UNIVERSITAT ROVIRA I VIRGILI

ESSAYS ON FINANCIAL CONTAGION

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ESSAYS ON FINANCIAL CONTAGION

by

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DOCTORAL THESIS

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WE STATE that the present study, entitled "Essays on Financial Contagion", presented by Jilber Andrés Urbina Calero for the award of the degree of Doctor, has been carried out under our supervision at the Department of Economics of this university, and that it fulfills all the requirements to be eligible for the International Doctorate Award.

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Chapter 1

International Financial Contagion: A review

> *"Blaming financial crises on contagion has proved to be highly contagious among economists and politicians alike..."*
>
> (Moser, 2003, p.157)

This chapter is devoted to provide a review on the different definitions of what contagion is, how it is measured, what causes contagion and mainly why it is important to account for it when designing policies and undertaking the decision making process.

Despite of the growing popularity of blaming "contagion" for international financial crisis, contagion remains being an elusive concern. Without a clear understanding of financial contagion and the mechanisms through which it works, we can neither assess the problem nor design appropriate policy measures to control for it (Moser, 2003).

A growing literature has emerged in an attempt to study the implications of the existence of financial contagion among countries. It is a clear fact that contagion has important economic implications in terms of international policies carried out by International Monetary Fund (IMF) jointly with the affected country or group of countries, since bailouts funds lent by the IMF has a weakening effect over the balance of payment of the countries when contagion is not evidenced as the source of crisis for the borrower country. On the other hand, investors need to understand the nature of changes in correlations of stock markets in order to evaluate the potential benefits of international portfolio diversification as well as the assessment of risks.

In the literature of financial contagion, there is yet little convergence of views about whether cross-county propagation of shocks through fundamental should be considered contagion. A number of authors call for discrimination between 'pure contagion' and shock propagation through fundamentals[1], which suggest labeling 'transmission' (Bordo and Murshid, 2001), 'spillovers' (Masson, 1998), interdependence (Forbes and Rigobon, 2001, 2002) or 'fundamental-based contagion' (Kaminsky and Reinhart, 1998). According to Moser (2003) the main reason for such discrimination is "that shocks propagation through fundamentals is the result of an optimal response to external shocks", which not constitutes a source of 'pure contagion'.

As a crisis in one country upsets the equilibrium in other countries, real and financial variables adjust to a new equilibrium. Financial market responses only reflect (anticipated) changes in fundamentals and speed up adjustment to the new equilibrium, but they do not cause the change in equilibrium. In other words, rather than causing the crisis, financial market responses bring the crisis forward, this can be thought as an example of fundamental-based contagion which is not a 'pure-contagion' crisis (Moser, 2003).

Market imperfections are the key to rely on when trying to explain the cross-country propagation of shocks when they are whether not related or explained by the fundamentals. Moser (2003) distinguishes two groups to classify the *mechanisms of pure contagion*:

1. Information Effects: information imperfections and costs of acquiring and processing information make a correct assessment of fundamentals difficult and a certain degree of ignorance rational. As a result, market participants are uncertain about the true state of a country's fundamentals. A crisis elsewhere might lead them to reassess the fundamentals of other countries and cause them to sell assets, to call in loans, or to stop lending to these countries, even if their fundamentals remain objectively unchanged. The literature offers a number of reasons why a crisis elsewhere could lead to a reassessment of objectively unchanged fundamentals:

[1] Financial, real, and political links constitute the *fundamentals* of an economy.

- Signal extraction failures[2]
- Wake-up call
- Expectations interaction
- Moral hazard plays
- Membership contagion

2. Domino Effects: In this group of explanations, a crisis in one country spreads to others rather mechanically in domino fashion as a result of direct or indirect financial connections. This story comes in three variations,

   - Counterparty defaults
   - Portfolio rebalancing due to liquidity constraints
   - Portfolio rebalancing due to capital constraints

1.1 What is Financial Contagion?

The word contagion has been widely used in the economics literature to refer a wide range of phenomena concerning financial economics, labor market, enterprise and individual behavior and other spheres of the broad economy within interrelated activities are embed. From very ancient times, economists have used the concept of contagion to refer situations such as: spread of bank runs and spread of strikes across firms or industries (Mavor, 1891), the spread of increases secured by labor unions to non-unions firms or sector (Ulman, 1955), the spread or business fluctuations across economies (Mack and Zarnowitz, 1958), the diffusion of technology and growth convergence across countries (Baumol, 1994; Findlay, 1978) and the spread of the speculative trading across individuals (White, 1940), here the common fact is the word *spread*, denoting contagion as a synonym to either spread or diffusion of something negative, namely contagion/spread of economic problems. In modern times, the word contagion still has negative connotations and is not an omen of good news.

In the recent literature, the concept is supposed to describe incidents in which a (suitably defined) financial crisis in one country brings about a crisis in another. In its broadest sense, therefore, financial contagion has to do with the propagation

[2]See Moser (2003) for further details on both, Information and Domino Effects.

of adverse shocks that have the potential to trigger financial crises. The crux of the matter is to identify potential propagation mechanisms and define those that represent contagion (Moser, 2003). As a first step it is helpful to understand what contagion does not mean and what does mean.

The first issue to be overcome to understand what contagion is has to do with its modern definition, indeed there is a widespread disagreement around it.

The World Bank has three definitions of contagion: *very restrictive, restrictive* and *broad* definition, where the classification is based on the degree of restriction which it has to do with the scope in terms of the events related to the timing, state of the world and the difficulty/easiness to identify contagion.

The *very restrictive definition* implies increase in linkages after a crisis, so that contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "tranquil times". Forbes and Rigobon (2002) define contagion using the *very restrictive definition*, as a significant increase in cross-market linkages after a (negative) shock to one country (or group of countries). According to this definition, if two markets show a high degree of co-movement during periods of stability, even if the markets continue to be highly correlated after a (negative) shock to one market, this may not constitute contagion. It is only contagion if cross-market co-movement increases significantly after the shock. If the co-movement does not increase significantly, then any continued high-level of market correlation suggests strong linkages between the two economies that exist in all states of the world. Forbes and Rigobon (2002) use the term interdependence to refer to this situation. Interdependence, as opposed to contagion, occurs if cross-market co-movements is not significantly bigger after a (negative) shock to one country or group of countries.

Currently this *very restrictive* definition is one of the most popular, because it has two important advantages: first, it provides a straightforward framework for testing whether contagion occurs or not by simply comparing linkages (such as cross-market correlation coefficients) between two markets during a relatively stable period with linkages after a shock or crisis and as a second benefit, it provides a straightforward method of distinguishing between alternative explanations of how crises are transmitted across markets. Several works are based on this definition: the seminal paper of King and Wadhwani (1990), Lee and Kim (1993) and Reinhart and Calvo (1996), Forbes and Rigobon (2002), Naoui et al. (2010a), Naoui et al. (2010b) and Wang and Nguyen Thi (2013), just to mention some of them.

The second definition of the World Bank about contagion is the *restrictive* definition: Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behavior. there are three major works that can be grouped into this category: Eichengreen et al. (1995), Eichengreen et al. (1996) and Bekaert et al. (2005).

According to Dungey et al. (2003), there are still formidable difficulties in reaching the appropriate set of fundamentals to use as control variables when contagion analysis is performed under the *restrictive* definition, suggesting that such models may not be effectively operational. Nevertheless, recent empirical research proposes two alternative means: Dungey et al. (2003) propose the use of latent factor models, which do not require the exact specification of the fundamental relationships, while Pesaran and Pick (2004) suggest controlling for fundamental-based market interdependencies using trade flow data and examining contagion as transmissions above that.

The *restrictive* definition of contagion does not need any type of link among countries, its nature only implies that contagion it is said to be explained by causes beyond any fundamental links, namely, herd behavior, financial panics, or switches of expectations across instantaneous equilibria (see Corsetti et al., 2001).

The third and last definition of contagion provided by The World Bank is the *broad* definition: Contagion is the cross-country transmission of shocks or the general cross-country spillover effects. Furthermore, this definition also claims that contagion can take place during both "good" times and "bad" times. Then, contagion does not need to be related to crises. However, contagion has been emphasized during crisis times.

Using the *broad* definition makes things harder since it does not provide the researcher with a framework to work with, no triggering event is involved and, a priori, no underlying relationships are supposed. Within this definition we can accommodate two recent works about spillovers propagation: Diebold and Yilmaz

(2009) and Diebold and Yilmaz (2012). Corsetti et al. (2001) specify that contagion occurs when country-specific shock becomes "regional" or "global", this work also belongs to the *broad* definition of contagion.

Apart from the World Bank's definitions there are also a number of *ad hoc* definitions of contagion and that is why the use of the word 'contagion' to describe the international transmission of financial crises has become fraught with controversy (Dungey and Tambakis, 2003).

This thesis uses the *very restrictive* definition of contagion, mainly for its advantages over the others and most importantly, because it provides an alternative explanation for transmission of crisis, namely interdependence, then the natural question on this context could be *Contagion or Interdependence?*, try to answer this question is the target of this thesis.

According to the definition of contagion chosen for this work, there should be a shock as a cause of contagion and this is represented by a crisis. Thus, Corsetti et al. (2001) claims that crises are characterized by what they call empirical regularities:

1. Sharp falls in stock markets tend to concentrate in periods of international financial turmoil.

2. Volatility of stock prices increases during crisis periods.

3. Covariance between stock market returns increases during crisis periods.

4. Correlation between stock market returns is not necessarily larger during crisis periods than during tranquil periods.

1.2 Causes of Contagion

According to Masson (1998); Dornbusch et al. (2000); Pristker (2000) and Forbes and Rigobon (2001) the causes of contagion can be divided conceptually into two categories: The first category emphasizes spillovers that result from the normal interdependence among market economies. This interdependence means that shocks, whether of a global or local nature, can be transmitted across countries because of their real and financial linkages. Reinhart and Calvo (1996) term this type of crisis propagation "*fundamentals-based contagion*". These forms of co-movements

Table 1.1: Fundamental causes of contagion

Macroeconomics causes	Investor's behavior as cause of contagion
1. Common shocks	1. Liquidity and incentive problems
2. Trade links and competitive devaluations	2. Information asymmetries and coordination problems
3. Financial links	3. Multiple equilibriums
	4. Changes in the rules of the game

would not normally constitute contagion, in the sense of the *restrictive* and *very restrictive* definitions.

The second category involves a financial crisis that is not linked to observed changes in macroeconomics or other fundamentals but is solely the result of the behavior of investors or other financial agents. Under this definition, contagion arises when a co-movement occurs, even when there are no global shocks and interdependence and fundamentals are not factors. A crisis in one country may, for example, lead investors to withdraw their investments from many markets without taking account of differences in economics fundamentals. This type of contagion is often said to be caused by "irrational" phenomena, such a financial panics, herd behavior, loss of confidence, and increased risk aversion. Some causes of contagion are listed in Table 1.1.[3].

The degree of financial market integration determines how immune to contagion countries are. The spread of a crisis depends on the degree of financial market integration. The higher the degree of integration, the more extensive could be the contagious effects of a common shock or a real shock to another country. Conversely, countries that are not financially integrated, because of capital controls or lack of access to international financing, are by definition immune to contagion (Dornbusch et al., 2000). This is true in our definition of contagion, but it might not be true under other definitions.

According to Forbes and Rigobon (2001), the theoretical literature of contagion could be split into two groups: *crisis-contingent* and *non-crisis-contingent* theories. Crisis-contingent theories as its name suggests are those that explain why transmission mechanisms change during a crisis and therefore why a shock leads to increase the cross-market linkages. On the other hand, Non-crisis-contingent theories assume that transmission mechanisms are the same during a crisis as during

[3]For a detailed explanation see Dornbusch et al. (2000), page 180.

more stable periods, and therefore cross-market linkages do not change (increase) after a shock. Theories belonging to the second group may be interpreted as pure interdependence not as contagion.

$$\text{Contagion may be explained by}\begin{cases}\text{Crisis-Contingent Theories}\begin{cases}\text{Multiple equilibria}\\ \text{Endogenous liquidity}\\ \text{Political economy}\end{cases}\\ \\ \text{Non-Crisis-Contingent Theories}\begin{cases}\text{Trade}\\ \text{Policy coordination}\\ \text{Country reevalution}\\ \text{Random aggregate shocks}\end{cases}\end{cases}$$

1.3 How contagion is testing?

Cross-market linkages can be measured by a number of different statistics, such as the correlation in asset returns, the probability of speculative attack, or the transmission of shocks or volatility (Forbes and Rigobon, 2001). This is the reason why there are three types of general approaches to achieve the test for contagion: 1) analysis of cross-market correlation coefficients, 2) probit models and 3) GARCH frameworks.

Tests based on cross-market correlation coefficients are the most straightforward and have two advantages previously mentioned. These tests compare the correlation between two markets during stable periods and turmoil periods and, if cross-country correlation coefficients increase significantly after a shock (in the turmoil period), then there is evidence enough to believe that contagion occurs. The first major paper that utilized this approach was King and Wadhwani (1990), they test for an increase in cross-market correlations between the US, UK and Japan and found that correlations increased significantly after the US crash. Then Lee and Kim (1993) extended the analysis using up to 12 major markets and they find evidence of contagion. Reinhart and Calvo (1996) use this approach to test for contagion after 1994 Mexican Peso crisis and also find contagion from Mexico to

Asian and Latin American emerging markets. The most extensive analysis using this framework was built by Goldfajn and Baig (1999) testing for contagion in stock indexes, currency prices, interest rates, and sovereign spreads in emerging markets during the 1997-1998 East Asian crisis, they reached the same conclusion: contagion occurred.

The second approach to test for contagion is constituted by probability models such as probit models. An extensive list of papers has included tests for contagion using this approach, mainly because it is simple and uses simplifying assumptions and exogenous events to identify a model and directly measure changes in the propagation mechanism. Such list of papers covers Eichengreen et al. (1996), Goldfajn and Baig (1999), Kaminsky and Reinhart (1998), and Forbes and Rigobon (2001). One important conclusion from these papers is that trade is the most important transmission mechanism through contagion spreads.

ARCH and GARCH framework constitute the third approach to test for contagion; this implies the estimation of the variance-covariance matrix of the transmission mechanism across countries which has been used to analyze the 1987 US stock market crash. Hamao et al. (1990) and Chou et al. (1994) find evidence of significant spillovers across markets but contagion did not occur. Another example of this methodology is Longin and Solnik (1995), they consider seven OECD countries from 1960 to 1990 and, by estimating a multivariate GARCH(1,1) as input to test for a Constant Conditional Correlation (Bollerslev, 1990) rejected the hypothesis of a Constant Conditional Correlation (CCC), nevertheless, such rejection of the null hypothesis is not directed linked with the existence of contagion. Other papers based on Dynamic Conditional Correlations (DCC) model of Engle (2002), are aimed to investigate whether contagion occurs by looking into the time-varying structure of the correlations are Naoui et al. (2010a) and Naoui et al. (2010b).

1.4 Policy Implications

Evaluating whether contagion occurs is important for several reasons. First, a critical tenet of investment strategy is that most economic disturbances are country specific, stock markets in different countries should display relatively low correlations. International diversification would therefore substantially reduce portfolio risk and increase expected returns. If contagion occurs after a negative shock, however, market correlations would increase in bad states, which would undermine much of the rational for international diversification, because ignoring the contagion can lead to poor portfolio diversification and an underestimation of risk. Second, many models of investor behavior are based on the assumption that investors react differently after a large negative shock. Knowing if contagion occurs is key to understand how individual behavior changes in good and bad states. Third, many international institutions and policy makers worry that a negative shock to one country can have a negative impact on financial flows to another country—even if the fundamentals of the second economy are strong and there is little real connection between the two countries. Even if this effect is temporary, it could lead to a financial crisis in the second country—a crisis completely unwarranted by the country's fundamentals and policies. If this sort of contagion exists, it could justify IMF intervention and the dedication of massive amounts of money to stabilization funds. A short-term loan could prevent the second economy from experiencing a financial crisis. On the other hand, if the crisis is due to interdependence instead of contagion, a bailout fund might reduce the initial negative impact, but it does not avoid the crisis by itself. It only gives more time to make necessary adjustments.

1.5 Data

This section is devoted to introduce the dataset used throughout this thesis. Our underlying data are daily nominal local-currency stock market indexes. We use six aggregate stock market indexes covering twelve countries: eleven developed stock markets (US, UK, Japan, Australia, France, Finland, Spain, Germany, Italy, Netherlands and Luxembourg, all the European markets are grouped into one unique index, Euro Stoxx50) and one emerging market (Brazil). Table 1.2 lists the countries and stock indexes to be analyzed.

In Chapter 2 we also use the indexes from Table 1.2 in US dollars. Moreover some interest rates are used as controls for global monetary shocks.

Table 1.2: Stock Market Indexes and Countries

Stock Market Index	Country	Stock Market Index	Country
S&P 500	US		France
FTSE 100	UK		Finland
BOVESPA	Brazil		Spain
NIKKEI	Japan	EURO STOXX50	Germany
S&P/ASX200	Australia		Italy
			Netherlands
			Luxemburg

Daily stock prices are the inputs to calculate daily stock returns defined as

$$R_t = (\ln P_t - \ln P_{t-1}) \times 100 = \ln \left(\frac{P_t}{P_{t-1}} \right) \times 100 \tag{1.1}$$

Following Forbes and Rigobon (2002), stock market returns are calculated as two days rolling-average, this allows us to control for the fact that markets in different countries are not open during this same trading hours. For volatility we assume that is fixed within periods (in this case, days) but variable across periods and following Garman and Klass (1980) we use daily high, low, opening and closing prices to estimate intraday volatility

$$\tilde{\sigma}_t^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2 \tag{1.2}$$

where H is the highest price in the day, L is the lowest price, O is the open day price and C is the close price (all in natural logarithms), the estimated intraday volatility will be the squared root of $\tilde{\sigma}_t^2$

Equation 1.2 is used in Chapter 4 as a proxy of the intraday volatility, however in Chapter 5 a GARCH(1,1) process is estimated to account for the time varying conditional volatility to be used in the Dynamic Conditional Correlation approach undertaken in that chapter.

1.5.1 Descriptive statistics

Table 1.3 and Table 1.4 provide some insights about the sample for both returns and volatility, respectively (in local currency). We use observations for daily estimations covering from June 16th, 2003 to September 16th, 2009.

Table 1.3: Stock market returns. Two-days rolling average.

	US	UK	EU	BRA	JPN	AUS
nobs	1632	1632	1632	1632	1632	1632
Minimum	−0.0662	−0.0649	−0.0644	−0.0731	−0.0840	−0.0507
Maximum	0.0620	0.0549	0.0635	0.0826	0.0852	0.0450
Mean	0.0000	0.0001	0.0001	0.0009	0.0001	0.0002
Median	0.0004	0.0004	0.0006	0.0016	0.0006	0.0008
Variance	0.0001	0.0001	0.0001	0.0002	0.0001	0.0001
Stdev	0.0090	0.0086	0.0095	0.0140	0.0114	0.0080
Skewness	−0.5428	−0.3407	−0.4223	−0.3086	−0.3105	−0.5301
Kurtosis	9.3147	9.0426	6.3215	3.7849	8.7028	6.2806

Table 1.4: Stock market volatility. Two-days rolling average.

	US	UK	EU	BRA	JPN	AUS
nobs	1632	1632	1632	1632	1632	1632
Minimum	0.0017	0.0021	0.0022	0.0034	0.0022	0.0012
Maximum	0.0690	0.0661	0.0759	0.0850	0.0653	0.0443
Mean	0.0090	0.0091	0.0098	0.0157	0.0095	0.0069
Median	0.0068	0.0070	0.0078	0.0137	0.0082	0.0053
Variance	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000
Stdev	0.0074	0.0067	0.0068	0.0088	0.0058	0.0048
Skewness	3.4838	2.8296	3.0987	3.1279	3.2903	2.2544
Kurtosis	16.6433	11.6567	15.1026	15.4763	17.3575	7.7421

As an descriptive exercise, we plot daily stock prices, daily volatility and rolling covariances (all in natural logs) to highlight the *empirical regularities* of a crisis. According to Corsetti et al. (2001), when a crisis hits a stock market we would expect sharp falls in prices, increases in volatility and also increases in covariances, Figure 1.1, Figure 1.2 and Figure 1.3 behave accordingly to Corsetti et al. (2001) regularities.

We plot the six markets' volatilities and covariances in Figure 1.2 and in Figure 1.3, respectively, and immediately we can see that all volatilities and covariances are higher during the crisis, with all markets displaying huge jumps. Since August 2008, stock market volatility/covariances reflect the dynamics of the subprime crisis quite well. The highest peak of S&P500 seen in Figure 1.2 was reached on October 14, 2008.

For the case of covariances, they are calculated using a moving windows of 160 days and only are plotted covariances corresponding to US with the other markets.

From the descriptives provided so far, we can see that the series capture quite well the crisis and all of them behaves as described in the *empirical regularities*. From Figure 1.1, Figure 1.2 and Figure 1.3 it seems that all stock markets reacted

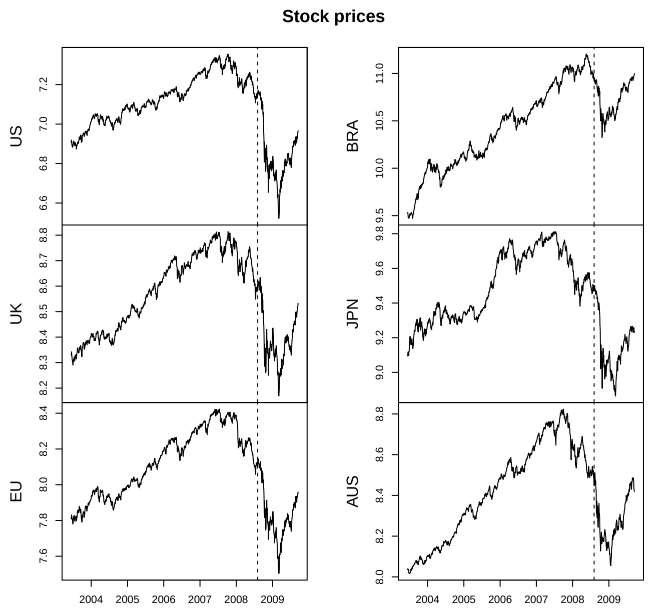

Figure 1.1: Daily closed price, in natural logs.

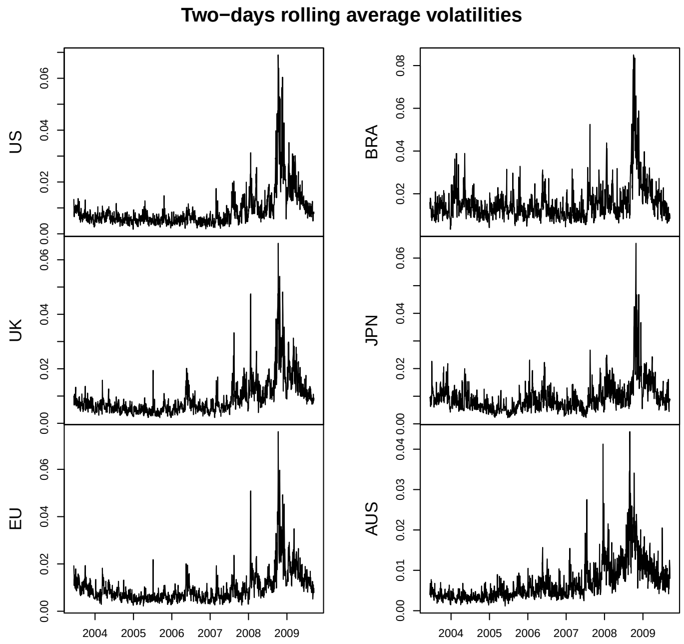

Figure 1.2: Daily volatility.

almost instantaneously to the shock hitting US which suggests that, somehow, such shock spills over the other markets in the sample.

Moreover, Figure 1.3 suggests that the non-standardized unconditional co-movements between US and the other countries were strengthened after the crisis, they are relative low before US is hit by the crisis and after that event they rise dramatically fast. If we divided the rolling covariances by the product of corresponding rolling standard deviation, we would end up having the rolling correlation which would suggest that, after the crisis, the linkages between US and other countries increased giving rise to some suspects about the existence of contagion.

