
C^{bad}	-0.003		0.114	*	0.005		-0.026		-0.009		0.372		0.237	*	0.114		0.781	***	0.091	
	(0.033)		(0.060)		(0.017)		(0.031)		(0.018)		(1.478)		(0.143)		(0.087)		(0.214)		(0.090)	
C^{good}	-0.089	***	-0.146	***	-0.035	***	-0.068	***	-0.031	**	-2.403	***	-0.510	***	-0.190	***	-0.264	**	-0.184	***
	(0.023)		(0.042)		(0.012)		(0.021)		(0.013)		(0.565)		(0.119)		(0.056)		(0.119)		(0.057)	
g	0.598		0.596		0.605		0.603		0.601		0.481		0.642		0.667		0.633		0.725	

June 2012 - June 2017

	AU		BG		FN		FR		NL		GR		IR		IT		PT		SP	
$VSTOXX$	0.002		0.001		0.001		0.001		0.002		0.072	**	0.007		0.015	**	0.045	***	0.018	**
	(0.002)		(0.002)		(0.001)		(0.002)		(0.001)		(0.035)		(0.005)		(0.006)		(0.011)		(0.008)	
C^{bad}	0.027	*	0.036	*	0.012		0.038	**	0.023	*	1.143	***	0.057		0.030		0.288	**	0.126	*
	(0.016)		(0.019)		(0.013)		(0.018)		(0.013)		(0.339)		(0.058)		(0.057)		(0.118)		(0.072)	
C^{good}	-0.027	**	-0.061	***	-0.011		-0.046	***	0.005		-0.453	*	-0.167	***	-0.218	***	-0.203	**	-0.192	***
	(0.012)		(0.015)		(0.010)		(0.014)		(0.010)		(0.244)		(0.039)		(0.044)		(0.088)		(0.049)	
g	0.566		0.577		0.571		0.572		0.552		0.515		0.444		0.555		0.499		0.552	

This table reports the GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i VIX_t + \sum \beta_{i,j}^{\text{bad}} C_{it}^{\text{bad}} + \sum \beta_{i,j}^{\text{good}} C_{i,j,t}^{\text{good}} + \epsilon_{it}$.

The dependent variables are the sovereign yield spreads of Austria, Belgium, Finland, France, Ireland, Italy, Netherlands, Portugal and Spain over the period 05/01/2007 - 05/06/2012 and 08/06/2012 - 30/06/2017 respectively. *VSTOXX* is a measure of European risk aversion. C_{it}^{bad} indicates upwards (bad) contagion, C_{it}^{good} downwards (good) contagion. The periphery countries are included as source countries individually. Standard errors are reported in brackets under the coefficient estimates. g is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

∗ Similar results are obtained when VSTOXX is replaced with VIX as control variable for monsoonal effects.

Table 3.4 Contagion (Individual Periphery Countries as Source, 5% VaR)

	AU		BG		FN		FR		NL		GR		IR		IT		PT		SP	
$VSTOXX$	0.005	*	0.012	***	0.003	*	0.007	***	0.004	***	0.051		0.032	***	0.019	**	0.020		0.017	**
	(0.003)		(0.005)		(0.001)		(0.002)		(0.001)		(0.076)		(0.011)		(0.008)		(0.019)		(0.008)	
GR^{bad}	-0.038		0.005		-0.008		-0.044		-0.003				0.183		-0.092		1.065	***	0.015	
	(0.046)		(0.088)		(0.027)		(0.042)		(0.027)				(0.199)		(0.150)		(0.412)		(0.161)	
GR^{good}	-0.048		-0.108		-0.013		-0.066	*	-0.006				-0.002		-0.144		-0.427		-0.131	
	(0.041)		(0.079)		(0.024)		(0.037)		(0.024)				(0.153)		(0.130)		(0.318)		(0.131)	
IR^{bad}	0.075		0.374	**	0.062		0.077		-0.045		-5.727	**			0.187		-1.501	*	-0.349	
	(0.084)		(0.157)		(0.048)		(0.075)		(0.049)		(2.561)				(0.230)		(0.793)		(0.328)	
IR^{good}	-0.003		0.021		0.001		-0.005		-0.006		-3.492	***			0.135		-0.187		0.125	
	(0.031)		(0.059)		(0.018)		(0.028)		(0.018)		(0.869)				(0.100)		(0.236)		(0.113)	
IT^{bad}	0.041		-0.241		-0.007		0.022		0.043		1.459		-0.265				-0.356		-0.218	
	(0.108)		(0.204)		(0.062)		(0.097)		(0.063)		(3.693)		(0.573)				(0.888)		(0.396)	
IT^{good}	0.034		0.076		0.056	*	-0.033		0.013		2.234		0.178				0.140		-0.567	***
	(0.050)		(0.095)		(0.029)		(0.045)		(0.029)		(1.543)		(0.211)				(0.411)		(0.130)	
SP^{bad}	-0.069		-0.060		-0.011		-0.018		-0.038		1.528		0.154		-0.013		1.097			
	(0.080)		(0.150)		(0.047)		(0.072)		(0.048)		(2.751)		(0.325)		(0.239)		(0.706)			
SP^{good}	-0.136	***	-0.343	***	-0.081	***	-0.060		-0.051	*	-0.556		-0.213		-0.215	*	-0.036			
	(0.052)		(0.099)		(0.030)		(0.048)		(0.030)		(1.542)		(0.222)		(0.119)		(0.417)			
PT^{bad}	0.057		0.044		0.012		-0.074		0.067		0.470		-0.144		-0.468	*			0.066	
	(0.093)		(0.176)		(0.056)		(0.085)		(0.025)		(2.988)		(0.555)		(0.282)				(0.340)	
PT^{good}	-0.035		0.016		0.002		-0.022		0.007		2.051		-0.630	***	-0.448	***			-0.585	***
	(0.043)		(0.082)		(0.025)		(0.039)		(0.025)		(1.397)		(0.169)		(0.132)				(0.175)	
g	0.208		0.216		0.210		0.208		0.204		0.188		0.121		0.236		0.174		0.203	

This table reports the GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \sum\beta_{i,j}^{\text{bad}}\mathcal{C}_{it}^{\text{bad}} + \sum\beta_{i,j}^{\text{good}}\mathcal{C}_{i,j,t}^{\text{good}} + \epsilon_{it}$. The dependent variables are the sovereign yield spreads of Austria, Belgium, Finland, France, Ireland, Italy, Netherlands, Portugal and Spain over the period 05/01/2007 - 30/06/2017. *VSTOXX* is a measure of European risk aversion. $\mathcal{C}_{it}^{\text{bad}}$ indicates bad contagion, $\mathcal{C}_{it}^{\text{good}}$ good contagion. The periphery countries are included as source countries individually. Standard errors are reported in brackets under the coefficient estimates. g is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

∗ Similar results are obtained when VSTOXX is replaced with VIX as control variable for monsoonal effects.

Table 3.2 presents the results of the equation 3.7 using the full data sample. There is significant evidence of both bad contagion and good contagion. There is however dichotomy between the numbers of countries affected by good contagion versus bad contagion are strikingly different. Bad contagion is only present for Belgium, a core country. This result partly corroborates the findings of Arghyrou and Kontonikas (2012) who also find that Belgium was affected by bad contagion during the EMU sovereign debt crisis, in their case only originating from Greece. The bad contagion coefficient for Italy is statistically significant, albeit with a negative sign on the coefficient. This is contrary to the apriori expectation for contagion to be confirmed and appears to be a reverse or inverse contagion effect i.e crisis triggered flight to quality effect captured through counter intuitive but statistically significant contagion indicators which fundamentals cannot explain.

On the other hand, all periphery countries were exposed to significant good contagion and four out of five core countries have benefited from good contagion, excluding the Netherlands only.

In terms of economic significance, the periphery countries also stand out from the other EMU countries. Looking at the average absolute size of the contagion coefficients, the periphery countries saw an average increase of 23 basis points decrease during good contagion episodes, whilst the other EMU countries only saw adjustments of 5 basis points, indicating that qualitatively the periphery countries were much more affected by contagion (in this case good contagion), than their core counterparts. From Table 3.2, there is evidence that monsoonal effects were captured through the VSTOXX index in all countries except Greece.

Table 3.3 present results that split the full 10-year sample into two sets of 5 years. This provides a layer of robustness around possible sample selection bias. The first half of the split is from January 2007 to June 2012 while the second half is from June 2012 to June 2017. Results from the first half are similar to table 3.2 results, as there is evidence of good contagion affecting all periphery and core countries investigated, including Netherlands which was previously not affected. In line with table 3.2, table 3.3 first half results show that Belgium is affected by bad contagion; Portugal and Ireland are also affected by bad contagion.

Results from the second half of the sample split follow suit with table 3.2 and the table 3.3 first half as all periphery countries are affected by good contagion. For core countries, only Netherlands and Finland are not affected by good contagion. Bad contagion effects are more rampant in the second half results as 3 out 5 periphery countries (Greece and Portugal, Spain) and 4 out of 5 core countries (Austria, Belgium, France and Netherlands) are affected. As in table 3.2 and table 3.3 first half results, coefficients in table 3 second half results for both good and bad contagion are much larger for periphery than core countries.

The aggregate results from tables 3.2 and 3.3 are very promising in that they have established that both good and bad contagion effects are present in the EMU sovereign debt crisis. However, the results also raise some further questions. Did the contagion originate from any particular source country, say Greece? or have news shocks from all periphery countries been similarly contributing to contagion during the crisis? To answer these questions the specification is extended to include crisis indicators for each of the periphery countries individually.

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i VSTOXX + \sum \beta_{i,j}^{\text{bad}} C_{it}^{\text{bad}} + \sum \beta_{i,j}^{\text{good}} C_{i,j,t}^{\text{good}} + \epsilon_{it}. \qquad (3.8)$$

Table 3.5 Contagion (Individual Periphery countries as Source, 5% VaR) Split Sample

Table 3.5a: January 2007 to June 2012

	AU		BG		FN		FR		NL		GR		IR		IT		PT		SP	
$VSTOXX$	0.007	***	0.019	***	0.004	**	0.009	***	0.004	***	0.171	**	0.039	**	0.017	***	0.002		0.023	***
	(0.003)		(0.005)		(0.001)		(0.003)		(0.001)		(0.081)		(0.018)		(0.006)		(0.016)		(0.006)	
GR^{bad}	-0.057		-0.040		-0.006		-0.051		-0.021				0.147		0.020		0.979	***	0.020	
	(0.043)		(0.077)		(0.022)		(0.040)		(0.021)				(0.300)		(0.106)		(0.273)		(0.107)	
GR^{good}	0.010		-0.098		0.025		-0.035		0.019				-0.499		0.001		-0.321		-0.207	
	(0.071)		(0.128)		(0.036)		(0.067)		(0.036)				(0.382)		(0.159)		(0.427)		(0.164)	
IR^{bad}	0.178		0.999	***	0.174	**	0.101		0.040		-3.387				0.695	**	-0.261		0.420	
	(0.139)		(0.237)		(0.068)		(0.127)		(0.064)		(4.245)				(0.332)		(0.782)		(0.489)	
IR^{good}	-0.021		0.014		-0.009		-0.007		0.005		-4.900	***			0.106		-0.352	*	0.182	*
	(0.038)		(0.069)		(0.020)		(0.036)		(0.019)		(0.979)				(0.093)		(0.192)		(0.096)	
IT^{bad}	0.196		-0.047		0.159		-0.225		0.106		-6.000		-3.276	*			-2.193	*	-0.300	
	(0.221)		(0.400)		(0.118)		(0.210)		(0.113)		(6.212)		(1.874)				(1.208)		(0.620)	
IT^{good}	0.024		-0.045		0.058	**	0.001		-0.004		0.623		-0.177				0.784	**	-0.520	***
	(0.059)		(0.104)		(0.029)		(0.053)		(0.028)		(1.755)		(0.354)				(0.310)		(0.116)	
SP^{bad}	-0.143		-0.168		-0.021		0.022		0.013		5.322		1.888		-0.407		0.181			
	(0.172)		(0.310)		(0.088)		(0.163)		(0.086)		(5.778)		(1.384)		(0.406)		(1.030)			
SP^{good}	-0.202	***	-0.345	***	-0.101	***	-0.125	**	-0.060	**	-0.042		0.035		-0.472	***	-0.832	***		
	(0.053)		(0.095)		(0.027)		(0.048)		(0.025)		(1.729)		(0.316)		(0.098)		(0.301)			
PT^{bad}	0.191	**	0.369	**	-0.002		0.024		0.009		1.335		0.439		0.154				0.167	
	(0.087)		(0.157)		(0.046)		(0.081)		(0.026)		(2.543)		(0.709)		(0.225)				(0.234)	
PT^{good}	-0.016		0.025		-0.020		-0.011		-0.042		2.799	*	-0.877	***	-0.289	**			-0.331	**
	(0.052)		(0.095)		(0.027)		(0.049)		(0.026)		(1.587)		(0.303)		(0.114)				(0.133)	
g	0.109		0.108		0.109		0.104		0.101		0.094		0.070		0.114		0.108		0.148	

This table reports the GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \sum\beta_{i,j}^{\text{bad}}C_{it}^{\text{bad}} + \sum\beta_{i,j}^{\text{good}}C_{i,j,t}^{\text{good}} + \epsilon_{it}$. The dependent variables are the sovereign yield spreads of Austria, Belgium, Finland, France, Ireland, Italy, Netherlands, Portugal and Spain over the period 05/01/2007 - 05/06/2012 and 08/06/2012 - 30/06/2017. *VSTOXX* is a measure of European risk aversion. C_{it}^{bad} indicates bad contagion, C_{it}^{good} good contagion. The periphery countries are included as source countries individually. Standard errors

are reported in brackets under the coefficient estimates. *g* is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

∗ Similar results are obtained when VSTOXX is replaced with VIX as control variable for monsoonal effects.

Table 3.5b: June 2012 to June 2017

	AU	BG	FN	FR	NL	GR	IR	IT	PT	SP
$VSTOXX$	0.004	0.003	0.000	0.000	0.002	0.056	0.005	0.013	0.036 ***	0.018
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.047)	(0.007)	(0.008)	(0.013)	(0.011)
GR^{bad}	-0.043	-0.021	0.026	0.010	-0.022		-0.007	0.057	0.048	-0.002
	(0.046)	(0.044)	(0.032)	(0.043)	(0.034)		(0.120)	(0.127)	(0.266)	(0.171)
GR^{good}	-0.002	-0.042 *	-0.017	-0.031	-0.018		-0.118 **	-0.013	-0.294 **	0.016
	(0.024)	(0.023)	(0.017)	(0.022)	(0.017)		(0.054)	(0.079)	(0.135)	(0.098)
IR^{bad}	0.076 **	0.032	0.040	0.064 *	0.019	1.086 **		0.140	0.308	0.110
	(0.035)	(0.034)	(0.025)	(0.033)	(0.025)	(0.520)		(0.112)	(0.211)	(0.137)
IR^{good}	-0.011	-0.047	-0.017	-0.034	0.013	-0.332		-0.140	0.254	0.065
	(0.032)	(0.030)	(0.022)	(0.029)	(0.023)	(0.426)		(0.086)	(0.197)	(0.129)
IT^{bad}	0.051	0.021	-0.015	-0.003	0.049	0.959	0.102		0.011	0.032
	(0.050)	(0.048)	(0.035)	(0.047)	(0.036)	(0.731)	(0.119)		(0.306)	(0.226)
IT^{good}	-0.054 *	-0.062 **	-0.003	-0.044	-0.002	-0.079	-0.146 *		-0.192	-0.386 ***
	(0.031)	(0.029)	(0.021)	(0.028)	(0.022)	(0.424)	(0.075)		(0.198)	(0.109)
SP^{bad}	0.020	0.001	-0.039	-0.003	-0.015	0.183	0.054	0.086	0.229	
	(0.037)	(0.037)	(0.027)	(0.035)	(0.027)	(0.652)	(0.104)	(0.121)	(0.203)	
SP^{good}	0.036	-0.010	-0.009	0.004	-0.021	-0.069	-0.012	-0.232 **	-0.240	
	(0.030)	(0.029)	(0.022)	(0.029)	(0.022)	(0.418)	(0.080)	(0.091)	(0.192)	
PT^{bad}	-0.088	-0.036	0.016	-0.018	0.001	0.039	-0.104	-0.261		-0.206
	(0.057)	(0.056)	(0.041)	(0.054)	(0.030)	(1.104)	(0.135)	(0.184)		(0.229)
PT^{good}	0.019	-0.007	-0.001	-0.042	0.048	-0.949	-0.221 **	-0.289 **		-0.479 ***
	(0.043)	(0.040)	(0.029)	(0.039)	(0.030)	(0.674)	(0.102)	(0.127)		(0.172)
g	0.147	0.149	0.147	0.149	0.139	0.122	0.164	0.179	0.176	0.202

This table reports the GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \sum\beta_{i,j}^{\text{bad}}\mathcal{C}_{it}^{\text{bad}} + \sum\beta_{i,j}^{\text{good}}\mathcal{C}_{i,j,t}^{\text{good}} + \epsilon_{it}$. The dependent variables are the sovereign yield spreads of Austria, Belgium, Finland, France, Ireland, Italy, Netherlands, Portugal and Spain over the period 05/01/2007 - 05/06/2012 and 08/06/2012 - 30/06/2017. *VSTOXX* is a measure of European risk aversion. $\mathcal{C}_{it}^{\text{bad}}$ indicates bad contagion, $\mathcal{C}_{it}^{\text{good}}$ good contagion. The periphery countries are included as source countries individually. Standard errors

are reported in brackets under the coefficient estimates. g is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

∗ Similar results are obtained when VSTOXX is replaced with VIX as control variable for monsoonal effects.

