EDGARDO CAYÓN

The effects of contagion during the Global Financial Crisis in Government Regulated and Sponsored Assets in Emerging Markets:

The case of Colombian pension funds and State Owned Enterprises (SOEs) in BRIC countries

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Abstract

The effects of financial contagion during the Global Financial Crisis (GFC) have been extensively studied in the finance literature. One of the key issues is the devastating effect of the crisis on wealth and asset prices. However, one key difference between this crisis and other crisis in the past was the resilience or the short term effect of the crisis on emerging markets. Of particular interest was the resilience of government regulated and sponsored assets such as pension funds, state owned enterprises, international government bonds and local currency bonds. This book contributes to the literature of the effects of financial contagion by analysing two cases of government regulated and sponsored assets during different episodes of the GFC. The first chapter examines contagion from US equity markets to emerging market autarchic assets (Colombian private pension funds) during different episodes of the GFC, in order to test for contagion via changes in correlation between financial asset returns and via additional volatility spillovers. We propose a DCC-GJR GARCH framework where the S&P500 is the source of transmission of contagion to the autarchic asset. We find no evidence of contagion measured as significant changes in correlation during the first two phases of the crises. In Chapter 2 we extend our analysis to government sponsored assets (State Owned Enterprises [SOEs]) and argue that these assets account for a substantial and increasing fraction of global foreign direct investment. While emerging economy SOEs are often vehicles for state-directed economic growth policy, the performance of SOEs compared with private enterprises is an open question, particularly during crisis periods. We estimate a four-factor model of SOE returns of the BRIC economies for the period 2000-2012, and show that certain SOEs offered some protection to investors during the financial crisis of 2007-2009. We use quantile regressions since this approach is robust to the presence of outliers and their impact on the factors during crisis periods. The results obtained in this chapter provide empirical evidence for the special role of the state in protecting and stabilizing state-owned enterprises. Our results make an interesting contribution to the real extent of the resilience of emerging markets under the postulates of the coupling/decoupling hypothesis and market integration.

Keywords: emerging markets, global financial crisis, regulation, stated owned enterprises, pension funds

JEL classification: C5, G1, G2, G14, G15, G28, G38

Chapter 1

Introduction

The effects of financial contagion during the Global Financial Crisis (GFC) have been extensively studied in the finance literature. One of the key issues is the devastating effect of the crisis on wealth and asset prices. However, one key difference between this crisis and other crises in the past was the resilience (immunity) or the short term effect of the crisis on emerging markets. Dooley and Hutchison (2009) were the first ones to find evidence in support of the decoupling hypothesis[1] of emerging markets during the early phases of the crisis. Since then the hypothesis have been tested by other researchers (for recent surveys see: Beirne and Gieck, 2014; Köksal and Orhan, 2013).

In this book we contribute to this body of knowledge by focusing on the effects of the crisis on government regulated and sponsored assets such as pension funds, state owned enterprises, international government bonds and local currency bonds. By doing this we hope to clarify the role that governments play in preventing loss of wealth by insulating their domestic markets either indirectly by regulation, which is the case of Colombian pension funds (Chapter 2), or by direct ownership, which is the case of State Owned Enterprises (Chapter 3). In both chapters we hypothesise that regulation and ownership are the main drivers behind the evidence of decoupling and recoupling during different episodes of the GFC. In the following subsections we provide more detail to the general content and method employed in each chapter.

1.1. Can financial autarchy prevent contagion? The case of Colombian pension funds during the subprime, financial and sovereign debt crises

The benefits and costs of regulation have been intensely debated in the context of financial crises. A key issue is the extent to which regulators and governments should attempt to quarantine domestic

1. The decoupling/coupling hypothesis states that in times of crisis emerging markets should exhibit lower correlations with external negative shocks originating from developed countries (decoupling), and coupling in the case of higher correlations.

assets from external shocks. This chapter analyses contagion originating from US equity markets during the GFC as it impacted on regulated assets in an emerging economy pension funds. In this chapter we divide the recent global financial crisis into three contiguous episodes: the Subprime, the Credit Crunch Crisis (CCC) and the European Sovereign Debt (ESD) crises. We define financial autarchy as an investment where the local investors have a restricted choice in portfolio selection, and investment in the financial autarchic asset is legally mandatory. It is within this definition that Colombian pension funds (the autarchic asset) provide an interesting case to test evidence of contagion.

In order to test for contagion we use a DCC-GARCH model as defined by Engle (2002) using the GJR extension proposed by Glosten et al. (1993), where the S&P500 is the source of transmission of contagion to the autarchic asset. Finally, we also propose the use of quantile regressions as an alternative way to test the magnitude of the contagion effect derived from a time varying systematic risk measure during different crisis episodes.

1.2. The performance of State Owned Enterprises in BRIC countries during the GFC

In recent years there has been a change in paradigm regarding Foreign Direct Investment (FDI) in emerging markets as these countries are shifting from being recipients to becoming investors in their own right. UNCTAD (2012) estimates that, for the first time, in 2010 developing countries received more than 50% of total global FDI, and that 30% of global FDI is coming directly from emerging markets. It is in this context that emerging markets State Owned Enterprises (SOEs) have become increasingly important agents for fostering economic growth and developing functional capital markets in their countries of origin.

This book focuses on the comparative return performance of the largest SOEs in Brazil, Russia, India and China, which are commonly known as the BRIC countries, against industry competitors in the US. In this book we assume that the returns of the SOEs and the comparable US industries can be explained by the Fama and French three factor model plus momentum, commonly known as the Carhart model (Carhart, 1997; Eugene F. Fama and French, 1993, 1998).

However, the aim of this book is not on the average performance of SOEs, but on their performance during crisis periods. If SOEs outperform their similar during a financial crisis, the government's stake in the firm is assumed to act like a cushion for the state-owned enterprise, and thus protects the value of the firm to some degree. In order for a firm to be classified as a SOE, the government should own at least 50% of all circulating stock. The economic rationale for this “cushion” effect is that the stake of the government is either so large that the firm is fully protected from general market conditions. We test for this “cushion” effect by analyzing the sensitivities of the FF model plus momentum during different phases of the GFC under a quantile regression framework.

Chapter 2

Can financial autarchy prevent contagion? The case of Colombian pension funds during the subprime, financial and sovereign debt crises[2]

2.1. Introduction

The benefits and costs of regulation have been intensely debated in the context of financial crises. A key issue is the extent to which regulators and governments should attempt to quarantine domestic assets from external shocks. This chapter analyses contagion originating from US equity markets during the global financial crisis, as it impacted on regulated assets in an emerging economy pension funds. We argue that in the particular case of Colombia, private pension funds act as an autarchic asset that somehow are insulated from shocks originated from different episodes of the GFC. In order to test this hypothesis, we divide the recent global financial crisis into three contiguous episodes, the Subprime, the CCC and the ESD crises. Using these three episodes we test for evidence of contagion to a restricted portfolio, or autarchic asset, in the Colombian pension funds. We found that in the case of the first two episodes of the GFC, there was no evidence of contagion from the US to the Colombian pension fund market.

We define financial autarchy as an investment where the local investors have a restricted choice in portfolio selection, and investment in the financial autarchic asset is legally mandatory. In Section 2.2 we provide a general background to the pension fund industry, and establish that the Colombian pension funds are a kind of financial autarchic asset under the previous definition.

In section 2.3 we define contagion as occurring when new volatility spillovers materialize from the crisis country to other countries, and as a significant new increase in co-movements of prices and quantities across markets. We also review the literature on contagion as it relates to financial autarchy.

2. Some of the partial results of this chapter were published in the article by Edgardo Cayon and Susan Thorp titled: "Financial Autarchy as Contagion Prevention: The Case of Colombian Pension Funds", *Emerging Markets Finance and Trade*, May-June 2014, Vol. 50, Supplement 3, pp. 127-145. (see: Published Work Section).

In section 2.4 we describe our data and crises episodes. In section 2.5 we present the behaviour of preliminary correlations and other descriptive statistics for the three crisis episodes.

In section 2.6 we present our contagion models and a new dynamic measure of systematic risk. In section 2.7 we discuss our results and perform robustness checks. Finally, in section 2.8 we present our general conclusions and their relation with the current research on the subject.

2.2. Background: Pension Funds

The growth of the pension fund industry over the past few decades has been staggering. The IMF estimated that, by 2007, assets under management by private pension funds in OECD countries were in the order of USD 18 trillion (Impavido and Tower, 2009). More recently, the TheCityUK (2011) estimated that in 2010, the assets under management by the pension fund industry worldwide were in the order of USD 29.9 trillion, and approximately 79% of that figure belonged to OECD countries.

In the case of emerging markets, and especially Latin America, private pension funds are relatively new when compared to those in OECD countries. By 2010, the approximate amount of assets under management in these funds in Latin America has been estimated around USD 445 billion[3,] and their rate of growth of assets under management has been 22% for the period 2003-2008 (Impavido and Tower, 2009). However, in 2008 the assets under management by private pension funds in Latin America, estimated at USD 283 billions[4], which gives us an average annual growth of 25.4%.

Since the 1950s, most Latin American countries have had a *mandatory occupational pension plan*, in which the payment of pensions was the responsibility of both the employer and the government. Although nowadays mandatory occupational pension plans are still in place, most of Them have migrated from *defined benefit pensions schemes (DB)* to *defined contribution pension schemes (DC)*. If we were to map Latin America within the World Bank pillars' classification, probably most of the plans in the region will fit either the Pillar 1 or Pillar 2 taxonomy, where the first pillar provides poverty alleviation in retirement, and second pillar provides consumption smoothing via mandatory earnings-linked contributions[5]. As defined by the OECD, a DB is a pension plan where the employer

3. Data retrieved from the Asociacion Internacional de Organismos de Supervision de Fondos de Pensiones (AIOS) [http://www.aiosfp.org/estudios_publicaciones/estudios_pub_boletin_estadistico.shtml].

4. (Impavido and Tower, 2009)

5. World bank pillar I and II pensions systems typically require a mandatory contribution from either or both the employees and the employers that belong to the formal sectors. Pillar II systems have in common that the amount of pension

and the employee have to pay fixed contributions to a fund, and the pension amount that is paid to the employee is defined by a formula that takes into account past wages, age, and, in most cases, a minimum benefit that is guaranteed; the key issue being that the national government, or a private pension provider, guarantees the benefit to the employee regardless of his/her level of savings. On the other hand, a DC is a pension plan where the employer and/or the employee pay a fixed contribution to a fund, and the amount of pension paid to the employee solely depends of his/her level of savings and investment returns net of administrative costs and taxes. In the case of an unfavourable outcome, all the risk is borne by the employee with no further legal responsibilities for either the government or the employer (Impavido and Tower, 2009). Within this framework, it is not hard to imagine why, in the context of Latin America, mandatory DC plans managed by the private sector have grown substantially in dollar terms from USD 119 billion in 2003 to USD 445 billion in 2010 (AIOS, 2011).

Also, there are crucial differences in the type of investments engaged in by DB and DC pension schemes, since DB plans are mostly run by governments that would tend to favour more liquid investments, preferably in local currency, and in the form of bonds and bills that in a way act as a deficit financing mechanism for the government (Arrau and Schmidt-Hebbel, 1995). On the other hand, private pension funds on the DC end of the spectrum would have an incentive to engage in riskier investments in order to compete, in terms of returns, with other participants in the market. Since, the consequences of an unfavourable outcome can be disastrous to the general public, and given the potential for agency problems in the investment process; governments tend to set regulatory constraints on the type of assets that private funds can invest in (Arrau and Schmidt-Hebbel, 1995).