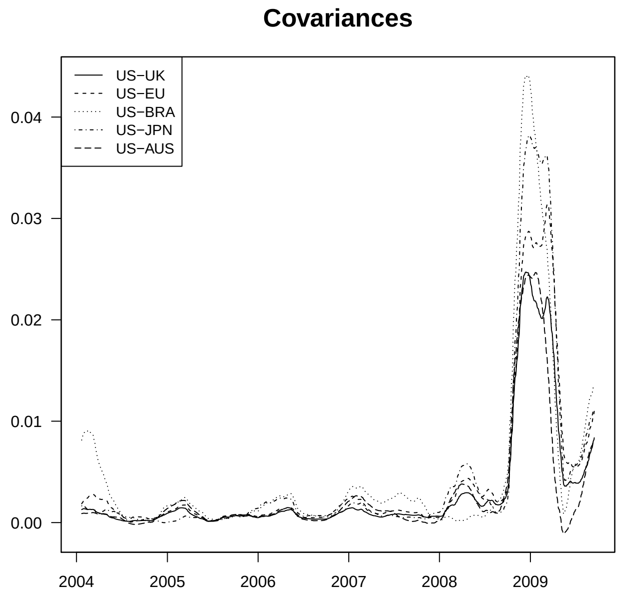

Figure 1.3: Rolling covariance, in natural logs, windows=160 days.

1.6 Conclusions

Summarizing, this thesis is devoted to test the existence of contagion by means of analyzing conditional co-movements, this analysis is not bounded by studying only the first order co-movements, but it goes further and looks into higher order co-movements to exploit some sort of asymmetries in the distribution of the series when shifting from non-crisis to crisis periods. This study is focused on analyzing the Subprime Crisis.

This introductory chapter shows that there is not a universally accepted definition of contagion, which is itself the first issue to be overcome. Through this entire thesis, the *very restrictive* definition provided by the World Bank is used as the benchmark for contagion testing, because it explicitly provides a measure to assess contagion, distinguishes two alternative channels through crises are spread all over and recently it is becoming into the most popular tool to test for contagion.

For contagion to exist, according to the *very restrictive* definition, it is necessary a crisis hitting one country or group of countries, additionally crises are characterized by some *empirical regularities* which our data clearly exhibits.

Three general approaches have been used to test for contagion when crises arrive, being the analysis of correlation the most extensively used. This thesis is focused on testing the existence of contagion by means of analyzing conditional co-movements, this analysis is not bounded by studying only the first order co-movements, e.g., correlations, but also it looks into higher order co-movements to exploit some sort of asymmetries in the distribution of the returns when shifting from stable to turmoils periods

The existence of contagion implies a number of political implications. Within the macroeconomics scope it has to do with portfolios rebalancing, positions of the balance of payments for borrower countries, currency appreciations and all its implications, just to mention few. In microeconomics terms, contagion can influence in the rationality of agents and in extreme cases can lead to irrational herding behavior provoking crisis and/or spreading crisis to other economies even when their fundamentals are solid.

The reminding of this thesis consists of five more chapters. Chapter 2 is entitle *Contagion or Interdependence in the recent Global Financial Crisis? An application to the stock markets using adjusted cross-market correlations.* In this chapter we use the *very restrictive* definition of contagion and we consider stock market contagion as a significant increase in cross-market linkages after a shock to one country or group of countries. Under this definition we study whether contagion occurred from the U.S. Financial Crisis to the rest of the major stock markets in the world by using the (adjusted) correlation coefficient approach developed by Forbes and Rigobon (2002) which consists of testing whether cross-market correlations increase significantly during the relevant period of turmoil.

The empirical strategy adopted in this chapter is using a vector autoregressive (VAR) framework for estimating the dynamic relationship among markets and afterwards performing the contagion test over the residual of the VAR previously estimated. The VAR residuals constitute our returns net from fundamental effects (Fry et al., 2010), therefore we use the VAR as a filter to distill any possible effect of fundamentals over the series. After adjusting for heteroskedasticity bias in the correlations as suggested by Forbes and Rigobon (2002), we failed in rejecting the null hypothesis of interdependence between US and the *i-th* country embedded in the sample. The empirical findings drawn from the analyzed sample strongly suggest not contagion, only interdependence, this means that shocks, whether of a global or local nature, can be transmitted across countries because of their real and financial linkages (Masson, 1998; Dornbusch et al., 2000; Pristker, 2000; Forbes and Rigobon, 2002).

In Chapter 3 we test for contagion adopting a different approach, the focus in on co-skewness (Fry et al., 2010) which describes the feedback of shocks from return to volatility and viceversa. The title of the chapter is *Was the late 2008 US Financial Crisis contagious? Testing using a higher order co-movement approach.* The starting point is the use of a generalized normal distribution that describes the co-skewness parameters. This chapter is aimed by the fact that crisis heightens the asymmetries in distribution of returns, so that looking into a higher order co-movement statistics can provide a different and more complete information about the transmission of shocks among countries. The contagion test based on the co-skewness is somehow quite similar to that of based on correlations, there is evidence of contagion if the co-skewness increases after a crisis. When taking into account the asymmetries and adjusting for heteroskedasticity, the co-skewness test suggests some evidence of contagion for feedback in higher order of co-movements.

Financial Spillover Across Countries: Measuring shock transmissions is the title of the fourth chapter where we measure interdependence in returns as well as in volatility among countries and summarizing into a spillover index. Spillover index is based on the forecast error variance decomposition (fevd) from a VAR model at h-step ahead forecast and we construct it using both the orthogonalized fevd and the generalized fevd, both of them provide similar results, but the generalized version is easier to handle, this is true since it does not depend on the restrictions imposed by the Choleski decomposition, this fact makes it attractive when economic theory is not available to identify variables relationship. This chapter is accompanied by the development of an R package named *Spillovers* to enable the reproducibility of the methodology as well as performing co-skewness tests.

The fifth chapter is entitled *A Component Model for Dynamic Conditional Correlations: Disentangling Interdependence from Contagion.* We propose using a MIDAS-DCC with GARCH(1,1) (Colacito et al., 2011) component to asses both contagion and interdependence. This methodology allows us to estimate both, long-run and short-run correlations, we relate the former with interdependence as this is driven by fundamentals and the latter is related with contagion episodes.

Spillovers: R package for estimating spillover indexes and performing Co-Skewness test is the sixth chapter, which describes the package developed for estimating the spillover indexes and performing co-skewness test. This package is written using the R language (R Core Team, 2012) under the version 3.0.1. A user manual is attached to this chapter on how to use the *Spillovers* package.

This thesis finishes with the seventh chapter which holds the general conclusions and future research.

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Chapter 2

Contagion or Interdependence in the recent Global Financial Crisis? An application to the stock markets using adjusted cross-market correlations

2.1 Introduction

During the last two decades, a growing literature has emerged in an attempt to study the importance of the existence of financial contagion between countries. It has been made clear that the existence of contagion has important economic implications in terms of international policies taken and carried out by International Monetary Fund (IMF) jointly with the affected country or group of countries. Moreover, investors need to understand the nature of changes in correlations of stock markets in order to evaluate the potential benefits of international portfolio diversification as well as the assessment of risks.

We define contagion, following King and Wadhwani (1990) and Forbes and Rigobon (2002), as a significant increase in cross-market linkages after a shock to one country (or group of countries). According to this definition, contagion does not occur if two markets show a high degree of co-movement during both stability and crisis periods. The term interdependence is used instead if strong linkages between the two economies exist in all states of the world. In the empirical analysis we follow Forbes and Rigobon (2002) using the correlation approach corrected for heteroskedasticity bias. Forbes and Rigobon (2002) call this approach *adjusted correlation procedure.*

In this chapter we study empirically the recent 2008 - 2009 US Financial Crisis using a straightforward approach based on cross-market correlation coefficients. Our results indicate that there is no empirical evidence of contagion; instead, we find evidence of interdependence in which the financial markets remain highly correlated over time.

The empirical strategy adopted in this chapter is using a vector autoregressive (VAR) framework for estimating the dynamic relationship among markets and then performing the contagion test over the residual of the VAR previously estimated. After adjusting for heteroskedasticity bias in the correlations as suggested by Forbes and Rigobon (2002), we failed in rejecting the null hypothesis of interdependence between US and any other country embedded in the sample. The empirical findings drawn from the analyzed sample strongly suggest not contagion, only interdependence, this means that shocks, whether of a global or local nature, can be transmitted across countries because of their real and financial linkages (Masson, 1998; Dornbusch et al., 2000; Pristker, 2000; Forbes and Rigobon, 2002).

The remainder of the chapter is arranged as follows. Section 2.2 discusses the traditional technique of measuring stock market contagion showing that the unadjusted correlation coefficient is biased, so adjusted correlation coefficient is used to perform the hypothesis test. Section 2.3 presents the model and data used to test for contagion while Section 2.4 discusses the results. Conclusions are summarized in Section 2.5.

2.2 Unadjusted and adjusted Correlations

This section is set up to show the bias of the unadjusted correlation due to the presence of heteroskedasticity.

Heteroskedasticity biases the cross-market correlation making the hypothesis tests for contagion an inaccurate tool for identifying whether contagion exists or not. For simplicity, the following discussion focuses on the two-market case. Consider two stochastic variables, x and y both related through the following equation:[1]

[1]Unadjusted Correlation is the term used by Forbes and Rigobon (2002) to refer to the correlation coefficient biased due to heteroskedasticity This analysis and demonstration is done in Forbes and Rigobon (2002). See Forbes and Rigobon (2002) for a formal proof.

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{2.1}$$

Considering the standard and classical assumptions for this Ordinary Least Squares (OLS) regression we have:

$$E(\epsilon_t) = 0, \tag{2.2}$$

$$E(\epsilon_t^2) = c < \infty, \tag{2.3}$$

where c is a constant

$$E(x_t, \epsilon_t) = 0 \tag{2.4}$$

Assumptions (2.2), (2.3) and (2.4) ensure OLS estimation of (2.1) to be consistent without omitted variables and with no endogeneity for both groups. Since we are assuming two periods (precrisis and crisis) and no contagion, therefore $\beta^h = \beta^l$, only these assumptions are required to make the proof and it is not required to make further assumptions about the distribution of the residuals.

Now, consider two groups: one group with high variance (h) and the other one, with the lower variance (l). Recall that in terms of our definition of contagion, in the lower variance group corresponds to the period of relative market stability and the high variance group is the period of turmoil, namely the period after and including the crisis. By construction we know that $\sigma_{xx}^h > \sigma_{xx}^l$, which when combine with the standard definition of β :

$$\beta^h = \frac{\sigma_{xy}^h}{\sigma_{xx}^h} = \frac{\sigma_{xy}^l}{\sigma_{xx}^l} = \beta^l, \tag{2.5}$$

Given $\sigma_{xx}^h > \sigma_{xx}^l$, it is clear that the covariance of each group is different and it must be greater in the high volatility group than the lower one as noted in Corsetti et al. (2001), this is because if the $\beta's$ are equal in the two groups and by construction we have stated $\sigma_{xx}^h > \sigma_{xx}^l$, so $\sigma_{xy}^h > \sigma_{xy}^l$ must be met. the empirical regularities in Corsetti et al. (2001).

From (2.1) we can define the variance of y as follows

$$\sigma_{yy} = \beta^2 \sigma_{xx} + \sigma_{ee} \tag{2.6}$$

and we can observe that since the variance of the residuals is assumed to remain constant over the entire sample, this implies that the increase in the variance of y across groups is less than proportional to the increase in the variance of x. Therefore:

$$\left(\frac{\sigma_{xx}}{\sigma_{yy}}\right)^h > \left(\frac{\sigma_{xx}}{\sigma_{yy}}\right)^l. \tag{2.7}$$

Finally, using the standard definition of the correlation coefficient we have:

$$\rho^h = \rho^l \sqrt{\frac{(1+\delta)}{\left(1+\delta\left[\rho^l\right]^2\right)}}, \tag{2.8}$$

where ρ^h is the unadjusted correlation coefficient that depends on the relative increase in the variance, hence affected by heteroskedasticity, ρ^l is the adjusted correlation coefficient and δ is the relative increase in the variance of x:

$$\delta \equiv \frac{\sigma_{xx}^h}{\sigma_{xx}^l} - 1. \tag{2.9}$$

where (2.8)[2] clearly shows that the estimated correlation coefficient is increasing in δ. Therefore, during periods of high volatility in market x, the estimated correlation (the unadjusted correlation) will be greater than the adjusted correlation, even if the adjusted correlation coefficient remains constant over the entire period, the unadjusted correlation coefficient will be biased upward and still being greater than the adjusted correlation and this has direct implications to test for contagion based on cross-market correlation coefficients.

This result implies that performing a test for contagion based on correlation leads to wrongly accept the null hypothesis and conclude that contagion occurs when this is false, providing a misleading conclusion.

Without adjusting for the bias, however, it is not possible to deduce if this increase in the unadjusted correlation represents an increase in the adjusted correlation or simply an increase in market volatility. According to our definition of contagion, only an increase in the adjusted correlation coefficient would constitute contagion.

[2]This same equation is also in Ronn et al. (2009), these authors called this equation as Stambaugh Theorem which comes from a bivariate normality. They also observe that the unadjusted correlation increases or decreases depending on the sign of the adjusted correlation is positive or negative, respectively.

The adjustment for this bias is a straightforward procedure under the assumptions discussed earlier and it only requires a simple manipulation of (2.8), solving for the adjusted correlation coefficient (ρ^l) and renaming by ρ^*, yields

$$\rho^* = \frac{\rho^h}{\sqrt{1+\delta\left[1-\left(\rho^h\right)^2\right]}} \tag{2.10}$$

Forbes and Rigobon (2002) prove that when a change greater than or equal to a given absolute size in one of the variables is produced, the absolute magnitude for the unadjusted correlation is increasing in the magnitude of that absolute change. According to Forbes and Rigobon (2002), one potential problem with this adjustment for heteroskedasticity is the assumption of no omitted variables and not endogeneity between markets (written as (2.2) and (2.4)). In other words, the proof of this bias and the adjustment is only valid if there are no exogenous global shocks and no feedback from stock market y to x.

The same conclusion was reached by Ronn et al. (2009), they consider the impact and implications of "large" changes in asset prices on the intra-market correlations in the domestic and international markets, however Ronn et al. (2009) use more restrictive assumptions about the distribution of the residuals. Actually, (2.10) is also provided in Ronn et al. (2009).

2.3 Base Model and Data

Following Forbes and Rigobon (2002), we use a Vector Autoregressive (VAR) framework to obtain a filtered version of the returns which are net of fundamentals effects Fry et al. (2010). In order to deal with the non-synchronous trading times we apply a 2-days rolling average to the filtered series, the specification of the model is as follows

$$X_t = \phi(L)X_t + \Phi(L)I_t + \eta_t \tag{2.11}$$

$$X_t = \left\{x_t^C, x_t^j\right\}' \tag{2.12}$$

$$I = \left\{i_t^C, i_t^j\right\}' \tag{2.13}$$

Where x_t^C is the stock market return in the crisis country; x_t^j is the stock market return in another market j; X_t is a transposed vector of returns in the same two stock markets; $\phi(L)$ and $\Phi(L)$ are vectors of lags; i_t^C and i_t^j are short-term interest rates for the crisis country and the country j, respectively; and η_t is a vector of reduced-form disturbances used as the pre-filtered returns. For each series of test, we first estimate the VAR model from (2.11). Once the VAR is estimated, we proceed to estimate the variance-covariance matrices for each pair of residuals during the full period, stable period and turmoil period. Afterwards, from the information given by the variance-covariance matrices we calculate the cross-market correlation coefficients for each set of countries and periods. Then, we apply the Fisher Transformation to each correlation coefficients in order to obtain a normal distribution of each of them.

Stock market returns are calculated as 2-days rolling-average based on each country's aggregate stock market index using US dollars as well as local currency, but focus on US dollars returns since these were most frequently used in past work on contagion, furthermore US dollars have the additional advantage of controlling for inflation (under non-fixed exchange rate regimes). We utilize five lags[3] for $\phi(L)$ and $\Phi(L)$ in order to control for serial correlation and mainly for any within-week variation in trading patterns. Interest rates have been included in order to control for any aggregate shock and/or monetary policy coordination.[4]. An extensive set of sensitivity tests show that changing the model specification has no significant impact on results.

We use six aggregate stock market indexes covering twelve countries. We compare the correlation coefficients between US stock index and each stock index of each single country. Countries and stock indexes are summarized in Table 1.2.

2.3.1 Hypothesis test

Using the specification in (2.11), we perform the test for stock market contagion. The hypothesis test consists of determining whether there is a significant increase

[3] A VAR Lag Order Selection Criteria was applied to select the best length of lag for the VAR estimation, the result of this was 5 lags as the best order.

[4] As Forbes and Rigobon (2002) remarked, interest rates are an imperfect measure of aggregate shocks, they are a good proxy for global shifts in real economic variables and/or policies that affect stock market performance.

in cross-market correlation coefficients after a shock, according to our definition of contagion we establish the following hypothesis:

$$H_0 : \rho^* \geq \rho^h$$
$$H_1 : \rho^* < \rho^h.$$

Where ρ^* is the correlation during the full period and ρ^h is the correlation during the turmoil period. Moreover, H_0 represents the interdependence hypothesis and H_1 is contagion. The t-statistic has the following form:

$$\text{t-stat} = \frac{\frac{1}{2}\ln\left[\frac{1+\hat{\rho}^h}{1-\hat{\rho}^h}\right] - \frac{1}{2}\ln\left[\frac{1+\hat{\rho}^*}{1-\hat{\rho}^*}\right]}{\sqrt{\left(\frac{1}{n_h-3}\right)+\left(\frac{1}{n_l-3}\right)}}. \tag{2.14}$$

Test statistics and results are reported in the next section.

2.4 Results

Using the US Financial Crisis as the event to drive contagion, we define our period of turmoil from August 5th, 2008 to September 16th, 2009. We define the period of relative stability as lasting from June 16th, 2003 to the start of the period of turmoil. The choice of the dates was made as a result from an analysis of the S&P500 behavior which is depicted in Figure 2.1 and this selection of dates also coincide with the World Bank's Crisis Timeline; but the extensive robustness tests performed below will show that period definition does not affect the central results.

The VAR models estimated in order to obtain the cross-market correlation coefficients are stable and none of the variables considered for these estimations have unit root, hence the hypothesis test performed for testing whether contagion occurred or not is valid and it is only affected by the presence of heteroskedasticity[5] and assuming that (2.2), (2.3) and (2.4) hold.

The estimated unadjusted correlation coefficients for stable, turmoil, and full period are shown in Table 2.1. Since Fisher transformation ensures normality, we use the normal critical value at 95%. The critical value for the t-test at the 5% level is 1.65, so any test statistic greater than this critical value indicates contagion (C), while any statistic less than or equal to this value indicates no contagion (N).

[5] No omitted variables is an assumption considered in this test.

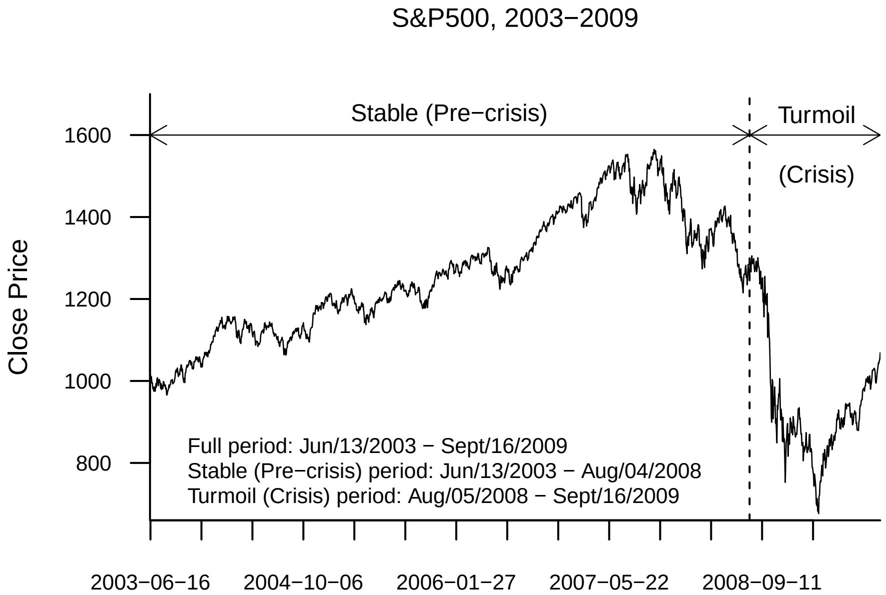

Figure 2.1: Daily Close Price of S&P500 Jun 13, 2003 - Sept 16, 2009.

We can observe that the average unadjusted correlation coefficient increased from 0.23 in the stable period to 0.53 in the turmoil period, it even has an increase from 0.40 in the full period to the 0.53 in the high volatility period. But, as previously discussed, these tests for contagion might be inaccurate due to the bias resulting from heteroskedasticity. The estimated increases in the unadjusted correlation could reflect either an increase in cross-market linkages and/or increased market volatility (Forbes and Rigobon, 2002). Before making the adjustment for

Table 2.1: Unadjusted correlations

	Correlation Coefficients			Full vs. Turmoil		Stable vs.Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.52	0.31	0.65	2.29	C	5.13	C
Australia	0.26	0.07	0.41	2.03	C	4.22	C
Brazil	0.56	0.35	0.73	3.58	C	6.54	C
Europe	0.53	0.32	0.66	2.41	C	5.32	C
Japan	0.14	0.08	0.20	0.80	N	1.43	N

Note: This table reports unadjusted cross-market correlation coefficients for US and each country in the sample. The stable period is defined as June 16th, 2003 through August 4th, 2008. The turmoil period is defined as August 5th, 2008 through September 16th, 2009. The full period is the stable period plus the turmoil period.

heteroskedasticity, it is necessary to test whether the residuals are heteroskedastic or not. Table 2.2 shows the results from White Heteroskedasticity Test with no-cross terms for each VAR, the null hypothesis is heteroskedasticity versus the alternative of heteroskedasticity As results show, the test suggests rejecting the null hypothesis, therefore correction provided in (2.10) is needed.

Table 2.2: Heteroscedasticity test.

	χ^2	Prob.
US - UK	1175.207	≈ 0
US - Australia	1599.046	≈ 0
US - Brazil	1054.196	≈ 0
US - Europe	1099.066	≈ 0
US - Japan	1347.977	≈ 0

Null hypothesis: homocedasticity

Adjusting for heteroskedasticity has an immediately and significant effect on estimated cross-market correlation coefficients and therefore on the conclusion of the test. One particular pattern highlighted by Forbes and Rigobon (2002) and Dungey and Zhumabekova (2001), is that in each country, the adjusted correlation is substantially smaller (in absolute value) than the unadjusted correlation during the turmoil period and is slightly greater in the stable period, as it can seen when comparing Table 2.1 and Table 2.3 or see Figure 2.2. During the turmoil period, the average unadjusted correlation coefficient for the entire sample is 0.53, while the average adjusted correlation is 0.33. During the stable period, the average unadjusted correlation is 0.23, while the average adjusted correlation is 0.33.

Based on Table 2.3, and according to this testing methodology, there is no evidence of contagion from US to the countries of the sample; but due to heteroskedasticity Table 2.1 reports contagion for the all countries in the sample, except for Japan.

Table 2.3: Adjusted correlations

	Correlation Coefficients			Full vs. Turmoil		Stable-Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.52	0.45	0.40	-1.76	N	-0.68	N
Australia	0.26	0.10	0.23	-0.38	N	1.47	N
Brazil	0.56	0.50	0.49	-1.16	N	-0.19	N
Europe	0.53	0.46	0.42	-1.78	N	-0.71	N
Japan	0.14	0.12	0.11	-0.35	N	-0.17	N

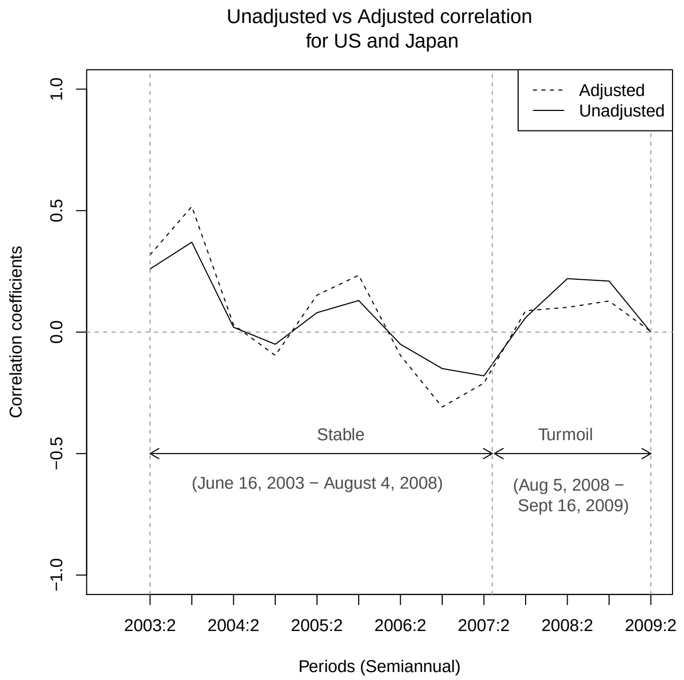

Figure 2.2: Cross-market correlation coefficients between US and Japan during the entire period

These economies are closely connected in all states of the world, and therefore it is not surprising that a large negative shock in US stock market is quickly passed on those countries. If this transmission of a large shock from the US to the rest of countries is a continuation of the same cross-market linkages that exist during more tranquil periods, then this should not be considered contagion, therefore according to Table 2.3 there is only a continuation of interdependence. The "contagion" evidence from the unadjusted correlation (given in Table 2.1) could be classified as *Spurious Contagion* (Dungey et al., 2005).