Table 3.4 contains full sample contagion results specified on a country-by-country basis. These results show a much more nuanced picture than the aggregate results.

Table 3.4 continues to corroborate tables 3.2 and 3.3 with respect to bad contagion effects to Belgium and Portugal. The results show Greece as a source of bad contagion to Portugal and Ireland as a source of bad contagion to Belgium.

The source of good contagion is also revealing: the main source of good contagion is Spain, and to a smaller extent, Portugal. Spain appears to be a source of good contagion mainly to core countries (Austria, Belgium, Finland, Netherlands and Italy.) while Portugal's good contagion effect is limited to periphery countries (Ireland, Italy and Spain); Greece does not appear to have benefitted from any good contagion effects. A potential explanation for this result is the idea that after the default of

Greece, Spain was perceived by many market participants to be in the line of fire. Furthermore, the size of the Spanish economy relative to that of the entire EU means that a potential default in Spain would be considerably more damaging to the rest of the union than further adverse events in Greece. Thus, good news originating from Spain may cause greater psychological effects in the markets than good news from other markets.

Good contagion in a crisis period might seem counter intuitive, it signifies a sharp reversal in the propagation of extreme negative shocks beyond what fundamentals can explain or predict which has the effect of wholly or partially taking an extreme negative shocks episode/crises towards normalcy.

With respect to Spain and in the context of the EMU sovereign crisis of 2010, good contagion is the Propagation of extreme positive shocks during a contagious sovereign crisis period, causing a sharp decline in yield spreads which fundamentals cannot explain or justify i.e relative confidence is suddenly restored to the affected markets.

Similar to table 3.3, table 3.5 present split sample results for table 3.4. In Table 3.5a (first half results), Portugal suffers bad contagion from Greece in line with table 3.4. Belgium and Finland also suffer bad contagion from Ireland. In terms of good contagion, Spain remains a source of good contagion to all core countries and two periphery countries (Italy and Portugal), whilst Portugal is a source of good contagion to all other periphery countries, its impact remains limited to within the periphery sub zone. Table 3.5b (second half results) deviate substantially from the trend of results seen from tables 3.2 to up until table 3.5 first half, apart from the fact that Portugal remains a source of good contagion to Ireland, Italy and Spain.

3.6 Conclusion

This chapter introduces the notion of good contagion, as opposed to just bad contagion, which is normally considered in the contagion literature. This chapter's framework is applied to the EMU sovereign debt crisis. Using a system of non-linear simultaneous equations, the model endogenously determines both the timing of crisis and the source country of a crisis event. All periphery (Greece, Italy, Ireland, Portugal, and Spain) act as potential source countries of contagion within the EMU area. Results suggest that, indeed, both good and bad contagion have occurred in the EMU sovereign risk crisis. The periphery countries, most especially Portugal, have suffered from bad contagion, and almost all countries (including most core countries) have benefitted from good contagion; in terms of

economic significance. It is clear from the results that the periphery countries experienced a larger effect of contagion (both good and bad) relative to the core EMU countries.

This chapter also shows that Greece is not the only source of contagion. Indeed, looking at the contribution of the individual periphery countries this chapter identifies Ireland as another source of bad contagion and Spain as a main source of good contagion. The fact that Spain is confirmed as a source of good contagion implies that policy makers could ameliorate systemic crisis by targeting policy intervention to one or more systemically important countries which could then further propagate the relief effect to other affected countries or countries at risk.

Portugal is another source of good contagion, but its effects are mainly limited to within the periphery countries. A potential explanation of this finding is that Spain is a much larger economy than Greece and failure of Spain would have much larger effects on the euro economy than the failure of Greece. Hence, good news about Spain might be reasonably expected to affect a wide range of Eurozone countries, whereas good news about Greece might be interpreted by markets as a proxy on the overall health of the periphery countries. Thus, this chapter qualifies the role of Greece in the current sovereign debt crisis and disputes the general perception that Greece was the only source of contagion.

The finding of good contagion shows that contagion effects are not only limited to negative crises but can also occur at the other extreme. As most of the literature exclusively focuses on finding contagion (or the absence of it) during bad episodes, they may have missed episodes of good contagion.

Chapter 4

Contagion in Commodities Markets

4.1 Introduction

The increasing connectivity and vulnerability of financially inclined/structured markets was again brought to the fore as a number of such markets experienced crisis between 2007 and 2010. Surprisingly, the exchange traded commodities markets (a market mainly designed for big producers and suppliers of essential commodities to trade and manage risk) was among those affected (commodities market crash of 2008). Joint commodity market crashes had not happened in recent history as the traded commodities market complex was a community of unique commodities markets with different fundamentals. Prior to the 2000's, commodities prices were not observed to co-move substantially with each other. The price of each commodity was therefore mainly driven by its own unique supply and demand fundamentals (Gorton and Rouwenhorst, 2006). This is in contrast with conventional financial markets where returns only carried premium for systemic risk and prices co-moved with each other even when they shared little fundamentals (Erb and Harvey, 2006). Tang and Xiong (2012) report increased correlation between energy and non-energy commodities markets.

Figure 4.1 Graph of daily spot price indices for Dow Jones-UBS commodity index and CRB commodity index respectively over the period 01/01/1999 - 01/03/2013.

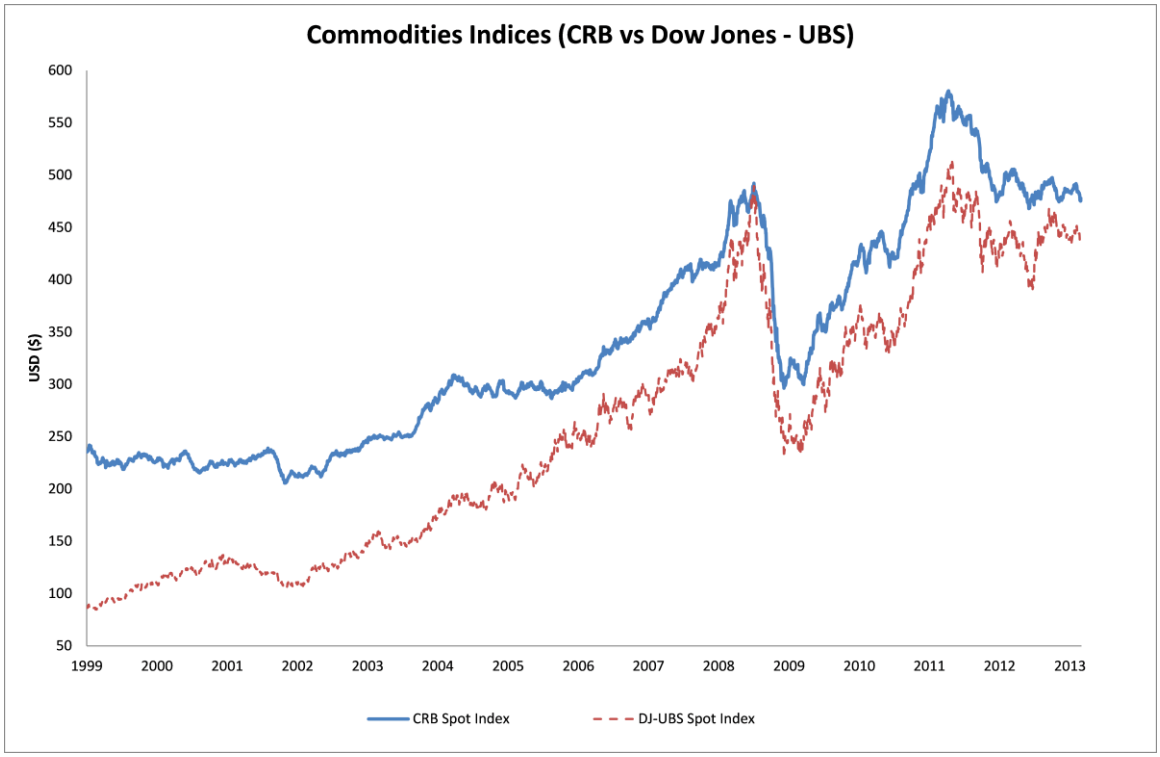
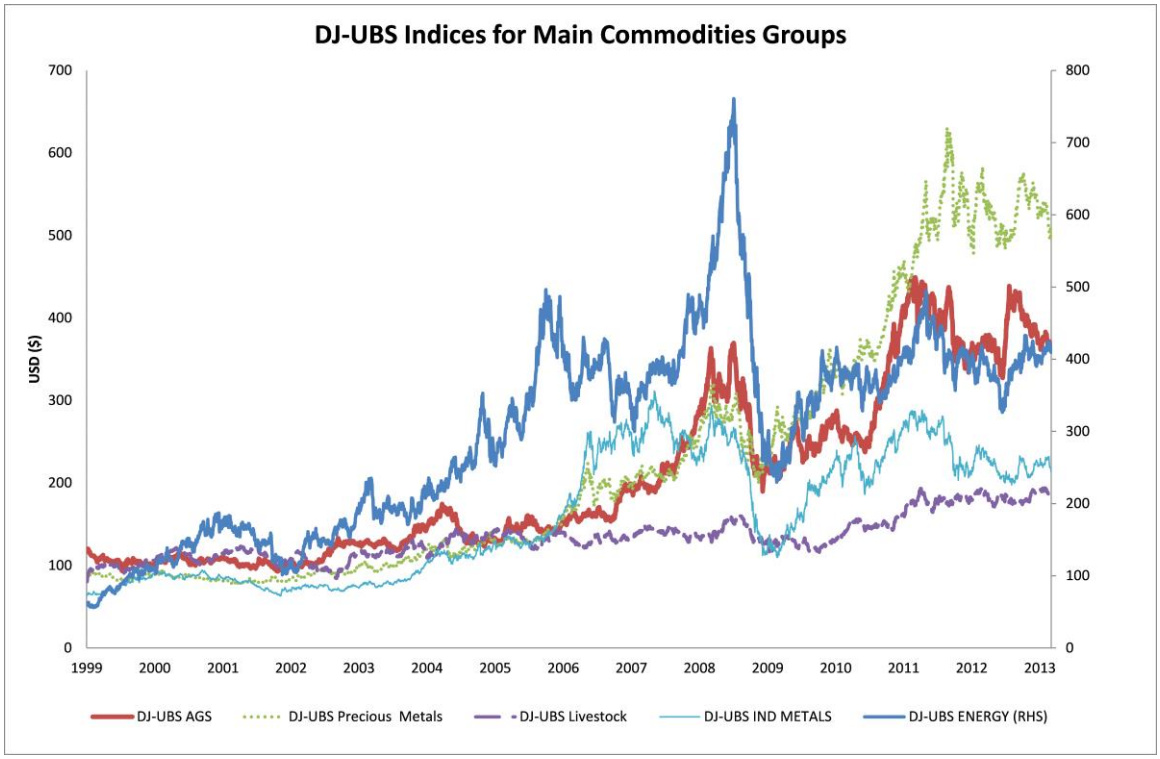


Figure 4.2 Graph of daily Dow Jones-UBS commodity spot indices for agriculture, energy, industrial metals, livestock, and precious metals over the period 01/01/1999- 01/03/2013.



From Figures 4.1 and 4.2, it is clear that from the early 2000's up until 2008, three major features defined the exchange traded commodities markets complex: higher correlation/co-movement, higher volatility and higher prices. These three features became particularly clear between 2006 and 2008 when the commodities markets experienced a co-boom which started in 2006 and a co-burst/joint price collapse which occurred in 2008.

Before now, an empirical investigation on contagion between various commodities markets with respect to the exchange traded commodities complex is not widely known to have been conducted within the empirical literature. In particular, this thesis has not identified other publications or studies which empirically examines the commodities market crash of 2008, to ascertain whether it was a result of contagion or other crisis period effects identified in the empirical literature such as interdependence; as in King and Wadwhani (1990), or monsoonal effects; as in Masson (1999) etc.

As discussed in chapter 1, financial contagion studies are usually related to the banking system and stock markets. More recently, on the back of the EMU sovereign crisis, a number of publications looking at sovereign contagion have also been added to the literature (for example Arghyrou and Kontonikas, 2010 and Caceres et al., 2010). The empirical literature has also mainly ascribed contagion to be between country or region specific markets such as equity, currency and bond markets but is yet to empirically consider contagion between markets which are not bound by

national borders (or structured in the dimension of nations/regions) such as exchange traded commodities markets, where each commodity market is global but different from the other.

Using the Pesaran and Pick (2007) empirical framework which is based on non-linear simultaneous equations, this chapter investigates the occurrence of the contagion phenomenon within the exchange traded commodities market complex, between log returns of DJ-UBS commodity market indices for major traded commodities groups (agriculture, energy, industrial metals, livestock, and precious metals) and between log returns of DJ-UBS indices for 18 major individual exchange traded commodities from January 1999 to February 2013.

This chapter enhances the empirical debate on contagion in the following ways. Firstly, the presence of both good and bad contagion effects within exchange traded commodities markets is reiterated and the fact that contagion effects can be explored or investigated in markets that are not region specific such as commodities markets is clearly demonstrated. Secondly, industrial metals and energy are found to be the most systemically important source of contagion within the exchange traded commodities complex. Thirdly, this chapter draws the attention of the empirical literature to another possible effect to look out for in/after an extreme shocks episode: reverse contagion. This chapter defines reverse contagion as the propagation of extreme shocks that are opposite in sign from one market to another beyond the interdependence regime of shock transmission which fundamentals cannot explain e.g. a negative tail event/crash in one market causes a positive tail event in another. The results in this chapter empirically corroborate the financialization of commodities markets; stronger synchronization of commodities markets is found to be widespread especially within the industrial metals sub complex. Given that the results in this chapter provide insight into the patterns of tail risk vulnerability within the exchange traded commodities complex, traders and commodities fund managers should find them useful in informing their marginal value at risk rules.

The chapter is organized as follows. Section 2 presents a review of the literature on contagion risk. Section 3 explains the estimation framework. Section 4 describes the data. Section 5 sets out the main results and section 6 Concludes.

4.2 Literature Review

4.2.1 Contagion

As discussed in chapter 2, the literature on financial contagion is vast and as such there are numerous definitions and no consensus on what the contagion phenomenon precisely represents. For example, Dornbusch et al. (2000) and Dungey et al. (2010) consider contagion simply as a spread of negative market disturbances. In another strain of literature, Eichengreen et al. (1996) define contagion as a situation that occurs when the probability of crisis in a country at a point in time is correlated with the incidence of crises in other countries at the same time, after controlling for the effects of political and economic fundamentals. In a similar manner, Ait-Sahalia et al. (2010) refer to contagion as cross-region transmission of shocks and an increase in the likelihood of successive shocks in the countries affected after an initial shock.

This chapter follows the second group of definitions discussed in chapter 2 such as Masson (1999) who defines contagion in terms of regime switches. This chapter defines contagion as an extreme departure from the interdependence regime of shock transmission between two or more markets which fundamentals cannot explain or predict. This implies a significant increase in cross market co-movement after a shock to one country (Forbes and Rigobon, 2002). Particularly, this chapter follows the measure of contagion proposed in Pesaran and Pick (2007); they define contagion as a jump between equilibria causing a largely unpredictable, higher correlation between markets during crises compared to normal times. To test for contagion, Pesaran and Pick (2007) use GIVE (Generalized Instrumental Variable Estimation) and endogenize crisis identification through a threshold mechanism. Their framework also allows for the introduction of both good and bad contagion.

The definitions of contagion used in this chapter are more dynamic as they view contagion in the light of regime switches, and importantly distinguish contagion from interdependence and monsoon effects. Interdependence is defined as the level of integration between markets present in normal times. Monsoon effects refer to a coincidence of crisis in different markets as a result of common global shocks (Masson, 1999).

As discussed in chapter 1, contagion remains a reoccurring feature in the contemporary global financial system. For example, the 1987 spread of shocks/crisis to markets in Europe and America from Hong Kong (King and Wadhwani, 1990), the East Asian currency crisis (e.g Forbes and Rigobon, 2002; Corsetti et al.,2005) and contagion during the ERM crisis (e.g. Favero and Giavazzi, 2002; Pesaran and Pick, 2007). More recently, Pais and Stork (2011) investigate banking contagion at the onset of the 2008 credit crisis while Arghyrou and Kontonikas (2012) examine contagion during the EMU sovereign debt crisis.

4.2.2 Commodities Markets Developments and Financialization

Since the early 2000's, commodities markets have been defined by three main features; higher prices, higher volatility and higher level of co-movement with each other (three defining features hereafter). There is no agreement in the literature on the key drivers of the three defining features. As such, the main drivers of the three defining features is a heavily debated point in the literature.