In Table 2.1 we show the asset composition for 12 countries' government operated DB pension funds for which data are available. It is interesting to see that in the US, 100% of the investments in social security are composed of government backed debt.

received is directly linked to the amount contributed before the retirement age. A major difference between the pillar I and II components is that in the first case poverty alleviation is typically funded via public "pay as you go" schemes as opposed to yields from financial investments, as in the second case (Holzmann et al., 2008)

Table 2.1
Asset composition of Social security and Sovereign Government operated pension funds in 2009

	Cash/CDs	Fixed income	Structured products	Loans	Shares	Land	Total private	Other invest-ments
Australia	14.47%	23.68%			44.24%	2.70%	12.70%	2.20%
Belgium		100.00%						
Canada	-0.26%	29.93%	0.88%	2.71%	43.89%	5.75%	17.10%	
France	6.99%	47.30%			44.21%		0.67%	0.84%
Ireland	12.09%	5.48%			72.03%		4.47%	5.94%
Mexico	10.96%	74.79%	14.25%					
New Zealand	8.02%	15.71%	1.25%		39.90%	0.37%	26.72%	8.04%
Norway	1.77%	35.88%	1.97%		61.45%			0.91%
Poland	8.72%	81.45%			9.83%			
Portugal	0.40%	70.06%			16.42%	2.31%		10.82%
Spain	3.34%	96.66%						
United States		100.00%						

Source: (OECD, 2011).

Although at first glance it would seem that there is a heavy allocation by sovereign funds to shares, this is due in part to the fact that investments in mutual funds are counted as shares for reporting purposes. This can lead to underestimates of fixed income allocations in pension funds, since most of the mutual funds involved in pension management participate actively in the fixed income market as well as equity markets.

OECD data for private DC funds offer more detailed information about the asset allocation of mutual. In Table 2.2, the investment in bonds and shares by mutual funds was added to the direct position of the funds in bonds and shares and subtracted from the amount invested in mutual funds to avoid double counting.

Table 2.2

Asset allocation among private pension funds in sample countries

	Bonds/cash and CDs	Shares	Mutual funds	Other Investments
Slovak Republic	94.96%	1.38%	3.42%	0.25%
*Czech Republic**	91.23%	0.82%	3.73%	4.23%
*Greece**	85.13%	3.01%	9.69%	2.17%
Israel	81.96%	5.84%	3.55%	8.66%
Mexico	81.88%	17.69%	0.00%	0.44%
Slovenia	80.61%	1.91%	14.06%	3.43%
Spain	71.17%	11.23%	7.43%	10.17%
*Denmark**	69.11%	15.21%	1.99%	13.69%
Korea	65.67%	0.07%	7.72%	26.54%
Poland	62.85%	36.27%	0.58%	0.31%
Iceland	62.78%	19.15%	0.16%	17.91%
Portugal	60.39%	21.74%	8.68%	9.19%
Norway	59.31%	34.19%	0.02%	6.48%
Turkey	57.91%	25.77%	0.00%	16.32%
*Hungary**	56.12%	9.20%	31.48%	3.20%
Austria	52.55%	32.24%	13.72%	1.49%
Chile	48.81%	43.86%	0.22%	7.11%
Italy	47.51%	10.28%	9.82%	32.39%
Belgium	45.79%	37.67%	10.59%	5.95%
Germany	44.05%	5.18%	17.49%	33.28%
Canada	38.15%	33.83%	16.62%	11.40%
Finland	31.21%	47.57%	0.00%	21.22%
Netherlands*	23.59%	12.69%	51.22%	12.50%
United States	21.01%	38.15%	22.55%	18.29%
Australia*	12.53%	25.06%	49.37%	13.04%
Average	57.85%	19.60%	11.36%	11.19%

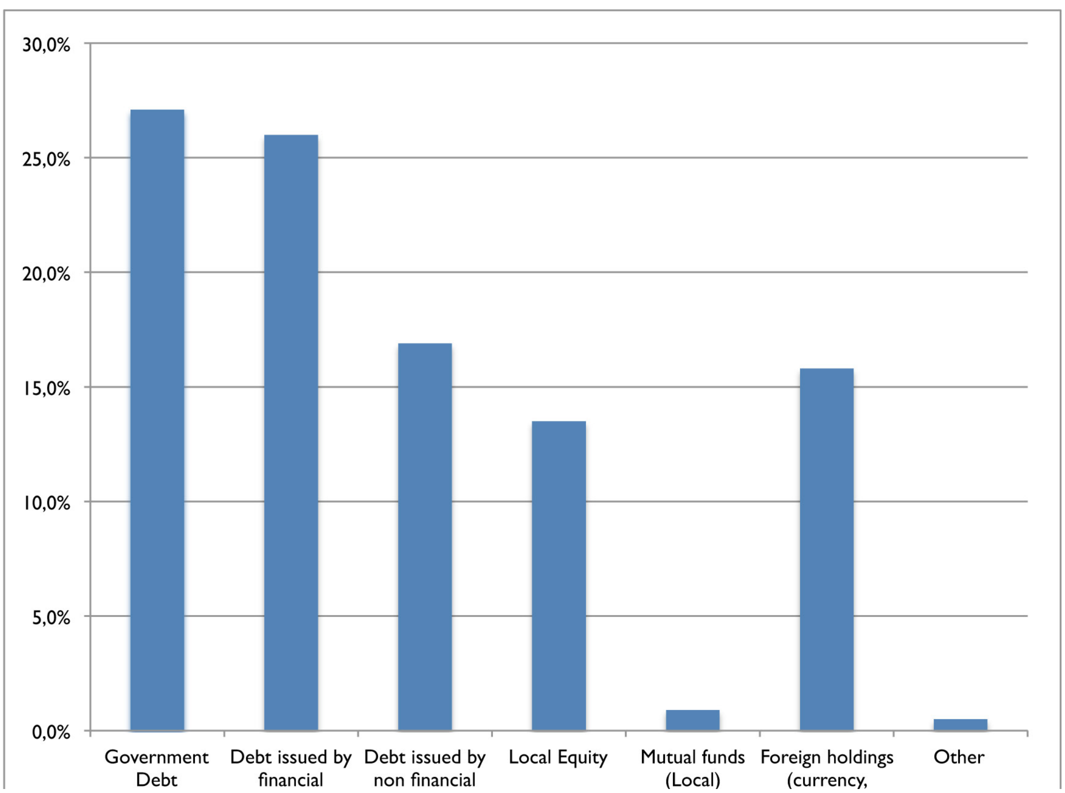
Source: (OECD, 2011).

* These countries did not report the average composition of their mutual funds investment.

It is interesting to see that the trend among emerging markets members of the OECD is to have a higher concentration in fixed income. This can be attributed mostly to the regulatory constraints that these countries put on private pension fund managers. Most English speaking countries tend to be more flexible regarding the regulation surrounding their private pension industry; usually they rely on the "prudent person" rule. On the other hand, and in the specific case of Latin America in which "Roman law" is the practice, quantitative investment limits are set by law. The World Bank has pointed out that restrictions on equity investments in Latin America are tighter than in OECD countries, which leads to a regulatory framework in which local public financing and local equity is favoured over other international investments where there can be a considerable exposure to exchange rate risk (OECD, 2011). Just as an example, while in Canada there are no limits set by law to the amount of investment by asset class by private pension funds managers, in certain countries like Uruguay the limit on equity investment is set by law to 1.5%. In Figure 1 we present the average investment limits by asset instrument in the Latin-American region 2010:

Figure 1

Average investment limits by asset class in private pension funds in Latin America 2010



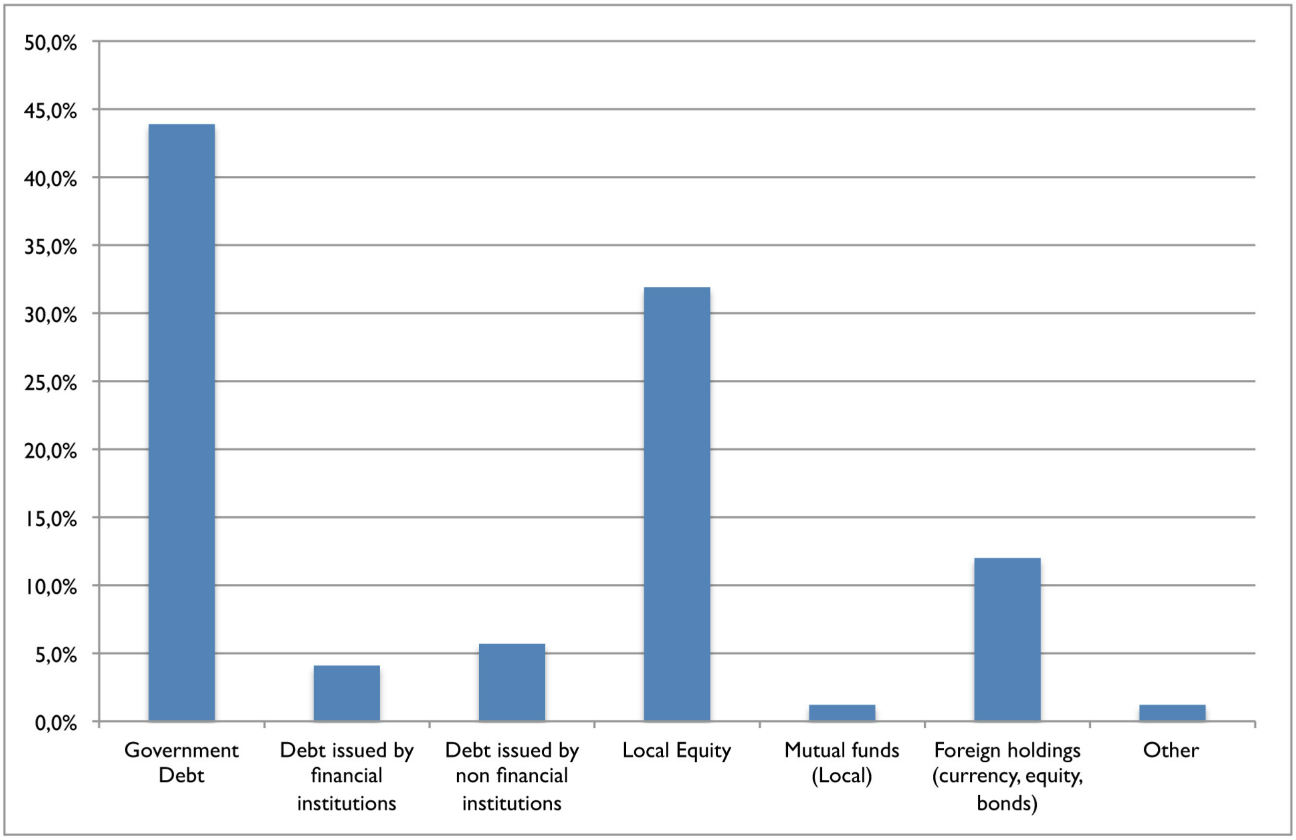
Source: (AIOS, 2011).

One interesting feature of the asset allocation in Latin America is the preference for local currency investments, on average 84.9% of total investment. In the case of foreign equity, bonds or currency investment the average amount is set to the remainder 15.8%. One possible motive behind this is that asset and liabilities should be denominated in the local currency since the pension paid will be in local currency. The second motive could be that by limiting overseas investment the pension funds provide a cushion to capital cash flows whose volatility has been the trigger to many crises in the region[6]. Third, limiting the amount of money that locals can invest overseas can help to increase the breadth and depth of local stock markets (AIOS, 2011).

In the specific case of Colombia, the composition of the investments held by the private pension funds is no exception to the rule (see Figure 2). However, it is important to mention that the concentration in government public debt is well above the regions' average. Also, it is always important to remember that although the legal limit allows for a maximum of 31.9% in local equity and 12% in foreign holdings this is often not the case. In practice, and based on the arguments mentioned before, the actual composition of the Colombian pension funds is on average 80% in fixed income instruments and 20% in all other asset classes. In Table 2.3, we can see the actual investments of the Colombian private pension funds as at August 2011:

6. The effects of capital flows as triggers for financial crisis in Latin America and its policy effects have been largely documented in the literature (see: G. L. Kaminsky, et al. ; G. L. Kaminsky and Reinhart (1999); Calvo and Reinhart (1999); Edwards , and more recently. Dufrénot, Mignon, and Péguin-Feissolle among many others).