Figure 2.2 compares the unadjusted to the adjusted correlation. In that figure correlations between US and Japan stock market through the S&P500 and NIKKEI are reported. Semiannual correlations are depicted in order to show their pattern, note that adjusted correlation is above (in absolute value) the unadjusted in the period of relative stability and it is below in turmoil period as previously mentioned.

The average unadjusted cross-market correlation coefficient between US and Japan in the stable period, measured as semiannual frequency reported in Figure 2.2, is 0.05 and it jumps up to 0.12 during the turmoil period, this could be contagion, but it is not, because the average adjusted (adjusted for heteroskedasticity) cross-market correlation coefficient during stable period is 0.06 and only changes and reaches the value of 0.08 during the turmoil period, this is a clear evidence of interdependence instead of contagion between US and Japan.

2.4.1 Robustness Analysis

In this section we test for the impact of modifying the interest controls, the currency denomination and the period definitions, in order to investigate how fundamentals affect the assessment of contagion. In each case the central results (those of adjusted correlation) do not change. Tests based on unadjusted correlation coefficients find some evidence of contagion, while tests based on the adjusted coefficients find no evidence of contagion.

Using no Interest Rate Controls

As a first set of robustness, we eliminate the interest rate controls. As discussed in Section 2.3, we utilize interest rate to control for any aggregate shocks and/or monetary policy coordination which simultaneously affect different stock markets. Table 2.4 and Table 2.5 summarize these results.

Note that both correlation coefficients and statistical significance in Table 2.1 and Table 2.4 are very similar, this is because the variable Interest Rate is not statistically significant in most of the equations of the model mainly because this variable is an imperfect measure to control for the effects of aggregate monetary shocks. It is also expected that the results of Table 2.1 and Table 2.5 are virtually unchanged and that the conclusion of interdependence achieved in the previous section continue to be the same.

Local Currency with interest rate controls

As another way to test the validity of the results we modify the currency denomination. Table 2.6 and Table 2.7 show the results in local currency of each country.

Table 2.4: No interest rate controls. Unadjusted correlations.

	Correlation Coefficients			Full vs.Turmoil		Stable-Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.52	0.30	0.64	2.24	C	5.18	C
Australia	0.26	0.05	0.42	2.07	C	4.52	C
Brazil	0.56	0.35	0.74	3.61	C	6.64	C
Europe	0.53	0.31	0.66	2.37	C	5.42	C
Japan	0.14	0.08	0.21	0.80	N	1.48	N

Table 2.5: No interest rate controls. Adjusted correlations.

	Correlation Coefficients			Full vs. Turmoil		Stable vs.Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.52	0.44	0.40	-1.81	N	-0.68	N
Australia	0.26	0.08	0.23	-0.42	N	1.75	C
Brazil	0.56	0.51	0.49	-1.23	N	-0.31	N
Europe	0.53	0.46	0.41	-1.85	N	-0.72	N
Japan	0.14	0.12	0.11	-0.39	N	-0.19	N

Measuring returns based on local currency instead of US dollars clearly has minimal impact on our central results. Cross-market correlations of Table 2.6 and Table 2.7 are calculated taking into account the local currency denomination of each country; for example, the correlation between US and UK with interest rate controls has been computed using the S&P500 and FTSE100 in Pounds, as well as the correlation between US and Australia has been calculated using the stock indexes S&P500 and S&P ASX200 in Australian dollars, and as the same way for the remaining countries.

One important thing that deserve to be highlighted is the result of the first part of Table 2.6 where everything indicates that contagion not occur, while the second part of the same table shows evidence of contagion, so as we said in the previous section, unadjusted correlation results are not stable, while adjusted correlations results are strongly stable.

Table 2.6: Unadjusted correlation results: local currency with interest rate controls

	Correlation Coefficients			Full vs. Turmoil		Stable vs. Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.42	0.33	0.49	1.14	N	2.26	C
Australia	-0.01	-0.07	0.07	0.89	N	1.60	N
Brazil	0.28	0.11	0.47	2.64	C	4.54	C
Europe	0.49	0.38	0.59	1.58	N	3.06	C
Japan	0.25	0.14	0.34	1.25	N	2.48	C

Table 2.7: Adjusted correlation results: local currency with interest rate controls

	Correlation Coefficients			Full vs. Turmoil		Stable vs. Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.42	0.43	0.30	-1.53	N	-1.62	N
Australia	-0.01	-0.10	0.04	0.56	N	1.53	N
Brazil	0.28	0.14	0.30	0.30	N	1.91	C
Europe	0.49	0.49	0.37	-1.67	N	-1.59	N
Japan	0.25	0.21	0.19	-0.68	N	-0.18	N

Local Currency and No Interest Rates Controls

In this set of robustness tests, we find two potential countries receiving contagion from US financial crisis, these countries are Australia and Brazil, but as explained above, this could be spurious contagion due to the effect of inflation and lack of controlling aggregate shocks or monetary implications. Also Table 2.8 and Table 2.9 support this potential contagion on Brazil and Australia.

After all, there is still evidence of interdependence instead of contagion. Despite of these results, data still support the interdependence, because results of Table 2.9 could be cause of policy coordination or aggregate shocks which we are not able to control due to a lack of an appropriate variable for this purpose.

Table 2.8: Unadjusted correlation results: local currency and no interest rate controls.

	Correlation Coefficients			Full vs. Turmoil		Stable vs. Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.42	0.33	0.49	1.12	N	2.31	C
Australia	0.00	-0.08	0.07	0.93	N	1.80	C
Brazil	0.30	0.11	0.50	2.89	C	5.14	C
Europe	0.49	0.38	0.57	1.46	N	2.97	C
Japan	0.25	0.14	0.34	1.25	N	2.48	C

Table 2.9: Adjusted correlation results: local currency and no interest rate controls.

	Correlation Coefficients			Full vs. Turmoil		Stable vs. Turmoil	
	Full	Stable	Turmoil	t-stat	Contagion?	t-stat	Contagion?
UK	0.42	0.43	0.30	-1.59	N	-1.74	N
Australia	0.00	-0.11	0.04	0.55	N	1.74	C
Brazil	0.30	0.14	0.32	0.26	N	2.20	C
Europe	0.49	0.50	0.36	-1.81	N	-1.89	N
Japan	0.25	0.21	0.19	-0.68	N	-0.18	N

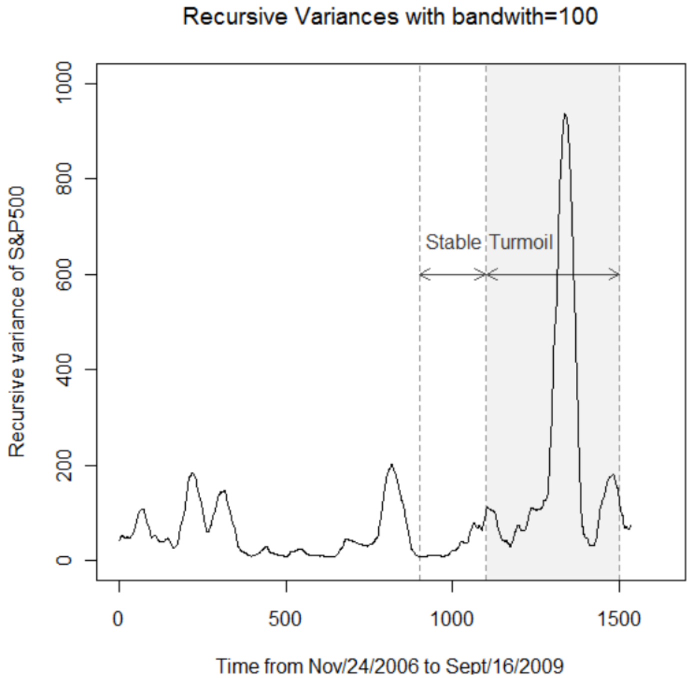

Figure 2.3: Recursive variance of S&P500, bandwidth = 100 days

Modifying Period Definitions

This section is aimed to determine the effects on correlations when period definition is changed. One of the recurrent facts in past crises is the difficulty to establish the beginning and the of the crisis, therefore we set several period definitions in order to find out what happens with the conclusion of the test.

As shown by Boyer et al. (1997) changes in the behavior of series cannot be detected reliably by splitting a sample according to the ex post realizations of the data generating process and creating sub-samples of the data based on a particular threshold value for one of the series . This is because valid statistical inference on the existence of structural change in the coefficients of a regression model differs when the date of potential change is unknown compared to the known date case. In this section we show that the conclusion of the test does not change, when we change the date. Moreover, the beginning and end of the crisis is dated in the World Bank's crisis timeline and there is a common agree on when crisis began.

To finish the sensitivity analysis, we modify definitions for the stable period and the turmoil period based on an analysis of recursive variances of S&P500. Figure 2.3 shows the new period definition. The recursive variances have been calculated using a bandwidth of 100 days.

The new period definition is as follows, stable period goes from November 24, 2006 to August 31, 2007; the crisis period lasts from September 3, 2007 up to September 16, 2009; Full period is stable period plus turmoil period. Daily returns are also adjusted for weekends and holidays as in the previous definition. Taking into account this new date specification, we compute the new set of cross-market correlation coefficients in US dollars with interest rate controls, also in US dollars with no interest rates, we also calculate the correlations in local currency with interest rates and we repeat the routine without controlling for interest rates. Results are summarizing from Table 2.10 to Table 2.13.

As we can see from Table 2.10 and Table 2.11 the adjusted cross-market correlation coefficient is highly robust to changes in dates, and the lack of robustness of the unadjusted correlation coefficient is evident, while the results of Table 2.1 and Table 2.4 based on unadjusted correlation suggest evidence of contagion, Table 2.10 suggests no evidence of contagion at all, this indicates that unadjusted correlation is sensitive to changes in period definitions. In contrast, we find that adjusted correlations remains almost without changes even if the period definitions are changed.

Table 2.10: Stable 11/24/2006 - 08/31/20007. Crisis 09/03/2007 - 09/16/2009.

	Full vs. Turmoil			
	In US dollars			
	Interest rates		No Interest rates	
	unadjusted Contagion?	adjusted Contagion?	unadjusted Contagion?	adjusted Contagion?
UK	N	N	N	N
Australia	N	N	N	N
Brazil	N	N	N	N
Europe	N	N	N	N
Japan	N	N	N	N

The conclusion reached is the same as before: there is no evidence of contagion, it is only interdependence.

Table 2.11: Stable 11/24/2006 - 08/31/2007. Crisis 09/03/2007 - 09/16/2009.

Stable vs. Turmoil				
	In US dollars			
	Interest rates		No Interest rates	
	unadjusted Contagion?	adjusted Contagion?	unadjusted Contagion?	adjusted Contagion?
UK	C	N	C	N
Australia	C	N	C	N
Brazil	C	N	C	N
Europe	C	N	C	N
Japan	C	C	C	C

The following last pair of tables not only show the lack of evidence of contagion, but also highlight the evidence in favor to interdependence and besides highlight the robustness of the adjusted correlation coefficient.

Table 2.12: Stable period 11/24/2006 - 08/31/20007. Crisis 09/03/2007 - 09/16/2009. In Local Currency

Full vs. Turmoil				
	In Local Currency			
	Interest rates		No Interest rates	
	unadjusted Contagion?	adjusted Contagion?	unadjusted Contagion?	adjusted Contagion?
UK	N	N	N	N
Australia	N	N	N	N
Brazil	N	N	N	N
Europe	N	N	N	N
Japan	N	N	N	N

Table 2.12 and Table 2.13 show the variability in the conclusion about whether contagion occurred or not based on unadjusted correlation. In Table 2.12 it is clear that contagion not occurred, but in Table 2.13 is evident that contagion affected almost the entire sample, but adjusted correlation remains almost invariant and the null hypothesis written in subsection 2.3.1 is not rejected, and with a lot of empirical evidence and with an extensive set of robustness analysis we conclude that there was not contagion, only interdependence.

Even by a more dramatic change in the period definitions the conclusion remains invariant, interdependence prevails, see Table 2.14. Another period definition established: stable period is 11/24/2006 to 1/08/2008, turmoil period is 4/08/2008 to 03/16/2009, and full period as defined as 11/24/2006 to 03/16/2009.

Table 2.13: Stable 11/24/2006 to 08/31/20007. Crisis 09/03/2007 - 09/16/2009. In Local Currency

Stable vs. Turmoil				
	In Local Currency			
	Interest rates		No Interest rates	
	unadjusted Contagion?	adjusted Contagion?	unadjusted Contagion?	adjusted Contagion?
UK	N	N	N	N
Australia	C	C	C	C
Brazil	C	N	C	N
Europe	C	N	C	N
Japan	C	N	C	N

Table 2.14: Stable period is 11/24/2006 to 1/08/2008, turmoil period is 4/08/2008 to 03/16/2009, and full period as defined as 11/24/2006 to 03/16/2009. Currency: US dollars

In US dollars				
	Full vs Turmoil		Stable v Turmoil	
	unadjusted Contagion?	adjusted Contagion?	unadjusted Contagion?	adjusted Contagion?
UK	N	N	C	N
Australia	N	N	C	N
Brazil	N	N	C	N
Europe	N	N	C	N
Japan	N	N	C	C

2.5 Conclusions

Hypothesis test using the correlation approach based on the *very restrictive* definition of contagion is a straightforward procedure and it provides the researcher with the framework to distinguish between alternatives channels of transmission of crisis: contagion or interdependence. Nevertheless it is biased by heteroskedasticity. Unadjusted correlation coefficient could be adjusted to perform more accurate hypothesis tests when evidence of heteroskedasticity is found.

The majority of our results based on unadjusted correlation suggest contagion, but these results are biased though. Unadjusted correlation not only suggests contagion for all the countries in the sample, but also indicates no contagion (interdependence) at the same time; this is clearly a lack of robustness.

It is shown after performing the robustness analysis that unadjusted correlation is unstable and very sensitive to changes in period definitions. Nevertheless, adjusted correlation performs much better, in terms of robustness, than the unadjusted correlation and the conclusions achieved with adjusted correlation-based tests are more stable than those reached by the correlation without adjustment.

The 2008 – 2009 US Financial Crisis has a significant effect all over the world; however, in the countries under examination in this chapter, these effects are a consequence of interdependence instead of contagion which implies that bailouts funds lent by the IMF might a weakening effect over the balance of payment of the countries since contagion is not evidenced as the channel of crisis transmission.

We find enough evidence that these economies are closely linked and therefore show a high level of market co-movement during all states of the world.

This chapter supports and highlights the presence of interdependence instead of contagion between US and the set of countries belong to the sample.

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Chapter 3

Was the late 2008 US Financial crisis contagious? Testing using a higher order co-movements approach

3.1 Introduction

The existence of financial contagion as the mechanism through crises are transmitted internationally have been faced using a wide range of models and tests focusing on: cross-market correlations (Forbes and Rigobon, 2002; King and Wadhwani, 1990; Lee and Kim, 1993; Reinhart and Calvo, 1996; Goldfajn and Baig, 1999), conditional variance shifting (Hamao et al., 1990; Chou et al., 1994), fundamental-based tests using probability models as in Eichengreen et al. (1996); Goldfajn and Baig (1999); Kaminsky and Reinhart (1998); Forbes and Rigobon (2001) some others prefer analyzing correlations with explicit modeling of the time-varying conditional variance (Longin and Solnik, 1995; Naoui et al., 2010a,b). Most of the popular procedure to test for contagion are aimed to analyze firsts conditional distributional moments: mean and variance, moreover when multivariate case arises, correlation approach is one of the favorite to perform bivariate tests in order to look for some evidence of contagious crises.

Tests for contagion are aimed to the identification of significant changes in the moments of the distribution, in this sense, contagion is defined as changes in the moments of the distribution during a financial crisis over and above changes due to market fundamentals (Dornbusch et al., 2000). This is because there are some

Table 3.1: Descriptive statistics of daily returns.

	US	UK	EU	BRA	JPN	AUS
			Precrisis			
Mean	0.04523	0.06125	0.07769	0.20005	0.04862	0.09330
Variance	0.28316	0.42111	0.53595	2.17622	0.77866	0.64708
Skewness	−0.07820	−0.25994	−0.05078	−0.58034	−0.26834	−0.89300
			Crisis			
Mean	−0.20367	−0.26794	−0.27522	−0.25793	−0.14289	−0.30950
Variance	2.58614	3.70419	3.64875	8.91117	2.89632	4.89742
Skewness	−0.15850	0.18719	0.06513	−0.14889	0.12596	−0.10750

Note:Values are expressed in percentages. Precrisis: February 21, 2003 to December 21, 2007. Crisis: December 22, 2007 to January 30, 2009.

empirical regularities (Corsetti et al., 2001) such that in crisis episodes returns falls sharply, volatility and covariances increases and skewness becomes positive (or more positive if it already was positive, Harvey and Siddique, 2000).

In this chapter we utilize a new test for contagion developed by Fry et al. (2010) which, based on a stochastic discount factor model, look for evidence of contagion by testing for changes in higher order co-moments, this test is known as *co-skewness test.*

Identification of the transmission channel of financial crises is undertaken by means of testing changes in higher order moments of the distribution of returns. We test the existence of contagion using the recently developed co-skewness test (Fry et al., 2010) applied to the US Subprime Crisis, this test allows to examine interactions of levels and volatility of returns which provide richer environment to drawn conclusions over contagion. Results suggests little evidence of contagion among pair of countries both in returns and volatility.

Table 3.1 highlights some common features of the assets behavior when shifting from a non-crisis period to the crisis one. First, average daily return for US index decreased from 0.045 prior to the crisis to -0.203 during the crisis, while daily volatility increases from 0.283 to 2.586. Returns experienced a decrease of 550.30 %, while volatility increases around 813.31%. The same pattern is observed for the other countries conforming the sample.

Skewness shows the typical empirical pattern of increase when passing from relative stable period to turmoil period. Table 3.1 shows this pattern for UK, EU and Japan, while for Brazil and Australia their skewness changed from very negative to less negative. This behavior of the skewness in the descriptive statistics suggests the appropriateness of using the co-skewness test.

The co-skewness test is applied to analyze the US Subprime Crisis in order to identify evidence of contagion from US stock market to others stocks markets. The empirical results reported reveal that contagion took place in transmitting the crisis from US to UK and Japan in contrast to the findings of no contagion suggested by Forbes and Rigobon test performed in Chapter 2.

In spite of the fact that the crisis under analysis in this chapter originated in US and it is assumed to spread to the other countries via contagion, we also perform the test in several directions taking each country of the sample as the transmitter country to analyze if this particular country triggers a crisis in other country via contagion. We not only analyze transmission from US to others countries, but from other countries among them.

Co-skewness test is a natural test for contagion as it captures the portfolio effects of financial crises extending from higher order moment where the expected excess returns on assets was expressed in terms of risk prices, which is a function of the risk preferences of investors and risk quantities, where is a function of higher order conditional moments (Fry et al., 2010).

This chapter is organized as follows: Section 3.2 reviews the basis of the co-skewness test and present the test develop in Fry et al. (2010) in Section 3.3 data, analyzed period and results from the application of the test to the US Subprime Mortgage Crisis are presented. Conclusions are in Section 3.4.

3.2 Contagion test based on changes in co-skewness

This section is intended to briefly review the methodology used in this chapter to test for contagion focusing on the third conditional comovements.

3.2.1 Generalized Normality

Fry et al. (2010) use a generalized exponential multivariate distribution which is an extension of the univariate work developed by Cobb et al. (1983) and Lye and Martin (1993) to derive the co-skewness statistic for the test.

The multivariate generalized exponential family of distribution presented in Fry et al. (2010) is

$$f(r) = \exp\left(\sum_{i=1}^{M} \theta_i g_i(r) - \eta\right), \tag{3.1}$$

where $\theta = \{\theta_1, \theta_2, \ldots, \theta_M\}$ is an M-dimensional vector of parameters, $g_i(r)$ is an arbitrary function of the K-dimensional random variable r and η is a normalizing constant defined as

$$\eta = ln \int \cdots \int \exp\left(\sum_{i=1}^{M} \theta_i g_i(r)\right) dr_1 dr_2 \ldots dr_K, \tag{3.2}$$

which ensures that $f(r)$ is a well defined probability distribution with the property that

$$\int \cdots \int \exp\left(\sum_{i=1}^{M} \theta_i g_i(r) - \eta\right) dr_1 dr_2 \ldots dr_K = 1.$$

Typical choices for $g_i(r)$ in (3.1) are polynomials and cross-products in the elements of r. For example, a bivariate example ($K = 2$) is given by setting $M = 3$ and choosing $g_1(r) = r_1^2$ and $g_2(r) = r_2^2$ and $g_3(r) = r_1 r_2$. This yields the bivariate normal distribution

$$f(r) = \exp(\theta_1 r_1^2 + \theta_2 r_2^2 + \theta_3 r_1 r_2 - \eta), \tag{3.3}$$

for the case of zero means, where θ_1 and θ_2 control the respective variances and θ_3 controls the degree of dependence which is a function of the correlation coefficient. A natural generalization of (3.3) that allows for higher order moments is given by the following bivariate generalized normal distribution with $M = 6$ in (3.1)

$$f(r) = \exp(\theta_1 r_1^2 + \theta_2 r_2^2 + \theta_3 r_1 r_2 + \theta_4 r_1 r_2^2 + \theta_5 r_1^2 r_2 + \theta_6 r_1^2 r_2^2 - \eta). \tag{3.4}$$

The terms $r_1 r_2^2$ and $r_1^2 r_2$ represent two measures of co-skewness between r_1 and r_2 which are controlled by the parameters θ_4 and θ_5, respectively, while the terms $r_1^2 r_2^2$ represents co-kurtosis between r_1 and r_2, which is controlled by the parameter θ_6.

According to the specification in (3.4), we can now distinguish three levels of dependence among assets: the first is the channel controlled by the parameter θ_3

which corresponds to the well known correlation parameter, the second channel consisting of θ_4 and θ_5 which capture the dependence through the interaction between the first moment, r_1 (second, r_1^2), of asset 1 and the second moment, r_2^2 (first, r_2) of asset 2, named co-skewness. The third channel is controlled by parameter θ_6 which captures the interaction between the second moments of both assets, this parameter is called co-kurtosis.

A Lagrange Multiplier test is valid in this framework to test the significance of the co-skewness parameters θ_4 and θ_5. A useful theorem for computing the standard errors of the estimators is the following,

Theorem 1 *Let r be an iid random variable of dimension K with the generalized exponential distribution*

$$f(r) = exp(h - \eta) \tag{3.5}$$

with corresponding log-Likelihood

$$\ln L_t = (h - \eta)$$

where $h = \sum_{i=1}^{M} \theta_i g_i(r)$, θ is an M vector of parameters summarizing the moments of the distribution, and η is the normalizing constant defined in (3.2). The information matrix is given by[1]

$$I = T\left(E\left[\frac{\partial h}{\partial \theta}\frac{\partial h}{\partial \theta'}\right] - E\left[\frac{\partial h}{\partial \theta}\right]E\left[\frac{\partial h}{\partial \theta'}\right]\right), \tag{3.6}$$

where $lnL_t = lnf(r_t)$ represents the log of the likelihood at the tth observation and T is the sample size.

Having derived the information matrix, the Lagrange Multiplier (LM) statistic is given by

$$LM = G'I^{-1}G, \tag{3.7}$$

where

$$G = \left.\frac{\partial \mathrm{ln} L_t}{\partial \theta}\right|_{\theta=\theta_0}, \qquad I = \left.\frac{\partial^2 \mathrm{ln} L_t}{\partial \theta \partial \theta'}\right|_{\theta=\theta_0}, \tag{3.8}$$

[1]See the proof in Fry et al., 2010, p. 427

are, respectively, the gradient vector and the information matrix of the log of the likelihood, both evaluated under the null $\theta = \theta_0$.