It appears that there are three main schools of thought on the drivers for the three defining features mention earlier/above. Tang and Xiong (2012), Hong and Yogo (2009) also report that there is no consensus in the literature as to the main driver of increased volatility in commodities prices/within the commodities complex since the early 2000's

The first school of thought considers the three defining commodity market features and the commodities co-boom and co-burst as being mainly driven by economic expansion and contraction in emerging markets. Krugman (2008) and Hamilton (2009) believe that the rise in commodities prices especially from 2006 was a function of higher commodities demand and supply fundamentals consistent with faster growth/industrial expansion in China and India while the price collapse in 2008 was a manifestation of recession by way of sharp decline in the demand for commodities. From Cheng et al. (2015) hedging demand might also be a key upward driver of prices.

The second school of thought believes that the three defining commodity market features are caused by a variety of factors. Baffes and Hanniotis (2010) posit that the price boom and burst of 2006-2008 is among other things fuelled by strong economic growth, low past investment in extractive commodities, weak United States dollar, fiscal expansion, lax monetary policy and speculative investment fund activity (index investment). Irwin et al. (2009) also believe that the three defining commodity market features are caused by a differentiated mix of factors: emerging markets growth, stagnating oil supply growth, lower consumer responsiveness to higher prices etc. Baffes and Haniotis (2010) also believe that the three defining commodity market features, especially for agricultural commodities, were driven by adverse weather and the diversion of some food commodities into biofuel.

The third school of thought posits that the three defining commodity market features are mostly driven by speculative fund flow into commodities markets. Tang and Xiong (2012) report that price co-movements between commodities picked up in 2004 when the flow of index investments into commodities was already in full swing. This phenomenon has been loosely termed financialization. While there is no agreement in the literature as to the main drivers of the three defining commodity

market features (especially with respect to the 2006-2008 boom and burst), this chapter subscribes to the third school of thought which sees financialization as the driver of the three observable features that have defined the exchange traded commodities market complex since the early 2000's: higher prices, higher correlation and higher volatility. These defining features which have serious implications for policy makers and market players are mostly consistent with index investment/speculative fund flows suggesting financialization.

This thesis considers financialization as the process by which financial markets participants through speculative investment are the main driver of observed increases in commodity prices, volatility and co-movement in the recent years. It is therefore imperative to empirically decipher the crisis related effects/phenomenon that manifested in the 2008 commodities market burst episode.

However, a section of the empirical literature uses the term financialization to refer precisely to the financial emergence of commodities i.e., when commodities were seriously considered as a financial asset class and therefore traded as such (Tang and Xiong, 2012).

Masters (2008) and the CFTC staff report (2008) describe the higher and more volatile commodities prices as a bubble and ascribe it to a continued increase in speculative commodity index investment which also flowed out quickly after the Lehman Brothers collapse/bankruptcy. Masters and White (2008) demonstrate that commodity index investment grew from $13 billion in 2003 to $317 billion before the collapse of commodities prices in 2008. This follows on from the belief that financialization of commodities was originally born out of a flight to quality behaviour from equities to commodities (which was seen then to be negatively correlated with equities) after the dot com bubble burst in 2000.

4.3 Methodology

4.3.1 Canonical Model

Similar to chapter 3, this chapter's canonical model based on Pesaran and Pick (2007) is specified below:

$$\Delta y_{it} = \alpha_{0i} + \boldsymbol{\alpha}_i' \boldsymbol{x}_{it} + \boldsymbol{\delta}_i' \boldsymbol{z}_t + \beta_i^+ \mathcal{C}_{it}^+ + \beta_i^- \mathcal{C}_{it}^- + \epsilon_{it}, \tag{4.1}$$

With Δy_{it} returns in the commodities indices, $\boldsymbol{x}_{it}$ a vector containing commodity specific regressors, and $\boldsymbol{z}_t$ a vector containing predetermined observed common factors. The good contagion effects are measured by the upside crisis dummy, C_{it}^+, which represents sudden unanticipated spikes in

commodities indices returns, while bad contagion effects are measured by the downside crisis dummy, C_{it}^{-}, which represents sudden unanticipated drops in commodities indices returns. The disturbance terms, ϵ_{it}, are assumed to be serially uncorrelated with conditional variances $\sigma_{i,t-1}^{2}$ and have a contemporaneous correlation equal to ρ_{ij}. Like Pesaran and Pick (2007), this chapter assumes the contemporaneous correlation to be constant over time. Although it would be possible to let the correlation be time varying this would detract from the interpretation of ρ_{ij} as the degree of interdependence in stable periods between commodities i and j, versus the contagion captured observed in crisis periods. This chapter's model captures baseline interdependence between countries and monsoonal effects through the control variables

4.3.2 Definition of the Crisis Periods

An important element of this chapter's methodology is the construction of the contagion dummies $\mathcal{C}_{it}^{+}$ and $\mathcal{C}_{it}^{-}$. It is assumed that contagion can only take place during tail events episodes i.e periods of extreme negative events or extreme positive events (whilst in normal periods there is only interdependence), in line with the rest of the contagion literature. Thus, finding the periods in which there is contagion is equivalent to identifying the crisis periods. This chapter defines two types of 'crises' each with their own associated contagion effect. First there is a large unanticipated increase in commodity index returns as an upside crisis. Such events would be associated with significant news about scarcity or supply disruptions or strong demand relating to the market fundamentals of a particular commodity. Thus, this chapter refers to contagion associated with this type of crisis as 'good contagion'. Conversely, there are also episodes when there are sudden unanticipated drops in commodities index returns, such as may be associated with negative news for the market (or sellers) about the fundamentals of a particular commodity, for example announcement of new and substantial investments in the production of a commodity. This chapter dubs contagion effects associated with this 'downside crisis' episodes as 'bad contagion'. If there are significant good contagion effects then these may potentially be interpreted as positive psychological effects that are associated with the good news about the source commodity market.

Similar to chapter 3, this chapter considers a VaR based approach to crisis identification as expedient because it only uses information available to market agents at time t, Ω_t. This approach is an improvement on the identification of exchange rate crisis in Eichengreen et al. (1996) in which an exchange rate market pressure (EMP) index constructed and the threshold c is arbitrarily set to 1.5.

This chapter endogenizes the threshold by employing a value-at-risk approach which is based on a 3 year rolling ARMA(1,1)-EGARCH(1,1) model, assuming a normal distribution and with a 5%

confidence level. ARMA(1,1)-EGARCH(1,1) is employed mainly because it is able to capture the asymmetry in volatility between positive and negative shocks, Nelson (1991).

Market participants are assumed to form one-day-ahead Value-at-Risk forecasts for both the right and the left tail of the distribution, capturing both large increases and decreases in log returns. Model parameters were re-estimated every period.

These VaR forecasts form a time-varying threshold for crisis identification. A period of bad contagion can thus be defined as a period in which the estimated VaR for the right tail is breached, ie. a period in which the increase of the log return is larger than the forecasted $VaR(\alpha)_{it}$:

$$\mathcal{C}_{it}^{+} = I(\Delta y_{it} - VaR_{i,\alpha}). \tag{4.2}$$

The downwards crisis episodes for commodity index returns can be defined in a similar way.

$$\mathcal{C}_{it}^{-} = \begin{cases} 1 & \text{if} \quad \Delta y_{it} < VaR(\alpha)_{it} \\ 0 & \text{else} \end{cases}. \tag{4.3}$$

with $I(\cdot)$ again defined as an indicator function that takes the value one if the value of the argument is larger than 0 and zero otherwise.

One of the advantages of this statistical model is that it can easily accommodate a setup in which there are multiple source commodities for crisis/extreme shock and multiple target commodities which could be affected by contagion. Therefore a generalization of the crisis dummy described above is considered.

$$\mathcal{C}_{it}^{+} = I\left(\sum_{j=1, j\neq i}^{P} I(\Delta y_{it} - VaR_{i,\alpha})\right), \tag{4.4}$$

and

$$\mathcal{C}_{it}^{-} = I\left(\sum_{j=1, j\neq i}^{P} I(-\Delta y_{it} - VaR_{i,\alpha})\right). \tag{4.5}$$

To close the model, the first two lags of the dependent variable are included as commodity specific variables. The inclusion of the lagged dependent variables allows for momentum in the commodity index returns, potentially created through overreaction/underreaction of the markets to news on the yield spreads. Interdependence with regards to the other innovations of the commodity index returns in the system are restricted to only occur contemporaneously as an identification restriction (see e.g.

Favero and Giavazzi, 2002). This restriction on the nature of the interdependence is not too restrictive as the frequency of the data is daily; a period in which information can be reasonably expected to be incorporated in the respective commodity index returns.

4.3.3 Estimation

To consistently estimate the contagion parameters β_i the system needs to be estimated using instrumental variable techniques. The crisis indicators $\mathcal{C}_{it}^{+}$ and $\mathcal{C}_{it}^{-}$ need to be instrumented with pre-determined commodity-specific regressors, in this case the lags of the commodity index returns. As the crisis indicators are non-linear transformations of the commodity index returns, a power series up to the sixth power is included to improve the strength of the instruments (Pesaran and Pick, 2007). The set of instruments for $\mathcal{C}_{it}^{+}$ and $\mathcal{C}_{it}^{-}$ of country $i \in P$ is thus,

$$\boldsymbol{W}_{i,t} = \left[\boldsymbol{w}_{1,t}, \boldsymbol{w}_{2,t}, \dots, \boldsymbol{w}_{i-1,t}, \boldsymbol{w}_{i+1,t}, \dots, \boldsymbol{w}_{P,t}\right], \tag{4.6}$$

with

$$\boldsymbol{w}_{j,t} = \left[\Delta y_{j,t-1}, \left(\Delta y_{j,t-1}\right)^2, \dots, \left(\Delta y_{j,t-1}\right)^6, \Delta y_{j,t-2}, \left(\Delta y_{j,t-2}\right)^2, \dots, \left(\Delta y_{j,t-2}\right)^6\right]. \tag{4.7}$$

Using these instruments the system is estimated for each commodity index return using the generalized instrumental variables estimation (GIVE) procedure.

4.4 Data

Central to this chapter's contagion investigation are daily natural log returns of spot Dow-Jones UBS commodity indices denominated in US dollars for agriculture, energy, industrial metals and precious metals. The agriculture spot index jointly proxies the spot price performance of sugar, cotton, coffee, soybeans, soybean meal, soybean oil, corn and wheat. The energy spot index is a representative index of the spot prices of WTI crude oil, Brent crude oil, natural gas, unleaded gasoline, heating oil etc. The industrial metals index incorporates spot price performance of aluminium, copper, nickel, zinc, tin, and lead. The precious metals index proxies the spot prices of gold and silver. Apart from considering contagion between indices of major commodities groupings, the following individual commodities are also considered; aluminium, brent, copper, corn, coffee, gold, henry hub (natural gas), lead, nickel, silver, soybean, sugar, soft wheat, tin and zinc. This chapter employs data from January 1999 – March 2013.

Table 4.1 Summary Statistics

Table 4.1a. DJ-UBS Sub-Indices

	AGRICULTURE	ENERGY	IND. METALS	LIVESTOCK	PREC. METALS
Mean	0.000	0.001	0.000	0.000	0.001
Median	0.000	0.000	0.000	0.000	0.000
Maximum	0.066	0.094	0.101	0.178	0.090
Minimum	-0.094	-0.147	-0.102	-0.087	-0.091
Std. Dev.	0.012	0.020	0.015	0.010	0.013
Skewness	-0.197	-0.193	-0.286	1.216	-0.255
Kurtosis	6.254	5.049	6.752	31.606	9.187

Summary statistics for the log returns of daily Dow Jones-UBS commodity indices for agriculture, energy, industrial metals, livestock and precious metals over the period 01/01/1999-01/03/2013.

Table 4.1b. DJ-UBS Metals Indices

	ALUMINIUM	COPPER	GOLD	LEAD	NICKEL	SILVER	TIN	ZINC
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.061	0.117	0.074	0.130	0.133	0.183	0.154	0.096
Minimum	-0.083	-0.104	-0.071	-0.132	-0.184	-0.187	-0.115	-0.115
Std. Dev.	0.014	0.018	0.011	0.022	0.025	0.021	0.018	0.020
Skewness	-0.270	-0.144	-0.176	-0.227	-0.148	-0.519	-0.236	-0.224
Kurtosis	5.443	7.165	8.015	6.243	6.499	12.924	9.436	5.766

Summary statistics for the log returns of daily Dow Jones-UBS individual metals commodity indices; aluminium, copper, gold, lead, nickel, silver, tin and zinc over the period 01/01/1999-01/03/2013.

Table 4.1c. DJ-UBS Energy Indices

	BRENT	HENRY HUB
Mean	0.001	0.000
Median	0.001	0.000
Maximum	0.135	0.623
Minimum	-0.136	-0.570
Std. Dev.	0.022	0.042
Skewness	-0.059	0.678
Kurtosis	5.619	32.177

Summary statistics for the log returns of daily Dow Jones-UBS individual energy commodity indices; Brent and Henry Hub over the period 01/01/1999-01/03/2013.

Table 4.1d. DJ-UBS Agriculture Indices

	CORN	COFFEE	COCOA	FEEDER CATTLE	SUGAR	SOYBEAN	SOFTWHEAT
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Median	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.109	0.186	0.194	0.075	0.186	0.073	0.139
Minimum	-0.121	-0.133	-0.193	-0.086	-0.133	-0.167	-0.226
Std. Dev.	0.020	0.016	0.020	0.010	0.016	0.017	0.026
Skewness	-0.107	0.211	-205.000	-0.238	0.211	-0.737	-0.275
Kurtosis	5.850	14.457	16.137	14.678	14.457	9.257	7.816

Summary statistics for the log returns of daily Dow Jones-UBS individual agriculture commodity indices; corn, coffee, cocoa, feeder cattle, sugar, soybean and softwheat over the period 01/01/1999 - 01/03/2013.

Table 4.2 Unit Root Test

Table 4.2a DJ-UBS Sub-Indices

	AGRICULTURE	ENERGY	IND. METALS	LIVESTOCK	PREC. METALS
t-stat (ADF)	-59.72	-63.2	-63.5	-59.61	-61.45
1% Critical Values	-3.43	-3.43	-3.43	-3.43	-3.43
t-stat Probability	0	0	0	0	0

T-statistics, 1% critical values and t-stat probabilities from the Augmented Dickey-Fuller test for unit root for the for the log returns of daily Dow Jones-UBS commodity indices for: agriculture, energy, industrial metals, livestock and precious metals 01/01/1999- 01/03/2013.

Table 4.2b Metal Indices

	ALUMINIUM	COPPER	GOLD	LEAD	NICKEL	SILVER	TIN	ZINC
t-stat (ADF)	-63.04	-64.25	-60.8	-57.96	-60.16	-67.11	-59.63	-62.1
1% Critical Values	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43
t-stat Probability	0	0	0	0	0	0	0	0

T-statistics, 1% critical values and t-stat probabilities from the Augmented Dickey-Fuller test for unit root for the for the log returns of daily Dow Jones-UBS individual metals commodity indices; aluminium, copper, gold, lead, nickel, silver, tin and zinc 01/01/1999 - 01/03/2013.

Table 4.2c Energy indices

	BRENT	HENRY HUB
t-stat (ADF)	-61.47	-48.86
1% Critical Values	-3.43	-3.43
t-stat Probability	0	0

T-statistics, 1% critical values and t-stat probabilities from the Augmented Dickey-Fuller test for unit root for the for the log returns of daily Dow Jones-UBS individual energy commodity indices; brent and henry hub 01/01/1999 - 01/03/2013.

Table 4.2d Agriculture Indices

	CORN	COFFEE	COCOA	FEEDER CATTLE	SUGAR	SOYBEAN	SOFTWHEAT
	-60.28	-57.34	-64.34	-12.64	-57.34	-62.87	-65.99
1% Critical Value	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43	-3.43
t-stat Probability	0	0	0	0	0	0	0

T-statistics, 1% critical values and t-stat probabilities from the Augmented Dickey-Fuller test for unit root for the for the log returns of daily Dow Jones-UBS individual agriculture commodity indices; corn, coffee, cocoa, feeder cattle, sugar, soybean and softwheat. 01/01/1999 - 01/03/2013.