Figure 2
Average investment by asset class in the Colombian private pension fund industry as of June 2010



Source: (AIOS, 2011).

Table 2.3
Actual investment composition Colombian Pension funds as of August 2011

Total government debt	60.2%	Total foreign debt	0.4%
Total debt other government entities	15.3%		
Other bonds	4.2%	Total foreign index funds and international equity	7.5%
Total local fixed income	79.6%		
Local equity	9.3%	Short-term deposits in foreign currency	2.4%
Local mutual funds	0.7%		
Total local equity	10.1%		
Total local currency	89.7%	Total foreign currency	10.3%

Source: (Superfinanciera, 2011).

As we can see from Table 2.3, around 90% of the investments are concentrated in local currency fixed income and equities, and just 10% of them is represented in foreign holdings[7]. It is important to mention that Colombia has a floating exchange regime, and its currency is allowed to float freely against the US dollar, which is the reserve currency of choice in the Latin American region.

The effect of these regulatory constraints has become more evident during the recent GFC. For example, Pino and Yermo (2010) observed that the real average annual rate of return for private pension funds in OECD countries in the year 2008 was -24.1%; this large loss was due to the exposure in equities by these funds during the early stages of the GFC. Also, the authors contrast this result with private pension funds from non-OECD countries, in which some of them (including Colombia) did not suffer losses at all during 2008, and attribute this performance to their high exposure to local government debt in their portfolios. Even more puzzling was the fact that some countries, like Hong Kong (China), Peru and Bulgaria, who experienced heavy losses in 2008 had recouped most of their losses by late 2009, as opposed to their OECD counterparts that, by 2009, were still 14% below their

7. In the short-term deposits in foreign currency there is also a negligible portion of hedging exchange derivates which amount to less than 0.005% of the total investment composition (Superfinanciera, 2011).

2007 levels (Pino and Yermo, 2010). Therefore, it would be interesting to see if the regulatory investment policy that governs Colombian private pension funds had some effect in preventing or mitigating contagion from the different crises episodes that aroused from the GFC.

It is in this context that the investments in Colombian private pension funds can be defined as autarchic financial assets. In this case financial autarchy was obtained through a restrictive regulatory framework that favours investments in local currency. In a broader sense, we define financial autarchy as an investment where the local investors have no choice in the portfolio selection and are forced to invest in the financial autarchic asset by mandate of law. If indeed regulation can act as a cushion for cash flow volatility in times of global financial crisis, then it should be possible that by creating regulatory frameworks in which financial autarchic assets are the norm, the contagion effect can be reduced in times of increased global market volatility. However, one important caveat is that by imposing the "quantitative restrictions" that favour a high proportion of bonds and domestic assets; pension fund managers are limited to investing in a constrained portfolio that does not grasp the full benefits of diversification (Davis, 2001). Therefore, it is possible that the reduction in contagion come at the cost of holding a suboptimal portfolio in terms of risk and return.

2.3. Literature Review

The large literature concerning the various definitions of contagion as well as the various methodologies to measure it is well beyond the scope of this chapter. However, for the sake of providing a common framework our proposed model of measurement uses elements drawn from the body of literature concerning the following two definitions[8]: 1) Contagion occurs when asset price volatility spills over from the crisis country to other countries. The first model used in this particular definition was the one proposed by Hamao, Masulis, and Ng (1990) and Edwards (1998). The first authors used a GARCH model to measure volatility spillovers between open and close prices among different stock exchanges, and the second author employed the term "volatility contagion" and used a GARCH model with fundamentals to test for contagion among different Latin American countries; 2) Contagion is a significant increase in co-movements of prices and quantities across markets, conditional on a crisis occurring in one market or group of markets. The most relevant work in contagion fall within this definition. Of special importance are the models proposed by: Longin and Solnik (1995), which introduced the notion of time-varying correlation; Forbes and Rigobon (2002), that set out an adjusted correlation test for distinguishing between normal market interdependence and real contagion;

8. We used the definitions proposed by Pericoli and Sbracia (2003) in their survey on contagion.

Bekaert, Harvey, and Ng (2005), who tested for contagion using an extended CAPM that accounted for fundamentals and also allowed for time-varying correlation and betas. Also within this definition, and using an arbitrage pricing framework, is the latent factor model proposed by Dungey et al. (2005), in which contagion is tested by using a common idiosyncratic shock represented by the residuals of a system of equations.

However, the literature in which contagion is tested in the context of financial autarchy is very limited. The most relevant study on this specific subject was conducted by Boyer, Kumagai, and Yuan (2006), where the authors devised a framework for testing whether contagion could be caused by investors re-balancing their portfolios ('investor-induced' hypothesis), or by change in a country's specific macroeconomic conditions ('fundamentals-based' hypothesis). Even though the authors do not mention financial autarchy directly, in order to conduct their test they classify the data as accessible or inaccessible (autarchic) assets. Their results lead to evidence in favour of the 'investor-induced' hypothesis by showing that in time of crisis the correlation of accessible assets in different countries was more pronounced than for inaccessible ones.

The 'investor-induced' hypothesis of contagion has received more interest in recent years due to the GFC, for example, a recent study by Agosin and Huaita (2011), in which they use the Kindleberger-Minsky[9] model applied to financial crisis in emerging countries, gave evidence that a "sudden stop" in capital inflows in a particular emerging economy explained capital account reversals in the form of contagion in other emerging economies. Even more puzzling is the fact that in the last few years, as opposed to the past decades, financial crises seem to have been originating from mature markets to emerging ones and not the other way around. For example Beirne et al. (2008) test the presence of volatility spillovers from mature markets to 41 emerging markets; their results demonstrated that spillovers from mature markets were persistent for all countries of Latin America with the exception of Venezuela, and all the countries in Asia with the exception of China.

However, one of the most intriguing aspects in the literature on contagion is the nature of the transmission channels through in which contagion spread from one market to the other, or in other words, what is the real cause of volatility spillovers or co-movements across markets? Although there is no agreement among academicians as to the cause of contagion, the transmission channels can be attributed mainly to three factors: 1) Common unobservable risk factors; 2) Counterparty risk, and 3) Investors updating their beliefs (investor induced hypothesis, herding, etc.) (Finnerty et al., 2011). In

9. The Kindleberger-Minskyis, commonly known as the "boom-bust cycle model", where the cause of a financial crisis is the result of a cycle of displacement, boom, euphoria, and profit taking in the financial sector.

their study, Finnerty et al. (2011) tested the investor-induced hypothesis by analysing how the uncertainty surrounding changes in the regulation of a special kind of a hybrid security created a contagion effect throughout all the hybrid security market, including those that were not affected by the regulatory changes.

The fact that countries are generally vulnerable to systemic crisis is not contentious, and indeed there is historical evidence that the causes behind local and global financial crisis are not at all unique to each event (Reinhart and Rogoff, 2008). In addition, Reinhart and Rogoff (2008) suggest that even though financial crisis can be seen as recurrent phenomena, the reality is that for some investors and policy makers there is the illusion that a current crisis is completely different to the previous ones therefore creating what the authors call the "this time is different" syndrome.

Although crises are and will be recurrent phenomena, there is new evidence that even though systemic crises cannot be avoided, at least their effects can be mitigated due to regulatory changes. For example, Dooley and Hutchison (2009) found evidence that in the early 2007, and until the summer of 2008, emerging markets were effectively decoupled (insulated or in a state of autarchy) from event and news generated at the earlier stages of the GFC. However, when the crisis unfolded at the height of the Lehman bankruptcy in September 2008 the monetary expansion policies put in place by the Federal Reserve in coordination with other central banks in emerging markets were ineffective to completely insulate these markets from the systemic events generated from the United States. The more significant variables that explained the daily changes in Credit Default Swaps spreads (CDS) in emerging markets were in their majority related to news concerning the unveiling of the Federal Reserve monetary expansion program and changes in US financial regulation (Dooley and Hutchison, 2009).

More recently, Felices and Wieladek (2012) use a Bayesian dynamic common factor model to further test if indeed there is evidence of decoupling in periods of stability. The authors use monthly data on real exchange rate appreciation and reserve growth between the period of 1995 and September 2007[10]. Their results showed that with the exception of Colombia, Romania, India and Malaysia there was no further evidence of decoupling from the other countries that composed their sample (Felices and Wieladek, 2012). Similar results were obtained by Frank and Hesse (2009) who used a Dynamic Conditional Correlation (DCC) GARCH model applied to the S&P 500 and the Emerging Market Bond Index (EMBI) for Latin America, Europe and Asia, finding there was no evidence of decoupling by the emerging markets after these markets reached their peak in November 2007.

10. The authors did not include the period in the height of the GFC to avoid model misspecification.

One plausible explanation for the cause of recoupling in the case of the GFC was a common transmission shock through trade. In a recent paper by Bagliano and Morana (2012), the authors used a factor VAR model in which they analysed more than 50 countries and incorporated more than 14 macroeconomic variables through a period of 30 years in which they included the GFC. One of their main objectives was to determine which variables had a greater impact as a transmission mechanism of contagion in time of crisis. They concluded that the variables with the greatest influence for Latin America and Asia were those macroeconomic variables linked with trade (Bagliano and Morana, 2012).

Although almost all of the recent empirical studies point out that there is no evidence of decoupling in emerging markets during times of crises, there are certain findings that are worth further exploration on the subject. For example, Dufrénot, Mignon, and Péguin-Feissolle (2011), using a time-varying transition probability Markov-switching model, found no evidence in favour of decoupling in Latin American markets, but their findings found support for the idea of heterogeneity among the Latin American countries in the sample. The author found that although interest rates spreads in Asset Backed Commercial Paper and the banking sector CDS (credit default swaps) had a huge effect in the changes in volatility of the stock market indices of Chile and Mexico; the changes of stock market volatility for the other countries in the sample (Brazil, Colombia and Peru) seemed more affected by changes in stock market volatility at the regional level (Dufrénot et al., 2011).

On the other hand, Powell and Martinez (2008) found evidence in favour of the decoupling (autarchy) hypothesis. In their study, the authors found evidence that in the case of sovereign risk measured by CDS spreads in emerging markets, changes in the VIX (volatility index) during the subprime crisis did not have more explanatory power than average changes in emerging markets sovereign spreads as measured by their respective CDS. According to the authors, one plausible explanation was the fact that investors nowadays are becoming more discriminating and that this fact may explain some degree of decoupling from mature markets (Powell and Martinez S., 2008). In the same order of ideas, Wang and Moore (2012) used a DCC-GARCH model to test the degree of integration of 38 countries that included both developed and emerging countries. Although their results showed a higher degree of integration during the subprime crisis, the results showed that the degree of integration as measured by the correlation was higher for developed than for emerging markets in the height of the crisis (Wang and Moore, 2012).

Our contribution to the current body of literature will be centred on the subject of financial contagion from the US to Colombian pension funds during the GFC. In this particular case, we test for contagion by analysing the co-movements of Colombian pension autarchic assets those of the US market index in time of crisis. As a by-product we seek to shed some light on the subject of regulation and contagion for a special kind of inaccessible asset. Although measuring the efficiency of the investment is not the primary objective of this book, as additional measure of robustness we will conduct a common performance test in order to measure the risk/return trade off of holding a regulated constrained portfolio of Colombian pension's funds, as opposed to a market portfolio represented by the benchmark index.

2.4. Data

The data for the present study has been retrieved from ASOFONDOS[11], the private pension funds (PPFs) association in Colombia. The information contains the daily Net Asset Value (NAV) per unit for each fund (as required by Colombian regulation) for the period between 2/01/2005 and 8/31/2011. In Colombia, the regulation concerning the private pension system and its investment regime is contained in the *Ley 100 de 1993*, as drafted and approved by the Colombian Congress. All subsequent regulations regarding the day-to-day operations of the private fund industry are the responsibility of the *Superintendencia Financiera de Colombia (SFC)*, which is the agency responsible for overseeing and regulating the activities of the financial sector and a part of the *Ministerio de Hacienda* (Ministry of Economics and Finance).