Considering the generalization of the bivariate normal distribution in (3.3) and for simplicity in the notation let us denote $z_{1,t} = \dfrac{r_{1,t} - \mu_1}{\sigma_1}$ and $z_{2,t} = \dfrac{r_{2,t} - \mu_2}{\sigma_2}$, then

$$f(z_{1,t}, z_{2,t}) = \exp\left[-\frac{1}{2}\left(\frac{1}{1-\rho^2}\right)(z_{1,t}^2 + z_{2,t}^2 - 2\rho z_{1,t} z_{2,t}) + \phi z_{1,t} z_{2,t}^2 - \eta\right], \quad (3.9)$$

where $\eta = \ln \iint \exp(h) dr_1 dr_2$ and

$$h = -\frac{1}{2}\left(\frac{1}{1-\rho^2}\right)(z_{1,t}^2 + z_{2,t}^2 - 2\rho z_{1,t} z_{2,t}) + \phi z_{1,t} z_{2,t}^2.$$

The interest is on testing the following hypothesis

$$H_0 : \phi = 0$$
$$H_1 : \phi \neq 0,$$

which constitutes a test of co-skewness. Under the null hypothesis, the distribution is (the classical) bivariate normal where the maximum likelihood estimators of the unknown parameters are the sample means, variances and correlation coefficient as shown below

$$\hat{\mu_i} = \frac{1}{T}\sum_t r_{i,t}$$
$$\hat{\sigma_i^2} = \frac{1}{T}\sum_t (r_{i,t} - \hat{\mu_i})^2$$
$$\hat{\rho} = \frac{1}{T}\sum z_{1,t} z_{2,t} \qquad i = 1, 2$$

where $z_{1,t}$ and $z_{2,t}$ are defined above.

The Lagrange multiplier statistic is

$$LM = \frac{T}{4\hat{\rho}^2 + 2}\left[\frac{1}{T}\sum_{t=1}^{T} z_{1,t} z_{2,t}^2\right]^2. \quad (3.10)$$

Under the null, LM is distributed asymptotically as $LM \xrightarrow{d} \chi_1^2$.

3.2.2 The Co-Skewness test for contagion

The co-skewness test of contagion is closely related to the idea of the correlation test of contagion in the sense that the aim is identifying significant changes in co-skewness when assets move from stable period to a turmoil one. This test consists of two alternatives: CS_1 and CS_2, these alternatives follows from (3.4) where it can seen that θ_4 and θ_5 are the parameters controlling the co-movements in the skewness.

For exposition purpose, the following notation is used, let x_t^l and x_t^h denote the series (prices, returns or volatility) in the precrisis (stable) period and crisis (turmoil) period, respectively. The correlation between assets is denoted as ρ^l (precrisis) and ρ^h (crisis), while the *adjusted correlation*[2] is denoted by ρ^*. Finally the sample sizes of the precrisis and crisis are, respectively, T^l and T^h.

Following Fry et al. (2010), we define contagion as significant changes (above or below) in co-skewness between a crisis period and a precrisis period, this definition is somehow related to that of Corsetti et al. (2005). The two variants of the test are as follows:

$$CS_1(r_i^1, r_j^2) = \left(\frac{\hat{\Psi}^h(r_i^1, r_j^2) - \hat{\Psi}^l(r_i^1, r_j^2)}{\sqrt{\frac{4(\hat{\rho}^*)^2 + 2}{T^h} + \frac{4\ (\hat{\rho}^h)^2 + 2}{T^l}}} \right)^2, \tag{3.11}$$

$$CS_2(r_i^2, r_j^1) = \left(\frac{\hat{\Psi}^h(r_i^2, r_j^1) - \hat{\Psi}^l(r_i^2, r_j^1)}{\sqrt{\frac{4(\hat{\rho}^*)^2 + 2}{T^h} + \frac{4\ (\hat{\rho}^h)^2 + 2}{T^l}}} \right)^2, \tag{3.12}$$

where

$$\hat{\Psi}^h(r_i^m, r_j^n) = \frac{1}{T^h} \sum_{t=1}^{T^h} \left(\frac{x_{i,t}^h - \mu_i^h}{\hat{\sigma}_{x,i}^h} \right)^m \left(\frac{x_{j,t}^h - \mu_j^h}{\hat{\sigma}_{x,j}^h} \right)^n,$$
$$\hat{\Psi}^l(r_i^m, r_j^n) = \frac{1}{T^l} \sum_{t=1}^{T^l} \left(\frac{x_{i,t}^l - \mu_i^l}{\hat{\sigma}_{x,i}^l} \right)^m \left(\frac{x_{j,t}^l - \mu_j^l}{\hat{\sigma}_{x,j}^l} \right)^n,$$

[2]Adjusted correlation is the same as the unconditional one according to Forbes and Rigobon (2002), see also (2.10).

and

$$\hat{\rho}^* = \frac{\hat{\rho}^h}{\sqrt{1 + \left(\frac{\hat{\sigma}^h_{xx}}{\hat{\sigma}^l_{xx}} - 1\right)(1 - \hat{\rho}^h)}}.$$

Under the null hypothesis of no contagion, the statistics for the tests are asymptotically distributed as

$$CS_k \xrightarrow{d} \chi^2_1. \qquad k = 1, 2. \tag{3.13}$$

3.3 Application to US Subprime Mortgage Crisis

Our interest is on assessing whether contagion existed as channel of transmission when US financial crisis took place. We analyze the period from February 21, 2003 to January 30, 2009, where the precrisis and crisis period are defined according to the beginning of the fall in the S&P500 index up to its recovery. Precrisis period is February 21, 2003 - December 21, 2007 while the crisis period goes from December 22, 2007 to January 30, 2009, the selection of these dates follows from Figure 3.1.

Looking at Figure 3.1 we identify two areas (subperiods): I and II, where area I represents the precrisis period which clearly shows a steady growth in S&P500's closed price and area II (crisis) comprises the days when stock price was systematically declining until reached it bottom after which recovery began. Two different series are depicted in Figure 3.1, the solid black line represents closed prices for S&P500 and the gray line depicts the Returns.

Our underlying data are daily nominal local-currency stock market indexes, the same as analyzed in previous chapter. Countries and stock indexes to be analyzed are described in Table 1.2.

The co-skewness test allows to evaluate two possible channels of contagion:

1. $CS_1(r^1_i, r^2_j)$ indicates contagion between the level of returns in country i and volatility in country j.

2. $CS_2(r^2_i, r^1_j)$ means contagion between volatility in country i and the levels of returns in country j.

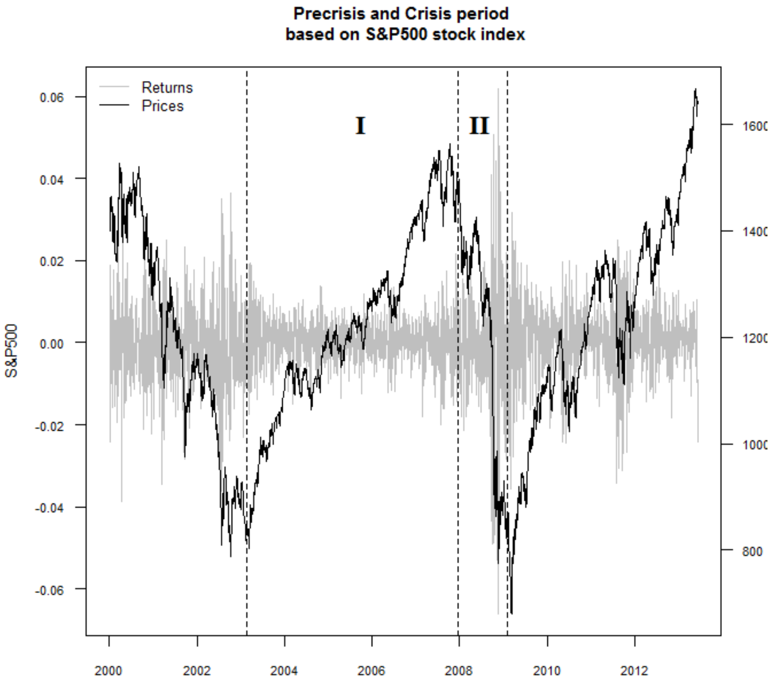

Figure 3.1: Daily S&P 500 close price and returns. Period January 3, 2000 - June, 10, 2013.

Table 3.2 shows the results of the test where we analyze the existence of contagion, co-skewness parameter, from levels of returns in S&P500 to the volatility of the other stock markets j = UK (FTSE 100), European Union (EURO STOXX50), Brazil (BOVESPA), Japan (NIKKEI) and Australia (S&P/ASX200), where we assume US is the transmitter country. In order to compute the conditional co-moments of third order, a 6-variables VAR(4) is estimated and the residuals from this VAR are used as the adjusted returns in computing $CS_k(\cdot) \quad k = 1, 2$ which according to Fry et al. (2010), are net of market fundamentals. P-values based on the asymptotic distribution for $CS1(\cdot)$ reveal that only UK experiences a contagion episode when US was hit by the subprime crisis, this finding is valid even for the 1% significant level, for the other stock markets in the sample we cannot reject the null of no contagion.

The contagion evidence found from US to UK goes from levels of returns in the American market to the volatility in the returns in the British market since

Table 3.2: Test of contagion between levels of returns/volatility of US S&P500 and volatility/returns in selected asset markets.

	FTSE100	EURO STOXX50	BOVESPA	NIKKEI225	SPASX200
$CS_1(r^1_{us}, r^2_j)$	11.8587***	0.5447	0.5473	1.8886	0.0230
	(0.0006)	(0.4605)	(0.4594)	(0.1694)	(0.8794)
$CS_2(r^2_{us}, r^1_j)$	8.3639***	2.1185	0.5298	5.9561***	0.0180
	(0.0038)	(0.1455)	(0.4667)	(0.0147)	0.8932

*** Indicates significant at 1%.
Number in parenthesis are p-values.

the test is performed using $CS_1(US \rightarrow UK; r^1_{us}, r^2_{uk})$.

On the other hand, we have the alternative test $CS_2(i \rightarrow j; r^2_i, r^1_j)$, for contagion from volatilities in the US stock market to the other countries in the sample. Table 3.2 suggests that contagion was involved between US and UK, and also between US and Japan.

The results of the co-skewness test of contagion is somehow opposite to the correlation test of Forbes and Rigobon shown in Table 2.3 where the conclusion based on the adjusted correlation test was unanimously the acceptance of the null hypothesis of no contagion, the evidence of the previous chapter was that the continuation of the highly interrelation of the markets for both states of the world is due to interdependence in terms of Forbes and Rigobon (2002).

It is worthy to highlight the fact that these tests are somehow opposite, but not contradictory, since correlation test is used to investigate contagion between levels of returns and the co-skewness test for contagion takes advantage of its broader scope to study contagion between levels and volatility, therefore it is not surprising that conclusions of the tests are not the same, since their scope are different.

Figure 3.2 depicts the behavior of stock close prices for all the markets in the sample which behaves very close to the movement of S&P500 as it is supported by the sample correlation coefficients for the period 2002-2013 in Table 3.3. Stock markets have a strong co-movement with US, except perhaps that of Japan which reports 27.31% of correlation with the American stock market.

Based on the results of Forbes and Rigobon test carried out in Chapter 2, the only explanation of the behavior depicted in Figure 3.2 is only due to interdependence, such explanation is partially supported by the results obtained from co-skewness test; the first alternative of the co-skewness $CS_1(\cdot)$ suggest not contagion for all markets except for the British market for both on the returns and on

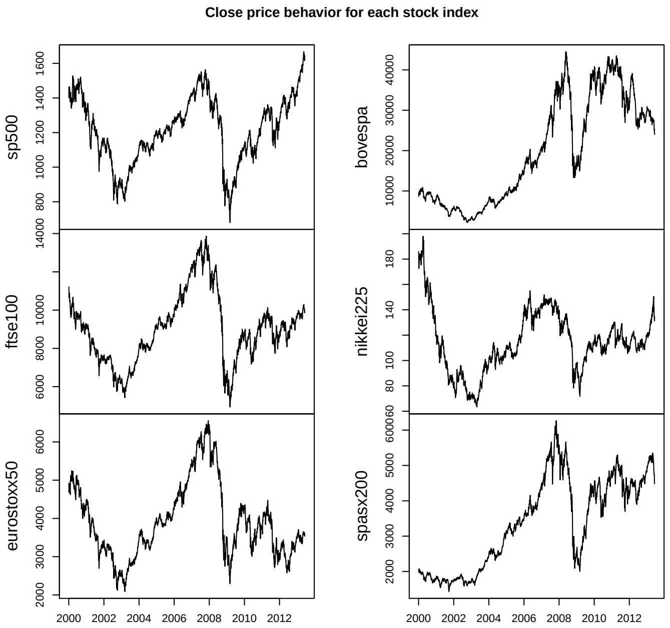

Figure 3.2: Daily close price. Period January 3, 2000 - June, 10, 2013.

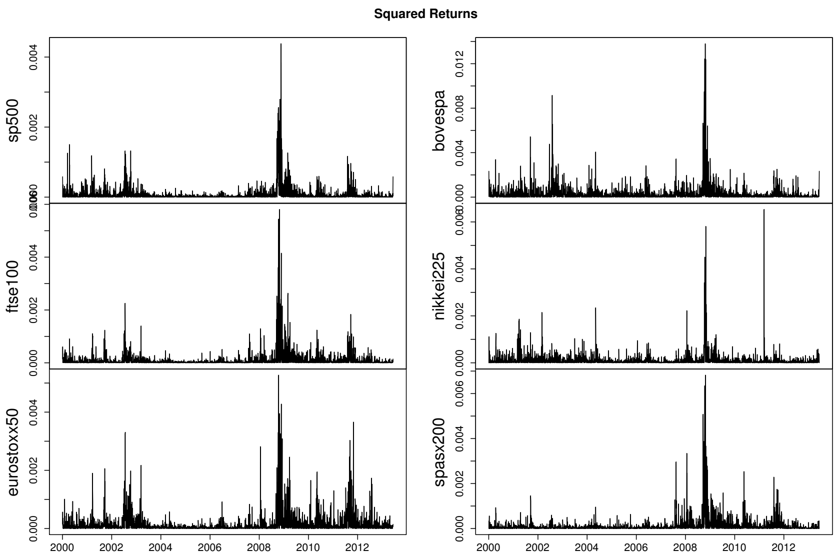

Figure 3.3: Daily squared returns.

Table 3.3: Unconditional correlation matrix among assets for the period 2002-2013.

	S&P500	FTSE100	EURO STOXX50	BOVESPA	NIKKEI225	SPASX200
S&P500	1.0000					
FTSE100	0.6712	1.0000				
EURO STOXX50	0.6899	0.8786	1.0000			
BOVESPA	0.6073	0.6129	0.5954	1.0000		
NIKKEI225	0.2731	0.3995	0.3938	0.2996	1.0000	
SPASX200	0.4720	0.6841	0.6382	0.5247	0.5668	1.0000

Table 3.4: Test of contagion between levels of returns in asset i and volatility in asset j.

	j					
i	S&P500	FTSE100	EURO STOXX50	BOVESPA	NIKKEI225	SPASX200
S&P500	—	YES (0.0006)				
FTSE100	YES (0.0046)	—			YES (0.0150)	
EUROSTOXX50			—		YES (0.0193)	
BOVESPA				—	YES ($\approx$ 0.00)	YES (0.0203)
NIKKEI225	YES (0.0189)		YES (0.0344)	YES ($\approx$ 0.00)	—	YES (0.0365)
SPASX200				YES (0.0151)	YES (0.0002)	—

Note: Number in parenthesis are p-values.

the volatility, this contagion is coming from volatility and the levels of returns in the US market. Furthermore, the Japanese market avoids to be affected via contagion in its volatility when returns in US were falling sharply during the crisis, but volatility in US indeed affected the returns in Japan provoking a decrease in its returns, this means that returns in Japan were affected due to contagion from volatility in US.

Volatility behavior is plotted in Figure 3.3, since stock returns are zero-mean variables, the volatility represented by the variance can be approximate by the squared returns. All markets seem to move almost instantaneously in the same direction, this can be thought in terms of either contagion or other linkage, the co-skewness test suggests a certain level of contagion in the volatility for both Japan and UK coming from US returns.

So far this point, our attention was focused on contagion from the US stock market to the other markets in the sample, clearly in this case the assumed directionality is $US \rightarrow j$ where j stands for the other 5 markets. Since this test does not depend on imposing any restriction about the direction of contagion, we can test the null hypothesis of no contagion between pair of countries changing in each round the source country in order to determine the strengthen of the linkages after the crisis hit US.

Table 3.4 shows the results of performing the co-skewness test from each stock markets' returns to the volatility of the other markets, this table can be useful to identify the more involved market in terms of contagion, there is not room to doubt about the participation of the Japanese market in Table 3.4. Volatility increase in Japan via contagion does not come from instability in S&P500 returns but from returns in all the other assets conforming the sample. Although Japan is the more involved market with contagion, this does not mean that it is the more volatile market, note that this test only indicates whether contagion is the channel of transmission of crisis or not and it does not provide any information about which market is the more volatile. Besides Japan is the most involved stock market as a result of the contagion after the crisis which means that Japan is the main transmitter/receptor of crisis.

The general conclusion stemming from Table 3.4 is that all markets experienced variations in the their linkages with other markets due to contagion, which is in line with the assertion of Fry et al. (2010) about that co-skewness test for contagion captures evidence that Forbes and Rigobon test, and general all correlation tests, are not able to do as a consequence of not looking forward in higher co-moments.

3.4 Conclusions

This Chapter tests for contagion based on changes in higher order comovements during financial crisis using the recently introduced co-skewness test. The scope of this test is beyond of that of the correlation-based tests since co-skewness test identifies contagion through the interaction of the levels and volatility returns and vice versa.

The novelty of the test is the test by itself and also the new family of bivariate distribution upon which it is based to allow for higher order comovements.

In the application of the test to the US subprime crisis, the higher order contagion test identified linkages across markets arising from contagion that were not detected by the Forbes and Rigobon test presented in Chapter 2, indicating the importance of accounting for higher order moments during crisis periods.

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Chapter 4

Financial Spillovers Across Countries: Measuring shock transmissions

4.1 Introduction

In the last three decades, financial crises have been occurring with more regularity and according to Reinhart and Rogoff (2008) and Corsetti et al. (2001) recent crises are not so different from historical ones and they even show some similarities. One of the most important facts when crises occur is that "financial market volatility generally increases and spills over across markets" (Diebold and Yilmaz, 2012), motivated by this consideration Diebold and Yilmaz (2009); Diebold and Yilmaz (2012) introduce a new measure based on the well-known forecast error variance decomposition from vector autoregressions to summarize such a transmission of crisis in a single number easy to interpret and also they provide several tools as spillovers tables, directional spillovers and net spillover tables to track this measurement.

Diebold and Yilmaz (2009); Diebold and Yilmaz (2012) methodology is not concerned about distinguishing contagion from interdependence, but it is concerned about providing a toolkit to measure the proportion of a crisis from one country that spills over another country or group of countries, this feature makes it useful when a policy-maker is willing to know what country (or group of countries) is more vulnerable when another country is hit by a crisis. One outstanding fact of this method is that it does not require a formal test for contagion for being able to provide a measurement of the spillover stemming from turmoil periods (it even works for stable periods).

In spite of the fact that spillover indexes do not represent a hypothesis test for contagion, there seems to be a pattern in the index that can be useful to anticipate a crisis, which can be due to contagion or interdependence. Such a pattern consists of a deeply decay before rising, this pattern is captured by the orthogonalized and the generalized index applied both for returns and volatility, if this pattern persists in all type of crises, then the dynamic spillover index could be helpful as a early-warning system to foresee a crisis as outlined in Diebold and Yilmaz (2012)

This Chapter is organized as follows: The econometric methodology and the form of the indexes are presented in Section 4.2, empirical results such as orthogonalized and generalized spillover indexes for both, daily returns and intraday volatilities are in Section 4.3. This chapter concludes with some comments in Section 4.4.

4.2 The base model and the Spillover Index

4.2.1 The VAR(p) model and its MA(∞) representation

This section is devoted to review some notation and features regarding to Sims (1980) K-variables Vector Autoregressive model of order p generally referred to as VAR(p). As this model is the workhorse for the subsequent analysis we present some definitions and preliminaries concerning the VAR(p) which has the following matrix form:

$$\mathbf{y}_t = \mathbf{v} + \mathbf{A}_1\mathbf{y}_{t-1} + \mathbf{A}_2\mathbf{y}_{t-2} + \ldots + \mathbf{A}_p\mathbf{y}_{t-p} + \varepsilon_t, \qquad t = 0, 1, \ldots, \tag{4.1}$$

where $\mathbf{y}_t = (y_{1t}, \ldots, y_{Kt})'$ is a $K \times 1$ random vector, the $\mathbf{A}_i$ are fixed $K \times K$ coefficients matrices, $\mathbf{v} = (v_1, \ldots, v_K)'$ is a fixed $K \times 1$ vector of intercept terms allowing for the possibility of the non-zero mean. Finally, $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Kt})'$ is a K-dimensional *white noise* or *innovation process*. For the vector ε to be *white noise* the following conditions hold: $E(\varepsilon_t) = 0$, $E(\varepsilon_t, \varepsilon_t') = \Sigma_\varepsilon < \infty$ and $E(\varepsilon_t, \varepsilon_s') = 0, \quad \text{for } t \neq s$.

In order to simplify the notation and make it more tractable, let us consider the simplest version of the VAR model by assuming $p = 1$ and $K = 2$, a bivariate VAR(1) model of the form:

$$\mathbf{y}_t = \mathbf{v} + \mathbf{A}_1 \mathbf{y}_{t-1} + \varepsilon_t, \qquad t = 0, 1, \dots \tag{4.2}$$

The model in (4.2) is said to be *stable* if all eigenvalues of $\mathbf{A}_1$ have modulus less than 1, which is equivalent to

$$\det(\mathbf{I_K} - \mathbf{A}_1 z) \neq 0 \qquad \text{for } |z| \leq 1. \tag{4.3}$$

Under the stability condition the process $\mathbf{y}_t$ in (4.2) is said to be invertible and has a Moving Average of infinity order (MA(∞)) representation[1]

$$\mathbf{y}_t = {}^{-} + \sum_{i=0}^{\infty} \mathbf{A}_1^i \varepsilon_{t-i}. \tag{4.4}$$

where $\mu := (\mathbf{I_K} - \mathbf{A_1} L)^{-1}\mathbf{v}$. Such a MA($\infty$) representation requires the VAR(1) to be stable in order to turns out in a sequence of matrix coefficients being absolutely summable, this ensures the MA(∞) process converges in quadratic mean and thus in probability to $\mathbf{y}_t$ (Lutkepohl, 1993). In the MA representation, the process $\mathbf{y}_t$ is expressed in terms of the past and present error vectors ε_t and the mean term ¯ which can be either zero or non-zero.

The MA representation in (4.4) can be re-written more compactly in terms of a polynomial in the lag operator,

$$\mathbf{y}_t = \mathbf{\Phi}(L)\varepsilon_t, \tag{4.5}$$

where μ is assumed to be zero, $\mathbf{\Phi}(L)$ is a polynomial[2] in the lag operator such that $\mathbf{\Phi}(L) := \sum_{i=0}^{\infty} \mathbf{A}_i L^i$ and L is the lag operator such that $L^j y_t = y_{t-j} \quad \forall j \in \mathbb{N}$.

The coefficients contained in $\mathbf{\Phi}$ are the impulse responses of the system. In other words, $\phi_{jk,i}$, the jk-the element of $\mathbf{\Phi}_i$ represents the reaction of the j-th variable of the system to a unit shock (forecast error) of variable k, i periods ago, provided of course, the effect is not contaminated by other shocks to the system (Lutkepohl, 1993).

[1] See Lutkepohl (1993) for further details on VAR models.