4.5 Results

This chapter estimates variants of the equation used in Pesaran and Pick (2007) and Favero and Giavazzi (2002) which also control for monsoon effects, a measure of shocks common to exchange traded commodities proxied by the Euro Dollar exchange rate as all commodities are denominated in US Dollars. The main results are presented in tables 4.3 to 4.7. Table 4.3 presents results from estimating equation 4.11 below

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i EURUSD_t + \beta_i^+ AGRC_{it}^+ + \beta_i^- AGRC_{it}^- + \beta_i^+ EGYC_{it}^+ + \beta_i^- EGYC_{it}^- + \beta_i^+ IMTC_{it}^+ + \beta_i^- IMTC_{it}^- + \beta_i^+ PMTC_{it}^+ + \beta_i^- PMTC_{it}^- + \epsilon_{it}. \quad (4.11)$$

Tables 4.4 to 4.7 present results from equation 4.12 presented below

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i EURUSD_t + \sum \beta_{i,j}^+ C_{it}^+ + \sum \beta_{i,j}^- ALC_{i,j,t}^- + \epsilon_{it}. \quad (4.12)$$

It is worth mentioning that in equations 4.11 and 4.12 above, C_{it}^{-} is indicative of periods in which there has been a huge and unexpected decrease in the returns of one of the source commodities or commodities groups. Therefore, a negative and significant β_i^{-} coefficient is evidence of bad contagion. Equally, positive, and significant β_i^{+} coefficient is indicative of good contagion. Apart from the good and bad contagion effects which this chapter set out to test for, it is also possible to capture/identify reverse contagion effects which are crisis triggered flight to quality effects. i.e when extreme negative shocks affecting one commodity spread in the opposite direction causing good contagion effects (extreme positive shocks) on another. This means that upon circulation of extreme negative news about a commodity or upon observance of substantial decrease in commodity returns, market participants fearfully exit the commodity and simultaneously buy into another commodity, thus in this case, the β_i^{-} coefficients will be statistically significant but have a positive sign. Theoretically, the reverse could be the case, where an extreme positive shock in one commodity causes extreme negative shocks in another: flight from quality in a positive crisis period (extreme positive shocks environment).

Reverse contagion effects are different from tranquil period flight to quality effects which may be driven by underperformance of a class of commodities return relative to others. The main difference between reverse contagion and flight to quality effects (which are well addressed in the wider empirical literature on financial markets) is that in reverse contagion, the propagation of shocks is to an extent that cannot be predicted or explained by fundamentals whilst with flight to quality effects, the propagation of shocks can be explained or predicted by fundamentals.

Monsoon effects are also captured which are controlled for by using the Euro/Dollar exchange rate. Apriori, positive and significant coefficients are expected for monsoon effects to be established.

From table 4.3, this chapter examines the outcome of estimating equation 4.11 which investigates contagion between index returns of the main exchange traded commodities groups while controlling for monsoon effects. It is found that between January 1999 and February 2013, the main sufferers of bad contagion have been precious metals (suffering bad contagion from industrial metals commodities).

From table 4.3, three occurrences of good contagion are established; agricultural commodities enjoy good contagion from energy, precious metals enjoy good contagion from industrial metals, while energy enjoys good contagion from precious metals. Precious metals interestingly experience both good and bad contagion from industrial metals.

There is evidence of reverse contagion effects as positive shocks to energy returns cause bad contagion effects in industrial metals. In this case, the reverse contagion is thought to be directionally intuitive given that most industrial metals are known to be energy intensive. All things being equal, a spike in energy price could make market players fearfully exit from industrial metals fearing that sudden and substantial hike in energy costs could lead to sizable reduction in industrial metals demand and by extension price. Extreme negative shocks in industrial metals also cause a spike in agriculture index returns. Significant evidence of monsoon effects is found in agriculture, industrial metals and precious metals.

There is also evidence of reverse contagion, effects from industrial metals to agricultural commodities. The reliance of mechanized farming (mostly made from industrial metals) could mean that a crash in industrial metals could provide a boost to agriculture markets.

Whilst the results from equation 4.11 establish or deny the presence of contagion and other effects between the major exchange traded commodities groupings, results from equation 4.12 provides empirical insight into contagion effects within the major commodities groupings, helping to understand the presence or otherwise of contagion effects between commodities within a certain group of commodities for example agriculture.

Table 4.3 Major Commodities Indices

	AGS		EGY		IMT		PMT	
α1	0.001		0.000		0.001		0.000	
	(0.001)		(0.001)		(0.001)		(0.001)	
Δyt-1	-0.140	*	-0.039		-0.070		0.014	
	(0.079)		(0.057)		(0.056)		(0.059)	
Δyt-2	-0.076		0.033		0.000		-0.108	**
	(0.060)		(0.050)		(0.044)		(0.051)	
EURUSD	1.701	***	0.301		1.482	***	0.830	*
	(0.634)		(0.576)		(0.562)		(0.488)	
AGR+			0.012		0.044		0.004	
			(0.020)		(0.018)		(0.023)	
AGR-			-0.010		-0.012		0.004	
			(0.018)		(0.022)		(0.018)	
EGY+	0.047	*			-0.043	***	-0.033	
	(0.025)				(0.016)		(0.034)	
EGY-	-0.018				-0.005		-0.001	
	(0.027)				(0.019)		(0.021)	
IMT+	-0.039		0.033				0.058	***
	(0.032)		(0.027)				(0.022)	
IMT-	0.038	**	-0.022				-0.045	***
	(0.017)		(0.022)				(0.016)	
PMT+	-0.021		0.060	*	0.002			
	(0.034)		(0.033)		(0.030)			
PMT-	-0.026		-0.047		-0.004			
	(0.029)		(0.032)		(0.030)			
g	0.221		0.450		0.351		0.296	

This table reports the results from GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i EURUSD_t + \beta_i^+ AGRC_{it}^+ + \beta_i^- AGRC_{it}^- + \beta_i^+ EGYC_{it}^+ + \beta_i^- EGYC_{it}^- + \beta_i^+ IMTC_{it}^+ + \beta_i^- IMTC_{it}^- + \beta_i^+ PMTC_{it}^+ + \beta_i^- PMTC_{it}^- + \epsilon_{it}$.

The dependent variables are the log returns of DJ UBS indices for commodities groups: agriculture, energy, industrial metals, precious metals. 04/01/1999 - 01/03/2013. *VIX* is the global measure of risk aversion. C+ indicates upwards (good) contagion, C- downwards (bad) contagion. All earlier mentioned commodities indices are included as crisis sources individually. Standard errors are reported in brackets under the coefficient estimates. *g* is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 4.4 lays out the results from equation 4.12 but specifically tells the contagion story within the industrial metals sub complex. Whilst the occurrences of contagion (both good and bad) appear to be rampant within the industrial metals sub complex, copper appears to be the most systemically important industrial metal overall as it is a source of one type of contagion or the other for all other industrials metals both as a result of it experiencing crashes or spikes. A crash in the copper market appears to cause bad contagion for lead, nickel and zinc. However, a reverse contagion effect is observed with aluminium and tin when copper crashes. From table 4.4, it is established that aluminium, lead, nickel and zinc enjoy good contagion from copper. Tin also suffers reverse contagion, as it is observed to crash when copper market experiences a spike.

Table 4.4 Industrial Metals

	AL		CP		LD		NC		TN		ZN	
α1	0.001		-0.001		0.000		-0.001		0.000		-0.003	
	(0.001)		(0.001)		(0.001)		(0.002)		(0.001)		(0.001)	
Δyt-1	-0.096	***	-0.100	***	-0.025	***	-0.068	***	-0.003	***	-0.063	***
	(0.027)		(0.026)		(0.029)		(0.033)		(0.035)		(0.026)	
Δyt-2	-0.020		-0.025		-0.041		-0.027		-0.016		-0.026	
	(0.026)		(0.025)		(0.028)		(0.031)		(0.036)		(0.026)	
EURUSD	0.202	*	0.212	*	0.200	*	0.151	*	0.356	*	0.177	*
	(0.156)		(0.208)		(0.255)		(0.286)		(0.214)		(0.228)	
AL+			-0.003		-0.015		-0.010		-0.001		0.008	
			(0.014)		(0.017)		(0.019)		(0.014)		(0.015)	
AL-			-0.004		0.005		-0.021		-0.002		-0.027	
			(0.012)		(0.015)		(0.016)		(0.012)		(0.013)	
CP+	0.025	**			0.011	**	0.024	**	-0.004	**	0.015	**
	(0.010)				(0.012)		(0.013)		(0.010)		(0.011)	
CP-	0.012	**			-0.037	**	-0.007	**	0.032	**	-0.006	**
	(0.011)				(0.018)		(0.019)		(0.016)		(0.017)	
LD+	0.010	**	0.037	**			0.004	**	0.031	**	0.014	**
	(0.012)		(0.015)				(0.014)				(0.016)	
LD-	-0.006		-0.001				0.015		-0.025		-0.030	
	(0.007)		(0.010)				(0.017)		(0.012)		(0.013)	
NC+	0.011		0.024		0.021				0.023		0.002	
	(0.011)		(0.013)		(0.017)				(0.010)		(0.011)	
NC-	-0.014		-0.022		0.000				-0.004		0.002	
	(0.008)		(0.011)		(0.014)				(0.008)		(0.009)	
TN+	0.004	*	-0.001	*	-0.017	*	0.027	*			-0.007	*
	(0.007)		(0.010)		(0.012)		(0.014)				(0.011)	
TN-	-0.005		-0.012		-0.012		-0.043				0.025	
	(0.006)		(0.008)		(0.010)		(0.011)				(0.013)	
ZN+	-0.011		0.006		0.015		-0.002		-0.003			
	(0.010)		(0.012)		(0.016)		(0.018)		(0.013)			
ZN-	-0.035	***	-0.032	***	-0.056	***	-0.021	***	-0.014	***		
	(0.009)		(0.012)		(0.016)		(0.017)		(0.013)			
g	0.305		0.321		0.301		0.313		0.307		0.310	

This table reports the industrial metals results from GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i EURUSD_t + \sum \beta_{i,j}^{+} C_{it}^{+} + \sum \beta_{i,j}^{-} ALC_{i,j,t}^{-} + \epsilon_{it}.$

The dependent variables are the log returns of DJ UBS indices for aluminium, brent, cocoa, coffee, copper, corn, feeder cattle, gold, henry hub, lead, nickel, silver, soft wheat, soyabean, sugar, tin and zinc. 04/01/1999 - 01/03/2013. *VIX* is the global measure of risk aversion. C+ indicates upwards (good) contagion, C- downwards (bad) contagion. All earlier mentioned commodities indices are included as crisis sources individually. Standard errors are reported in brackets under the coefficient estimates. *g* is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Zinc appears to be the most systemically important source of bad contagion, being a source of bad contagion to all other industrial metals. Lead on the other hand appears to be the most systemically important source of good contagion, being a source of good contagion to all other industrial metals. Tin causes good contagion effects for aluminium and nickel with significant reverse contagion "flight

to safety effects" to copper lead and zinc. Monsoonal effects are captured/established for all industrial metals.

This chapter establishes several cases of crisis related effects (bad contagion, good contagion, reverse contagion and monsoonal effects) in industrial metals but relatively less crisis period effects in the agriculture sub complex. From the results shown in Table 4.5, which are also from equation 4.12 and specific to the agriculture sub complex. There is evidence of good contagion from soybean to corn and soft wheat. There is also evidence that corn suffered bad contagion from soybean whilst feeder cattle enjoyed reverse contagion effect from soybean. This is directionally intuitive as soybean is a major food source for feeder cattle, a crash in soybean prices would normally provide a boost to feeder cattle prices. There is also evidence of a similar phenomenon between corn and feeder cattle following the same intuition. Monsoonal effects are captured in cocoa, corn and sugar.

This chapter makes a few noteworthy observations with respect to the agricultural commodities complex. Coffee does not appear to be a source of good or bad contagion to any other agricultural commodity. It is also not impacted by good or bad contagion from any other agricultural commodity.

In the case of sugar, it is a source of good contagion only to soybeans but does not experience good or bad contagion from any other agricultural commodity. Feeder cattle is also not observed to be a source of contagion to any other agricultural commodity.

Overall, parts of the agricultural sub index have not been heavily financialized. As such, there is relatively less financialization within the agricultural commodities sub complex, which might provide tail event hedging opportunities for portfolio managers.

Table 4.5 Agriculture

	CC		CF		CR		FC		SW		SY		SG	
α1	0.002		-0.001		0.000		-0.001		-0.001		0.002		0.000	
	(0.001)		(0.001)		(0.001)		(0.000)		(0.002)		(0.001)		(0.002)	
Δyt-1	-0.046		0.188	***	-0.020		0.090		-0.118	***	-0.053		-0.064	
	(0.061)		(0.063)		(0.031)		(0.073)		(0.037)		(0.039)		(0.060)	
Δyt-2	0.056		-0.022		-0.040		0.062		0.045		-0.008		0.032	
	(0.074)		(0.061)		(0.029)		(0.068)		(0.035)		(0.036)		(0.057)	
EURUSD	0.722	***	0.229		0.430	*	-0.077		0.323		0.071		0.640	**
	(0.251)		(0.171)		(0.227)		(0.082)		(0.295)		(0.206)		(0.260)	
CC+			0.010		0.003		0.004		0.008		0.016	**	0.015	
			(0.008)		(0.008)		(0.003)		(0.011)		(0.008)		(0.010)	
CC-			-0.006		-0.012		-0.001		0.012		-0.015	**	0.010	
			(0.010)		(0.008)		(0.003)		(0.010)		(0.007)		(0.009)	
CF+	-0.003				0.023		-0.001		0.015		0.014		0.022	
	(0.010)				(0.014)		(0.005)		(0.019)		(0.013)		(0.017)	
CF-	-0.003				0.006		0.001		0.023		0.023		-0.018	
	(0.008)				(0.016)		(0.006)		(0.020)		(0.015)		(0.018)	
CR+	0.008		0.003				0.003		0.017		-0.002		0.007	
	(0.012)		(0.008)				(0.004)		(0.012)		(0.009)		(0.011)	
CR-	0.002		0.001				0.012	***	-0.001		-0.006		0.006	
	(0.017)		(0.011)				(0.005)		(0.013)		(0.009)		(0.013)	
FC+	0.011		0.005		0.012				0.024		0.002		-0.007	
	(0.010)		(0.007)		(0.009)				(0.015)		(0.011)		(0.013)	
FC-	-0.007		-0.011		-0.001				-0.015		-0.012		-0.010	
	(0.011)		(0.007)		(0.010)				(0.012)		(0.009)		(0.011)	
SW+	0.012		0.001		0.021	*	0.004				-0.002		0.018	
	(0.014)		(0.009)		(0.011)		(0.004)				(0.010)		(0.011)	
SW-	0.025	*	-0.010		-0.003		0.002				-0.011		-0.001	
	(0.014)		(0.009)		(0.013)		(0.005)				(0.012)		(0.017)	
SY+	-0.007		0.004		0.028	***	0.002		0.031	**			0.011	
	(0.012)		(0.008)		(0.009)		(0.003)		(0.013)				(0.012)	
SY-	-0.004		-0.009		-0.031	**	0.010	**	-0.022				-0.010	
	(0.015)		(0.010)		(0.013)		(0.005)		(0.018)				0.016	
SG+	-0.012		-0.001		0.016		-0.001		-0.001		0.015	*		
	(0.011)		(0.007)		(0.010)		(0.004)		(0.013)		(0.009)			
SG-	-0.016		-0.006		-0.006		0.000		-0.007		0.002			
	(0.010)		(0.008)		(0.009)		(0.004)		(0.012)		(0.009)			
g	0.289		0.289		0.305		0.269		0.312		0.305		0.280	

This table reports the agriculture results from GIVE estimates of the system

$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i EURUSD_t + \sum \beta_{i,j}^{+} C_{it}^{+} + \sum \beta_{i,j}^{-} ALC_{i,j,t}^{-} + \epsilon_{it}.$

The dependent variables are the log returns of DJ UBS indices for aluminium, brent, cocoa, coffee, copper, corn, feeder cattle, gold, henry hub, lead, nickel, silver, soft wheat, soyabean, sugar, tin and zinc. 04/01/1999 - 01/03/2013. *VIX* is the global measure of risk aversion. C+ indicates upwards (good) contagion, C- downwards (bad) contagion. All earlier mentioned commodities indices are included as crisis sources individually. Standard errors are reported in brackets under the coefficient estimates. *g* is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 4.6 presents equation 4.12 results which are specific to energy. Henry Hub appears to suffer bad contagion when there is an extreme negative shock to Brent. This chapter captures monsoon effects in commodity index returns for brent. From table 4.7, monsoon effects are captured in commodity returns for gold and silver. Gold is also found to suffer bad contagion from silver.

Looking altogether at the intra group and inter group results, as expected the contagion coefficients for the inter group results are relatively larger in absolute terms.