Before 2005, the Colombian PPFs were required by law to pay a guaranteed minimum rate of return which was usually a few basis points higher than the inflation reported by the government, on a monthly basis. The requirement was later modified by the *Decreto 1592 de 2004*, which created a benchmark index that consisted of a weighted average of the reported annual returns of all Colombia PPFs, the Colombian equity market index, and an international benchmark equity index (the S&P 500) multiplied by 70% and adjusted for the amount of local equity or international investments held in each PPFs portfolio[12].

This regulation introduced changes in the investment regime that had been left largely unchanged since 1996. It permitted the PPFs more flexibility to allocate their investments across the

11. The data was retrieved from de Centro de Informacion Consolidada Asofondos website (Asofondos, 2011).

12. See Appendix A for the formula used to calculate the minimum guaranteed rate of return

financial instruments[13] allowed by the SFC investment regime. Therefore, we omit the period between January 2001 and January 2005 since that data exhibits the bias caused by the guaranteed minimum rate of return in the previous legislation. Additionally, the operational regulatory framework which includes the mandatory investment regime for PPF operators as well as the guidelines for calculating the NAV[14] for each fund at the end is contained a series of documents issued by the SFC[15] (AIOS, 2011).

For the purpose of our study we will use the NAVs for the period between 02/02/2005 and 31/08/2011, in order to measure the composite fund performance. For the period under study, an aggregate measure was created by simply adding all the funds reported NAV unit for a given day. The summary statistics for each fund and the aggregate measure in terms of returns are presented in the following table:

Table 2.4

Summary statistics of pension funds data from 02/02/2005 to 31/08/2011

	CitiColfondos	Horizonte	Porvenir	Proteccion	ING	Aggregate
Mean (annual)	8.29%	9.38%	7.97%	9.87%	8.44%	8.80%
Median (annual)	7.75%	9.84%	8.75%	8.78%	8.19%	8.61%
Maximum (annual)	22.48%	21.98%	18.95%	25.04%	21.07%	21.35%
Minimum (Annual)	-3.10%	-1.88%	-3.57%	-2.83%	-4.10%	-3.02%
Std. Dev. (annual)	5.88%	5.82%	5.79%	6.20%	6.03%	5.83%
Skewness (daily)	-0.75	-0.62	-0.39	-0.71	-0.67	-0.71
Kurtosis (daily)	8.60	8.83	8.64	8.98	9.69	8.73
Jarque-Bera (daily)	2402.35	2535.13	2314.50	2695.86	3321.87	2489.58
Probability (daily)	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***

13. A comprehensive list of the financial instruments can be found in the relevant articles of the *Decreto 2555 de 2011*, which collects all previous regulations on the matter, available at [http://www.asofondos.org.co/VBeContent/newsdetail.asp?id=19&idcompany=3]; one limitation of our data set is that we do not count with the exact portfolio composition of each fund, just their NAV per unit.

14. See Appendix B for a summary of the regulatory methodology employed for the PPFs NAV unit calculation.

15. These documents are: Circular Externa 007 de 1996, Circular Externa 036 de 2003, Decreto 1592 de 2004, Decreto 2175 de 2007, Decreto 4935 de 2009 and Decreto 2555 de 2011, which can be found at the SFC website [*http://www.superfinanciera.gov.co]*.

Observations (daily)	1714	1714	1714	1714	1714	1714
Members*	1,532,844	1,700,996	3,096,289	2,050,074	1,160,936	9,541,139
Assets USD millions*	$7,045.17	$8,076.84	$15,073.73	$12,562.94	$6,507.76	$49,266.46

*As reported by Superfinanciera in January 2012.
***1%; **5%; and *10% significance.

From table 2.4 we can observe that the pension funds returns are negatively skewed with a high kurtosis. This fact is important for our choice of volatility model in section 2.7. Furthermore, in order to conduct the tests described in section 2.5, the S&P 500 (S&P) was used as the benchmark for the origin of the contagion effect. Additionally, and in order to check for robustness, we used the EMBI[16] global and the EFFA[17] fixed income indices as the common factor in order to account for the bias generated by the large investments on Colombian local government debt in AGGREGATE[18]. Also, for robustness purposes, we used MCSI Emerging Market Latin American (MXLA)[19] index to test for unobservable effects attributable to regional contagion. Furthermore, the US dollar Colombian exchange (COPFX) rate was used to control for the effect of the exchange rate in the fund's performance. All of the previous datasets were extracted from Bloomberg for the period between 02/02/2005 and 31/08/2011.

16. The Emerging Market Bond Index Global is a market weighted capitalization index of Us dollar denominated bonds and Eurobonds from sovereign and quasi-sovereign entities, and is a worldwide recognized benchmark for emerging markets debt (JPMorgan, 1999).

17. The EFFA/Bloomberg index includes all of the Eurozone government debt with maturities of more than one year; is the most comprehensive Eurobond index, which includes more than 364 issues from all members. The EFFA is a market weighted capitalization index (Bloomberg).

18. AGGREGATE is a proxy measure for the Colombian pension funds, and is simply the sum of the NAVs reported by the different funds during a specific time period.

19. The MSCI EM (Emerging Markets) Latin America Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of emerging markets in Latin America. It consists of the following five emerging market country indices: Brazil, Chile, Colombia, Mexico, and recently Peru as of May 30 of 2011 (MSCI, 2011).

2.5. Preliminary Analysis: Correlations

Since we are working with the notion that contagion is a significant increase in co-movements of prices (or returns) across markets, conditional on a crisis occurring in one market or group of markets, it is important to further discuss the dynamics of the correlation measures presented in this book. In this specific case we will measure the correlation between the S&P500 and all other assets (MXLA, COPFX and AGGREGATE) for the total sample period as well as for the three phases of the GFC, that is the US subprime crisis, the Lehman Brothers bankruptcy (CCC) and the ESD crisis. Since our proposed framework requires a tranquil and crisis period, for purposes of simplicity, each crisis is assumed to be an independent event. Therefore, the total sample period is from 02/02/2005 until 31/08/2011, the subprime crisis dates are 26/07/2007 to 12/09/2008, and the CCC crisis dates are between 15/09/2008 and 23/10/2009. Finally, for the ESD, the crisis dates are between 26/10/2009 and 31/08/2011[20]. In Table 2.5 we have the summary Pearson correlations, and for our observed financial series with the S&P 500 for the precrises, crisis and total sample period:

Table 2.5

Summary [correlations] for the pre-crisis, crisis and total sample period

	Tranquil period (Precrisis)		
	sp-aggregate	*sp-mxla*	*sp-copfx*
Correlation	0.26	0.64	-0.23
T-Statistic	6.91***	21.31***	-6.06***
P-Value	0.01	0.00	0.01

	Total sample		
	sp-aggregate	sp-mxla	sp-copfx
Correlation	0.33	0.70	-0.25
T-Statistic	14.60***	41.06***	-10.82***
P-Value	0.00	0.00	0.00

	Crisis Subprime		
	sp-aggregate	*sp-mxla*	*sp-copfx*
Correlation	0.22	0.58	-0.15
T-Statistic	3.95***	12.31***	-2.58***
P-Value	0.03	0.00	0.06

	Crisis CCC		
	sp-aggregate	*sp-mxla*	*sp-copfx*
Correlation	0.30	0.72	-0.24
T-Statistic	7.58***	24.93***	-5.87***
P-Value	0.01	0.00	0.01

	Crisis ESD		
	sp-aggregate	*sp-mxla*	*sp-copfx*
Correlation	0.36	0.72	-0.26
T-Statistic	12.63***	34.06***	-8.72***
P-Value	0.00	0.00	0.01

In this table we have a summary of the Pearson correlations and for our observed financial series with the S&P 500 for the precrises, crisis and total sample period. The total sample period is from 02/02/2005 until 31/08/2011, the subprime crisis

20. The key dates for the crisis were taken from the financial turmoil timeline chart from The Federal Reserve Bank of New York (FEDNewYork, 2011), and the crisis timeline from Bloomberg.

dates are 26/07/2007 to 12/09/2008, and the CCC crisis dates are between 15/09/2008 and 23/10/2009. Finally, for the ESD, the crisis dates are between 26/10/2009 and 31/08/2011. ***1%; **5%; and *10% significance.

Forbes and Rigobon (2002) make a clear distinction between *contagion* and *market interdependence*. They argue that even though some stock markets could be highly correlated in times of stability, a sudden increase of correlation in times of crisis does not necessarily imply contagion, but simply the continuation of the normal market interdependence in all possible states of the economy. Their main argument is that simple Pearson correlations are biased due to heteroskedasticity. The formal proof of this bias is based on the assumptions behind a single index model[21] which is consistent with the method outlined in section 2.5 (the authors also assume that there is no endogeneity or omitted variables between the markets studied). Forbes and Rigobon proposed the following adjustment for bias in the correlation coefficient for returns between two connected markets:

$$\rho^l = \frac{\rho^h}{\sqrt{1+\delta\left[1-(\rho^h)^2\right]}} \quad \delta = \frac{s^2_{x^h}}{s^2_{x^l}} - 1 \tag{2.1}$$

where ρ^l is the unconditional correlation between the two market returns series adjusted for upward bias, ρ^h = the conditional correlation, and δ is the scalar bias adjustment, $s^2_{x^h}$ is the variance for the crisis period and $s^2_{x^l}$ is the variance for the total sample of the security under observation. We begin by working with the Forbes and Rigobon set up while noting that although this statistic has been widely applied in the literature, it makes strong assumptions about the independence of the crisis and total sample periods which bias contagion tests towards zero. Dungey et al. (2005) present a more general and robust version of the Forbes and Rigobon test which we implement later.

Using equation (2.1) and rolling windows of 60 days we calculated the unconditional and conditional correlation coefficients between the S&P and the other assets (MXLA, COPFX, and AGGREGATE) for both the pre crisis and the three crisis periods (highlighted). Since the crisis periods are contiguous at the end of the sample, we also test for overlapping periods for the second and third stage of the crisis.

21. For more detail on the proof of the bias, see: (Forbes and Rigobon, 2002, pp. 2251-2252)

Figure 3
Conditional and Unconditional correlation, S&P 500:
total sample period between the S&P and AGGREGATE