[2] Alternatively $\mathbf{\Phi}(L) := (\mathbf{I_K} - \mathbf{A}L)^{-1}$

In order to avoid such "contamination", let $\mathbf{\Sigma}_\varepsilon$ be the variance-covariance matrix of the reduced form residuals resulting from estimating a VAR(p) model with $E(\varepsilon_t, \varepsilon_s') \neq 0, \quad \text{for } t \neq s$, nevertheless as long as this matrix is positive definite symmetric matrix, it can be factorized as $\mathbf{\Sigma}_\varepsilon = \mathbf{PP}'$ where $\mathbf{P}$ is the lower triangular Choleski matrix[3] and $\mathbf{P}'$ is its correspond transpose, this is the so-called Choleski orthogonalization which prevents the "contamination" of variables by shocks coming from other variables in the system and also guarantees that $\mathbf{P}^{-1}\varepsilon_t$ is now a vector of orthogonalized (independent under normality assumption) innovations, therefore $E(\mathbf{P}^{-1}\varepsilon_t, \mathbf{P}^{-1}\varepsilon_s') = 0, \quad \text{for } t \neq s$ and in general $E(\mathbf{P}^{-1}\varepsilon_t, \mathbf{P}^{-1}\varepsilon_t') = \mathbf{I_K}$ holds. The Choleski factorization allows to re-write the process (4.5) as:

$$
\begin{aligned}
\mathbf{y}_t &= \mathbf{\Phi}(L)\mathbf{PP^{-1}}\varepsilon_t && (4.6)\\
&= \mathbf{\Theta}(L)u_t && (4.7)
\end{aligned}
$$

Where $\mathbf{\Theta}(L) = \mathbf{\Phi}(L)\mathbf{P}$ and $\mathbf{u}_t = \mathbf{P}^{-1}"_t$, being $\mathbf{P}$ the unique lower-triangular Choleski factor of the covariance matrix of ε_t for a given variable ordering. This transformation ensures $E(\mathbf{u}_t\mathbf{u}_t') = \mathbf{I}$ as mentioned above by imposing a recursive causal structure from the top variables to the bottom variables but not the other way around.

The advantage of represent a VAR(p) model as an MA(∞) model consists of its easiness to determine autocovariances and forecast error variance decomposition which is the target of the next section.

4.2.2 Orthogonalized Forecast Error Variance Decomposition

The MA(∞) representation (4.7) with orthogonal white noise is suitable to collect all the variances (for each variable k) when forecasting with the VAR and then properly account for by its contribution to the total variance produced by the whole system, that is variance decompositions allow us to split the forecast error variances of each variable into parts attributable to the various system shocks.

[3]This factorization is order-dependent, which means that there is not only a unique $\mathbf{P}$ associated to a Σ_ε, but also there are $K!$ $\mathbf{P}$'s associated to Σ_ε each of them corresponding to each specific order of the variables.

Relying on (4.7), the error of the optimal h-step ahead forecast is

$$\mathbf{y}_{t+h} - \mathbf{y}_t(h) = \sum_{i=0}^{h-1} \mathbf{\Theta}_i u_{t+h-i} \tag{4.8}$$

where $\mathbf{y}_{t+h}$ is the realization of the random vector at time $t+h$, whereas $\mathbf{y}_t(h)$ is the expectation of the process conditional on the information set available up to time t, denoted by $E(\mathbf{y}_{t+h}|\Im_t)$ and also frequently denoted by $\mathbf{y}_{t+h,t}$ which is a function of h.

Denoting the mn-element of $\mathbf{\Theta}_i$ by $\theta_{mn,i}$, the h-step forecast error of the j-th component of $\mathbf{y}_t$ is

$$\begin{aligned} y_{j,t+h} - y_{j,t}(h) &= \sum_{i=0}^{h-1}(\theta_{j1,i}u_{1,t+h-i} + \ldots + \theta_{jK,i}u_{K,t+h-i}) && (4.9)\\ &= \sum_{k=1}^{K}(\theta_{jk,0}u_{k,t+h} + \ldots + \theta_{jk,h-1}u_{k,t+1}). && (4.10) \end{aligned}$$

Thus, the forecast error of the j-th component potentially consists of innovations of all other components of $\mathbf{y}_t$ as well. Of course, some of the $\theta_{mn,i}$ may be zero, due to the orthogonalization, so that the innovations of some components may not appear in (4.10). Note that, due to the orthogonalization, $u_{k,t}$ are uncorrelated and have variance one, hence the Mean Squared Error (MSE) associated to the prediction, $y_{j,t}(h)$ is

$$E(y_{j,t+h} - y_{j,t}(h))^2 = \sum_{k=1}^{K}(\theta^2_{jk,0} + \ldots + \theta^2_{jk,h-1}). \tag{4.11}$$

Therefore

$$\theta^2_{jk,0} + \theta^2_{jk,1} + \ldots + \theta^2_{jk,h-1} = \sum_{i=0}^{h-1}(e_j'\mathbf{\Theta}_i e_k)^2, \tag{4.12}$$

is sometimes interpreted as the contribution of innovations in variable k to the forecast error variance or MSE of the h-step ahead forecast of variable j (Lutkepohl, 1993). Here e_k is the k-th column of $\mathbf{I_K}$. Dividing (4.12) by

$$\text{MSE}\left[(y_{j,t}(h))\right] = \sum_{i=0}^{h-1}\sum_{k=1}^{K}\theta^2_{jk,i},$$

gives the decomposition

$$\tilde{\alpha}^{o}_{jk,h} = \frac{\sum_{i=0}^{h-1}(e_j'\boldsymbol{\Theta}_i e_k)^2}{\text{MSE}\left[(y_{j,t}(h))\right]} = \frac{\sum_{i=0}^{h-1}(e_j'\boldsymbol{\Theta}_i e_k)^2}{\sum_{i=0}^{h-1}\sum_{k=1}^{K}\theta^2_{jk,i}} \tag{4.13}$$

which is the proportion of the h-step ahead forecast error variance of variable j accounted for by innovations in variable k. In this way the forecast error variance is decomposed into component accounted for by innovations in the different variables of the system. From (4.8) the h-step ahead MSE matrix is

$$\Sigma_y(h) = \text{MSE}\left[(y_t(h))\right] = \sum_{i=0}^{h-1}\Theta_i\Theta_i' = e_j'\Phi_i\Sigma_\epsilon\Phi_i'e_j \tag{4.14}$$

The diagonal elements of this matrix are the MSE of the y_{jt} variables which may be used in (4.13), consequently the full expression is

$$\tilde{\alpha}^{o}_{jk,h} = \frac{\sum_{i=0}^{h-1}(e_j'\boldsymbol{\Theta}_i e_k)^2}{\sum_{i=0}^{h-1} e_j'\Phi_i\Sigma_\epsilon\Phi_i'e_j} \tag{4.15}$$

So far, it is an easy matter to realize that forecast error variance decomposition answers the questions: What fraction of the h-step ahead error variance in forecasting y_j is due to shocks to y_k?

4.2.3 Generalized Forecast Error Variance Decomposition

As subsection 4.2.2 shows, the Orthogonalized Error Variance Decomposition (OFEVD) at h-step ahead forecast horizon lies on the structure of the impulse-response of the system, the Generalized Forecast Error Variance Decomposition (GFEVD), also lies on the same idea. The former decomposition needs an ordering-based orthogonalization procedure to ensure zero correlation between the errors and allows to claim *"ceteris paribus"* when analyzing economics relationships, whereas, the latter does not need such procedure, instead of controlling the impact of correlation among residuals, Generalized Impulse-Response Function (GIRF) follows the idea of nonlinear impulse response function and compute the mean impulse response function. When one variable is shocked, other variables also vary as is implied by the covariance which is not diagonal. GIRF computes the mean of the responses by integrating out all other shocks (Pesaran and Shin, 1998).

Using (4.5) and defining the GIRF as:

$$GI_y(h, \delta_j, \Im_{t-1}) = E(y_{t+h}|\varepsilon_{jt} = \delta_j, \Im_{t-1}) - E(y_{t+h}|\Im_{t-1}), \tag{4.16}$$

which means that instead of shocking all elements in ε, only the j-th element is shocked and the effect of other shocks is integrated out assuming an observed distribution of the errors. Assuming the errors follows a multivariate normal distribution, Koop et al. (1996) show

$$E(\varepsilon_t|\varepsilon_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \ldots, \sigma_{Kj})'\sigma_{jj}^{-1}\delta_j = \mathbf{\Sigma}_\varepsilon e_j \sigma_{jj}^{-1}\delta_j. \tag{4.17}$$

Hence, the $K \times 1$ vector of the unscaled GIRF of the effect of a shock in the j-th equation at time t on t_{t+h} is given by

$$\left(\frac{\mathbf{\Phi}_h \mathbf{\Sigma}_\varepsilon e_j}{\sqrt{\sigma_{jj}}}\right)\left(\frac{\delta_j}{\sqrt{\sigma_{jj}}}\right), \qquad h = 0, 1, 2, \ldots \tag{4.18}$$

And the scaled GIRF is obtained by setting $\delta_j = \sqrt{\sigma_{jj}}$

$$\psi_j^g(h) = \sigma_{jj}^{-\frac{1}{2}} \mathbf{\Phi}_h \mathbf{\Sigma}_\varepsilon e_j \qquad h = 0, 1, 2, \ldots, \tag{4.19}$$

which measures the effect of one standard error shock to the j-equation at time t on expected values of $\mathbf{y}$ at time $t + h$.

Finally, the GIRF can be used to define the GFEVD which has the same interpretation as the OFEVD, namely, is the proportion of the h-step ahead forecast error variance of variable j which is accounted for by the innovations in variable k in the VAR. Denoting the GFEVD by $\alpha_{jk,h}^g$ we have

$$\alpha_{jk,h}^g = \frac{\sigma_{jj}^{-1} \sum\limits_{i=0}^{h-1} (e_j' \mathbf{\Phi}_i \Sigma_\epsilon e_k)^2}{e_j' \Phi_i \Sigma_\epsilon \Phi_i' e_j} \tag{4.20}$$

Note that by construction $\sum_{k=1}^{K} \tilde{\alpha}_{jk,h}^o = 1$ in (4.15). However, due to the non-zero covariance between the original (non-orthogonalized) shocks, in general

$\sum_{k=1}^{K} \alpha_{jk,h}^{g} \neq 1$ (Pesaran and Shin, 1998), but we can normalize $\alpha_{jk,h}^{g}$ by dividing it by the row sum and redefined as $\tilde{\alpha}_{jk,h}^{g}$ to be

$$\tilde{\alpha}_{jk,h}^{g} := \frac{\alpha_{jk,h}^{g}}{\sum\limits_{k=1}^{K} \alpha_{jk,h}^{g}}.$$

Note that, by construction, now $\sum_{k=1}^{K} \tilde{\alpha}_{jk,h}^{g} = 1$ and $\sum_{j,k=1}^{K} \tilde{\alpha}_{jk,h}^{g} = K$

4.2.4 Total Spillover Index

Diebold and Yilmaz (2009); Diebold and Yilmaz (2012) introduced the *spillover index* or the *cross-variance shares index* to be the fractions of the h-step ahead error variances in forecasting y_j due to shocks to y_k for $j, k = 1, 2, \ldots, K$ and $j \neq k$ and *own variance shares* to be the fractions of the h-step ahead error variances in forecasting y_j due to shocks to y_k for $j = k$. To make this idea clearer, let us allocate all the elements of $\tilde{\alpha}_{jk,h}^{o}$ and $\tilde{\alpha}_{jk,h}^{g}$ into a matrix structure and denote them by Λ_h^o and Λ_h^g, respectively, where both matrices are of dimension $K \times K$,

$$\Lambda_h^i = \begin{pmatrix} \tilde{\alpha}_{11,h}^{i} & \tilde{\alpha}_{12,h}^{i} & \cdots & \tilde{\alpha}_{1K,h}^{i} \\ \tilde{\alpha}_{21,h}^{i} & \tilde{\alpha}_{22,h}^{i} & \cdots & \tilde{\alpha}_{2K,h}^{i} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\alpha}_{K1,h}^{i} & \tilde{\alpha}_{K2,h}^{i} & \cdots & \tilde{\alpha}_{KK,h}^{i} \end{pmatrix}, \qquad i = \text{o, g}. \tag{4.21}$$

Thus, the spillover index is the cross-variance shares obtained from (4.21) and it is denoted by S_h^i, the superscript i denotes we are referring to whether the orthogonalized (i = o) or the generalized (i = g) forecast error variance decomposition and h denotes the number of steps ahead of the forecast.

$$S_h^i = \frac{\sum\limits_{\substack{jk=1 \\ j \neq k}}^{K} \tilde{\alpha}_{jk,h}^{i}}{K} \times 100 \qquad i = \text{o, g}. \tag{4.22}$$

In order to look for the idea behind (4.22), let us consider the simplest case where $h = 1$ and $K = 2$, this means a spillover index based on a bivariate VAR with 1 step ahead forecast, furthermore, suppose we rely on the OFEVD (when i = o) and recall (4.13), therefore Λ_h^i boils out to Λ_1^o , we have

$$\Lambda_1^o = \begin{pmatrix} \tilde{\alpha}_{11,1}^{o} & \tilde{\alpha}_{12,1}^{o} \\ \tilde{\alpha}_{21,1}^{o} & \tilde{\alpha}_{22,1}^{o} \end{pmatrix},$$

there are two possible spillovers in this simple example: y_{1t} shocks that affect the forecast error variance of y_{2t} with relative contribution $\tilde{\alpha}^o_{21,1}$ and y_{2t} shocks that affect the forecast error variance of y_{1t} with relative contribution $\tilde{\alpha}^o_{12,1}$, therefore, the *Spillover Index* is

$$S^o_1 = \frac{\tilde{\alpha}^o_{12,1} + \tilde{\alpha}^o_{21,1}}{2} \times 100,$$

where $\tilde{\alpha}^o_{21,1} = \frac{\theta^2_{21,1}}{\theta^2_{21,1}+\theta^2_{22,1}}$ and $\tilde{\alpha}^o_{12,1} = \frac{\theta^2_{12,1}}{\theta^2_{11,1}+\theta^2_{12,1}}$ (see (4.13)) and 2 in the denominator follows from the fact that $\sum_{k=1}^{2} \tilde{\alpha}^o_{jk,h} = 1$ by construction, therefore $\sum_{j,k=1}^{2} \tilde{\alpha}^o_{jk,h} = 2$.

For obtaining the spillover index based on the GFEVD, the steps are the same. Consider we now have Λ^g_1 with $\tilde{\alpha}^g_{jk,1}$ as its typical element, then spillover index is

$$S^g_1 = \frac{\tilde{\alpha}^g_{12,1} + \tilde{\alpha}^g_{21,1}}{K} \times 100,$$

where $\tilde{\alpha}^g_{12,1} = \frac{\alpha^g_{12,1}}{\alpha^g_{11,1}+\alpha^g_{12,1}}$ and $\tilde{\alpha}^g_{21,1} = \frac{\alpha^g_{21,1}}{\alpha^g_{21,1}+\alpha^g_{22,1}}$ and $\tilde{\alpha}^g_{jk,1}$ is defined in (4.20).

It is worthy to highlight from (4.20), the spillover index has the same specification either for the OFEVD or GFEVD, the only difference between them is the way how $\tilde{\alpha}_{jk,h}$ is computed. Furthermore, the *total spillover* index measures the contribution of spillovers of shocks across financial markets to the total forecast error variance (Diebold and Yilmaz, 2012).

In spite of the fact that spillover index based either on the OFEVD or GFEVD has the same form, it is clear that the orthogonalized spillover requires the Choleski factorization which depends on the order of the variables in the VAR model, therefore, to make such a factorization we need to impose a causality restriction to identify the directionality of the shocks, this fact can be seen whether as an advantage or a disadvantage; it is an advantage when we have an economic theoretical framework to impose restrictions on the directionality of the shocks, if so, then Choleski factorization is the tool to handle and extract that directionality, hence we can claim about *directionality* and *causality* in terms of shocks. On the contrary, when such theoretical framework is absent, we are not able to claim neither directionality nor causality and identification through Choleski decomposition is not reachable anymore, nevertheless, the generalized spillover index overcome by providing the effects of shocks to variable k that affect variable j by integrating out all the effects as described above.

According to Diebold and Yilmaz (2012) the advantages of the GFEVD over the orthogonalized OFEVD are clear:

1. It allows to estimate a number of spillover alternatives at a lower computational cost, because we do not need to estimate $\mathbf{P}$ any more.

2. We will not require any theoretical restrictions for identifying the forecast error variance decomposition.

3. It enables us to provide a richer analysis due to the variety of volatility spillover indexes.

4. Directional spillovers and net spillovers are reachable now.

5. Volatility and return spillovers tables do make sense and are more informative than those ones based on OFEVD[4]

All these assertions, mentioned above, are inconclusive since GFEVD does not allow to identify directionality of the shocks; reduced form residuals are still correlated in the general framework of Pesaran and Shin (1998) making impossible to disentangle the idiosyncratic shock from common shocks in the system modeled by the VAR approach. A simple simulation exercise shows that the directionality of the spillover from country j to country k with $j \neq k$ under the GFEVD is not identified.

One alternative strategy to use when no theory is available to impose the restrictions in $\mathbf{P}$ is to compute all the $K!$ possible $\mathbf{P}$'s to cover all the possibilities and then take the mean from all Λ_h^o generated by this highly cost computational procedure, which yields $\bar{\alpha}_{jk,h}^o$ as the typical element of $\bar{\Lambda}_h^o$; the other alternative is just estimate a certain number out of the $K!$, instead of all $K!$ and again take the mean from all the new Λ_h^o generated, however this constitutes a methodological limitation (Diebold and Yilmaz, 2012).

It is worthy to point out that the so-called *"directional spillovers"* (Diebold and Yilmaz, 2012) are only attainable when the researcher have a theoretical framework for the Choleski decomposition. Once the researcher identifies the directionality and proceeds to apply the orthogonalization, then she already is

[4] Those tables based on orthogonalized fevd do not provide information about directional patterns of transmission among variables.

able to claim *directionality* in the spillover spread, hence *directional spillovers* make sense, otherwise, when directionality is not reachable, neither directional spillovers are.

4.2.5 Directional and Net Spillovers

Directional spillovers measure the spillover received by country j from all other countries k,

$$S^o_{j\cdot,h} = \frac{\sum_{\substack{k=1 \\ k\neq j}}^{K} \tilde{\alpha}^o_{jk,h}}{K} \times 100$$

and the spillover transmitted by country j to all other countries k is

$$S^o_{\cdot j,h} = \frac{\sum_{\substack{k=1 \\ k\neq j}}^{K} \tilde{\alpha}^o_{kj,h}}{K} \times 100$$

One can think of the set of directional spillovers as providing a decomposition of the total spillovers to those coming from (or to) a particular source (Diebold and Yilmaz, 2012).

Note that directional spillovers require the identification of $\mathbf{P}$. Once the researcher is able to estimate the directional spillovers, she is also able to account for the *net spillovers*, namely the difference between the gross shocks transmitted *to* and those received *from* all other markets, formally

$$S^o_{j,h} = S^o_{\cdot j} - S^o_{j\cdot} \tag{4.23}$$

If we were to use either $\bar{\Lambda}^o_h$ or Λ^g_h in (4.23), then the resulting value would not be a *net* spillover index, since directionality is not identified, instead, we would replace the word *net* of the resulting value by *position of the k variable relative to the total mean spillover transmitted and received*, consequently, it will not be a *net spillover* anymore, it is a *mean relative net spillover* instead.

4.2.6 Spillovers table

To summarize all the types of spillovers previously presented, we provide an extended version of the matrix in (4.21) by appending *directional spillovers* and *total* *spillovers*, the new matrix is now renamed and it is called *Spillovers Table*.

Table 4.1: Spillover Table

Variable	1	2	...	K	C. from others
1	$\tilde{\alpha}^i_{11,h}$	$\tilde{\alpha}^i_{12,h}$	...	$\tilde{\alpha}^i_{1K,h}$	$\sum_{k=2}^{K} \tilde{\alpha}^i_{1k,h}$
2	$\tilde{\alpha}^i_{21,h}$	$\tilde{\alpha}^i_{22,h}$	...	$\tilde{\alpha}^i_{2K,h}$	$\sum_{\substack{k=1 \\ k\neq 2}}^{K} \tilde{\alpha}^i_{2k,h}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
K	$\tilde{\alpha}^i_{K1,h}$	$\tilde{\alpha}^i_{K2,h}$	...	$\tilde{\alpha}^i_{KK,h}$	
Contribution to others (Spillover)	$\sum_{j=2}^{K} \tilde{\alpha}_{j1,h}$	$\sum_{\substack{j=1 \\ j\neq 2}}^{K} \tilde{\alpha}_{j2,h}$	...	$\sum_{j=1}^{K-1} \tilde{\alpha}_{jK,h}$	$\frac{\sum_{\substack{jk=1 \\ j\neq k}}^{K} \tilde{\alpha}^i_{jk,h}}{K} \times 100$
Contribution to others including own	$\sum_{j=1}^{K} \tilde{\alpha}^i_{j1,h}$	$\sum_{j=1}^{K} \tilde{\alpha}^i_{j2,h}$	...	$\sum_{j=1}^{K} \tilde{\alpha}^i_{jK,h}$	$K \times 100$

The *Spillovers Table* has as its jk^{th} entry the estimated contribution *to* the forecast error variance of variable j coming *from* innovations to variable k. The off-diagonal column sums are the *Contributions to Others* or *Cross-variance shares* or *Spillovers*, while the row sums represent *Contributions from Others*, when these are totaled across variables then we have the numerator of the *Spillover Index*. Similarly, the columns sums or rows sums (including diagonal), when totaled across variables, give the denominator of the Spillover Index, which is 100 fold the number of variables ($100 \times K$).

Our objective is estimating Table 4.1 and based our analysis on it. In following sections we fill Table 4.1 with the estimated spillovers.

4.3 Empirical Results

Following Forbes and Rigobon (2002), stock market returns are calculated as two days rolling-average, this allows us to control for the fact that markets in different countries are not open during this same trading hours. For volatility we assume that is fixed within periods (in this case, days) but variable across periods, thus following Garman and Klass (1980) we use daily high, low, opening and closing prices to estimate daily volatility using (1.2).

Stock markets and countries analyzed in this chapter are the ones shown in Table 1.2.

4.3.1 Static Spillovers

Returns

Here we provide a full-sample analysis of global stock market return spillovers based on both OFEVD and GFEVD. As part of this analysis, firstly, we present a single characterization of the full-sample spillovers providing a description in Table 4.2 over the sample period 17/6/2003 – 16/9/2009.

Table 4.2: Total spillover index at 10 step-ahead forecast horizon.

Index	Statistic	VAR(1)	VAR(6)	VAR(9)	VAR(10)
	Min.	41.096	42.066	42.330	42.321
	Max.	45.111	45.201	45.491	45.433
Orthogonalized	Range	4.016	3.135	3.161	3.112
	Mean	43.363	43.834	44.124	44.117
Generalized		54.192	54.818	54.733	54.795

Table 4.2 provides some *orthogonalized* and *generalized* spillover index results based upon different VAR specifications as far as the lag length is concerned and fixing $h = 10$. We estimate different VAR models as suggested by the selection criteria in Table 4.3: VAR(6), VAR(9) and VAR(10), additionally a VAR(1) is also estimated; under these circumstances we have no more information for using just one out of them and leave out the other ones.

Table 4.3: Lag length order selection criteria for returns.

Lag	AIC(p)	HQ(p)	SC(p)
1	−60.890	−60.838	−60.750
2	−61.669	−61.572	−61.409
3	−62.028	−61.887	−61.649
4	−62.244	−62.059	−61.745
5	−62.392	−62.162	−61.774
6	−62.512	−62.238	**−61.774**
7	−62.598	−62.280	−61.741
8	−62.664	−62.301	−61.686
9	−62.721	**−62.314**	−61.624
10	**−62.762**	−62.311	−61.545

AIC(p): Akaike Information Criterion.
HQ(p): Hannan and Quinn Information Criterion.
SC(p): Schwarz Information Criterion.
Numbers in bold represents the minimum of each criteria.

The top panel of Table 4.2 contains a descriptive statistical summary about the orthogonalized spillover, while the generalized index is placed in the bottom of the table. Independently of the VAR model used, the orthogonalized spillover index is near 44% and the generalized rounds 54%.

In spite of the fact that VAR(1) is not chosen by any selection criterion, its results shown in Table 4.2 are slightly different from those provided by any other VAR suggested by the criteria, therefore our estimations and hence the subsequent analysis are based on the first order VAR, two main reasons support this selection:

1. VAR(1) results are not so different from other specifications, besides, a VAR(1) specification needs fewer parameters to be estimated than the other VAR models, hence it provides us with more degrees of freedom. Recalling that a VAR model with intercept requires the estimation of $K(1+Kp)$ parameters, where K is the number of variables and p is the lag length, we have 6 variables and for VAR(1) we need to estimate 42 parameters which is considerably less than 222 for a VAR(6) for example, not to say for a higher order VAR.

2. Orthononalized Spillover index gets stable more quickly when using a VAR(1) as it is shown in Figure 4.1. This aspect plays an important role when deciding how many steps-ahead to use when computing the spillover index. Furthermore, when all VAR get the stability, the difference between VAR(1) and other VARs is minimal.