Table 4.6 Energy

	BR		HH	
α1	0.001		0.004	
	(0.001)		(0.003)	
Δyt-1	-0.001		0.207	***
	(0.048)		(0.073)	
Δyt-2	0.053		-0.030	
	(0.044)		(0.075)	
EURUSD	0.446	*	0.739	
	(0.253)		(0.501)	
BR+			-0.013	
			(0.016)	
BR-			-0.025	*
			(0.014)	
HH+	0.010			
	(0.016)			
HH-	-0.002			
	(0.013)			
g	0.319		0.325	

Table 4.7 Precious Metals

	GL		SL	
α1	0.001		-0.001	
	(0.001)		(0.002)	
Δyt-1	0.007		0.255	***
	(0.037)		(0.044)	
Δyt-2	-0.029		-0.203	***
	(0.035)		(0.050)	
EURUSD	0.812	***	1.030	***
	(0.133)		(0.319)	
GL+			0.026	
			(0.021)	
GL-			0.008	
			(0.016)	
SL+	0.007			
	(0.007)			
SL-	-0.018	***		
	(0.006)			
g	0.306		0.289	

These tables reports the precious metals and energy results respectively from GIVE estimates of the system

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1,i}\Delta y_{it-1} + \alpha_{2,i}\Delta y_{it-2} + \delta_i EURUSD_t + \sum \beta_{i,j}^{+} \mathcal{C}_{it}^{+} + \sum \beta_{i,j}^{-} ALC_{i,j,t}^{-} + \epsilon_{it}.$$

The dependent variables are the log returns of DJ UBS indices for aluminium, brent, cocoa, coffee, copper, corn, feeder cattle, gold, henry hub, lead, nickel, silver, soft wheat, soyabean, sugar, tin and zinc. 04/01/1999 - 01/03/2013. *VIX* is the global measure of risk aversion. C+ indicates upwards (good) contagion, C- downwards (bad) contagion. All earlier mentioned commodities indices are included as crisis sources individually. Standard errors are reported in brackets under the coefficient estimates. *g* is the Cragg – Donald statistic. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Four interesting lessons can be learned from the results. Firstly, the results suggest that both good and bad contagion has occurred both between the index returns of the 5 broad commodities groups and between individual commodities within each of the groups. This demonstrates that contagion effects can be captured between markets outside the country/region specific framework which the literature has mostly worked with but also that contagion can be captured in financial markets different from the conventional financial markets (equities, currencies, and more recently bonds) which most contagion studies investigate. This chapter also empirically reiterates the view (as demonstrated in

chapter 3) that contagion can be as a result of extreme positive shocks given that the empirical literature is largely focused on identifying contagion effects associated with extreme negative shocks episodes.

Secondly, looking at the group level analysis which takes an inter group view, industrial metals and energy appear to be the most systemically import source of contagion overall, affecting both agriculture (bad contagion) and precious metals (reverse contagion). Higher than average absolute coefficients of contagion from industrial metals (inter group results) is observed which is a pointer to strong shock propagation from industrial metals. The intra-group findings corroborate the indication of high systemic importance; the highest prevalence of bad and good contagion cases is observed within the industrial metals sub complex where all industrial metals commodities have suffered from bad contagion, with copper being the most systemically important overall, zinc being the most systemically important source of bad contagion and lead being the most systemically important source of good contagion.

The third lesson learned from the empirical investigation is that when sudden market crashes or spikes occur, apart from good and bad contagion, reverse contagion can also occur i.e crisis triggered flight to quality effects captured through counter intuitive but statistically significant contagion indicators which fundamentals cannot explain. The group level results reveal that agriculture enjoyed reverse contagion from industrial metals as sudden extreme negative shocks to industrial metals appear to contagiously trigger a spike in agricultural commodities markets. Similarly, from the group results, industrial metals appear to suffer reverse contagion from energy. The propagation of extreme positive shocks from energy appears to contagiously cause a crash in the industrial metals' markets. Reverse contagion is clearly another important possible outcome of extreme shocks episodes that the literature might not have given a lot of attention to while being over drawn to capturing bad contagion effects.

The fourth lesson learned is that the results empirically establish (indirectly) the financialization of commodities markets as discussed in the commodities literature even though they have been obtained via the estimation of a contagion testing methodology. The contagion testing methodology employed in this chapter, goes beyond what is required to clearly demonstrate the occurrence of financialization or its attributes: higher, prices, higher volatility, and higher co-movement.

4.6 Conclusion

This chapter empirically investigates contagion effects within the exchange traded commodities complex in relations to the 2008 commodities market crash using non-linear simultaneous equations. This chapter also distinguishes contagion effects from interdependence, and monsoon effects.

Two main sets of estimations are carried out; looking broadly at contagion effects between the index returns for the 5 major commodity groups and between the returns for 18 individual exchange traded commodities. Results are however presented in a way that helps see contagion patterns within each commodity group thus giving dual perspective and a relatively higher level of insight on contagion within the commodities complex.

This chapter employs a model in which the timing of crisis and the source of a crisis event are endogenously determined. The endogenous crisis source selection employed in this chapter allows the testing of all the individual commodities indices as possible sources of contagion. There is no need to make assumptions about systemically important commodities. Additionally, the model identifies three type main types of contagion: bad contagion (resulting from a sharp decrease in commodity returns), good contagion (resulting from a sharp spike in commodities returns) and reverse contagion.

Summarily, the results demonstrate the following three points: firstly, both good and bad contagion has occurred both between the index returns of the five broad commodities groups and between individual commodities within each of the groups. Secondly, industrial metals and energy appear to be the most systemically important group within the exchange traded commodities complex. Thirdly, when sudden market crashes or spikes occur, apart from good contagion and bad contagion, reverse contagion can also occur i.e extreme negative (positive) shock to one market can contagiously trigger extreme positive (negative) shocks in another beyond what fundamentals can explain. Given that the results in this chapter provide insight into the patterns of tail event vulnerability within the exchange traded commodities complex, traders and commodities fund managers should find them useful in informing their marginal value at risk rules. Finally, the results contribute to the financialization debate by empirically corroborating the occurrence of financialization in the exchange traded commodities complex.

Chapter 5

Financialization: Commodities and Conventional Assets

5.1 Introduction

The financialization of commodities markets has gained a lot of attention in the academic literature. Commodities index investment over the last decade attracted a huge inflow of institutional funds into the exchange traded commodities complex. This meant that funds flowed in and out of a wide range of commodities and conventional financial assets markets simultaneously, causing a synchronization of price movements between commodities and the conventional financial markets; Tang and Xiong (2012). Tang and Xiong (2012) also report that price co-movements between commodities picked up in 2004 when the flow of index investments into commodities was already in full swing.

The 2000's boom in commodities markets coincided with a boom in conventional financial markets. This period which was also characterised with higher prices and higher volatility signalled a possible change in the commodities market complex which was hitherto mainly driven by supply/demand fundamentals unique to each market. The fact that the exchange traded commodities markets complex did not only co crash/co-burst with conventional assets but also experienced a crash within itself (meaning that individual commodities markets also appeared co crash with each other) was further confirmation of the changing dynamics in the commodities markets (Figures 5.1 and 5.2). These two related patterns of co-burst have been associated with the transformation of commodities markets, commonly referred to as financialization in the empirical literature.

Figure 5.1 Graph of daily spot price indices for Dow Jones-UBS commodity index and CRB commodity index respectively over the period 01/01/1999 - 01/03/2013.

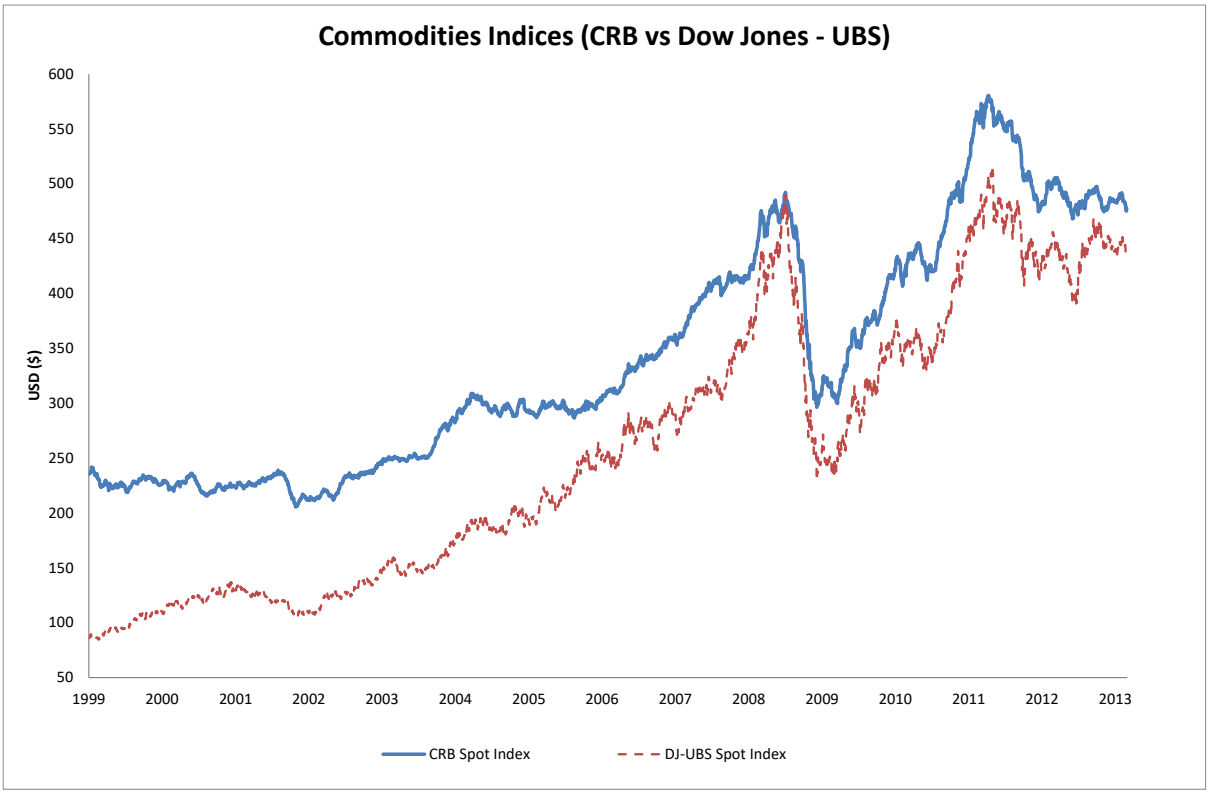
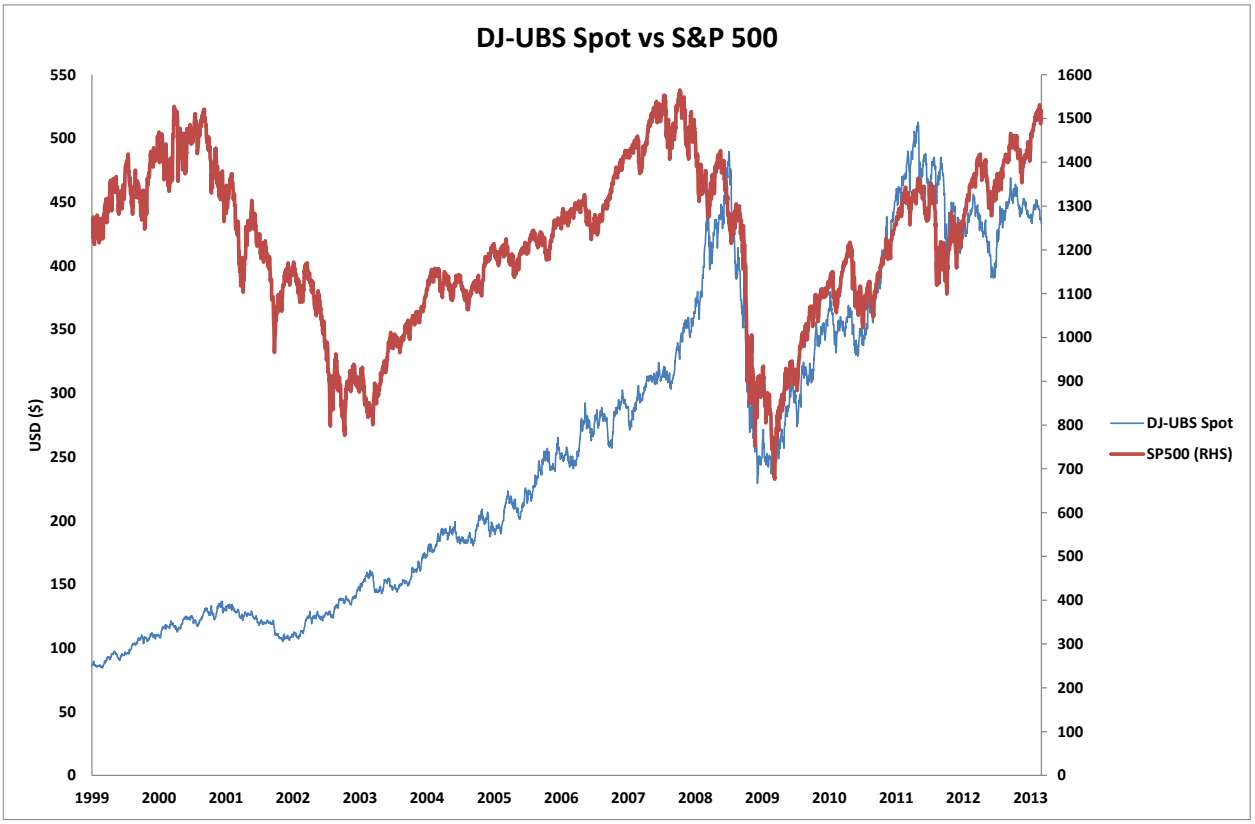


Figure 5.2 Graph of daily spot Dow Jones-UBS commodity indices versus S&P 500 over the period 01/01/1999 - 01/03/2013.



The 2008 joint crash (between exchange traded commodities and conventional assets) highlights the need to properly understand patterns of contagion within the exchange traded commodities markets complex (chapter 4 addresses this). It also highlights the need to understand the patterns of commodities market vulnerability to contagion in the event of a crash or crisis in the conventional financial assets markets, which is what this chapter endeavours to address. In line with chapter 4, this chapter considers three major types of contagion, i.e. not only bad contagion, due as a result of propagation of extreme negative shocks beyond the interdependence regime of shock transmission, but also good contagion resulting from propagation of extreme positive shocks beyond the interdependence regime of shock transmission and "reverse" contagion in which a negative tail event/crash in one market is propagated to another market as a positive tail event/boom beyond the interdependence regime of shock transmission. Better insight into the tail event relationship between commodities and conventional assets could be of importance to fund managers.

In this chapter, the aim is to empirically establish the presence of contagion in major exchange traded commodities markets from conventional financial asset markets such as equities.

This chapter employs a variant of the Baur and Schulze (2005) empirical framework. The empirical framework combines quantile regressions with a coexceedance approach to estimate bad contagion, good contagion and reverse contagion between conventional financial asset markets and key commodities markets between 2001 and 2013. There is evidence of bad contagion from conventional assets markets to exchange traded energy markets. There is also evidence of good contagion from conventional asset markets to exchange traded precious metals markets.

This chapter adds to the financialization literature by empirically assessing and establishing the vulnerability of exchange traded commodities markets to contagion from conventional assets which might have occurred because of financialization. The empirical framework provides deeper insight into tail dependence structure (by delivering a full profile across the entire distribution whilst revealing potential non-linearities), it also goes beyond detecting contagion but also gives insight into the degree of contagion detected given that for quantile regressions distributional assumptions do not need to be made. Deeper insight into tail dependence structure between conventional assets and commodities markets might assist cross asset portfolio managers with building portfolios that are resilient/defensive with respect to tail events. The chapter is organized as follows. Section 2 presents a review of the literature on commodities market financialization, section 3 explains the estimation framework. Section 4 describes the data, section 5 sets out the main results and section 6 concludes.

5.2 Literature Review

5.2.1 Financialization and Cross Asset Linkages

This chapter considers commodities market financialization from a cross asset point of view, specifically between exchange traded commodities and conventional financial assets. There is no agreement on the main driver(s) of stronger cross asset linkages between conventional assets and commodities leading up to the 2008 market crash, see for example Tang and Xiong (2010). The most prominent school of thought posits that commodities market financialization is mostly driven by speculative fund flows into commodities. Masters (2008) and the CFTC staff report (2008) describe the higher and more volatile commodities prices as a bubble and ascribe it to a continued increase in speculative commodity index investment which also flowed out quickly after the Lehman Brothers collapse/bankruptcy. Masters and White (2008) demonstrate that commodity index investment grew from $13 billion in 2003 to $317 billion before the collapse of commodities prices in 2008. Buyuksahin and Robe (2013) empirically confirm that speculative funds flows were a big driver of stronger cross asset correlation between commodities and conventional assets.

The other main school of thought posits that a combination of speculative fund flows and macroeconomic growth were responsible for the strong cross asset linkage between conventional assets and commodities. It considers the commodities co-boom and co-burst as being mainly driven by economic expansion and contraction in emerging markets. Krugman (2008) and Hamilton (2009) posit that the rise in commodities prices especially from 2006 was a function of higher commodities demand and supply fundamentals consistent with faster growth/industrial expansion in China and India while the price collapse in 2008 was a manifestation of recession by way of sharp decline in the demand for commodities. Silvennoinen and Thorp (2013) also empirically confirm that hedge fund positioning and macroeconomic growth were responsible for stronger correlation between exchange traded commodities and conventional financial assets such as equities.

While there is no agreement in the literature as to the main drivers of the financialization of commodities markets especially with respect to the 2006-2008 boom and burst, it is however apparent that huge volumes of speculative funds flowed into commodities markets and commodities markets commoved with each other and with other financial assets. This has serious implications for policy makers, market players and the overall safety of the global financial system. It is therefore imperative to empirically decipher extreme event vulnerability patterns between commodities and conventional financial assets: bad contagion, good contagion and reverse contagion in line with chapters 3 and 4 respectively.

5.2.2 Coexceedances

Bae et al. (2003) introduced the term exceedance to the empirical literature; they define it as an extreme return (i.e., a return value that is higher (lower) than a predetermined threshold) of a financial market at a specific time t. According to Bae et al. (2003), the threshold that defines an exceedance is the 5th (95th) quantile of the overall (unconditional) return distribution. Baur and Schulze (2005) agree with Bae et al. (2003) in defining coexceedance as the joint occurrence of exceedances in two or more markets at the same point in time.