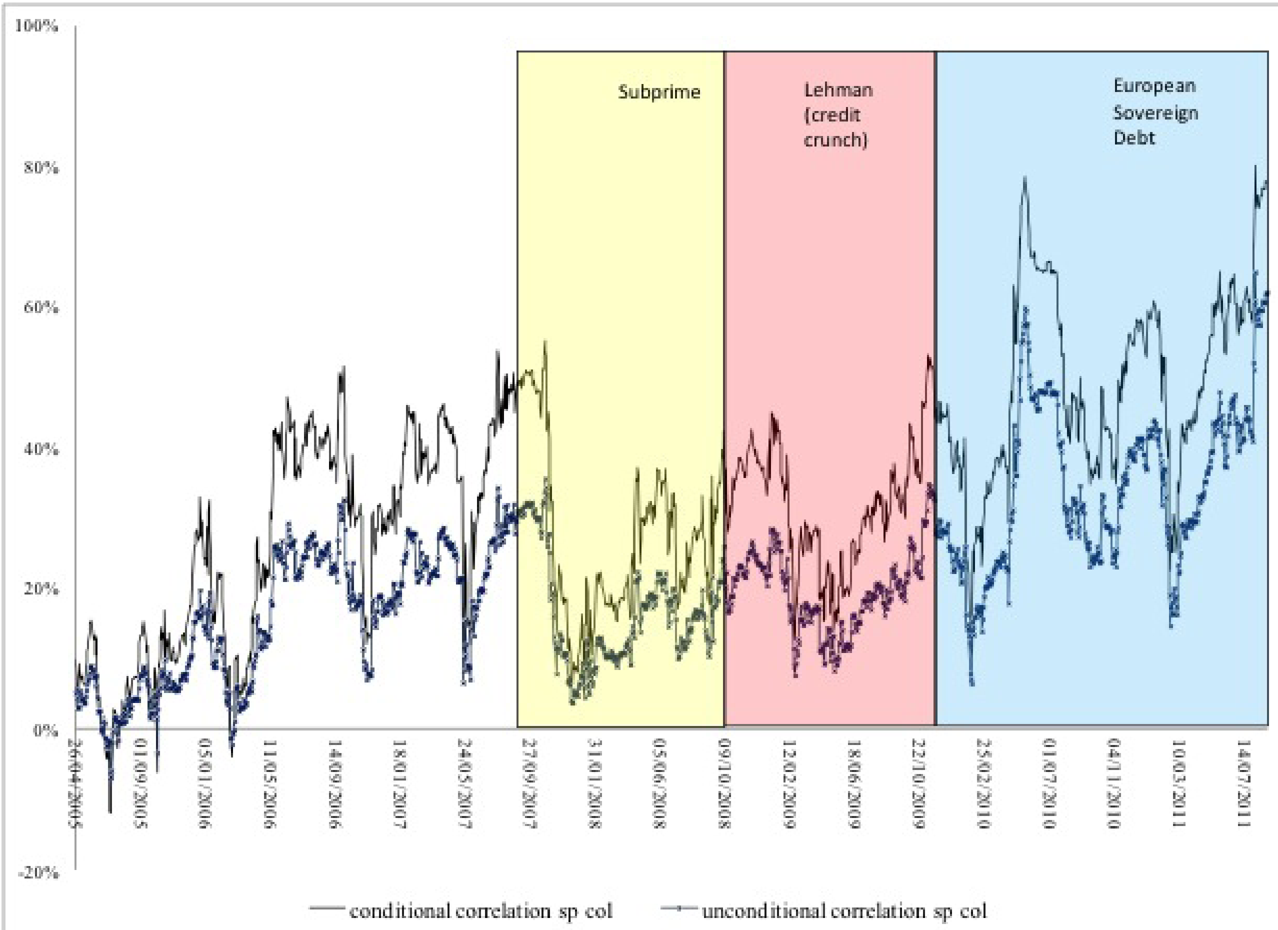


Figure 4
Conditional and Unconditional correlation, S&P 500:
total sample period between the S&P and MXLA

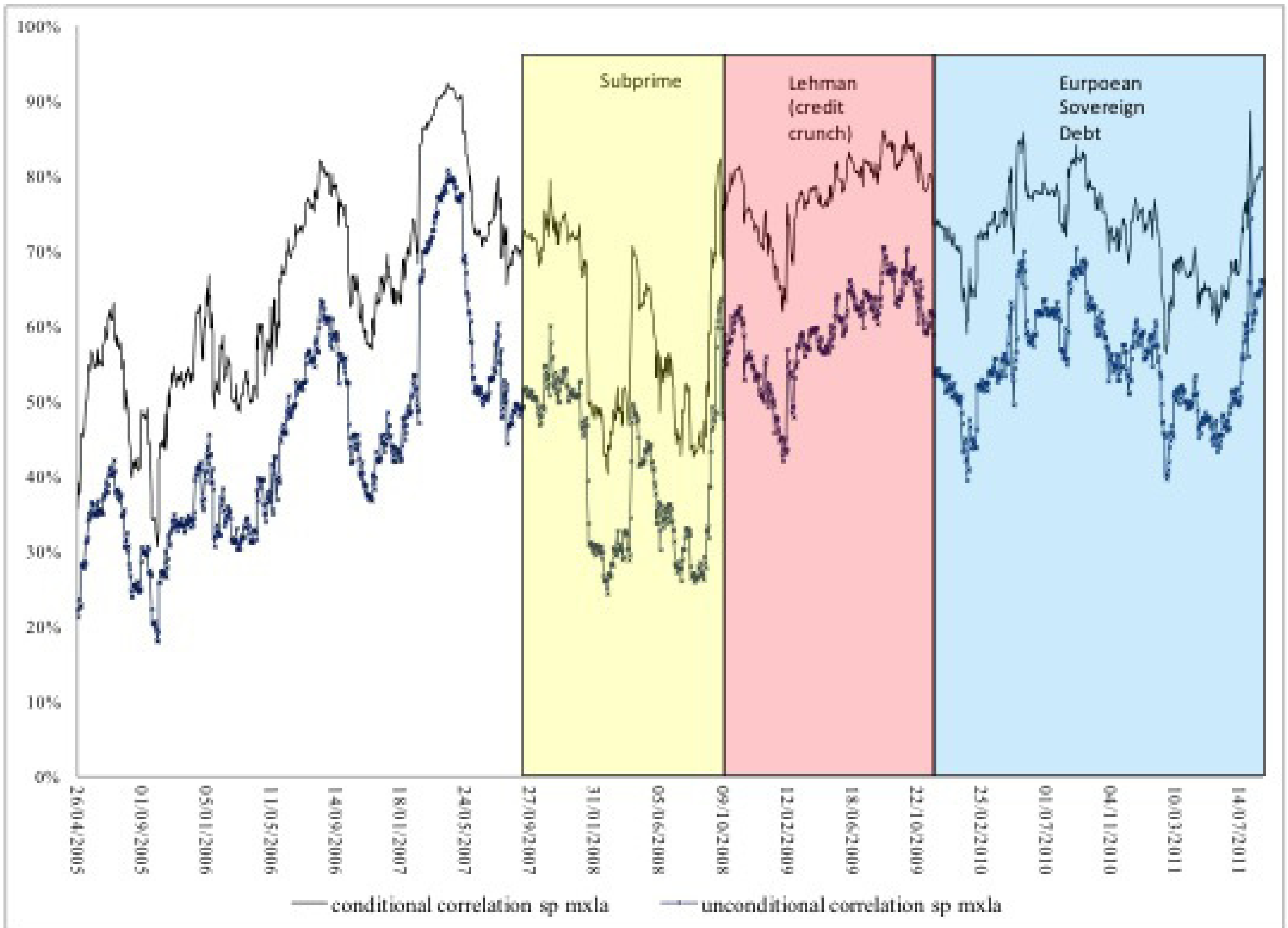
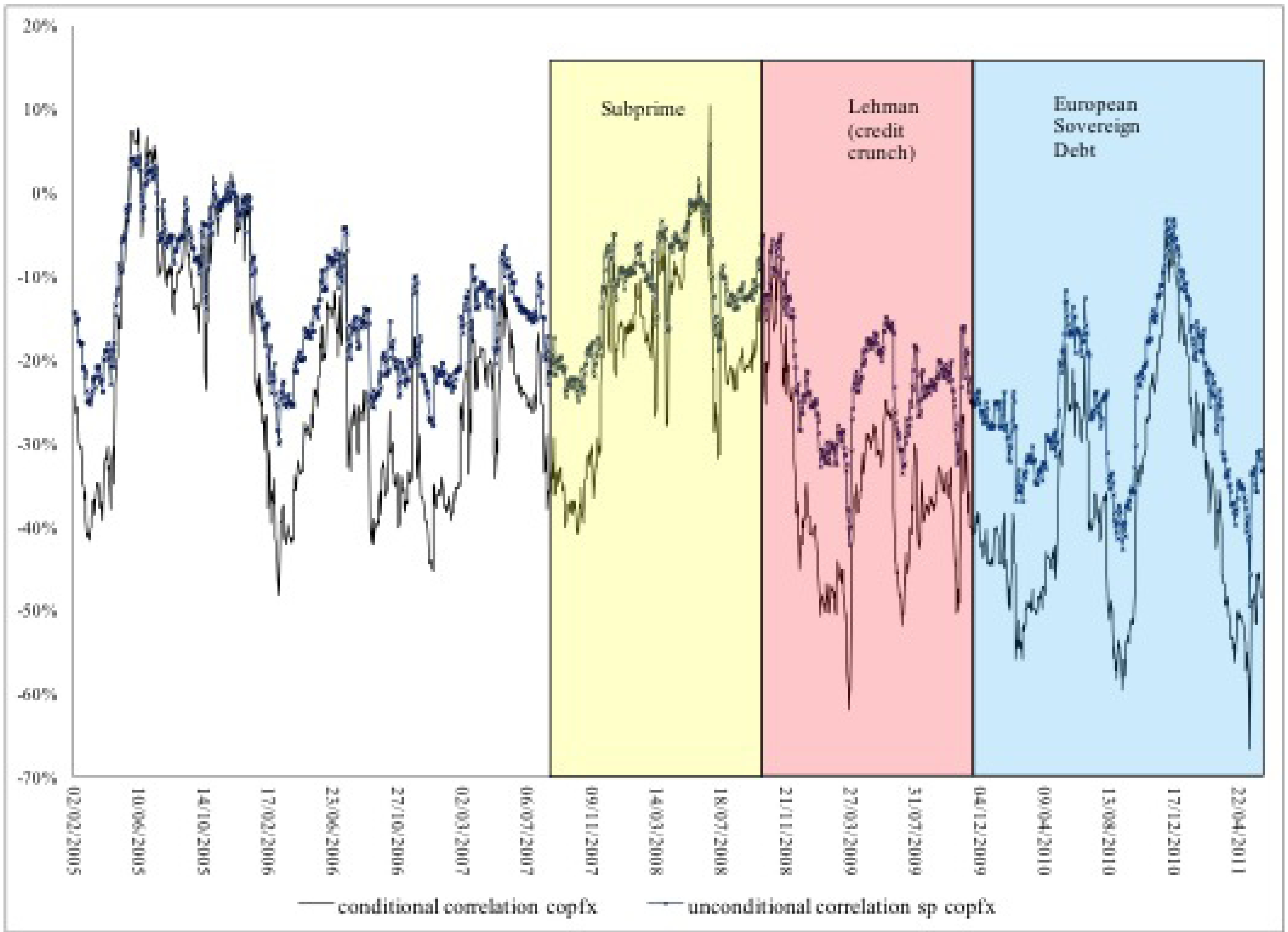


Figure 5
Conditional and Unconditional correlation, S&P 500:
total sample between the S&P and COPFX



From the graphs in figures 3, 4, and 5 it is possible to observe the changes in correlation during the different crises. In the case of the returns to Colombian pensions funds, AGGREGATE, the unconditional correlation with the S&P500 is relatively high at the beginning of the subprime crisis, then it decreases, before rising with the advent of the ESD crisis. In the case of returns to the Latin American stock index, MXLA, the unconditional correlation with the S&P500 hits a high point just before the subprime crisis, and then during the crisis it goes slightly down but remains relatively constant for the remainder of the subsequent crises. In the case of the exchange rate, COPFX, the correlation has the expected sign (an appreciation of the US dollar relative to the Colombian peso is expected in times of crisis) and it obviously depreciating during the subprime crisis, but curiously shows a strong reversal during the subsequent crisis. The relationship between the total sample and crises periods for all the assets under study can be observed in the following descriptive statistics tables:

Table 2.6

Descriptive statistics for the data during the pre-crisis and crisis period for the subprime, CCC and ESD crises*

Precrisis period	*returns aggregate*	*returns sp*	*returns MXLA*	*Returns COPFX*
Average	7.13%	9.38%	38.85%	-8.24%
Standard Deviation:	**3.40%**	**10.34%**	**23.12%**	**8.44%**
Sharpe Ratio	0.570	-0.285	1.195	-1.523
Sample 02/2/2005 -	941			
25/7/2007				

Subprime crisis	*returns aggregate*	*returns sp*	*returns MXLA*	*Returns COPFX*
Average	5.75%	-16.37%	-8.35%	4.87%
Standard Deviation:	**2.81%**	**20.75%**	**33.75%**	**15.08%**
Sharpe Ratio	0.351	-0.684	-0.255	0.007
Sample 26/7/2007 -	297			
12/9/2008				

Subprime crisis	*returns aggregate*	*returns sp*	*returns MXLA*	*Returns COPFX*
Mean Ratio	**0.81**	-1.75	-0.21	-0.59
SD ratio	**0.82**	2.01	1.46	1.79

CCC crisis	*returns aggregate*	*returns sp*	*returns MXLA*	*returns COPFX*
Average	9.96%	-14.63%	1.14%	-0.46%
Standard Deviation:	**3.39%**	**33.17%**	**47.61%**	**18.10%**
Sharpe Ratio	1.615	-0.579	-0.090	-0.274
Sample 26/7/2007 -	587			
22/10/2009				

CCC crisis	*returns aggregate*	*returns sp*	*returns MXLA*	*returns COPFX*
Mean Ratio	**1.40**	-1.56	0.03	0.06
SD ratio	**0.99**	3.21	2.06	2.15

ESD crisis	*returns aggregate*	*returns sp*	*returns MXLA*	*returns COPFX*
Average	8.89%	-5.17%	0.89%	-2.04%
Standard deviation	**4.28%**	**27.59%**	**38.78%**	**14.87%**
Sharpe Ratio	1.057	-0.417	-0.160	-0.430
Sample 26/7/2007 -	1070			
31/8/2011				

ESD crisis	returns aggregate	returns sp	returns MXLA	returns COPFX
Mean Ratio	**1.25**	-0.55	0.02	0.25
SD ratio	**1.26**	2.67	1.68	1.76

* Annualized daily data.