As a simple empirical criterion for choosing how many steps-ahead (h) to use when estimating the spillover index is needed, then the criterion we use in order to pursue a reasonable h, consists of selecting an h at which the estimated spillover index experiments small variations, we refer to this situation as the *"stability"* of the index, so we are after an h such that the spillover index *gets stable.*

Figure 4.1 shows the behavior of several spillover indexes throughout different forecast horizons which spans from 1 up to and including 20 periods (days), we can note that all indexes get stable at different values of h. VAR(1) gets stable from ahead 7, VAR(6) shows an almost flat curve from ahead 8, both VAR(9) and VAR(10) are much slower to get stability.

In this context *stability* do not be confused with the *stability condition* (stationary condition for a VAR process), here what we meant with "a VAR gets stable at h ahead" is concerning with the limit of the index. When FEVD and hence the spillover index experiments small changes after h aheads then this VAR estimation reached its *'stability'* so the index associated to this VAR "gets stable". Following

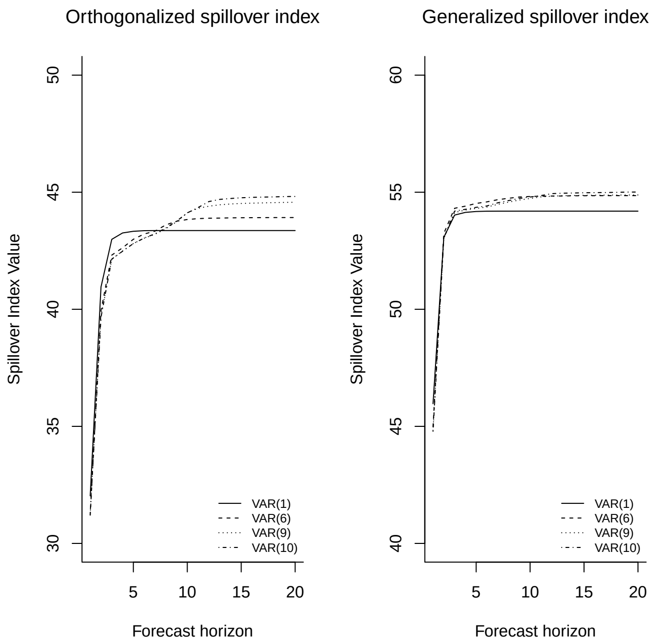

Figure 4.1: Spillover index for returns throughout different forecast horizons

this definition we will use that step-ahead from which the spillover index does not change dramatically as a *good* choice for our analysis, this means that we should choose 7 step-aheads for VAR(1) in order to estimate the spillover index for returns when using the orthogonalized index and $h = 7$ when using the generalized spillover index. If we were to use VAR(6) then we would choose at least 8 aheads. Figure 4.1 shows the idea of what *'stability'* is in this context.

It is worthy to highlight the fact that when each VAR get stable, the value of the spillover index slightly differ from each other, therefore choosing that model with less number of parameters and which stability is not so different from the other ones is a good option.

Following Diebold and Yilmaz (2009) we also provide a full sample analysis of global stock market return spillovers by decomposing the Spillover index (*Contribution to others* in Table 4.4 and Table 4.5) into all the forecast error variance components for country j coming from country k, for all j and k. We report Spillover Indexes in the last column of the row named *C. to others (spillover)*. The jk-th entry in the table is the estimated contribution *to* the forecast error variance of country j coming from innovations to country k.

Table 4.4: Mean spillover table based on OFEVD, 7 steps-ahead.

	US	UK	EU	BRA	JPN	AUS	C. from others
US	9.7449	1.8137	2.1251	2.3436	0.4610	0.1784	6.9218
UK	4.1073	6.0702	3.7913	1.6531	0.8352	0.2096	10.5965
EU	4.2722	3.7571	6.0975	1.5667	0.8075	0.1656	10.5691
BRA	3.1451	1.2359	1.2225	10.5489	0.4172	0.0970	6.1178
JPN	3.7667	1.5100	1.8193	1.5940	7.7372	0.2395	8.9295
AUS	0.0650	0.0654	0.0352	0.0302	0.0314	16.4394	0.2273
C. to others (spillover)	15.3564	8.3823	8.9933	7.1877	2.5522	0.8901	43.3619
C. to others including own	25.1013	14.4524	15.0909	17.7365	10.2894	17.3295	100.0000

Note that static spillover tables shown in this section are the estimation of Table 4.1, though all spillover tables inhere are *standardized* by means of dividing all elements by K.

Paraphrasing Diebold and Yilmaz (2009), the Spillover table provides an *'input-output'* decomposition of the Spillover Index. We can learn from Spillover Table 4.4 that innovations to US are responsible, in mean, for 4.1073% of the error variance in forecasting 7-days-ahead UK returns. We can also see that the total spillover from US to other countries account for 15.3564%, meanwhile the spillover from other countries to US is 6.9218%, this evidences that the recent Global Financial Crisis triggered in US and spilled over the rest of countries. Results in Table 4.4 refer to the mean of the 720 orthogonalized spillover in returns.

One of the key results from Table 4.4 is the *Total Spillover Index* which accounts for the portion of the forecast error variance error coming from spillovers in returns, is 43.3619% for our full $2003 - 2009$ data sample.

Table 4.5: Spillover table based on GFEVD, 6 steps-ahead.

	US	UK	EU	BRA	JPN	AUS	C. from others
US	5.9757	1.7631	2.4799	5.9427	0.4610	0.0442	10.6910
UK	3.6858	3.6547	3.7081	4.8574	0.6966	0.0641	13.0119
EU	3.8191	2.9132	4.5829	4.6205	0.6790	0.0520	12.0838
BRA	2.6853	1.0724	1.3911	11.1502	0.3512	0.0164	5.5165
JPN	3.5090	1.7129	2.4189	4.8180	4.1165	0.0913	12.5501
AUS	0.0569	0.0662	0.0688	0.0567	0.0879	16.3301	0.3366
C. to others (spillover)	13.7561	7.5278	10.0668	20.2954	2.2757	0.2681	54.1900
C. to others including own	19.7318	11.1826	14.6497	31.4456	6.3922	16.5981	100.0000

Table 4.5 shows slightly different situation as its results are based on the general forecast error variance decomposition. In this table, some relevant changes take place, for example, US decreases its spillover from 15.3564% (according to Table 4.4) to 13.7561%, also UK suffers a reduction in its spillover, while Europe and Brazil experienced an increase. In this new scheme Brazil becomes the main contributor in terms of spillovers. We already expect these discrepancies on the indexes, because each of them is using a different structure of residuals for esti-

Table 4.6: Net spillovers, returns.

	Orthogonalized Index				Generalized Index			
	To	From	Net	Net Transmitter?	To	From	Net	Net Transmitter?
US	15.3564	6.9218	8.4346	Yes	13.7561	10.6910	3.0651	Yes
UK	8.3823	10.5965	−2.2142	No	7.5278	13.0119	−5.4841	No
EU	8.9933	10.5691	−1.5758	No	10.0668	12.0838	−2.0170	No
BRA	7.1877	6.1178	1.0699	Yes	20.2954	5.5165	14.7789	Yes
JPN	2.5522	8.9295	−6.3773	No	2.2757	12.5501	−10.2744	No
AUS	0.8901	0.2273	0.6628	Yes	0.2681	0.3366	−0.0685	No

mating the corresponding forecast error variance decomposition, as we mentioned before, the orthogonalized index is built upon uncorrelated errors since Choleski decomposition makes them to be independent (under normality), however due to the lack of theoretical background for imposing restrictions on the directionality of the shocks, we construct the spillover index by taking the mean of all the indexes calculated for all possible Choleski decomposition, which is not longer an index which directionality can be identified. For the case where we have generalized spillover index, from subsection 4.2.3 we know that the GFEVD is order invariant because it does not relies on any kind of orthogonalization, thus the residuals remains correlated and also identification of directionality is not possible. As a conclusion from this part we can say that using either the mean orthogonalized or the generalized spillover index, directionality is not possible to be established and the quantities inside the Spillover Tables should be used cautiously. Because directionality is not recognizable, we base all the analysis on the total spillover.

Just to mention the inaccuracy stemming from the lack of identifiability of the directionality in the spillover tables, the mean relative net spillover is presented in Table 4.6; when using the average orthogonalized spillover index we have that US, Brazil and Australia are net transmitters while the other countries are net receivers, in contrast, when using the generalized index, Australia is not longer a net transmitter, instead it happens to be a net receiver, while US and Brazil remain being net transmitters.

Net spillovers need one unique Choleski decomposition to be valid. When using taking mean of all possible decompositions, the *net* spillover becomes into *mean relative net spillover* as we pointed out in subsection 4.2.5.

Volatility

In this section, the static volatility spillovers are analyzed, all the decision process about the lag length and the selection of h is undertaken as in the previous section. Volatility in this chapter is estimated using (1.2) which is found in Garman and Klass (1980).

Table 4.7: Lag length order selection criteria for intraday volatility.

Lag	AIC(p)	HQ(p)	SC(p)
1	−70.737	−70.685	−70.598
2	−70.802	−70.705	−70.542
3	−71.061	−70.920	**-70.682**
4	−71.095	−70.910	−70.596
5	−71.187	−70.957	−70.569
6	−71.219	−70.946	−70.482
7	−71.287	−70.969	−70.430
8	−71.343	−70.981	−70.367
9	−71.399	**-70.992**	−70.302
10	**-71.400**	−70.949	−70.184

AIC(p): Akaike Information Criterion.
HQ(p): Hannan and Quinn Information Criterion.
SC(p): Schwarz Information Criterion.
Numbers in bold represents the minimum of each criteria.

For similar reasons as before, a VAR(1) is used to estimate the spillover for volatilities, Other alternatives to VAR(1), suggested by the selection criteria, are VAR(3), VAR(9) and VAR(10), see Table 4.7 and Figure 4.2. Here the difference between VAR(1) and VAR(3) are negligible and at the limit there are not big differences with VAR(9) or VAR(10) in terms of the value of the spillover index.

Using a VAR(1) and $h = 70$ as the best value for the forecasting horizon, Table 4.8 and Table 4.9, are estimated.

Table 4.8: Mean spillover table based on OFEVD, 70 steps-ahead.

	US	UK	EU	BRA	JPN	AUS	C. from others
US	8.1701	2.2711	1.5784	1.7334	0.7509	2.1628	8.4966
UK	4.6543	5.0116	2.3485	1.4564	0.7246	2.4713	11.6550
EU	4.7382	3.3597	4.6830	1.2482	0.7313	1.9063	11.9836
BRA	3.3817	1.5489	1.0369	8.7603	0.5944	1.3445	7.9063
JPN	3.3543	1.6729	1.4531	1.0216	7.8508	1.3139	8.8159
AUS	1.4978	1.4262	0.4834	0.4974	0.1787	12.5830	4.0836
C. to others (spillover)	17.6263	10.2788	6.9003	5.9570	2.9800	9.1987	52.9411
C. to others including own	25.7964	15.2905	11.5834	14.7174	10.8307	21.7817	100.0000

We learn from Table 4.8 that total volatility spillovers from US to others accounts for 17.63% (*C. to others (spillover)*) which is twice as big as total volatility spillovers from others to US (contributions from others) which only amounts about to 8.4966%. As intuitively was expected, volatility transmissions from US to the rest of the countries are much bigger than the transmissions from any other coun-

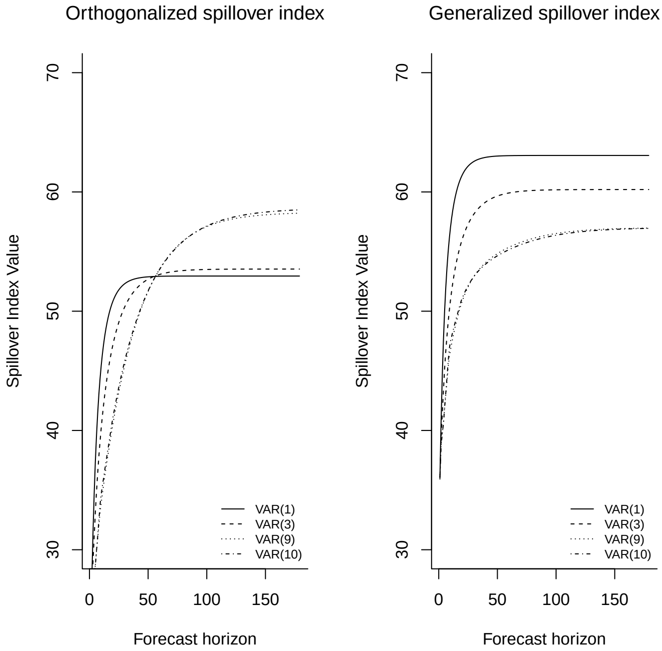

Figure 4.2: Spillover index for volatility throughout different forecast horizons

try to the rest of the stock markets, this result is plausible since US is the country where the GFC took place before to be spilled over the major stock markets.

Now consider the total volatility spillover, which indicates that on average, 52.9411% percent of volatility forecast error variance in all 6 stock markets comes from spillovers in volatility.

In Table 4.9, we see almost the same pattern exhibited in Table 4.8, nevertheless in the generalized version of the spillover for volatility the main contributor is Brazil followed by US while in the orthogonalized case, the main contributor is US followed by UK.

Here again, we show the 'net' spillover table where volatility exhibits the same

Table 4.9: Spillover table based on GFEVD, 70 steps-ahead.

	US	UK	EU	BRA	JPN	AUS	C. from others
US	5.7385	2.2865	2.1376	4.9569	0.7604	0.7868	10.9282
UK	3.9583	3.8317	2.8213	4.4119	0.7424	0.9011	12.8350
EU	4.0173	3.2173	4.0617	3.9409	0.7390	0.6905	12.6050
BRA	2.6178	1.3712	1.2441	10.5412	0.4959	0.3963	6.1254
JPN	3.4491	2.0636	2.1391	3.7252	4.7150	0.5747	11.9517
AUS	2.5025	1.9413	0.9690	2.7988	0.3958	8.0592	8.6075
C. to others (spillover)	16.5451	10.8800	9.3110	19.8338	3.1336	3.3493	63.0528
C. to others including own	22.2836	14.7116	13.3727	30.3750	7.8486	11.4085	100.0000

Table 4.10: Net spillovers, volatility.

	Orthogonalized Index				Generalized Index			
	To	From	Net	Net Transmitter?	To	From	Net	Net Transmitter?
US	17.6263	8.4966	9.1297	Yes	16.5451	10.9282	5.6169	Yes
UK	10.2788	11.6550	−1.3762	No	10.8800	12.8350	−1.9550	No
EU	6.9003	11.9836	−5.0833	No	9.3110	12.6050	−3.2940	No
BRA	5.9570	7.9063	−1.9493	No	19.8338	6.1254	13.7084	Yes
JPN	2.9800	8.8159	−5.8359	No	3.1336	11.9517	−8.8181	No
AUS	9.1987	4.0836	5.1151	Yes	3.3493	8.6075	−5.2582	No

pattern as returns. When using the orthogonalized spillover US and Australia are net transmitter and this result changes when using the generalized because in this case US remains being a net transmitter while Australia is not anymore and Brazil change position from being a net receiver to be a net transmitter.

4.3.2 Rolling sample analysis: Studying the dynamics of the spillovers

We prepare this section because several events might have taken place within our series as stock prices move from relative stable periods to turmoil ones, therefore with this financial market evolution, it is unlikely that prices remain constant over time so that any single fixed-parameter model would apply properly over the entire sample and gives rich information about its evolution.

Hence the full-sample spillover tables constructed earlier, although providing a useful summary of the average total spillover behavior, likely miss potentially important secular and cyclical movements in spillovers. To address this potential lose of dynamics, we now estimate spillover using 160-days[5] rolling windows which we examine graphically in the co-called total spillover plots (Diebold and Yilmaz, 2009, 2012). We provide results from both the orthogonalized and the generalized spillover index.

We can note, on October 2008, a increasing trend with a big jump capturing the Global Financial Crisis (GFC) triggered on August 4, 2008. The jumps previous to the biggest one clearly reflects how volatile the stock markets were during the Subprime Mortgage Crisis (hereafter: SMC) and this fact triggered the GFC. See daily dynamic plot in Figure 4.3.

Figure 4.4 shows the dynamic spillover index for volatilities using 160-days rolling windows. There are some common features between dynamic spillover in

[5] The width of the rolling windows does not affects the main findings. Diebold and Yilmaz (2009) performs an extensive set of robustness checking on this particular point showing that dynamic spillover index is strongly robust to the size of the window.

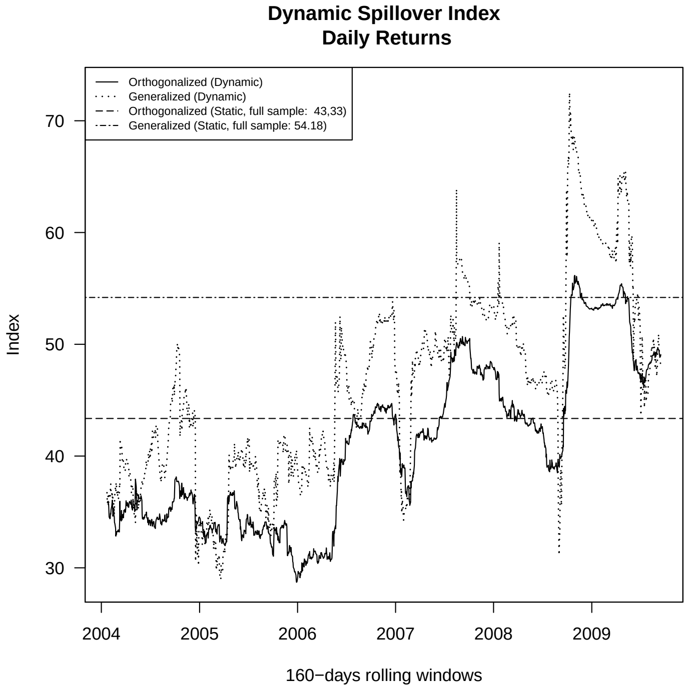

Figure 4.3: Dynamic spillovers for returns.

returns and dynamic spillover in volatilities, we see that both captures quite well the turbulence in late 2008, both have three main jumps corresponding to mid 2006, early 2007 and late 2008.

Figure 4.5 and Figure 4.6 shows the 'net' spillover dynamically. The dashed line at point zero indicates that values above this line suggest the country is a net transmitter and values below indicate the country is a net receptor of shocks.

Figure 4.5 shows the US as net transmitter of shocks over the entire sample period while Brazil and Australia are net transmitters for most of the period, while UK and Europe are most of the time net receptor. Japan is always a net receptor for all period. Figure 4.6 shows very similar results except for US which behaves as a net receptor of shocks before 2008 and after the crisis in 2008 it becomes into a net transmitter and Brazil becomes into a net transmitter for all the period, the rest of countries behave the same as in Figure 4.5. It is important to note that the word net in this context should be use cautiously as neither in the (mean) orthogonalized nor in the generalized version of this section, directionality is identified.

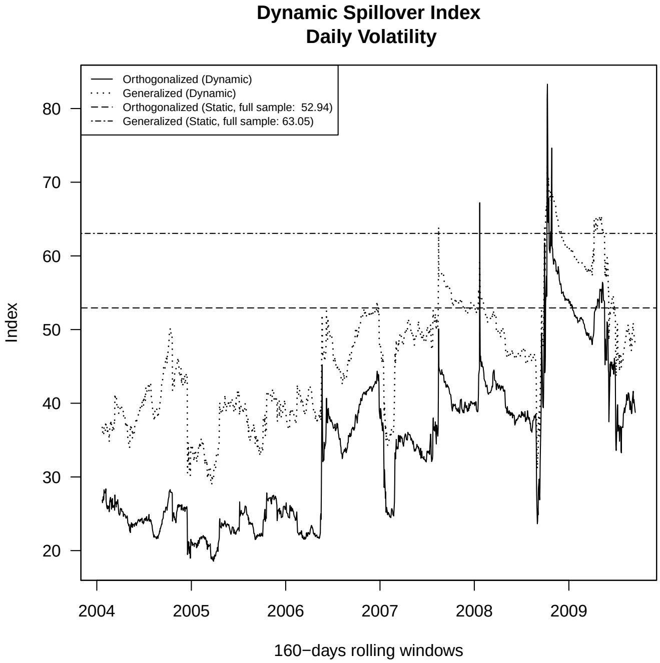

Figure 4.4: Dynamic spillovers for volatilities.

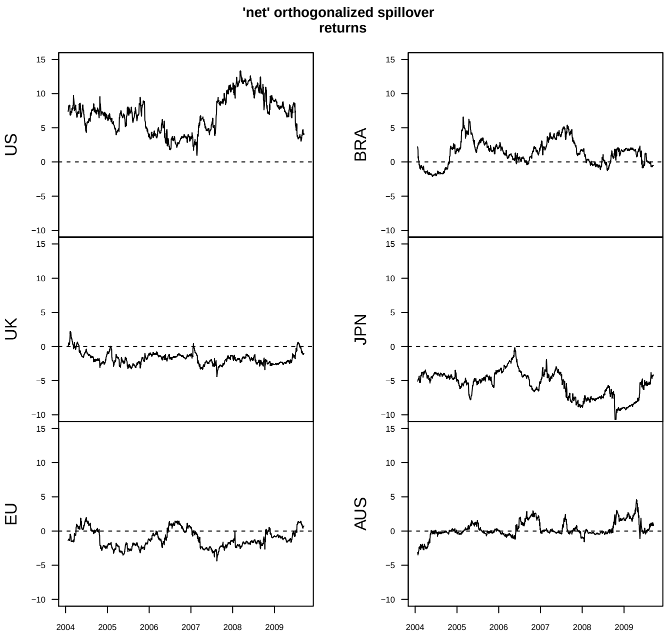

Figure 4.5: Dynamic orthogonalized 'net' spillovers for returns.

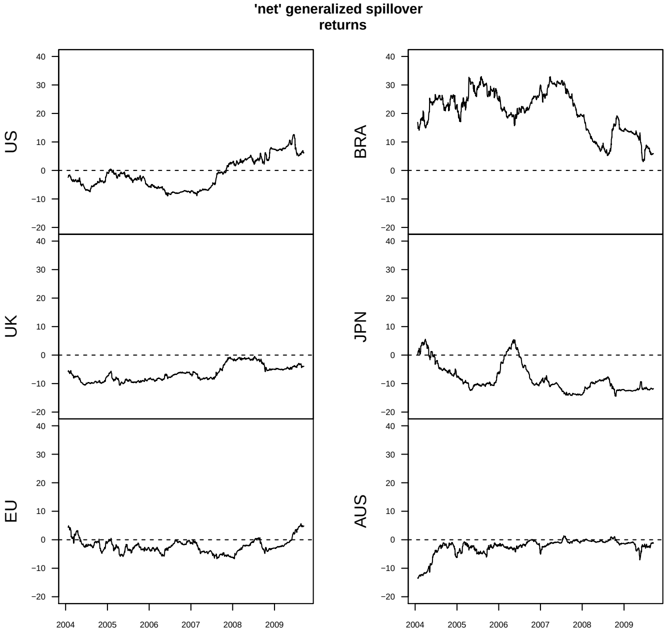

Figure 4.6: Dynamic generalized 'net' spillovers for returns.

4.4 Conclusions

We utilize a spillover index to assess the proportion of variance that on average comes from spillover in other countries. Two versions of this spillover index are used in this work: the orthogonalized and the generalized version, where the former is based on the traditional forecast error variance decomposition using the Choleski orthogonalization, hence the order-dependence becomes a drawback; the latter is based on the generalized forecast error variance decomposition, which not depends on the ordering. It is worthy to note that the ordering dependence of the orthogonalized spillover index is a drawback when lack of a theoretical framework for imposing restrictions is involved, if we had such a theoretical background, then order dependence will not longer be a drawback, instead it would be an advantage since it will provide us with directionality, the spillover table would be meaningful and net spillovers indeed would account for net effects and the highly computational procedure will decreases dramatically.

Our empirical results suggest that around one-half of the total variance comes from spillovers in returns as well as in volatility.

Since the impossibility of identifying the shocks in the spillover tables, we consider that this procedure is useful to obtain total spillovers but not directional spillovers, therefore net spillovers are conclusive.

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Chapter 5

A Component Model for Dynamic Conditional Correlations: Disentangling Interdependence from Contagion

5.1 Introduction

Assessment of the transmission mechanisms of financial crisis across countries based on correlations have been payed a lot of attention since King and Wadhwani (1990) and then reinforced by Forbes and Rigobon (2002). Correlation approach is useful since it provides a straightforward way to test for contagion (see Forbes and Rigobon, 2002), nevertheless the *"static"* correlation approach is very simplistic, it splits the sample into two subsamples (pre-crisis and post-crisis periods) and performs a test of significant increase in correlations over these two periods where the underlying correlations are fixed within periods, none dynamic is involved in the correlations.