Building on Bae et al. (2003), Baur and Schulze (2005) treat positive and negative returns separately. They consider coexceedance as the joint occurrence of exceedances in two or more markets at the same point in time. The number of coexceedances at time t is determined by the number of markets/countries jointly exceeding their thresholds. Bae et al. (2003) employ a multinomial logistic regression, with the dependent variable derived from the number of countries that jointly exceed their thresholds at the same time, they also consider the impact of exogenous variables like exchange rates, interest rates and volatilities on the number of coexceedances in their estimation. Baur and Schulze

(2005) espouse a different approach that does not only specify the existence of coexceedances but also reveals information about their degree.

Ultimately, Baur and Schulze (2005) empirical framework builds on Bae et al. (2003), incorporating more flexibility by taking into account the degree of contagion and without the need to make any distributional assumptions due to the fact quantile regressions are used instead of multinomiual logit used by Bae et al. (2003).

5.2.3 Contagion

Contagion is a topical phenomenon in the financial markets and in the empirical literature which can be defined as an extreme departure from the interdependence regime of shock transmission between two or more markets which fundamentals cannot explain or predict. This definition is in line with the second group of definitions discussed in chapter 2 such as Masson (1999) Whilst there is little agreement in the literature on what contagion really is, it is important to distinguish contagion from the interdependence already present in normal times, and the occurrence of monsoonal effects. Interdependence is defined as the level of integration between markets present in normal times. Monsoonal effects refer to a coincidence of crisis in different markets as a result of common global shocks (Masson, 1999). In the global financial system, contagion remains a reoccurring feature. For example, well documented cases of contagion are the spread, in 1987 of shocks from Hong Kong to markets in Europe and America (King and Wadhwani, 1990), the Asian Crisis crisis (e.g Forbes and Rigobon, 2002; Corsetti et al. ,2005), and contagion during the ERM crisis (e.g. Favero and Giavazzi ,2002; Pesaran and Pick, 2007). Of more recent interest is evidence of banking contagion at the onset of the credit crisis (Pais and Stork, 2011). In the empirical literature on contagion several estimation techniques have been employed, ranging from correlation-based tests, as in King and Wadhwani (1990); Conditional probabilities as in Eichengreen et al. (1996); ARCH/GARCH as in Hamao et al. (1990); Markov switching models as in Fratzcher (1999); Simultaneous equations as in Pesaran and Pick (2007).

5.3 Methodology

This chapter builds on the empirical framework of Baur and Schulze (2005) and uses a quantile regression framework to analyse extreme coexceedances between conventional financial markets and commodities markets during the 2008 financial crisis.

In chapters 3 and 4, non-linear simultaneous equations were employed to empirically address research questions. This chapter adopts the Baur and Schulze (2005) empirical framework which presents an equally sound methodology. Both methodologies are interchangeably appropriate for this chapter, chapter 3 and chapter 4 as they as both enable estimations where assumptions do not have to be made about the source of crisis, timing of crisis, and whether a crisis has occurred on the left or right tail of the distbution.

In line with Baur and Schulze (2005), this chapter defines coexceedance as the joint occurrence of exceedances in two or more markets at the same point in time. Bae et al. (2003) defined exceedance as the occurrence of an extreme return of a financial market at certain time t, extreme returns are considered as return values above or below a pre specified threshold. Positive and negative returns are treated separately. A bivariate coexceedance, Φ_t of a pair of returns $r1t,\ r2t$ is defined such that:

$$\Phi_t(r1,\ r2) = \begin{cases} \min(r_{1t},\ r_{2t}) \text{ if } r_{1t} > 0 \wedge r_{2t} > 0 \\ \max(r_{1t},\ r_{2t}) \text{ if } r_{1t} < 0 \wedge r_{2t} < 0 \\ \quad 0 \text{ otherwise} \end{cases} \tag{5.1}$$

The coexeedance measure can therefore be construed as the value of tail movement shared by both markets.

Coexceedance Coex$_t$ can be shown to be associated to lower and upper tail dependence in the following way:

$$Prob(Coex_t \leq a) = Prob(\forall_i : r_i \leq a) \tag{5.2}$$

which is equal to lower tail dependence if the scalar a is sufficiently small or if $u \to 0$ for $a = F_{Coex^{-1}}(u)$

To estimate the coexceedance measure, this chapter uses the quantile regression framework espoused by Koenker and Basset (1978). Employing a quantile regression model to analyse extreme (negative and positive) coexceedances, it makes it feasible to consider any values of the lowest or highest coexceedances without specifying a priori any distribution or threshold, it also means the degree of the coexceedance can ascertained unlike the case of a multinomial logistic regression. A simple linear quantile regression equation is set out as follows:

$$Q_{COEX_t} = \boldsymbol{X}\beta(\tau) + \varepsilon(\tau) \quad \text{with} \quad Q_{\varepsilon(\tau)}(\tau|\boldsymbol{X}) = 0 \tag{5.3}$$

where $\boldsymbol{Coex_t}$ denotes the $(n \times 1)$ vector of the coexceedances, $\boldsymbol{X}$ is a $(n \times k)$ matrix of k exogenous variables, $\beta(\tau)$ represents a $(k \times 1)$ parameter vector and $\varepsilon(\tau)$ stands for the $(n \times 1)$ error term. The τ-th quantile of the error term conditional on the regressors is assumed to have the

value zero. Based on the foregoing specification, the τ-th quantile of the coexeedance can be expressed as:

$$Q_{COEX_t}(\tau|\boldsymbol{X}) = \boldsymbol{X}\beta(\tau) \tag{5.4}$$

To simplify the interpretation of the coexeedance measure, which is based on absolute values of markets returns, markets returns are standardized to have zero mean and unit variance before the calculation of coexceedances.

The simple benchmark quantile regression model of Baur and Schulze (2005) is followed:

$$Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau)D_t^{crisis} + \varepsilon. \tag{5.5}$$

where $Q_{COEX_t}(\tau)$ is the τ-th conditional quantile of the coexceedance between a pair of returns at time t, $\beta_0(\tau)$ is a constant, $\beta_1(\tau)$ is the parameter estimating the effect of crisis indicator D_t^{crisis} which takes the value 1 one if t is in the crisis period and zero otherwise. The crisis period is exogenously set by institutional information as such sample selection bias is avoided.

The US equity market uncertainty index from Economic Policy Uncertainty (EPU hereafter) designed by Baker et al. (2016) is used as the proxy for institutional information. The EPU index for US equity which is based on newspaper coverage frequency has been widely cited and is also used by commercial data providers such as Bloomberg and Reuters according to Baker et al. (2016).

The EPU index for US equity incorporates data from 1985 to present, pertaining only to US newspapers ranging from large national papers to small local newspapers. Specifically, the EPU index for US equity index is based on about 1800 US newspapers using the Newsbank news aggregator.

Baker et al. (2016) construct the EPU index for US equity, by tracking daily counts of articles containing the following terms: 'uncertainty' or 'uncertain', 'economic' or 'economy' and one or more of the following: 'equity market', 'equity price', 'stock market', or 'stock price'. To meet the criteria for inclusion, articles must include terms in all three categories related to: uncertainty, the economy, and the stock market.

As the number of newspapers covered by Newsbank increased drastically from 18 to 1800 between 1985 and 2008, Baker et al. (2016) adjust for this growth in newspaper coverage by scaling the raw daily counts of articles about equity market uncertainty by the total count of articles in the same newspapers. They then normalize the time-series of scaled counts to an average value of 100 between 1985 and 2010.

The equity uncertainty index series are transformed into a crisis indicator D_t^{crisis} such that data points lower than the 5th percentile and those higher than the 95th percentile takes the value 1 and zero otherwise. The 5th and 95th percentiles are chosen in line with Bae et al. (2003), however this chapter's crisis indicator does not suffer from sample selection bias as it is backward looking. This is because the underlying index is constructed using information available to rational economic agents at time, t.

The crisis dummy coefficient, β_1 (τ) captures the degree of abnormal behaviour in a crisis period compared to the full sample period. Bad contagion is detected when β_1 the crisis dummy coefficient is statistically significant and smaller than zero. Conversely, good contagion is detected when β_1 the crisis dummy coefficient is statistically significant and greater than zero.

Using the model in equation 5.5, this chapter looks to confirm or deny the presence of three major types of contagion, i.e. not only bad contagion, due as a result propagation of extreme negative shocks beyond the interdependence regime of shock transmission, good contagion resulting from propagation of extreme positive shocks beyond the interdependence regime of shock transmission and reverse contagion in which a negative tail event/crash in one market is propagated to another market as a positive tail event/boom (or vice versa) beyond the interdependence regime of shock transmission.

The empirical framework used in this chapter is generally more conservative than most other methodologies in terms of detecting contagion as it does not flag contagion only on account of larger values in the tails as quantile regression models control for different regimes of coexceedances.

In line with Baur and Schulze (2005), 10 different conditional quantiles are estimated (τ = 0.02, 0.04, 0.06, 0.08, 0.10, 0.9, 0.92,0.94, 0.96, 0.98) of the coexceedances without selecting any quantile a priori. As such, the probability of tail events can therefore be interpreted as endogenously estimated, this chapter therefore avoids introducing some sort of quantile selection bias. Estimating extreme quantiles with the quantile regression model means that the financial markets tendency to realize more extreme returns during a crisis period even in the absence of contagion is already controlled for. Quantile regressions also provide deeper insight into the tail dependence structure better than most other methods of estimating contagion as it delivers a full profile of across the entire distribution whilst revealing potential non linearities.

The volatility of the MSCI and Euro/US Dollar exchange rate returns are incorporated to control for the possibility of higher volatility leading to larger extreme coexceedances during crisis periods even when the data generating process might still be stable.

Euro/US Dollar exchange rate is selected as a regional market proxy mainly because the global exchange traded commodities markets are known to be mainly denominated in US Dollars. There is an established effect in commodities markets were depreciation of the USD versus other global currencies drives commodity prices higher through a demand surge as the commodities become relatively cheaper in other currencies, the Euro/US Dollar exchange rate controls for this effect.

Equation 5.6 below is a full model which controls for the influence of regional or global markets and persistence of coexceedances such that:

$$Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis} + \beta_2(\tau)\, r\_MSCI_{Mt} + \beta_3(\tau)\, GARCH\ MSCI_{Mt} + \beta_4(\tau)\, r\_EURUSD_{Mt} + \beta_5(\tau)\, GARCH\ EURUSD_{Mt} + \beta_6(\tau)\, COEX_{t-1} + \varepsilon. \quad (5.6)$$

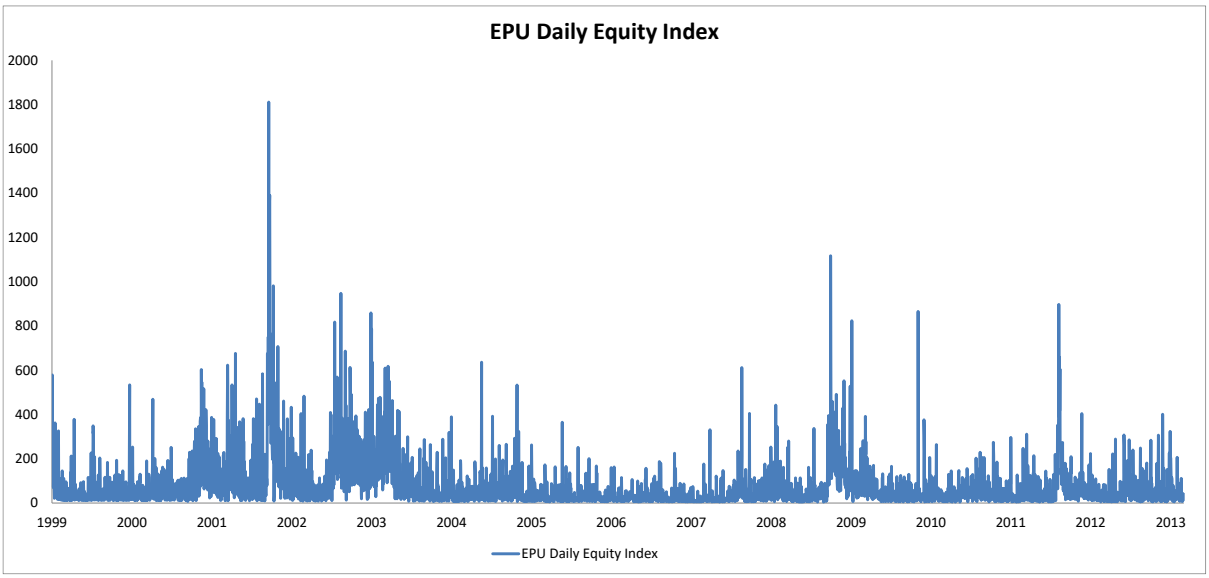
Where $Q_{COEX_t}(\tau)$ is the coexceedance between the market return of a commodity market and that of a conventional financial asset. $\beta_0(\tau)$ is the coefficient for the constant while $\beta_1(\tau)$ is the coefficient for the crisis indicator. $\beta_2(\tau)$ is the coefficient for the returns of the MSCI which is the global markets proxy, $\beta_3(\tau)$ is the coefficient for the estimated conditional variance for of the MSCI returns. $\beta_4(\tau)$ is the coefficient for the returns of the Euro/US Dollar exchange rate which is the regional market proxy, whilst $\beta_5(\tau)$ is the coefficient for estimated conditional variance for the Euro/US Dollar exchange rate. $\beta_6(\tau)$ is the coefficient for the lagged coexceedance which controls for persistence of coexceedances.

5.4 Data

This chapter focuses on the daily log returns of Dow-Jones UBS commodity indices and the S&P 500. The Dow-Jones UBS commodity indices are US dollars denominated data for copper, corn, Brent Crude and gold. Each of these commodities indices serve as proxies for the major exchange traded commodity markets groupings; copper is the industrial metals proxy, corn is the agriculture proxy, Brent Crude is the energy proxy and gold is the proxy for precious metals. Each of these proxies are selected based on having the highest correlation to their group indices as demonstrated in table 5.3. The natural log returns of S&P 500 is a proxy for conventional financial assets markets. The control variables for co exeedances are; the log returns and volatility of the MSCI (global markets proxy) and the Euro/US Dollar exchange rate (regional market proxy). This chapter also uses the US equity market uncertainty index from Economic Policy Uncertainty (EPU hereafter) which is the proxy for institutional information from which a crisis period indicator is derived. This chapter employs data from 1 October 2001 to 1 March 2013. The US equity market uncertainty index is

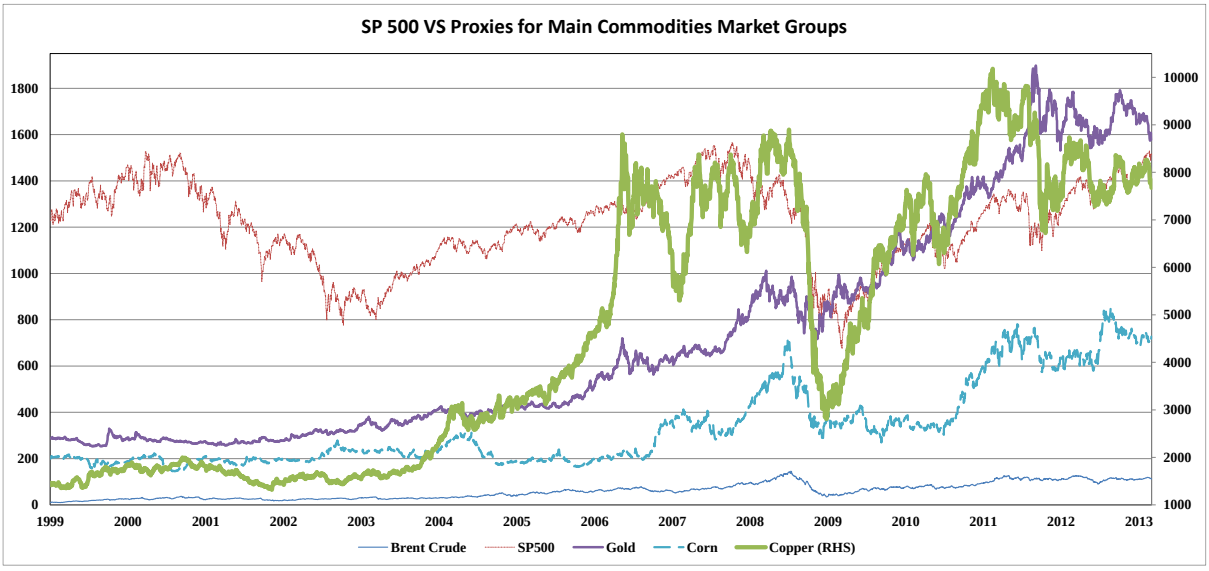
downloaded from http://www.policyuncertainty.com/index.html, all other data are obtained from Data Stream.

Figure 5.3



Graph of daily economic policy unit (EPU) equity index for the United States. Over the period 01/01/1999 - 01/03/2013.

Figure 5.4



Graph of daily spot Dow Jones-UBS commodity indices for copper, corn, gold and crude oil versus S&P 500 over the period 01/01/1999 - 01/03/2013.