If we recall the information from Table 2.5, we can observe that the correlation between the S&P 500 and AGGREGATE increased in the CCC and ESD crises periods, and decreased in the subprime. This can be further corroborated by the Standard Deviation (SD) ratios[22] which is greater than one for the ESD crisis and less than one in the subprime crisis. For all the other variables (SP, MXLA and COPFX) the SD ratio is greater than one for all cases. For all assets under scrutiny, with the exception of AGGREGATE, the SD ratio was greater than one during the CCC. One plausible explanation for the behavior of AGGREGATE during the ESD crisis could be that this crisis was mainly related to fixed income markets, and due to the component of fixed income assets in the Colombian funds, the specific nature of the crisis had a larger effect on the funds' values. Also, the Sharpe Ratio (SR)[23] for AGGREGATE tends to outperform all other investments during all the crises periods under observation, although we note that we cannot compare across negative SRs. It is important to mention that the SR for AGGREGATE is calculated from the perspective of the Colombian investor and that the returns are adjusted for the exchange rate. That is the reason behind the negative SR during the subprime period; for all other periods AGGREGATE shows a more efficient risk return relationship.

Even though "quantitative restrictions" such as allocation caps can limit the upward risk/return potential of AGGREGATE by constraining the investment portfolio, these same measures can also limit the downside potential for losses as observed by a higher SR during the different episodes of the crisis. Returns to Colombian pension funds in USD still outperform all other investments during all the periods under observation with the exception of the ESD period.

22. The SD ratio and mean ratios are calculated using the figured statistic during the crisis period in the numerator, and the pre-crisis period in the denominator. A ratio greater than one signals an increase in volatility/return during the crisis period with respect to the tranquil period.

23. The Sharpe ratio is the most common performance investment measure, and is defined as where = is the average return of the security, = the average return of the proxy of the risk free rate, in which our case is the US 10 Years Treasury Index adjusted by the Colombian country premium, and= the standard deviation of the security. The interpretation is straightforward in the sense that a higher Sharpe ratio denotes a more efficient risk/return relationship.

2.6. Model

As seen from the previous section, correlation patterns during subsamples give some insight into market integration and contagion, as a means to our objective of measuring the degree of integration of the inaccessible asset in time of crisis, the correlation approach has certain shortcomings that can be corrected by the use of time-varying factor models.

Bekaert and Harvey (1995) point out that the advantage of time varying factor models is that integration and segmentation of a particular country or market can be explained by the predictive power of one or more common factors. Therefore, by using allowing time-variance into a common factor model it is possible to see the evolution and degree of integration or segmentation of a particular market using variance decomposition.

The most common approach to estimating the time-varying volatilities needed for these models is to use GARCH. For example, Fujii (2005) used a series of cross-correlation function tests in the residuals taken from a GARCH volatility model to examine the linkages between Latin American and Asian markets during the Asian and Mexican crises, and found that the relation between those markets increased substantially in times of crises. More recently, Chiang, Jeon, and Li (2007) provide several arguments in favor of the use of a multivariate GARCH model in estimating Dynamic Conditional Correlations (DCC) when studying contagion. They argue that DCC models can also account effectively for heteroskedasticity and endogeneity through the use of AR terms and additional explanatory variables in the conditional mean equation. Furthermore, Ping and Moore (2008) used a DCC-GARCH framework to investigate the degree of integration between the European Union and the three major eastern European markets. However, Pesaran and Pesaran (2010) found evidence that DCC-GARCH models tend to underestimate risk in time of crisis, and that the use of fat tailed distributions could lead to improvement of the estimates. Finally, and in the context of market integration, the variance decomposition approach, when implemented within a structural GARCH framework, has proven effective in identifying structural shocks without the need for an arbitrary restriction to classify the unobserved shocks as contagion; therefore, further economic insight can be gained from the analysis of the data using variance decomposition (Dungey et al., 2010). From here we proceed to a more detailed analysis of contagion using a time-varying volatility model.

In order to allow for dynamic variation, we use the GJR-GARCH extension of Glosten et al. (1993) of Engle (2002) DCC framework. First, let us consider a simple GJR-GARCH extension in the following functional form and conditional return equation:

$$R_i = \alpha_i + \varepsilon_t$$
$$h_t = \alpha_t + \alpha\varepsilon_{t-1}^2 + \lambda I_{t-1}\varepsilon_{t-1}^2 + \eta h_{t-1}\ , \quad \varepsilon_t|\Omega_{t-1} :\ N(0, h_t) \qquad (2.2)$$

Where R_t = the conditional return of the market index under scrutiny explained by a constant, h_t = the conditional variance of the market index under scrutiny ,ε_{t-1}^2 are the filtered squared returns of the series under observation, I_{t-1} is a dummy variable that takes either the value of 0 or 1 when ε_{t-1}> 0 or 0 < ε_{t-1}, and h_{t-1} is the conditional variance from the previous period and Ω_{t-1} includes all the information available in the previous period. We filter returns with a standard ARMA model to ensure serial independence of residuals. Furthermore, using the method proposed by Bekaert, Harvey, and Ng (2005), we assume that the source of contagion in our sample was the US, and we write the covariance between the US index and any other market indices of interest as:

$$h_{us_t} = \alpha_{0us} + \alpha_{us}\varepsilon_{us_{t-1}}^2 + \lambda_{us} I_{us_{t-1}}\varepsilon_{us_{t-1}}^2 + \eta_{us} h_{us_{t-1}}$$
$$h_{us_t, i_t} = \alpha_{0us,i} + \alpha_{us,i}\varepsilon_{us_{t-1}}\varepsilon_{i_{t-1}} + \lambda_{us,i} I_{us_{t-1}}\varepsilon_{us_{t-1}} I_{i_{t-1}}\varepsilon_{i_{t-1}} + \eta_{us,i} h_{us,i_{t-1}}$$
$$h_{i_t} = \alpha_{0i} + \alpha_i\varepsilon_{i_{t-1}}^2 + \lambda_i I_{i_{t-1}}\varepsilon_{i_{t-1}}^2 + \eta_i h_{i_{t-1}}$$
$$\begin{pmatrix} \varepsilon_{us_{t-1}} \\ \varepsilon_{i_{t-1}} \end{pmatrix} \Big| \Omega_{t-1} :\ N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} h_{us_t} & h_{us_t, i_t} \\ h_{us_t, i_t} & h_{i_t} \end{pmatrix} \right) \qquad (2.3)$$

where h_{us_t} = the variance in the US (origination country), h_{i_t} = the variance of the local or regional market index under scrutiny, and h_{us_t, i_t} = the covariance between the US market and the local or regional market index which yields us conditional covariance model that allows for time varying co-variance with asymmetric volatility.

Also, we can rewrite the previous specification as a single factor model in which the only channel of transmission is the US market index, and by assuming that the returns of any other asset index can be explained by a single factor index model. We can rewrite our conditional variance in factor or conditional correlation form as:

$$\beta_{i_t} = \frac{h_{us_t, i_t}}{h_{us_t}} \quad \text{or} \quad \rho_{us_t, i_t} = \frac{h_{us_t, i_t}}{\sqrt{h_{us_t}}\sqrt{h_{i_t}}} \qquad (2.4)$$

The functional advantage of this specification is that allows us to write the variance of the local index returns in the following form:

$$h_{i_t} = \beta_{i_t}^2 h_{us_t} + h_{ei_t} \qquad (2.5)$$

Where h_{i_t} is the variance of the index under scrutiny, $\beta_{i_t}^2 h_{us_t}$ is the part of the variance attributed to a common transmission mechanism, which for the purpose of our book is the crisis origination point, and h_{ei_t} is the part of the variance attributed to an idiosyncratic factor. Therefore, expressing the variance decomposition as a percentage of systematic and idiosyncratic risk is straightforward:

$$u_{sys} = \frac{\beta_{i_t}^2 h_{us_t}}{h_{i_t}}$$

$$u_{idio} = \frac{h_{ei_t}}{h_{i_t}} \qquad (2.6)$$

Additionally, let us assume that the dates of the crisis are well specified so that D_t denotes an indicator variable taking the value of zero for dates of the pre-crisis period and one for the crisis. In order to avoid auto-correlation among daily returns we used the following specifications for the conditional mean equations of AGGREGATE, MXLA and COPFX:

$$R_{AGGREGATE} = \alpha_{AGGREGATE} + \alpha R_{AGGREGATE,t-1} + \varepsilon_{AGGREGATE} + \theta\varepsilon_{AGGREGATE,t-1} + \theta\varepsilon_{AGGREGATE,t-2},\ \varepsilon_{AGGREGATE} : N(0, h_{AGGREGATE})$$
$$R_{MXLA} = \alpha_{MXLA} + \alpha R_{MXLA,t-1} + \varepsilon_{MXLA},\ \varepsilon_{MXLA} : N(0, h_{MXLA})$$
$$R_{COPFX} = \alpha_{COPFX} + \alpha R_{COPFX,t-1} + \varepsilon_{COPFX},\ \varepsilon_{COPFX} : N(0, h_{MXLA}) \qquad (2.7)$$

Now, let us assume that $\varepsilon_{S\&P_{t-1}}^2$ and h_t both show evidence of volatility shocks at the same time, and we make the assumption that the crisis originated from $\varepsilon_{S\&P_{t-1}}^2$. Therefore, we can then rewrite our GRJ-GARCH equation as:

$$h_t = \alpha_0 + \alpha_1 \varepsilon^2_{i_{t-1}} + \lambda_1 I_{t-1} \varepsilon^2_{i_{t-1}} + \eta_1 h_{t-1} + \gamma_0 X_t + \gamma_1 I_L X_t + \sum_{C=2}^{4} \gamma_C D_C \varepsilon^2_{S\&P_{t-1}} + \sum_{L=5}^{7} \gamma_L D_C I_L \varepsilon^2_{S\&P_{t-1}} \tag{2.8}$$

Where h_t is the conditional variance of the index under scrutiny, X_t are the squared returns of the source of contagion, D_C denotes a crisis dummy for each of the subprime, CCC and ESD crises, I_L is a dummy variable that measures the effect of negative returns on the S&P and takes either the value of 0 or 1 when $\varepsilon_{S\&P_{t-1}} < 0$ or $0 > \varepsilon_{S\&P_{t-1}}$. By using this specification with the S&P500 as a common factor, we can test for the null of no volatility spillover ($H_0 : \gamma_0 = 0$) for the whole sample period or for additional transmission during the crises ($H_0 : \gamma_C = 0$) just for the crises. Alternatively, we can also test the null that there is no asymmetry effect from the S&P500 ($H_0 : \gamma_1 = 0$) for the whole sample period or whether additional channels emerge during the crises ($H_0 : \gamma_L = 0$).