The lack of temporal dynamics in the correlations can be overcome by using a Dynamic Conditional Correlation (DCC) model, first introduced by Engle (2002). Several attempts have been done to test for contagion by averaging the dynamic correlations belonging to each subsamples and then performing a classical t-test for mean differences, see for instance Wang and Nguyen Thi (2013), Naoui et al. (2010a), Naoui et al. (2010b) and Chiang et al. (2007). These works rely on defining contagion as an increase in cross-market linkages after a exogenous negative shock in one country or group of countries (such definition corresponds to the World

Bank's *"very restrictive"* definition), but none of them show the time varying behavior of both interdependence and contagion.

We try to shed some light on the gap, which in terms of Rigobon (2003), no satisfactory procedure has been developed to be able to answer the question whether contagion occurs or not using the correlation-based definition since the seminal contribution by King and Wadhwani (1990).

We use a component model for the DCC to capture both, interdependence and contagion via a parsimonious parameter structure and still rely on the *very restrictive definition* of contagion, but allowing the correlations to be time varying. Using the DCC-MIDAS[1] introduced by Colacito et al. (2011) we can disentangle both, the long run and short run components of the time varying correlations which can allows us to associate the former with contagion and the latter with interdependence.

Within this framework we identify interdependence which is in itself a contribution since it helps to better understand contagion. Forbes and Rigobon (2002) discussed the influence of heteroscedasticity over the correlations and furthermore, a correction is also proposed. Nevertheless, the test over the corrected correlation operates in a static environment such that contagion can be wrongly diagnosed, mainly because interdependence effects have not been discounted from the correlations.

As discussed in Forbes and Rigobon (2002) correlation after a negative shock can increase because of heteroscedasticity, however, as markets moves more and more together due to market integration, it is plausible to think that interdependence also varies over time and moves in the same direction of market integration, therefore, correlations also can be increased by the effect of integration and such integration is represented by interdependence which is not explicitly taken into account in previous works.

The above ideas are relevant since financial links play an important role in economic integration of an individual country into the world market (Dornbusch et al., 2000), this means that a financial crisis in one country can lead to direct financial effects to other countries. In line with Dornbusch et al. (2000) the spread of a financial crisis depends primarily on the investors' behavior and on the degree

[1]DCC-MIDAS: Dynamic Conditional Correlation - Mixed Data Sampling Model.

of financial market integration, they claims that in this sense, financial markets facilitate the transmission of real or common shocks but do not cause them. As these kind of links (financial and trade) give rise to market integration (interdependence) play and important role for transmitting crisis, a measure of such links over time become crucially important, this measure is provided in this context by the long-run correlation given by the MIDAS filter.

Long-run component can be seen as the measure of financial market integration which is plausible to be modeled as a slowly moving average of correlations due to the fact that such integrations are neither constant overtime nor fast-moving, it evolves slowly.

Empirical works on contagion has been focused mainly on the co-movements in asset prices rather than on "excessive" co-movements among them (Dornbusch et al., 2000). We provide such *excess* of comovements by discounting from the potential contagion the effects of interdependence, this is done by subtracting from the short-run correlation at time t, the corresponding long-run correlation. Once we have the correlation without the effects of interdependence, we can perform a test for contagion.

In order to estimate both kind of correlation, we use recently introduced DCC-MIDAS model of Colacito et al. (2011). DCC-MIDAS model is not a new model since is was introduced by Colacito et al. (2011), nevertheless the novelty of our approach is the application of this model to the context of contagion vs interdependence, where we associate contagion to short-lived events (short run correlations) and interdependence is directly linked to long-run correlations.

After adjusting the correlations by discounting the interdependence effects we perform a test for contagion leading to the conclusion that the Global Financial Crisis triggered in US was spread to other countries through interdependence. We only find evidence of contagion for one pair of countries: Brazil - Japan.

The remaining of this work is arranged as follows: in Section 5.2 we present the model, its notation, the estimation procedure and the hypothesis test strategy. Empirical application is developed in Section 5.3, some concluding remarks are in Section 5.4.

5.2 Model Specification

5.2.1 Notation and Preliminaries

We begin this section by providing the meaning of the notation used throughout this chapter.

Let $\mathbf{r}_t = [r_{1,t}, \ldots, r_{n,t}]'$ be a vector of returns such that follows the process $\mathbf{r}_t \sim N(^-, \mathbf{H}_t)$ with:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{Q}_t \mathbf{D}_t, \tag{5.1}$$

where $^-$ is the vector of unconditional means, $\mathbf{H_t}$ is the conditional covariance matrix, $\mathbf{Q_t}$ is the conditional correlation matrix and $\mathbf{D_t}$ is a diagonal matrix with conditional standard deviations on the diagonal, with:

$$\mathbf{Q}_t = E[\xi_t \xi_t' \mid \Omega_{t-1}] \tag{5.2}$$

$$\xi_t = \mathbf{D}_t^{-1}(\mathbf{r}_t - \mu), \tag{5.3}$$

where ξ_t is a vector of standardized residuals and Ω_{t-1} is the information set available up to $t-1$. Therefore, we can write the vector of returns as $\mathbf{r}_t = {}^- + \mathbf{H}_t^{1/2}\xi_t$ with $\xi_t \sim N(0, \mathbf{I_n})$

5.2.2 The DCC–MIDAS model

The DCC-MIDAS model is a natural extension to DCC model, they both are very similar in their formulation and the main difference between them is that DCC-MIDAS has two components: a long-run and a short-run component for correlations. The standard formulation of a DCC models is shown in (5.4) and the one corresponding to a DCC-MIDAS model is (5.5), one can tell that the difference between them is the construction of $\bar{\mathbf{R}}$. For the standard DCC model $\bar{\mathbf{R}}$ represents the matrix of unconditional correlations which is time invariant, in contrast for the DCC-MIDAS, $\overline{\mathbf{R}}$ becomes into $\bar{\mathbf{R}}_t(\omega)$, which is time varying and its behaviour is entirely determine by a slowly moving average weighting, ω. $\bar{\mathbf{R}}_t(\omega)$ is interpreted as the long-run component and its counterpart, the short-run component, is left to be represented by $\mathbf{Q_t}$:

$$\mathbf{Q_t} = (1-a-b)\bar{\mathbf{R}} + a\xi_{t-1}\xi'_{t-1} + b\mathbf{Q_{t-1}} \tag{5.4}$$

$$\mathbf{Q_t} = (1-a-b)\bar{\mathbf{R}}_\mathbf{t}(\omega) + a\xi_{t-1}\xi'_{t-1} + b\mathbf{Q_{t-1}} \tag{5.5}$$

where the long-run component is $\bar{\mathbf{R}}_\mathbf{t}(\omega) = \sum_{l=1}^{K} \Phi_l(\omega) \odot \mathbf{C_{t-1}}$ a slowly moving average of some correlation matrix denoted by $\mathbf{C_{t-1}}$ with typical element being $c_{i,j,t-l}$. The operator $\odot$ denotes the Hadamard product. For the short-run component to be a correlation, the following transformation is needed $\mathbf{Q_t}^* = \{\text{diag}(\mathbf{Q_t})^{-1}\mathbf{Q_t}\text{diag}(\mathbf{Q_t})^{-1}\}$ (Engle, 2002), where $q^*_{i,j,t}$ is a typical element of $\mathbf{Q_t}^*$.

If we denote the typical element of $\mathbf{Q_t}$ as $q_{i,j,t}$ and if the typical element of matrix $\bar{\mathbf{R}}_\mathbf{t}$ is denoted by $\bar{\rho}_{i,j,t}$, then we can write the full formulation of the DCC-MIDAS as follows:

$$\begin{aligned}
q_{i,j,t} &= (1-a-b)\bar{\rho}_{i,j,t} + a\xi_{i,t-1}\xi_{j,t-1} + bq_{i,j,t-1} \\
q^*_{i,j,t} &= \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \\
\bar{\rho}_{i,j,t} &= \sum_{l=1}^{K} \varphi(\omega)c_{i,j,t-l} \\
c_{i,j,t-l} &= \frac{\sum_{k=t-l-N}^{t-l} \xi_{i,k}\xi_{j,k}}{\sqrt{\sum_{k=t-l-N}^{t-l} \xi^2_{i,k}}\sqrt{\sum_{k=t-l-N}^{t-l} \xi^2_{j,k}}} \\
\varphi(\omega) &= \frac{\left(1-\frac{1}{K}\right)^{\omega-1}}{\sum\limits_{j=1}^{K}\left(1-\frac{j}{K}\right)^{\omega-1}}
\end{aligned} \tag{5.6}$$

According to the formulation of system (5.6), the value of N is needed for estimating the weighted correlation $c_{i,j,t-l}$ which only accounts for the last N past observations in its calculation, then over these correlations, a long run correlation is estimated as a weighting average of all the K past values giving weights $\varphi(\omega)$.

Under this formulation $q^*_{i,j,t}$ is the *short run* correlation between assets i and j, whereas $\bar{\rho}_{i,j,t}$ is a slowly moving *long run* correlation. Furthermore, $\varphi(\omega)$ are the so called Beta weights which governs the movements of the long run component, this weighting scheme allows us to extract the slowly moving secular component around which the short-run component evolves. Lag lengths are denoted by N and span lengths of historical correlations are left to be represented by K, we consider N and K are constant for all assets.

Rewriting the first equation of system (5.6) as:

$$q_{i,j,t} - \bar{\rho}_{i,j,t} = a(\xi_{i,t-1}\xi_{j,t-1} - \bar{\rho}_{i,j,t}) + b(q_{i,j,t-1} - \bar{\rho}_{i,j,t}), \tag{5.7}$$

conveys de idea of short run fluctuations around a time-varying long run relationship.

5.2.3 Estimation procedure

The estimation procedure is fully described in Colacito et al. (2011), here we briefly point out the main aspects. In order to estimate the parameters of the DCC-MIDAS model we follow the two step procedure of Engle (2002). Let ψ[2] be the collection of parameters of the univariate GARCH model and let Ξ be the vector of DCC parameter (a, b, ω), the quasi-maximum likelihood (QL) takes the following form:

$$\begin{aligned} QL(\psi, \Xi) &= QL_1(\psi) + QL_2(\psi, \Xi) \\ &= -\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \mathbf{r}_t' D_t^2 \mathbf{r}_t) - \sum_{t=1}^{T}(\log|R_t| + \xi_t' R_t^{-1}\xi_t + \xi_t'\xi_t). \end{aligned} \tag{5.8}$$

The separation of $QL(\psi, \Xi)$ into $QL_1(\psi)$ and $QL_2(\psi, \Xi)$ indicates that we can first estimate the parameters of the univariate GARCH-type processes contained in ψ by maximizing $QL_1(\psi)$ to obtain $\hat{\psi}$, then we can plug $\hat{\psi}$ in $QL_2(\psi, \Xi)$ so that it becomes into $QL_2(\hat{\psi}, \Xi)$ where standardized residuals $\hat{\xi} = \hat{D}_t^{-1}(\mathbf{r}_t - \hat{\mu})$ are used in the second stage.

System (5.6) requires setting two extra parameters: N the MIDAS lag length and K, the span lengths of historical correlations, both are chosen from the parameter space by maximum likelihood profiling. The profiling procedure of the likelihood function is performed over the maximization of $QL_2(\psi, \Xi)$, once we get the "optimal" N and K we reestimate the entire model using the complete likelihood defined by

[2]This ψ could be a standard GARCH, or an EGARCH or even a Beta-t-EGARCH

$$\log \mathcal{L} = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \xi_t'\xi_t + \log|R_t| + \xi_t' R_t^{-1}\xi_t), \tag{5.9}$$

maximizing it in one step to obtain the relevant standard errors of the estimated coefficients to perform individual hypothesis tests.

5.2.4 Testing procedure

In this section we present the strategies to test for contagion based on the dynamic correlations estimated under the DCC-MIDAS scheme.

One of the alternatives consist of testing $H_0 : a = 0$ which implies that under the null, $q_{i,j,t}$ is determined by $(1-b)\overline{\rho}_{i,j,t}(\omega) + b_{i,j,t-1}$ with $0 \leq b < 1$. If the empirical evidence do not reject the null, then interdependence can be reached as the conclusion of the test. However, if $H_0 : a = 0$ turns out to be rejected, then this constitutes contagion defined as in Corsetti et al. (2005) who consider that "*for contagion to occur, the observed pattern of comovements in asset prices must be too strong (or too weak) relative to what can be predicted conditional on a constant mechanism of international transmission*".

Corsetti et al. (2005) definition conveys the idea that contagion can be assessed through performing a test for increases or decreases in the conditional correlations, in our context this boils out to be a test over $H_0 : a = 0$ to determine whether the co-movements are too strong or too weak, this is the reason why the one-step estimation of the DCC-MIDAS is required.

Another approach to test for contagion is using directly the time-varying conditional correlations produced by the model. Considering contagion as an increase in the mean correlation after a crisis, if such increase stemmed from a model which acts like a filter discounting the economic fundamentals, then it is plausible to assume that the increase (positive excess) in correlations is due to irrational reactions of the agents in the markets. A way to measure this excess based on the daily conditional time-varying correlation from the DCC-MIDAS model is:

$$\overline{q}_{i,j}^{l*} = \frac{1}{T^l}\sum_t \left(q_{i,j,t}^{*} - \overline{\rho}_{i,j,t}(\omega)\right) \mathbb{1}\left(t \in precrisis\right) \tag{5.10}$$

$$\overline{q}_{i,j}^{h*} = \frac{1}{T^h}\sum_t \left(q_{i,j,t}^{*} - \overline{\rho}_{i,j,t}(\omega)\right) \mathbb{1}\left(t \in crisis\right) \tag{5.11}$$

where $\mathbb{1}(\cdot)$ is an indicator function that takes value 1 when condition in () is met and 0 otherwise. $T^l = \mathbb{1}\sum_t (t \in precrisis)$ is the sample size corresponding to the stable period, while $T^h = \mathbb{1}\sum_t (t \in crisis)$ is the sample size in the turmoil period.

The proposed test of contagion interprets an increase in mean excess of correlations as evidence of contagion because it represents additional comovements in asset returns during the crisis period not present in the precrisis period. As contagion represents the additional comovements in asset returns over that predicted by changes in the market fundamentals, the identification of contagion requires the extraction of market fundamentals from the returns series (Fry et al., 2010). Within the DCC-MIDAS approach here proposed, we associate market fundamentals with the long-run correlations mainly because the MIDAS part filters the series and the result can be used as a proxy for the fundamentals, leading to identification of contagion as any excess of short-run correlation from the levels of long-run correlations. As a consequence the hypothesis test boils out to be as follows:

$$H_0 : \overline{q}_{i,j}^{h*} \leq \overline{q}_{i,j}^{l*} \tag{5.12}$$

$$H_1 : \overline{q}_{i,j}^{h*} > \overline{q}_{i,j}^{l*} \tag{5.13}$$

which is a traditional mean difference based on the standard t-test as that of Naoui et al. (2010b). For that we use:

$$\widehat{\overline{q}_{i,j}^{l*}} = \frac{1}{T^l}\sum_t \left(\widehat{q_{i,j,t}^{*}} - \overline{\rho}_{i,j,t}(\widehat{\omega})\right) \mathbb{1}\left(t \in precrisis\right) \tag{5.14}$$

$$\widehat{\overline{q}_{i,j}^{h*}} = \frac{1}{T^h}\sum_t \left(\widehat{q_{i,j,t}^{*}} - \overline{\rho}_{i,j,t}(\widehat{\omega})\right) \mathbb{1}\left(t \in crisis\right) \tag{5.15}$$

where $\widehat{q_{i,j,t}^{*}}$ and $\widehat{\omega}$ are obtained from the MLE of the DCC-MIDAS model.

Another alternative to test for contagion is using Corsetti et al. (2005) definition and to test whether contagion occurs by setting a threshold (τ). Testing whether deviation of the short-run correlation from the long-run correlation is bigger (smaller) than τ is in line with the idea that the comovements should be too strong (or too weak) for contagion to exist. In this case, the hypothesis test can be written as follows

$$H_0 \quad : \quad \left|\overline{q}^*_{i,j,t} - \overline{\rho}_{i,j,t}(\omega)\right| \leq \tau \tag{5.16}$$

$$H_1 \quad : \quad \left|\overline{q}^*_{i,j,t} - \overline{\rho}_{i,j,t}(\omega)\right| > \tau \tag{5.17}$$

where H_0 implies interdependence and H_1 contagion. Usually τ is proportional to the standard deviation of $\left|\overline{q}^*_{i,j,t} - \overline{\rho}_{i,j,t}(\omega)\right|$.

5.3 Empirical application

One of the tests of contagion presented in the previous section is now applied to identify potential contagious linkages from the US stock market to other stock markets during the subprime mortgage crisis. Our analyzed period goes from January 1, 2004 to December 31, 2012. Stock indexes and countries chosen for the analysis are in Table 1.2.

First, we estimate the short and long run correlation of asset returns. As we pointed out before, we address the problem of selecting MIDAS lags by following Colacito et al. (2011) and Engle et al. (2006), we compare different DCC-MIDAS models with different time spans via profiling of the likelihood function.[3]

In Table 5.1 we report the coefficients of the DCC-MIDAS and also the resulting estimates of a DCC. Our estimation is somehow restrictive because we only consider one parameter (ω) to account for the long run dynamics. For the short run dynamics we use DCC of order (1,1), which means only one a and one b.

Table 5.1: DCC MIDAS and DCC results.

		a	b	ω
DCC-MIDAS	Estimates	0.1086	0.6789	2.3654
	t-stat	11.6943	17.8802	3.3204
	P-value	0.0000	0.0000	0.0009
DCC	Estimates	0.1192	0.6775	-
	t-stat	4.0027	7.4565	-
	P-value	0.0001	0.0000	-

Note: The top panel reports the estimates of the DCC-MIDAS while the bottom panel shows the DCC estimates. We set $K = N = 528$ as suggested by the likelihood profiling.

[3]See details of the procedure in Engle et al. (2006).

Table 5.2: Contagion test results.

	Precrisis	Crisis	P-value	Result
sp500-ftse100	0.0225	−0.0060	1.0000	N
sp500-eurostoxx50	0.0142	−0.0116	1.0000	N
sp500-bovespa	0.0014	−0.0089	0.9755	N
sp500-nikkei225	0.0264	0.0093	0.9861	N
sp500-spasx200	0.0369	−0.0200	1.0000	N
ftse100-eurostoxx50	−0.0020	0.0004	0.1795	N
ftse100-bovespa	0.0106	−0.0028	0.9969	N
ftse100-nikkei225	0.0068	−0.0042	0.9327	N
ftse100-spasx200	0.0141	−0.0104	1.0000	N
eurostoxx50-bovespa	0.0050	0.0004	0.8019	N
eurostoxx50-nikkei225	0.0033	−0.0058	0.8656	N
eurostoxx50-spasx200	0.0095	−0.0288	1.0000	N
bovespa-nikkei225	0.0051	0.0278	0.0010	C
bovespa-spasx200	0.0122	−0.0101	0.9999	N
nikkei225-spasx200	0.0052	−0.0180	0.9999	N

Note: column 1 indicates the pairs of countries for which correlation is computed, columns 2 and 3 have the mean of those correlations, column 4 holds the p values associated to the test and the last column contains an N when No-contagion and it has a C when there is empirical evidence of contagion.

Results in Table 5.1 show that DCC-MIDAS parameters are very close to the DCC parameters as is recurrent feature in Engle et al. (2006), the superiority of DCC-MIDAS over DCC is the capability of disentangling the short run from the long run correlation which permits analyzing the behavior of them simultaneously.

Time varying correlations based on the DCC-MIDAS scheme are plotted on Figure 5.1, Figure 5.2 and Figure 5.3, the black lines in each plot represents the short run correlation meanwhile the long run correlation is shown in red, the dashed line splits the entire sample into two subsamples: precrisis period and crisis period as it is conventionally done in the contagion literature based on correlation. A visual analysis of these figures suggests no relevant changes in the linkages between countries neither in the general short run correlation behavior nor in the long run, from this fact we can derive the cautious "conclusion" that the economies exhibits strong linkages in all states of the world, this situation can be interpreted as interdependence, nevertheless, in order to formally draw any conclusion about the absence of contagion during the analyzed period, we perform a statistical hypothesis testing.

Table 5.2 consists of all the possible combinations of pairwise correlations for the analyzed sample, since we have 6 countries (stock markets) then we can compute 15 $\bar{q}^{l}_{i,j,t}$ and $\bar{q}^{h}_{i,j,t}$ and perform the test specified in subsection 5.2.4. Hypothesis test suggests no contagion for all pair of countries except for Brazil and Japan

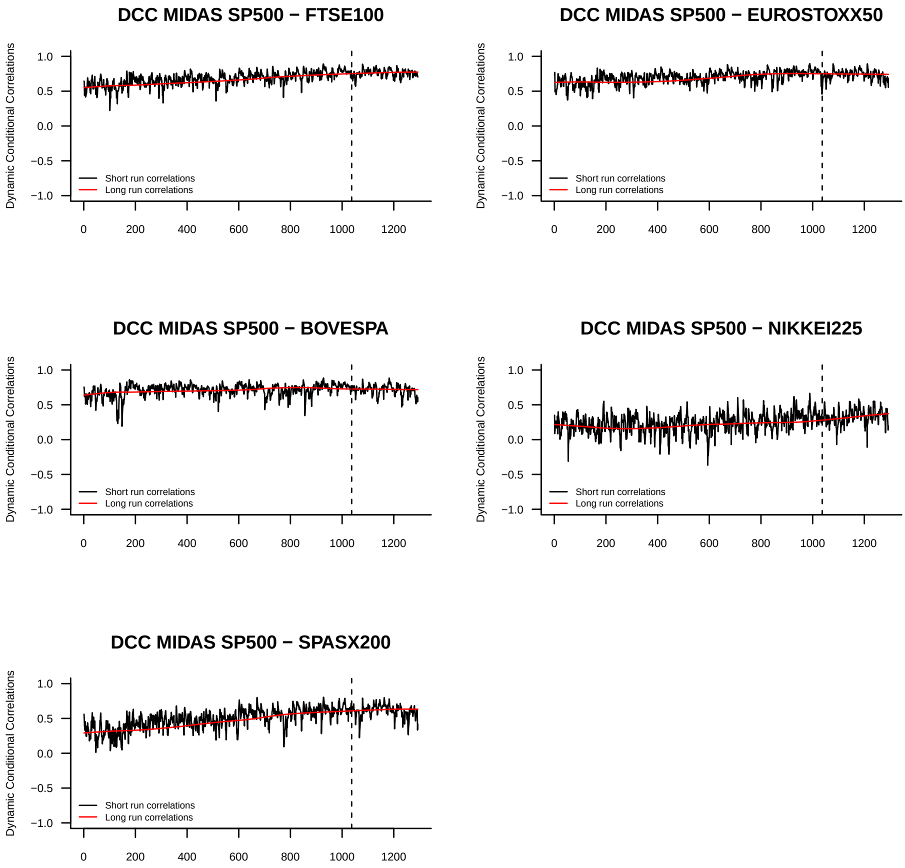

Figure 5.1: Long and short correlations for returns.

where the p-value confirm the rejection of the null even at 1% significance level.

The results of the test confirm that transmission of the crisis was due to real linkages, this conclusion stems from the failure in rejecting the hypothesis of interdependence.