Table 5.1 Summary Statistics

	COPPER	CORN	BRENT	GOLD	S&P 500
Mean	0.000	0.000	0.000	0.000	0.000
Median	-0.030	-0.022	0.006	0.001	0.017
Maximum	6.143	5.320	6.310	5.785	8.358
Minimum	-5.483	-5.966	-5.247	-6.118	-7.240
Std. Dev.	1.000	1.000	1.000	1.000	1.000
Skewness	-0.163	-0.092	0.058	-0.388	-0.195
Kurtosis	6.629	5.694	5.748	6.861	11.963

Summary statistics for the log returns of daily Dow Jones-UBS individual commodity indices; copper, corn, brent crude and gold over the period 01/01/1999-01/03/2013.

Table 5.2 Unit Root Test

	COPPER	CORN	BRENT	GOLD	S&P 500
t-stat (ADF)	-58.131	-54.574	-55.890	-54.645	-60.453
1% critical values	-3.432	-3.432	-3.432	-3.432	-3.432
t-stat Probability	0.000	0.000	0.000	0.000	0.000

T-statistics, 1% critical values and t-stat probabilities from the Augmented Dickey-Fuller test for unit root for the for the log returns of daily Dow Jones-UBS commodity indices for: copper, corn, brent crude and gold over the period 01/01/1999-01/03/2013.

Table 5.3 Correlation Between Commodities by Groupings

Commodity Group	Group Level Indices	Correlations					
1. Agriculture		COCOA	COFFEE	CORN	SOFT WHEAT	SOYBEAN	SUGAR
	DJ UBS AGRICULTURE	0.812	0.921	**0.964**	0.900	0.956	0.861
2. Energy		UKNBP	BRENT	HENRY HUB			
	DJ UBS ENERGY	0.790	**0.897**	0.562			
3. Precious Metals		GOLD	SILVER				
	DJ UBS PRECIOUS METALS	**0.997**	0.983				
4. Industrial Metals		COPPER	LEAD	NICKEL	TIN	ZINC	ALUMINIUM
	DJ UBS INDUSTRIAL METALS	**0.977**	0.911	0.885	0.839	0.888	0.926

Correlation between Dow Jones-UBS individual commodity indices and Dow Jones-UBS group level commodity indices over the period 01/01/1999-01/03/2013.

5.5 Results

This section presents the empirical results from equations (5.5)(benchmark model) and (5.6) (full model) set out in the methodology section, section 5.3.

With respect to the empirical estimations in this chapter, the a priori expectations are set out as follows; a priori, it is expected that if the S&P 500 crashes (or spikes) and contagion is observed or established, copper, brent or corn are likely to be suffering bad contagion or enjoying good contagion from S&P 500.

In the case of gold, the a priori expectation will be that if a contagion episode is observed relating to gold, it will be a reverse contagion episode i.e a crash in S&P 500 might lead to a contagious spike in Gold and vice versa, mainly due to the safe haven status of the gold markets and the flight to safety effects historically linked to it.

In table 5.4, the benchmark model for the copper estimations show a statistically significant coefficient for the crisis dummy in the 2nd, 8th and 10th quantiles respectively (with the 2nd quantile having the largest sized coefficient), all demonstrating that copper suffered bad contagion from S&P

500, this assertion is not corroborated by the results from the full model where only the crisis dummy in the second quantile is statistically significant albeit with a positive sign, indicating reverse contagion.

Table 5.4 Copper

	q2		q4		q6		q8		q10		q50		q90		q92		q94		q96		q98	
Benchmark Model																						
Pseudo R2	0.001		0.000		0.002		0.003		0.004		0.000		0.003		0.006		0.007		0.003		0.000	
Constant	-1.276	***	-0.893	***	-0.693	***	-0.554	***	-0.434	***	0.000		0.432	***	0.545	***	0.636	***	0.797	***	1.098	***
	(0.059)		(0.048)		(0.033)		(0.031)		(0.030)		(0.001)		(0.028)		(0.022)		(0.031)		(0.045)		(0.070)	
Crisis Dummy	-0.171	**	-0.043		-0.126		-0.167	*	-0.168	***	0.000		0.071		0.042		0.040		0.063		0.073	
	(0.086)		(0.066)		(0.085)		(0.095)		(0.064)		(0.003)		(0.065)		(0.093)		(0.071)		(0.145)		(0.144)	
Coex Lag	-0.002		-0.014		0.053		0.079		0.033		0.000		-0.118	**	-0.174	***	-0.187	***	-0.099		-0.084	
	(0.091)		(0.041)		(0.074)		(0.054)		(0.024)		(0.001)		(0.056)		(0.023)		(0.051)		(0.069)		(0.143)	
Full Model																						
Pseudo R2	0.577		0.527		0.493		0.470		0.448		0.156		0.375		0.394		0.417		0.447		0.495	
Constant	-0.523	***	-0.381	***	-0.318	***	-0.256	***	-0.226	***	-0.001		0.232	***	0.278	***	0.284	***	0.334	***	0.388	***
	(0.066)		(0.027)		(0.024)		(0.022)		(0.036)		(0.009)		(0.021)		(0.028)		(0.032)		(0.033)		(0.038)	
Crisis Dummy	0.098	*	0.056		0.036		0.006		0.009		0.015		0.042		0.030		0.052		0.051		0.032	
	(0.055)		(0.040)		(0.034)		(0.035)		(0.038)		(0.015)		(0.034)		(0.037)		(0.042)		(0.040)		(0.056)	
MSCI	0.427	***	0.430	***	0.423	***	0.408	***	0.407	***	0.285	***	0.362	***	0.374	***	0.388	***	0.407	***	0.432	***
	(0.020)		(0.013)		(0.011)		(0.011)		(0.012)		(0.013)		(0.014)		(0.009)		(0.010)		(0.012)		(0.018)	
MS GARCH	-0.168	**	-0.147	***	-0.129	***	-0.127	***	-0.127	***	-0.028	***	0.068	***	0.075	***	0.075	*	0.087	*	0.157	***
	(0.076)		(0.032)		(0.025)		(0.011)		(0.019)		(0.005)		(0.019)		(0.014)		(0.040)		(0.049)		(0.046)	
EURUSD	0.039	**	0.033	**	0.016		0.010		0.004		-0.013	**	0.015		0.010		0.014		0.012		0.009	
	(0.016)		(0.014)		(0.010)		(0.009)		(0.009)		(0.006)		(0.012)		(0.012)		(0.014)		(0.013)		(0.020)	
EU GARCH	0.013		-0.026		-0.024		-0.022		-0.008		0.021	*	0.040	*	0.041		0.096	**	0.107	*	0.112	**
	(0.043)		(0.038)		(0.030)		(0.022)		(0.048)		(0.011)		(0.021)		(0.033)		(0.038)		(0.059)		(0.045)	
Coex Lag	-0.029		-0.066		-0.059		-0.059		-0.040		-0.074	***	-0.100	***	-0.077	**	-0.096	**	-0.103	**	-0.044	
	(0.049)		(0.076)		(0.069)		(0.038)		(0.039)		(0.009)		(0.038)		(0.033)		(0.039)		(0.049)		(0.093)	

This table reports two sets of estimates for several quantile regressions. The first set of estimates is for the benchmark model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis}$ which only contains a constant and a crisis dummy. The second set of estimates is for the full model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis} + \beta_2(\tau)\, r\_MSCI_{Mt} + \beta_3(\tau)\, GARCH\ MSCI_{Mt} + \beta_4(\tau)\, r\_EURUSD_{Mt} + \beta_5(\tau)\, GARCH\ EURUSD_{Mt} + \beta_6(\tau)\, COEX_{t-1}$ which also includes relevant regional indices, their volatility and the lagged coexceedance as regressors. The dependent variable for models is the coexceedances between S&P 500 and DJ UBS commodities indices for Copper. Standard errors are reported in brackets under the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

This might be indicative of an opportunistic buying effect, where market agents having observed that a crash in conventional asset markets has driven copper prices to a historical low (relative to fundamentals), consider the new low price as an opportunity for big upside returns on the copper price post crisis and decide to buy copper causing a spike in copper price.

With respect to the brent estimates in table 5.5, the benchmark model reveals evidence of bad contagion in the 2nd, 4th, 6th, 8th, and 10th quantiles respectively, again the 2nd quantile coefficient being the largest, each consecutive significant quantile coefficient thereafter appears smaller, this presents some evolution dynamics (bad contagion effects appear relatively more pronounced on the extreme of the left tail). The full model which tends to be more conservative corroborates the occurrence of bad contagion from S&P 500 to brent at the 2nd and 10th quantiles respectively, with the 2nd quantile coefficient remaining the larger coefficient of the two. The second quantile

coefficient is also the largest bad contagion coefficient observed amongst all investigated commodities. There is also a significant crisis dummy coefficient at the 96th quantile in the brent benchmark model which would normally be evidence of good contagion (implying that brent also enjoyed good contagion from S&P 500) but the sign of the coefficient is negative and counterintuitive which might be indicative of reverse contagion effects however, this is not corroborated by the full model results.

Table 5.5 Brent

	q2		q4		q6		q8		q10		q50		q90		q92		q94		q96		q98	
Benchmark Model																						
Pseudo R2	0.032		0.015		0.012		0.008		0.005		0.000		0.004		0.005		0.008		0.011		0.005	
Constant	-1.011	***	-0.760	***	-0.605	***	-0.498	***	-0.362	***	0.000		0.411	***	0.481	***	0.575	***	0.733	***	1.022	***
	(0.073)		(0.033)		(0.031)		(0.027)		(0.036)		(0.000)		(0.019)		(0.026)		(0.022)		(0.043)		(0.040)	
Crisis Dummy	-0.866	***	-0.441	***	-0.307	***	-0.294	***	-0.224	**	0.000		-0.071	**	-0.084		-0.042		-0.113	**	-0.050	
	(0.129)		(0.121)		(0.077)		(0.085)		(0.095)		(0.001)		(0.035)		(0.054)		(0.061)		(0.056)		(0.156)	
Coex Lag	0.199	***	0.072	*	0.091	***	0.075	*	0.081	***	0.000		-0.092	***	-0.108	***	-0.129	***	-0.165	***	-0.228	***
	(0.060)		(0.039)		(0.023)		(0.038)		(0.019)		(0.001)		(0.011)		(0.012)		(0.011)		(0.018)		(0.012)	
Full Model																						
Pseudo R2	0.503		0.452		0.428		0.407		0.387		0.059		0.324		0.347		0.376		0.415		0.459	
Constant	-0.378	***	-0.321	***	-0.266	***	-0.239	***	-0.201	***	0.000		0.246	***	0.259	***	0.306	***	0.323	***	0.414	***
	(0.074)		(0.031)		(0.033)		(0.019)		(0.022)		(0.007)		(0.026)		(0.022)		(0.021)		(0.039)		(0.029)	
Crisis Dummy	-0.386	*	-0.164		-0.122		-0.053		-0.067	*	-0.010		0.020		0.029		0.019		0.013		0.043	
	(0.211)		(0.114)		(0.078)		(0.045)		(0.037)		(0.013)		(0.033)		(0.034)		(0.037)		(0.036)		(0.058)	
MSCI	0.368	***	0.357	***	0.333	***	0.340	***	0.340	***	0.182	***	0.326	***	0.337	***	0.344	***	0.354	***	0.361	***
	(0.024)		(0.012)		(0.012)		(0.009)		(0.009)		(0.022)		(0.013)		(0.016)		(0.010)		(0.012)		(0.014)	
MS GARCH	-0.206		-0.143	***	-0.135	***	-0.083	***	-0.081	***	-0.019	***	0.072	***	0.080		0.079	***	0.103		0.151	***
	(0.164)		(0.014)		(0.014)		(0.024)		(0.010)		(0.006)		(0.021)		(0.052)		(0.023)		(0.088)		(0.024)	
EURUSD	0.007		0.013		0.021	*	0.013		0.006		-0.005		0.014		0.020		0.021		0.029	*	0.024	
	(0.031)		(0.018)		(0.012)		(0.009)		(0.008)		(0.005)		(0.011)		(0.015)		(0.014)		(0.015)		(0.015)	
EU GARCH	-0.077		-0.045		-0.028		-0.048	**	-0.048	*	0.017	*	0.032		0.060		0.059	**	0.101		0.057	
	(0.107)		(0.030)		(0.039)		(0.024)		(0.025)		(0.010)		(0.032)		(0.045)		(0.028)		(0.065)		(0.036)	
Coex Lag	-0.085		-0.063		-0.059		-0.046		-0.043		-0.020	**	-0.123	***	-0.129	***	-0.142	***	-0.173	***	-0.108	
	(0.08)		(0.05)		(0.05)		(0.04)		(0.04)		(0.01)		(0.03)		(0.05)		(0.042)		(0.061)		(0.070)	

This table reports two sets of estimates for several quantile regressions. The first set of estimates is for the benchmark model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis}$ which only contains a constant and a crisis dummy. The second set of estimates is for the full model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis} + \beta_2(\tau)\, r\_MSCI_{Mt} + \beta_3(\tau)\, GARCH\ MSCI_{Mt} + \beta_4(\tau)\, r\_EURUSD_{Mt} + \beta_5(\tau)\, GARCH\ EURUSD_{Mt} + \beta_6(\tau)\, COEX_{t-1}$ which also includes relevant regional indices, their volatility and the lagged coexceedance as regressors. The dependent variable for both models is the coexceedance between S&P 500 and DJ UBS commodities indices for Corn. Standard errors are reported in brackets under the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Results from the corn benchmark model in table 5.6 show evidence of bad contagion from S&P 500 at the 2nd and 10th quantile. Similar to the case of brent and copper the crisis dummy coefficient at the 2nd quantile of the brent benchmark model is the larger of the two. From the benchmark model estimates, good contagion is also established at 98th quantile. The 98th quantile coefficient also appears to be the largest coefficient size across all results obtained in this study, this implies a relatively higher degree of contagion between S&P 500 and exchange traded corn. The full model does not confirm any of the results from the benchmark model.

Table 5.6 Corn

	q2		q4		q6		q8		q10		q50		q90		q92		q94		q96		q98	
Benchmark Model																						
Pseudo R2	0.005		0.004		0.004		0.002		0.003		0.000		0.005		0.006		0.009		0.004		0.003	
Constant	-0.996	***	-0.701	***	-0.557	***	-0.430	***	-0.313	***	0.000		0.354	***	0.456	***	0.556	***	0.701	***	0.989	***
	(0.047)		(0.036)		(0.025)		(0.036)		(0.024)		(0.000)		(0.025)		(0.020)		(0.021)		(0.033)		(0.118)	
Crisis Dummy	-0.398	*	-0.211	***	-0.178	*	-0.223	***	-0.134	*	0.000		0.008		-0.045		-0.078		-0.031		0.299	**
	(0.215)		(0.071)		(0.100)		(0.068)		(0.070)		(0.000)		(0.093)		(0.028)		(0.080)		(0.146)		(0.128)	
Coex Lag	0.082		-0.002		0.068	***	0.002		-0.031		0.000		-0.095	*	-0.090	***	-0.154	***	-0.152		-0.169	
	(0.134)		(0.021)		(0.025)		(0.093)		(0.052)		(0.000)		(0.051)		(0.024)		(0.034)		(0.104)		(0.309)	
Full Model																						
Pseudo R2	0.466		0.389		0.342		0.313		0.286		0.007		0.255		0.278		0.308		0.339		0.385	
Constant	-0.464	***	-0.361	***	-0.281	***	-0.263	***	-0.224	***	-0.009	**	0.253	***	0.264	***	0.316	***	0.389	***	0.502	***
	(0.079)		(0.038)		(0.066)		(0.049)		(0.037)		(0.004)		(0.033)		(0.023)		(0.034)		(0.029)		(0.032)	
Crisis Dummy	0.063		0.005		-0.030		-0.013		-0.023		0.007		0.034		0.017		0.015		0.021		0.084	
	(0.079)		(0.050)		(0.052)		(0.042)		(0.032)		(0.006)		(0.028)		(0.037)		(0.041)		(0.057)		(0.100)	
MSCI	0.364	***	0.360	***	0.353	***	0.320	***	0.295	***	0.051	***	0.256	***	0.287	***	0.300	***	0.308	***	0.325	***
	(0.012)		(0.011)		(0.021)		(0.018)		(0.012)		(0.013)		(0.012)		(0.012)		(0.009)		(0.010)		(0.020)	
MS GARCH	-0.178		-0.127	***	-0.120		-0.111	***	-0.107	***	-0.004	*	0.074	***	0.079	**	0.118	***	0.109	***	0.102	***
	(0.108)		(0.019)		(0.083)		(0.016)		(0.016)		(0.002)		(0.009)		(0.037)		(0.022)		(0.017)		(0.033)	
EURUSD	0.010		-0.025		-0.019		-0.014		-0.022	*	-0.004	*	-0.025	*	-0.029	**	-0.018		-0.017		-0.007	
	(0.027)		(0.020)		(0.019)		(0.017)		(0.013)		(0.002)		(0.013)		(0.011)		(0.013)		(0.016)		(0.028)	
EU GARCH	-0.102		-0.099	***	-0.089		-0.030		-0.014		0.008	*	0.013		0.068	**	0.039		0.050		0.069	**
	(0.068)		(0.031)		(0.090)		(0.065)		(0.041)		(0.004)		(0.047)		(0.031)		(0.044)		(0.031)		(0.028)	
Coex Lag	-0.164		-0.098		-0.110		-0.096		-0.098		-0.016	***	-0.119	**	-0.151	***	-0.144	***	-0.126	***	-0.139	
	(0.115)		(0.093)		(0.086)		(0.078)		(0.066)		(0.005)		(0.058)		(0.037)		(0.037)		(0.045)		(0.094)	

This table reports two sets of estimates for several quantile regressions. The first set of estimates is for the benchmark model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis}$ which only contains a constant and a crisis dummy. The second set of estimates is for the full model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis} + \beta_2(\tau)\, r\_MSCI_{Mt} + \beta_3(\tau)\, GARCH\ MSCI_{Mt} + \beta_4(\tau)\, r\_EURUSD_{Mt} + \beta_5(\tau)\, GARCH\ EURUSD_{Mt} + \beta_6(\tau)\, COEX_{t-1}$ which also includes relevant regional indices, their volatility and the lagged coexceedance as regressors. The dependent variable for both models is the coexceedances between S&P 500 and DJ UBS commodities indices for Brent Crude. Standard errors are reported in brackets under the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

The 90th quantile crisis dummy in the gold benchmark model in table 5.7 is statistically significant but negative, which would have established good contagion if the coefficient had a positive sign. This might be indicative of reverse contagion which is expected for a safe haven asset such as gold. Gold is expected to benefit from a crash in conventional financial assets. The full model for gold establishes good contagion at the 96th and 98th quantiles respectively. The crisis dummy coefficient of the 98th quantile is the larger of the two, with the coefficient in the full model substantially larger than the significant one in the benchmark model. Gold appears to enjoy an opportunistic good contagion where a spike in conventional asset markets which would normally mean a dip in gold prices sparks an opportunistic rush for gold; given that the dip pushes gold to a historical low relative to market fundamentals.