In order to test for contagion defined as an increase in co-movements, we will use the adjusted correlation test devised by Forbes and Rigobon (2002), and a later version of the same test but in different functional form derived by Dungey et al. (2005). In the first version we use the unconditional correlation (ρ^l) from equation (2.1):

$$FR_{t-stat} = \frac{\frac{1}{2}\ln\left(\frac{1+\rho^l}{1-\rho^l}\right) + \frac{1}{2}\ln\left(\frac{1+\rho^{ts}}{1-\rho^{ts}}\right)}{\sqrt{\left(\frac{1}{T^l - 3}\right) - \left(\frac{1}{T^{ts} - 3}\right)}} \tag{2.9}$$

Where ρ^{ts} = is the simple Pearson correlation for the whole sample, T^l = sample size for the specified crisis period, and T^{ts} = total sample size for the whole period. According to Dungey et al. (2005), one critique of this test is that it relies on the assumption of independent variance across the two sample periods, an assumption that it is violated by the use of overlapping data in the computations and that can lead to negative serial correlation. This creates a bias of the FR t-statistic towards zero which can lead to the failure to reject the null hypothesis of interdependence. In order to obtain a more robust estimator, Dungey et al. (2005) propose an alternative way to implement the FR test using ordinary least squares in the following form:

$$\left(\frac{z_{2,i}}{s_{x^l}}\right) = \gamma_0 + \gamma_1 D_t + \gamma_2\left(\frac{z_{1,sp}}{s_{sp^l}}\right) + \gamma_3\left(\frac{z_{1,sp}}{s_{sp^l}}\right) D_t + \eta_t \qquad (2.10)$$

where $z_i = (R_i, R_{sp})$ = the returns of the securities under observation for the total sample period (including crisis and tranquil periods), s_{x^l} is the standard deviation for the total sample for the asset under observation, s_{sp^l} is the standard deviation for the total sample for the common factor which in this case is the S&P 500, and D_t = a dummy variable that denotes the crises dates.

A conclusion that contagion due to an increase in co-movements exists requires a rejection of the null ($H_0 : \gamma_3 = 0$).

In order to further check the consistency of our results another test will be conducted to observe the evidence of contagion caused by the S&P500 by testing the significance of the time varying statistics during the subprime, CCC and ESD crises. This test is based on the one proposed by Bekaert, Harvey, and Ng (2005) or the BHN test, where:

$$S_{i,t} = \alpha_{0,i} + \alpha S_{i,t-1} + \phi D_{i,t} + e_{i,t} \qquad (2.11)$$

Where $S_{i,t}$ = the corresponding time varying statistics (u_{sys} as defined in equation (6) and β_{i^t} as defined in equation (2.4)) for AGGREGATE, MXLA, and COPXF using the model in equation (2.3), $D_{i,t}$ = a dummy variable that denotes the respective crisis dates. In this setup we test for contagion by testing ($H_0 : \phi = 0$) against a two-sided alternative. Furthermore, in order to correct for serial correlation we add an AR(1) term to the equation represented by $S_{i,t-1}$. Since the distributions of u_{sys} and β_{i^t} are highly asymmetric, and can lead to biased interpretations based on OLS statistics a quantile regression, analysis will be conducted for robustness[24].

24. See Appendix C.

2.7. Results

2.7.1. Contagion as an increase in correlation

Table 2.7 reports the Forbes and Rigobon, and Dungey et al. (2005) (DGFM) tests. The volatility delta for the SP is the scaling factor for adjusting the upward bias presented in equation (2.1). Similarly, the unconditional correlation was calculated using equation (2.1) and the FR statistic with equation (2.9). For robustness purposes the FR statistic was also calculated using the specification in equation (2.10) along with a standard LM test to test for serial correlation:

Table 2.7
Conditional and unconditional correlation coefficients
and FR statistics all crises periods

	Unconditional correlation	Conditional correlation			FR-Test statistic equation (9)	DFGM adjusted FR-Test statistic equation (10)	LM test p-value	Serial correlation?
SUBPRIME	Crisis	Subsample	Pre crisis	Overlapping Subprime				
Aggregate	**0.10**	0.22	0.26	0.22	**-1.88****	**-3.71*****	**0.00**	**Y**
MXLA	**0.30**	0.58	0.64	0.60	**-5.72*****	**-4.90*****	**0.00**	**Y**
COPFX	**-0.07**	-0.15	-0.23	-0.18	**1.74****	1.52	**0.00**	**N**

CCC	Unconditional correlation	Conditional correlation			FR-Test statistic Equation (10)	DFGM adjusted FR-Test statistic Equation (11)	LM test p-value	Serial Correlation?
	Crisis	Subsample	Pre crisis	Overlapping CCC				
Aggregate	**0.18**	0.30	0.26	0.25	-1.52	**-3.38****	**0.00**	**Y**
MXLA	**0.52**	0.72	0.64	0.70	**-5.79*****	-1.33	**0.00**	**Y**
COPFX	**-0.14**	-0.24	-0.23	-0.23	**1.90****	0.21	**0.00**	**N**

ESD	Unconditional correlation	Conditional correlation			FR-Test statistic Equation (10)	DFGM adjusted FR-Test statistic Equation (11)	LM test p-value	Serial Correlation?
	Crisis	Subsample	Pre crisis	Overlap-ping ESD				
Aggregate	**0.24**	0.36	0.26	0.33	**-2.63*****	**6.28*****	**0.00**	**Y**
MXLA	**0.55**	0.72	0.64	0.70	**-6.52*****	**-2.12*****	**0.00**	**Y**
COPFX	**-0.17**	-0.26	-0.23	-0.25	**-2.30*****	-0.79	0.47	**N**

**Significant at 95% ***Significant at 99%

This reports the Forbes and Rigobon and Dungey et al. (2005) (DGFM) tests. The volatility delta for the SP is the scaling factor for adjusting the upward bias presented in equation (2.1). Similarly, the unconditional correlation was calculated using equation (2.1) and the FR statistic with equation (2.9). For robustness purposes the FR statistic was also calculated using the specification in equation (2.10) along with a standard LM test to test for serial correlation.

As we can see from Table 2.7, the conditional correlation for the subsample period was higher in the CCC and ESD than for the pre-crisis and the overlapping periods specified for each crisis. Interestingly, in the case of the subprime crisis, the conditional correlation for the subsample was lower than the pre-crisis and overlapping sample periods. Although is not common to observe a lower conditional correlation during the crisis periods, there are examples of this phenomena in other studies. Kallberg et al. (2005) reported the same phenomena for Thailand in the early phase of Asian crisis in 1997; their hypothesis concerning this phenomena is that in the early phase of the crisis the investors base their decisions just on local fundamentals, but as the crisis progresses global fundamentals become more important which leads to an increase in correlation in a later stage of the crisis. In a subsequent study, Chiang et al. (2007) observed the same phenomena between the conditional correlation of Thailand and other five countries during the early stages of the Asian crisis. Furthermore, Chiang et al. (2007) state that the hypothesis in the FR test is based in increasing correlations as a source of contagion, therefore decreasing correlations should be omitted from the results they can be interpreted as evidence of no contagion. The DFGM variation of the FR test is flexible enough for either case.

The unconditional correlation coefficients for the crisis period are lower than the conditional ones in all three crises as expected from the correction of the upward bias due to heteroskedasticity. When we base our estimates of the FR statistic on the total sample period, we can observe the rejection of the null hypothesis of interdependence in favor of contagion in the case of the MXLA in all three crises episodes; in the case of AGGREGATE there is evidence of contagion during the subprime and the ESD crises. However, when we base our estimates of the FR statistic using just the pre-crisis period there is evidence of contagion during the subprime crisis for AGGREGATE, MXLA and COPFX. Furthermore, by using the pre-crisis sample period for the CCC and ESD there is evidence of contagion just for MXLA. Additionally, when we compute the FR statistic using equation (2.9) we find that the null of no contagion is rejected in all three cases for AGGREGATE. In the case of MXLA there is evidence of contagion during the Subprime and ESD episodes. Finally, in the case of COPFX the results are exactly the opposite using the two methods. Our explanation regarding the discrepancy of the results can be to the bias generated by serial correlation as seen by the significant p-value of the LM test when applied to equation (2.10). Only in the case of COPFX we fail to reject the null of no serial correlation for all three cases. Due to the previous reason and those explained in section 6 regarding the possible bias in the FR statistics, we conducted other tests on the statistics obtained using the framework of section 2.6. This is important since the FR statistic makes the strong assumption that the conditional correlation is constant throughout the pre-crisis and crisis period as explained in the previous section.

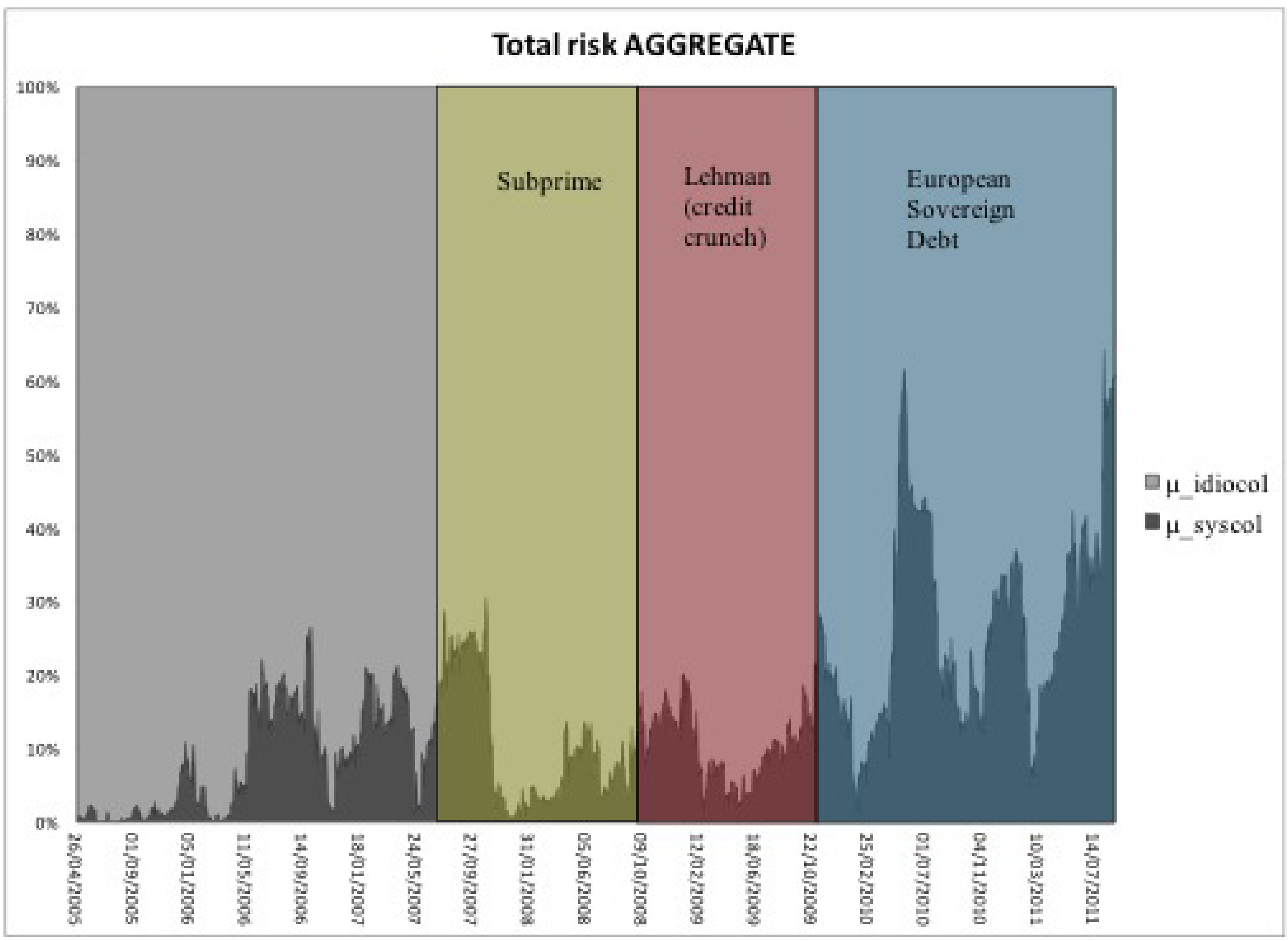
By using the specifications of equation (2.3) some of the issues arising from conditional correlation can be corrected. By using equation (2.3), and presenting the results as factors rather than correlations, a further insight in the nature of contagion can be obtained using the framework detailed in section 2.5.