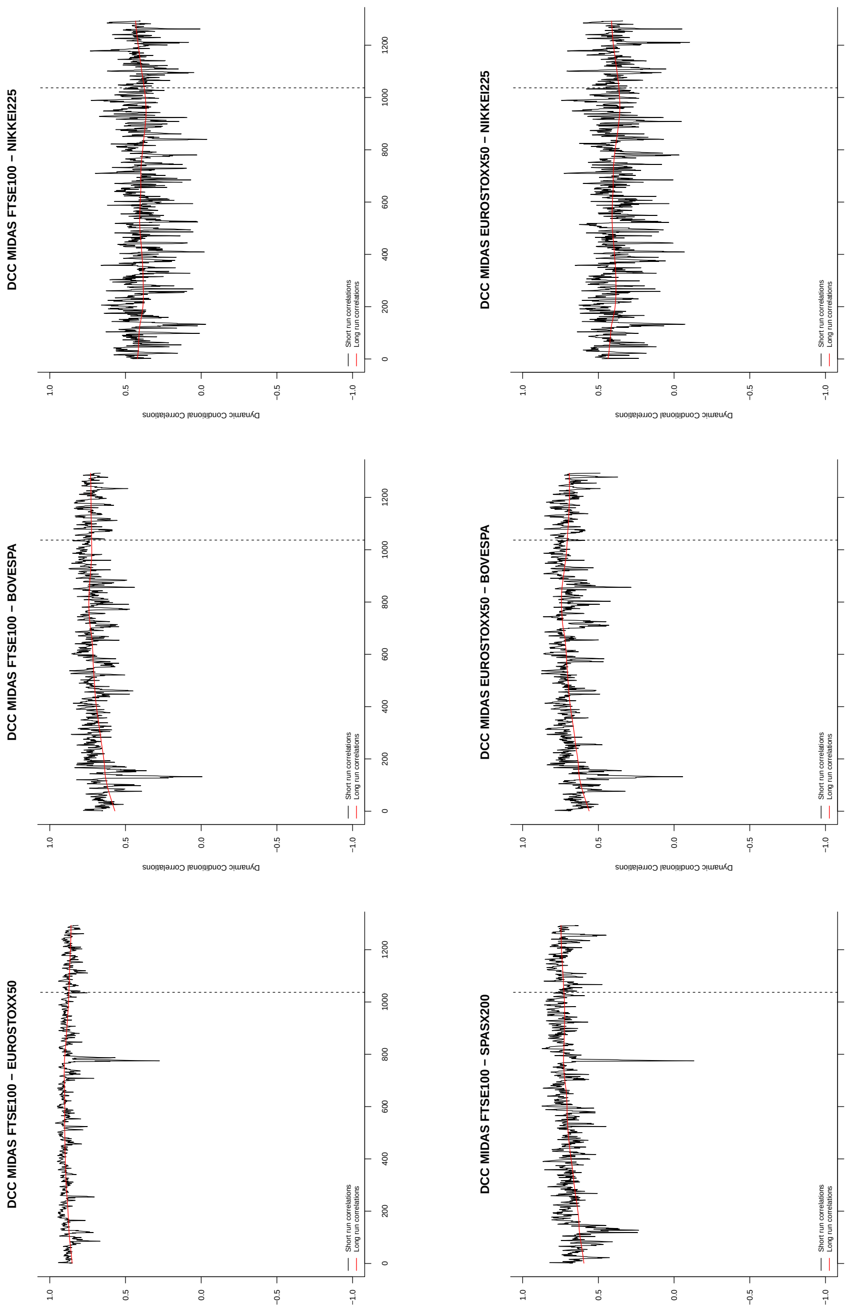

Figure 5.2: Long and short correlations for returns.

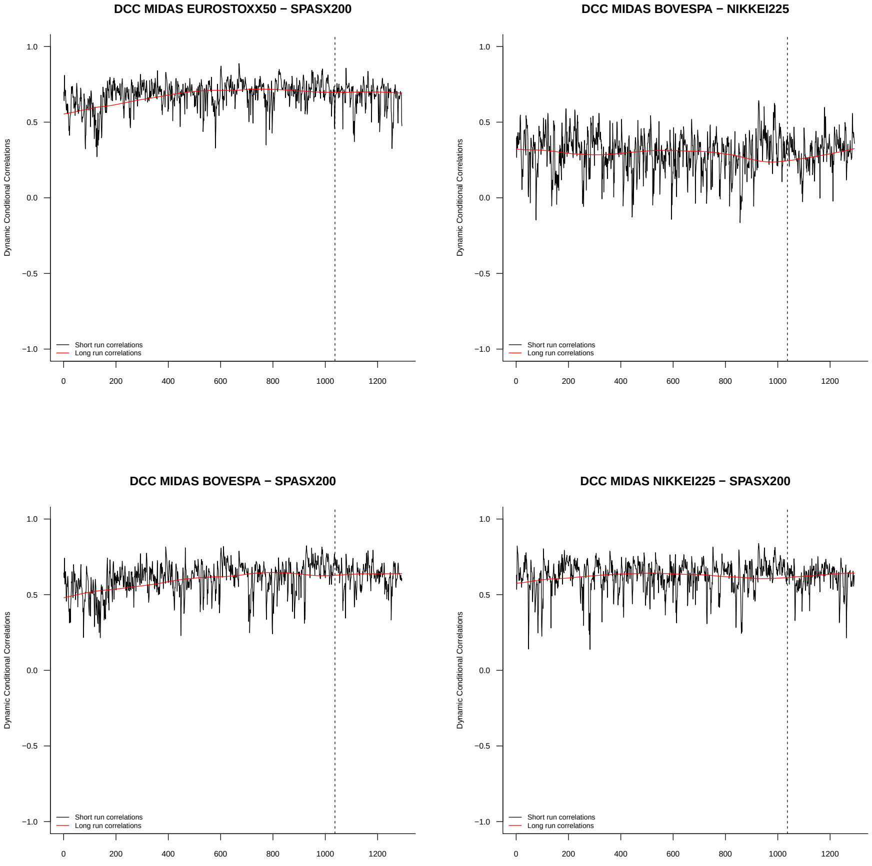

Figure 5.3: Long and short correlations for returns.

5.4 Conclusions

In this chapter we analyzed whether the crisis sourced in US is spread over the world by contagion or just through real linkages known as interdependence. Within this chapter, contagion is defined as a significant increase in cross-correlations after a crisis hits a country, we assumed that correlations are not constant over time and also assuming that they evolve according to a GARCH(1,1)-type structure which give rise to the use of the popular DCC model introduced by Engle (2002) and extended in Colacito et al. (2011) to distill the short run and long run component of the total correlation of the portfolio under study.

Our results suggest that linkages between stock markets remains the same before and after the crisis, there is no evidence of significant increase in correlations, therefore interdependence is the main channel of transmission of the crisis which is plausible since stock markets are more and more integrated and the lagged values of the correlation associated to the interdependence are dominant over the influence of the short run correlations.

Evidence of contagion is only found for Brazil and Japan. It is worthy to say that the test only identifies the existence/non-existence of contagion but it is not allow to identify the directionality of such a contagion, for the case of Brazil and Japan we found the correlation strengthened after the crisis in US providing evidence of contagion but we do not know if contagion ran from Brazil to Japan or in the other way around.

References

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Chapter 6

Spillovers: R package for estimating spillover indexes and performing Co-Skewness test

6.1 The Spillover Package

`Spillovers` is an R package developed to be used for estimating spillover indexes by providing a friendly-user interface. We have developed `Spillovers` to provide a complete open source tool embeddable on the R language (R Core Team, 2012) comprising all steps for estimating the spillover indexes discussed on Chapter 4. `Spillovers` is written using S3 object oriented programming and depends on four packages: `vars` (Pfaff, 2008), `tseries` (Trapletti and Hornik, 2013), `zoo` (Zeileis and Grothendieck, 2005) and `fastSOM` (Klossner and Wagner, 2012).

As far to our best knowledge, `fastSOM` is the only package published on The Comprehensive R Archive Network (CRAN) that allows the estimations of indexes based on Diebold and Yilmaz (2009). The current version of this package is 0.9 and is was released on August 29, 2013. `Spillovers` is different from `fastSOM` since it provides the user with more functions devoted to the estimation of the spillover indexes. It not only makes possible the estimation of index in Diebold and Yilmaz (2009), but also all indexes in Diebold and Yilmaz (2012) including dynamics indexes as well and the Co-Skewness test for contagion of Fry et al. (2010).

This Chapter holds a complete user manual wrote following the standard CRAN criteria using `roxygen2` of Wickham et al. (2011). All functions are well documented and some examples are provide at the end of each function.

Package 'Spillovers'

Description:

`Spillovers` Computes both orthogonalized and generalized spillover indexes based on VAR modeling as described in Chapter 4.

Details:

Package:	Spillovers
Type:	Package
Version:	0.1
Date:	2013-08-15
License:	LGPL ($\geq$ 2)

Author:

Jilber Urbina

Maintainer:

Jilber Urbina *jilberandres.urbina@estudiants.urv.cat*

R documentation

of all in 'man'

November 18, 2013

R topics documented:

`cs.test` *Coskewness Test*

Description

Performs the two types of Coskewness test based on Fry et al. (2010)

Usage

```
cs.test(data, type = c("cs1", "cs2"),
  precrisis = list(start = NULL, end = NULL),
  crisis = list(start = NULL, end = NULL), assets)
```

Arguments

`data`	Object of class '`zoo`'.
`type`	A character string indicating whether perform Coskewness test of type I or type II, see details.
`precrisis`	A list consisting of two objects: the `start` date of the precrisis period and the end or the precrisis period.
`crisis`	A list specifying the begining and the end of the crisis period, the same as `precrisis`.
`assets`	A two dimensional vector consisting of the names of the asses for which the coskewness test is to be performed.

Details

This function computes the Coskewness test over two assets (vectors) given the precrisis and crisis period. The Coskewness test is based on in Fry et al. (2010).

Value

A list containing the following components:

`statistic` the value of the CS-statistic.

`p.value` the p-value for the test.

Author(s)

Jilber Urbina

References

Fry, R.; Martin, V. L. \& Tang, C. *A New Class of Tests of Contagion With Applications*. Journal of Business \& Economic Statistics, 2010, 28, 423-437

`g.fevd` *Generalized Forecast Error Variance Decomposition*

Description

Computes the generalized forecast error variance decomposition of a VAR(p) for `n.ahead` steps.

Usage

```
g.fevd(x, n.ahead = 10, normalized = TRUE)
```

Arguments

`x`	Object of class '`varest`' generated by `VAR()`.
`n.ahead`	Integer specifying the steps ahead.
`normalized`	a logical value indicating whether the result should be normalized to sum up to 1, see Details

Details

When `normalized=FALSE` this function computes the generalized forecast error variance decomposition proposed by Pesaran and Shin (1998) which takes the form:

$$\alpha^g_{ij}(h) = \frac{\sigma_{ii}^{-1}\sum_{l=0}^{h-1}(\mathbf{e}'_i\Theta_l\Sigma_\varepsilon\mathbf{e}_j)^2}{\sum_{l=0}^{h-1}(\mathbf{e}'_i\Theta_l\Sigma_\varepsilon\Theta'_l\mathbf{e}_i)}, \quad i,j = 0,1,2\ldots,K$$

Where $\mathbf{\Theta}_l$, are the coefficients matrix of the MA representation of the VAR model, $\mathbf{\Sigma}_\varepsilon$ is the variance matrix of the reduced-form error vector ε, σ_{ii} is the standard deviation of the error term for the ith equation and e_i and e_j are selection vectors with ones as the *ith* element and zeros elsewhere.

If `normalized=TRUE` (the default value) then `g.fevd` computes:

$$\tilde{a}^g_{ij}(h) = \frac{a^g_{ij}(h)}{\sum_{j=1}^{K} a^g_{ij}(h)}$$

This fact implies the normalization is simply each entry of the generalized fevd divided by the its corresponding row sum.

Value

A list length *K* holding the generalized forecast error variances as matrices.

Author(s)

Jilber Urbina

References

Pesaran, M. H. and Shin, Y. (1998). *Generalized impulse response analysis in linear multivariate models*. Economics Letters, 58(1):17-29.

See Also

`o.fevd`

Examples

```
library(vars)
data(stock.prices)
stocks <- stock.prices[,1:2]
VAR.1 <- VAR(stocks)
g.fevd(VAR.1, n.ahead = 10) # normalized
g.fevd(VAR.1, n.ahead = 10, normalized=FALSE) # Not normalized
```

`G.spillover` *Generalized spillover index*

Description

Computes the generalized spillover index proposed in Diebold and Yilmaz (2010) which is based on the General Forecast Variance Decompositon introduced by Pesaran and Shin (1998).

Usage

```
G.spillover(x, n.ahead = 10, standardized = TRUE)
```

Arguments

`x`	Object of class '`varest`' generated by `VAR()`.
`n.ahead`	Integer specifying the steps ahead.
`standardized`	A logical value indicating whether the values should be divided by the number of columns to get a percentage.

Details

This function computes the Generalized Directional Spillover Table which has as its ij^{th} entry the estimated contribution *to* the forecast error variance of variable *i* coming *from* innovations to variable *j*. The off-diagonal column sums are the *Contributions to Others*, while the row sums represent *Contributions from Others*, when these are totaled across countries then we have the numerator of the Spillover Index. Similarly, the columns sums or rows sums (including diagonal), when totaled across countries, give the denominator of the Spillover Index, which is 100%.

`G.spillover` is based upon the General Forecast Error Variance Decompositon introduced by Pesaran and Shin (1998) and its explicit formulation can be found in Diebold and Yilmaz (2010).

Value

A `data.frame` consisting of the spillover index.

Author(s)

Jilber Urbina

References

Diebold, F. X. & Yilmaz, K.(2010). *Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers*. International Journal of Forecasting.

Pesaran, M. H. and Shin, Y. (1998). *Generalized impulse response analysis in linear multivariate models*. Economics Letters, 58(1):17-29.

See Also

O.spillover

Examples

```
library(vars)
data(stock.prices)
stocks <- stock.prices[,1:2]
VAR.1 <- VAR(stocks)
G.spillover(VAR.1) # with 10 steps ahead, default value.
```

---

garman.klass *Garman-Klass intraday volatility*

Description

Computes Garman and Klass (1980) intraday stock return volatility.

Usage

```
garman.klass(x)
```

Arguments

x	A four column matrix consisting of low, high, open and close prices of stock indices.

Details

This function computes historial intraday volatility using the following equation:

$$\tilde{\sigma}_t^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2$$

Where H_t, L_t, O_t, C_t, stand for high, low, open and close daily stock prices.

Note that object x must contain only four columns named as follows: High, Low, Open, Close, all this colnames can be either upper or lower case; it is also allowed to use only the first letter as: H, L, O, C. There is not need for a fixed ordering for columns as is shown in the examples, but the only requirement is the names of each columns. `garman.klass` functions can deal with matrix, data.frame, and zoo objects.

Value

A vector holding the intraday (squared) volatilities (variances).

Author(s)

Jilber Urbina

References

Garman, M. B. and Klass, M. J. (1980). *On the estimation of security price volatilities from historial data*. Journal of Business, 53(1):67-78.

Examples

```
library(tseries)
sp500 <- get.hist.quote(instrument = "^gspc", start = "2013-01-01", end = "2013-07-20")

# with different colnames
SP <- sp500
colnames(SP) <- c("OPEN", "high", "LoW", "CLose")
colnames(sp500)
# scrambling columns
SP <- SP[,c(3,1,4,2)]
head(SP) # Both colum order and colnames in SP are different from those of sp500
head(sp500)

# Using garman.klass funcion over the first 6 obs of SP and sp500
garman.klass(head(sp500))
garman.klass(head(SP))  # same results for both calls
```

`net` *Net spillovers*

Description

Computes the net spillover index.

Usage

```
net(x)
```

Arguments

`x`	Object of class '`spillover.table`' generated by either `O.spillover()` or `G.spillover()`.

Value

A list length K holding the generalized forecast error variances as matrices.

Author(s)

Jilber Urbina

References

Pesaran, M. H. and Shin, Y. (1998). *Generalized impulse response analysis in linear multivariate models*. Economics Letters, 58(1):17-29.

See Also

O.spillover G.spillover

`o.fevd` *Orthogonalized Forecast Error Variance Decomposition*

Description

Computes the orthogonalized forecast error variance decomposition of a VAR(p) for `n.ahead` steps for all the possible combination of endogenous variables used in `VAR()` this means $K!$ different decompositions, where K is the number of endogenous variables in the VAR.

Usage

```
o.fevd(x, n.ahead = 10)
```

Arguments

`x`	Object of class '`varest`' generated by `VAR()`.
`n.ahead`	Integer specifying the steps ahead.

Details

`o.fevd()` computes the Forecast Error Variance Decompostion for all possible combination of variables order. The orthogonalization is based on Choleski decompostion.

Value

A list length K holding the orthogonalized forecast error variances as matrices.

Author(s)

Jilber Urbina

References

Hamilton, J. (1994), *Time Series Analysis*, Princeton University Press, Princeton.

Lutkepohl, H. (2006), *New Introduction to Multiple Time Series Analysis*, Springer, New York.

See Also

g.fevd

Examples

```
library(vars)
data(stock.prices)
stocks <- stock.prices[,1:2]
VAR.1 <- VAR(stocks)
o.fevd(VAR.1, n.ahead = 10) # fevd for all combinations
o.fevd(VAR.1)[[1]][,,1] # this is the same of fevd from vars package
fevd(VAR.1)[[1]]
```

`O.spillover` *Orthogonalized spillover index*

Description

Computes the orthogonalized spillover index proposed in Diebold and Yilmaz (2009) which is based on the Orthogonalized Forecast Error Variance Decompositon.

Usage

```
O.spillover(x, n.ahead = 10,
  output = c("table", "summary"), standardized = TRUE)
```

Arguments

`x`	Object of class '`varest`' generated by `VAR()`.
`n.ahead`	Integer specifying the steps ahead.
`output`	A character string denoting what kind of result we want, alternatives are: `table` and `summary`.
`standardized`	A logical value indicating whether the values should be divided by the number of columns to get a percentage.

Details

This function computes the Orthogonalized Directional Spillover Table which has as its ij^{th} entry the estimated contribution *to* the forecast error variance of variable *i* coming *from* innovations to variable *j*. The off-diagonal column sums are the *Contributions to Others*, while the row sums represent *Contributions from Others*, when these are totaled across countries then we have the numerator of the Spillover Index. Similarly, the columns sums or rows sums (including diagonal), when totaled across countries, give the denominator of the Spillover Index, which is 100%.

`O.spillover` is based upon the Orthogonalized (using Choleski orthogonalization) Forecast Error Variance Decompositon (see Lutkepohl, 2006) and its explicit formulation can be found in Diebold and Yilmaz (2009).

Since `O.spillover` is based on `o.fevd`, then the result is as many indexes as combinations is allowed according to the number of variables in the VAR model, this is exactly equal to $K!$, then `output` has three options: `table`, `summary` and `all.ind`. `table` produces a `data.frame` holding the (orthogonalized) directional mean spillover indexes.

When `output="table"`, a `data.frame` is generated consisting of either mean or median directional spillover indeces, this because for each possible order of the variables the `o.fevd` is computed and over this result a spillover index is generated and this procedure repeats until reaching the last order (this means all the possible combinations given by $K!$). When `output="table"` a mean directional spillover table is generated, but this can be changed using `stat="median"` for a median directional spillover to be genereated. Note that `stat` argument only affects the results of `output="table"`.

When `output="summary"` an vector is generated, this contains `Mean, Min, Max`.

Value

When `output="table"`, a `data.frame` consisting of the spillover index.

When `output="summary"`, a `summary` of all spillover indeces.

Author(s)

Jilber Urbina

References

Diebold, F. X. & Yilmaz, K. (2009). *Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets*. The Economic Journal, 119, 158-171

Lutkepohl, H. (2006), *New Introduction to Multiple Time Series Analysis*, Springer, New York.

See Also

`G.spillover`

Examples

```
library(vars)
data(stock.prices)
stocks <- stock.prices[,1:2]
VAR.1 <- VAR(stocks)
O.spillover(VAR.1, n.ahead=5, output="table")
O.spillover(VAR.1, n.ahead=5, output="summary")
```

`rol.returns` *Two-days Rolling Average Returns*

Description

A dataset of class zoo consisting of 1632 two-days rolling average observations on returns based on closed price for six leading stock indices: S&P 500 (US), FTSE 100 (UK), EURO STOXX 50 (Eurozone), BOVESPA (Brazil), NIKKEI 225 (Japan) and S&P ASX 200 (Australia). EURO STOXX 50 covers 50 stocks from 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The period for this dataset is from June 16, 2003 to September 15, 2009. All series are in US Dollars.

Format

a zoo-class dataset

Examples

```
data(rol.returns)
head(rol.returns)  # First 6 observations
tail(rol.returns)  # Last 6 observations
```

---

rol.vol *Two-days Rolling Average Intra-day Volatilities*

Description

A dataset of class zoo consisting of 1633 two-days rolling average observations on intraday volatilities based on Garman and Klass (1980) for six leading stock indices: S&P 500 (US), FTSE 100 (UK), EURO STOXX 50 (Eurozone), BOVESPA (Brazil), NIKKEI 225 (Japan) and S&P ASX 200 (Australia). EURO STOXX 50 covers 50 stocks from 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The period for this dataset is from June 13, 2003 to September 15, 2009. All series are in US Dollars.

Format

a zoo-class dataset

Examples

```
data(rol.vol)
head(rol.vol)  # First 6 observations
tail(rol.vol)  # Last 6 observations
```

---

roll.net *Dynamic Spillover Index*

Description

Estimates the dynamic spillover indexes given a moving windows as described in Diebold and Yilmaz (2012).

Usage

```
roll.net(data, width, n.ahead = 10,
  index = c("orthogonalized", "generalized"),
  ortho.type = c("partial", "total"), ...)
```

Arguments

`data`	Object of class 'zoo'.
`width`	An integer specifying the window width which is aligned to the original sample.
`n.ahead`	An integer indicating the ahead at which the spillover is to be compute.
`index`	A character string indicating whether the orthogonalized or the generalized index is computed.
`ortho.type`	A character string indicating the type of orthogonalized index is required. `"partial"` takes a random sample out of all the possible combinations generated for the Choleski decomposition, while `"total"` uses all the combinations, therefore it takes more time to finish.
`...`	Further arguments to be passed to `var` function.

Value

A `zoo` object holding all the net spillover indexes.

Author(s)

Jilber Urbina

References

Diebold, F. X. & Yilmaz, K.(2012). *Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers*. International Journal of Forecasting.

`roll.spillover` *Dynamic Spillover Index*

Description

Estimates the dynamic spillover indexes given a moving windows as described in Diebold and Yilmaz (2012).

Usage

```
roll.spillover(data, width, n.ahead = 10,
  index = c("orthogonalized", "generalized"),
  ortho.type = c("partial", "total"), ...)
```

Arguments

`data`	Object of class '`zoo`'.
`width`	An integer specifying the window width which is aligned to the original sample.
`n.ahead`	An integer indicating the ahead at which the spillover is to be compute.
`index`	A character string indicating whether the orthogonalized or the generalized index is computed.
`ortho.type`	A character string indicating the type of orthogonalized index is required. `"partial"` takes a random sample out of all the possible combinations generated for the Choleski decomposition, while `"total"` uses all the combinations, therefore it takes more time to finish.
`...`	Further arguments to be passed to `var` function.

Value

A `zoo` object holding all the indexes.

Author(s)

Jilber Urbina

References

Diebold, F. X. & Yilmaz, K.(2012). *Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers.* International Journal of Forecasting.

`Spillovers` *Spillovers*

Description

Computes spillovers based on either orthogonalized or generalized forecast error variance decompositions.

Author(s)

Jilber Urbina

References

Diebold, F. X. & Yilmaz, K. (2009). *Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets*. The Economic Journal, 119, 158–171

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`stock.prices` *Daily Stock Prices*

Description

A dataset consisting of 3507 daily observations on closed price for six leading stock indices: S&P 500 (US), FTSE 100 (UK), EURO STOXX 50 (Eurozone), BOVESPA (Brazil), NIKKEI 225 (Japan) and S&P ASX 200 (Australia). EURO STOXX 50 covers 50 stocks from 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The period for this dataset is from December 31, 1999 to June 10, 2013. All series are in US Dollars.

Format

a `zoo`-class dataset

Examples

```
data(stock.prices)
head(stock.prices)  # First 6 observations
tail(stock.prices)  # Last 6 observations
```

`struct2reduced` *From structural VAR to reduced form VAR*

Description

Converts both the structural coefficients from a Bivariate-VAR(1) and the structural covariance matrix of the structural residuals into its reduced form counterparts.

Usage

```
struct2reduced(AR, Sigma)
```

Arguments

`AR`	An `array` of dimension `c(2,2,2)` consisting of the structural VAR(1) coefficients, see Details.
`Sigma`	a 2x2 definite positive variance-covariance matrix.

Value

A list of length two, first element in the list is a matrix holding the reduced form coefficients of a 2 variables-VAR(1) and the second element is the covariance matrix of the reduced form residuals.

Author(s)

Jilber Urbina

References

Lutkepohl, H. (2006), *New Introduction to Multiple Time Series Analysis*, Springer, New York.

Examples

```
Sigma <- matrix(c(1,0,0,5),2)   # Structural variance-covariance matrix, see Details
AR <- array(c(1, -0.8, 0, 1,
              0.3, 0, 0, 0.3),
              dim=c(2,2,2) )    # Structural coefficients
struct2reduced (AR, Sigma)      # obtaining the reduced forms.
```

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References

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