Table 5.7 Gold

	q2		q4		q6		q8		q10		q50		q90		q92		q94		q96		q98	
Benchmark Model																						
Pseudo R2	0.003		0.010		0.006		0.004		0.002		0.000		0.002		0.001		0.000		0.000		0.003	
Constant	-0.946	***	-0.647	***	-0.503	***	-0.357	***	-0.270	***	0.000		0.330	***	0.405	***	0.500	***	0.633	***	0.906	***
	(0.041)		(0.021)		(0.031)		(0.030)		(0.018)		(0.000)		(0.016)		(0.029)		(0.024)		(0.031)		(0.054)	
Crisis Dummy	-0.136		-0.064		0.004		-0.054		-0.037		0.000		-0.065	*	0.000		-0.026		0.002		0.110	
	(0.133)		(0.076)		(0.072)		(0.049)		(0.041)		(0.000)		(0.036)		(0.068)		(0.044)		(0.041)		(0.117)	
Coex Lag	0.136	***	0.145	***	0.136		0.080	***	0.060	***	0.000		-0.054	**	-0.039	**	-0.002		0.015	*	0.105	***
	(0.024)		(0.007)		(0.139)		(0.008)		(0.006)		(0.000)		(0.021)		(0.017)		(0.020)		(0.008)		(0.026)	
Full Model																						
Pseudo R2	0.407		0.352		0.317		0.289		0.263		0.001		0.219		0.242		0.269		0.314		0.380	
Constant	-0.406	***	-0.235	***	-0.146	***	-0.140	***	-0.145	***	0.001		0.176	***	0.201	***	0.252	***	0.328	***	0.416	***
	(0.046)		(0.032)		(0.026)		(0.028)		(0.021)		(0.002)		(0.034)		(0.030)		(0.030)		(0.030)		(0.042)	
Crisis Dummy	0.039		-0.070		-0.037		-0.026		-0.017		0.003		0.046		0.063		0.119		0.128	*	0.149	**
	(0.048)		(0.060)		(0.080)		(0.061)		(0.042)		(0.002)		(0.036)		(0.058)		(0.078)		(0.072)		(0.071)	
MSCI	0.291	***	0.272	***	0.248	***	0.228	***	0.212	***	0.017	***	0.218	***	0.230	***	0.245	***	0.271	***	0.287	***
	(0.023)		(0.019)		(0.013)		(0.011)		(0.009)		(0.004)		(0.021)		(0.011)		(0.011)		(0.012)		(0.015)	
MS GARCH	-0.235	***	-0.183	**	-0.145	**	-0.124	**	-0.097	***	-0.001		0.120	**	0.136	***	0.163	***	0.209	***	0.196	***
	(0.042)		(0.088)		(0.059)		(0.061)		(0.014)		(0.001)		(0.056)		(0.018)		(0.062)		(0.070)		(0.016)	
EURUSD	0.120	***	0.088	***	0.073	***	0.063	***	0.062	***	0.007	***	0.047	***	0.057	***	0.047	**	0.033	*	0.030	
	(0.009)		(0.012)		(0.011)		(0.011)		(0.009)		(0.002)		(0.011)		(0.012)		(0.019)		(0.018)		(0.031)	
EU GARCH	-0.036		-0.091		-0.124	*	-0.080		-0.045	**	0.000		0.030		0.046		0.035		0.006		0.082	
	(0.042)		(0.071)		(0.070)		(0.052)		(0.022)		(0.002)		(0.062)		(0.042)		(0.051)		(0.051)		(0.050)	
Coex Lag	-0.142	***	0.015		0.049		0.042		0.016		-0.005	**	-0.046		-0.038		-0.031		-0.024		0.000	
	(0.032)		(0.099)		(0.051)		(0.040)		(0.035)		(0.002)		(0.058)		(0.049)		(0.042)		(0.082)		(0.088)	

This table reports two sets of estimates for several quantile regressions. The first set of estimates is for the benchmark model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis}$ which only contains a constant and a crisis dummy. The second set of estimates is for the full model: $Q_{COEX_t}(\tau) = \beta_0(\tau) + \beta_1(\tau) D_t^{crisis} + \beta_2(\tau)\, r\_MSCI_{Mt} + \beta_3(\tau)\, GARCH\ MSCI_{Mt} + \beta_4(\tau)\, r\_EURUSD_{Mt} + \beta_5(\tau)\, GARCH\ EURUSD_{Mt} + \beta_6(\tau)\, COEX_{t-1}$ which also includes relevant regional indices, their volatility and the lagged coexceedance as regressors. The dependent variable for models is the coexceedances between S&P 500 and DJ UBS commodities indices for Gold. Standard errors are reported in brackets under the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

A number of the covariates in the full model (equation 5.6) appear to demonstrate their influence on the structure of the coexeedances investigated as postulated by Baur and Schulze (2005). $\beta_2(\tau)$ and β_3 the coefficients for the returns of the MSCI which is the global markets proxy and its estimated conditional variance respectively appear to both be statistically significant across most quantiles in all the commodities markets investigated. The coefficient for the Euro/Dollar exchange rate is also statistically significant in many cases but not as much as the MSCI and its conditional variance.

The norm in the empirical literature would be to test for contagion at the 5th or 10th percentile (Bae et al. 2003), not finding statistically significant crisis dummy/contagion coefficients at these conventional percentiles would imply no evidence of contagion. In the case of brent, bad contagion is only robustly established at the second percentile from both models whilst in the case of gold, contagion is robustly established at the 98th percentile. This observation proves the additional value set out by Baur and Schulze (2005) in using a quantile regression approach as it gives the opportunity to investigate contagion across quantiles, thus providing relatively deeper insight.

From the results, it is evident that energy commodities proxied by brent appear to be the most vulnerable to bad contagion from conventional asset markets, whilst industrial metals appear to benefit from reverse contagion possibly related to opportunistic buying. Precious metals benefit from good contagion, even though this is counterintuitive for a safe haven asset, opportunistic buying could also be at play.

Ultimately, the fact that contagion is empirically established between conventional assets and commodities empirically corroborates the view in the literature (Tang and Xiong; 2012, Adams and Gluck; 2015, Henderson et al.; 2015) that commodities have indeed become financialized.

5.6 Conclusion

This chapter empirically assesses the financialization of exchange traded commodities markets by investigating the vulnerability of major exchange traded commodities (copper, corn, brent crude and gold) to contagion from conventional assets such as equities (S&P 500) with respect to the 2008 financial market crash. This chapter adopts an empirical framework which takes a coexceedances approach using quantile regression. The empirical framework is shown to provide more insight into crisis period dependence structure by allowing to test for contagion across quantiles through the entire distribution and avoid a quantile selection bias. Deeper insight into crisis period dependence structure between conventional assets and commodities markets might assist cross asset portfolio managers to build portfolios that are more resilient/defensive with respect to tail events.

The results empirically and robustly establish that exchange traded brent crude suffers bad contagion from S&P 500, with exchange traded copper benefitting from reverse contagion and exchange traded gold benefiting from good contagion. This chapter's findings ultimately indicate that exchange traded energy are the most vulnerable group of exchange traded commodities to contagion from conventional assets. It is also noteworthy that industrial metals and precious metals appear to benefit from reverse contagion and good contagion respectively via possible opportunistic behaviour of economic agents.

It is also clear from the 2008 commodities market crash that extreme events in the conventional financial markets could potentially spill over into commodities markets and possibly vice versa.

The contagion vulnerability of commodities markets to conventional assets has also demonstrated empirically the existence of financialization of commodities markets, corroborating the views of empirical studies such as Henderson et al. (2015) and Adams and Gluck (2015).

Chapter 6

Conclusion

6.1 Overview

This chapter summarises this thesis, bringing together research questions, empirical analyses, results and contributions to the empirical literature on financial contagion.

This thesis contributes to the empirical literature on contagion, specifically it explores financial markets which are relatively less prominent in the empirical literature on contagion but have also experienced crashes/crises.

The empirical literature on contagion is awash with studies on banking, currency, and stock crises/contagious crises episodes. For example: stock market contagion of 1987 (King and Wadhwani (1990)) East Asian currency contagion of 1998 (Forbes and Rigobon, 2002 and Corsetti et al., 2005), banking contagion of 2008 (Pais and Stork (2011)). The literature has relatively less contributions related to sovereign debt and commodities markets and has mostly seen contributions relating to markets in distinct geographical locations; exchange traded commodities markets do not always fit into this structure. The pre-existing literature also implies that contagion is mostly related to crashes or extreme negative events.

This thesis addresses the following research questions which are focused on two financial market crises episodes: the first is the 2010 EMU sovereign debt crisis of 2010, and the second is the commodities markets crises of 2008:

1. Is contagion only associated with negative disturbances, negative crises, and extreme negative events?
2. In the EMU sovereign debt crisis of 2010, is Greece the empirically established source of the crisis? If so, was Greece the only source of the crisis?
3. Can contagion effects resulting from extreme negative shocks be propagated as extreme positive shocks and vice versa?
4. What are the tail event patterns of vulnerability to contagion within the exchange traded commodities complex?
5. What are the patterns of contagion vulnerability to commodities markets from conventional financial asset markets?

This thesis identifies methodologies and empirical approaches that are consistent with its espoused definition of contagion and deemed adequate to answer the research questions set out earlier. As in Pesaran and Pick (2007), non-linear simultaneous equations are chosen as they can empirically identify/capture both the contagion and interdependence phenomena in the same crisis period. Moreover, with non-linear simultaneous equations, crisis periods are identified endogenously, eliminating the need to arbitrarily specify pre and post crises periods and the associated problems with results being potentially impacted by sample selection bias. This thesis explores addressing research questions 1 to 4 using non-linear simultaneous equations as in Pesaran and Pick (2007).

This thesis also chooses a co exceedance/quantile regression approach espoused by Baur and Schulze (2005). This approach seeks to explain the joint occurrence of extreme returns in two different markets using a quantile regression approach which incorporates more flexibility by taking into account the degree of contagion and without the need to make any distributional assumptions as such it is well suited to address research question 5.

Summarily, this thesis addresses five research questions relating to the existing empirical literature on contagion, the 2010 EMU sovereign debt crisis and the commodities markets crises of 2008. In addressing the five research questions, the thesis explores two different methodologies: non-linear simultaneous equations and coexeedances.

6.2 Summary of Findings

Research questions 1 and 2 are addressed in Chapter 3 using a system of non-linear simultaneous equations in line with Pesaran and Pick (2007). This empirical framework is applied to the EMU sovereign debt crisis, endogenously determining both the timing of crisis and the source country of a crisis event. All periphery (Greece, Italy, Ireland, Portugal and Spain) countries act as potential source countries of contagion within the EMU area. Greece is found not to be the only source of contagion, Ireland and Portugal also acted as sources of contagion.

Whilst the contagion literature has traditionally focused on the contagion resulting from extreme negative shocks, i.e. bad contagion, chapter 3 introduces the notion of good contagion associated with the propagation of extreme positive shocks beyond what fundamentals can explain or predict. In particular, this thesis shows that both bad contagion and good contagion can be present and need not come from the same sources or affect the same targets. Results suggest that, indeed, both good and bad contagion have occurred in the EMU sovereign risk crisis. Controlling for interdependence and monsoonal effects, it is found that the periphery (Greece, Italy, Ireland, Portugal and Spain) countries

were most exposed to bad contagion. Notably, core countries such as Belgium were also exposed to significant bad contagion originating from periphery countries. It is also noteworthy that Spain caused significant good contagion to almost the entire Eurozone. Policy wise, the fact that Spain caused good contagion to other Eurozone markets implies that policy makers could leverage good contagion or the propagation of extreme positive shocks to ameliorate systemic crisis. This could be achieved by targeting policy intervention to one or more systemically important markets which could then further propagate the relief effect to other affected markets or markets at risk.

Research questions 3 and 4 are tackled in chapter 4 also using non-linear simultaneous equations. Contagion is investigated within the exchange traded commodities complex with respect to the 2008 commodities market crash using a system of which considers both bad and good contagion. Non-linear simultaneous equations also allow both the endogenisation of crisis periods and the investigation of contagion to and from multiple sources, as such there is no need to make assumptions about systemically important commodities.

Two main sets of estimations are carried out. The first set looks broadly at contagion effects between the index returns for the 5 major commodity groups, and the second considers contagion between the returns for 18 individual exchange traded commodities. Controlling for interdependence and monsoon effects, industrial metals and energy are found to be the most systemically important sources of contagion. Chapter 4 also introduces reverse contagion effects i.e crisis triggered flight to quality effects captured through significant bad and good contagion indicators which demonstrates that contagion effects resulting from extreme negative shocks can be propagated as extreme positive shocks and vice versa. Given that the results in chapter 4 provide insight into the patterns of tail risk vulnerability within the exchange traded commodities complex, traders and commodities fund managers should find them useful in informing their marginal value at risk rules.

Chapter 5 addresses research question 5 using a coexeedance/quantile regression methodology. This chapter investigates the vulnerability of exchange traded commodities markets such as copper, corn, brent crude and gold to contagion from conventional asset markets such as equities. The empirical framework gives more insight into tail dependence structures relative to other methodologies. Deeper insight into tail dependence structure between conventional assets and commodities markets might assist cross asset portfolio managers with building portfolios that are resilient/defensive with respect to tail events. Results indicate that exchange traded energy commodities appear most vulnerable to suffering bad contagion from conventional asset markets. Industrial metals and precious metals appear to benefit from reverse contagion and good contagion respectively via possible opportunistic behaviour of economic agents. Chapter 5 also empirically corroborates the fact that commodities

markets have been financialized as contagion could not have occurred in the commodities markets if they were not first financialized.

Summarily, this thesis makes the following novel contributions to the empirical literature on contagion: firstly, this thesis introduces the notions of good contagion, bad contagion and reverse contagion.

This thesis also highlights the fact that contagion effects can be identified within exchange commodities markets, which are not structured along lines of sovereignty. The vulnerability of exchange traded commodities markets to contagion from conventional markets is also highlighted.

Ultimately, this thesis demonstrates that in extreme event episodes relating to financial markets, it is possible to empirically identify the following effects: interdependence, monsoonal effects, good contagion, bad contagion and reverse contagion.

6.3 Future Research

A number of research opportunities exist in continuation of the work in this thesis. Chapter 5 considers the vulnerability of exchange commodities to good, bad and reverse contagion from conventional asset markets. In continuation of this work, it will be expedient to empirically explore the vulnerability of conventional assets markets to contagion from commodities markets.

New and evolving financial asset markets that are in line to be potentially financialized such as crypto currencies (e.g. bitcoin) might present research opportunities in the empirical literatures on contagion and financialization respectively. In particular, at least 2 sets of research opportunities exist in this regard. The first set of research opportunities exist in terms of exploring good, bad and reverse contagion effects within the exchange traded crypto currencies complex in line with chapter 4. The second set of research opportunities relates exploring good, bad and reverse contagion between exchange traded crypto currency assets and conventional financial asset classes in line with chapter 5 of this thesis.

The future research opportunities highlighted above might provide stakeholders in the global financial markets (traders, portfolio managers, policy makers, risk managers etc) with deeper insight into the exposure of evolving and non-conventional asset markets to tail events in conventional asset markets and vice versa. This is particularly important from a systemic risk point of view.

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