From Figure 6 we can appreciate the difference between the systematic risk (as explained by the S&P) and idiosyncratic risk (as explained by AGGREGATE) when using rolling window conditional betas (Panel A) that are often plagued with serial correlation, and using conditional time varying betas (Panel B) that correct for this effect as observed from a faster dampening effect of systematic risk. Figures 7 and 8 show the same effects for MXLA and COPFX as the source of contagion. In all cases we used equations (2.3) and (2.4) in order to decompose the variance in terms of systematic and idiosyncratic risk using equations (2.5) and (2.6) during the pre-crisis and highlighted crises periods:

Figure 6
Conditional and time varying beta decomposition for S&P and AGGREGATE

Panel A
60 day rolling window

Note: The $\beta_{Aggregate}$ statistics are the estimated linear regression coefficients of the single index model specification $E(R_{Aggregate}) = \alpha_{Aggregate} + \beta_{Aggregate} R_{sp} + e_{Aggregate}$ for 60 day rolling windows using the total sample period between 2/02/2005 and 31/08/2011. Where $R_{Aggregate}$ = Aggregate daily returns, R_{sp} = daily returns of the S&P500, $\alpha_{Aggregate}$ = constant, and $e_{Aggregate}$ = an error term. The $\mu_{idiocol}$ and the μ_{syscol} are obtained discomposing $\beta_{Aggregate}$ using the relationships in equations (2.5) and (2.6).



Panel B
DCC GJR-GARCH-Time varying

Note: The time-varying $\beta_{Aggregate}$ statistics are calculated using the DCC system specified in equation (2.3) in the following form:

$$h_{sp} = \alpha_{0sp} + \alpha_{1sp}\varepsilon^2_{sp_{t-1}} + \lambda_{1sp}I_{sp_{t-1}}\varepsilon^2_{sp_{t-1}} + \eta_{1sp}h_{sp_{t-1}}$$

$$h_{sp,aggregate} = \alpha_{0sp,aggregate} + \alpha_{1sp,aggregate}\varepsilon_{sp_{t-1}}\varepsilon_{aggregate_{t-1}} + \lambda_{1sp,aggregate}I_{sp_{t-1}}\varepsilon_{sp_{t-1}}I_{aggregate_{t-1}}\varepsilon_{aggregate_{t-1}} + \eta_{1sp,aggregate}h_{sp_{t-1},aggregate_{t-1}}$$

$$h_{aggregate} = \alpha_{0aggregate} + \alpha_{1aggregate}\varepsilon^2_{aggregate_{t-1}} + \lambda_{1aggregate}I_{aggregate_{t-1}}\varepsilon^2_{aggregate_{t-1}} + \eta_{1aggregate}h_{aggregate_{t-1}}$$

where: h_{sp} = the estimated conditional daily variance of the S&P, $h_{aggregate}$ = the estimated conditional daily variance of aggregate and $h_{sp,aggregate}$ = the estimated conditional covariance of S&P and Aggregate using the DCC model as explained in section 1.5. The $\beta_{Aggregate}$, uniquecol and systematiccol are obtained by rearranging the estimated conditional daily variances and covariances by the relationships explained in equations (2.4), (2.5) and (2.6)

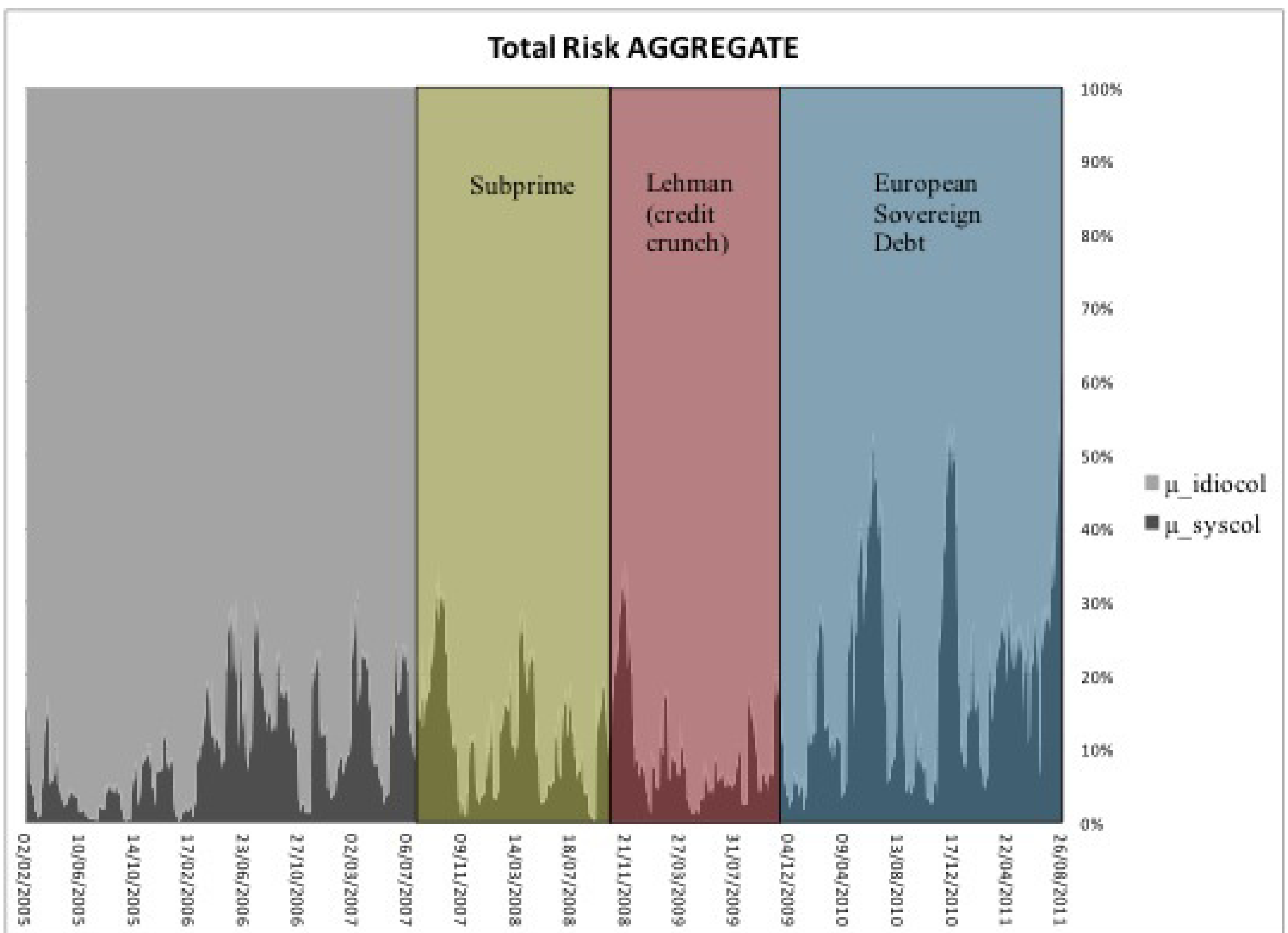
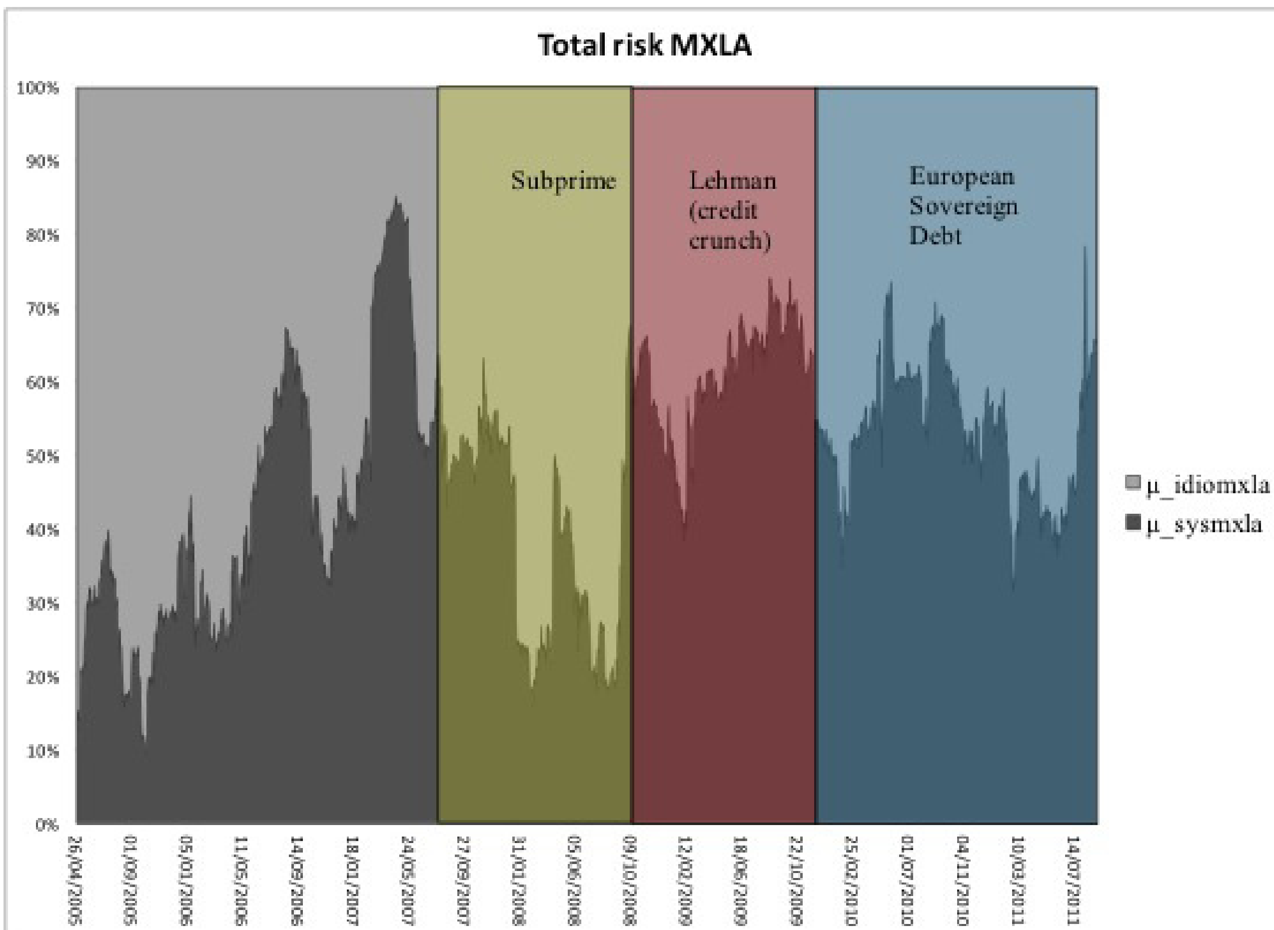


Figure 7

Conditional and time varying beta decomposition for S&P and MXLA

Panel A
60 day rolling window

Note: The β_{MXLA} statistics are the estimated linear regression coefficients of the single index model specification $E(R_{MXLA}) = \alpha_{MXLA} + \beta_{MXLA} R_{sp} + e_{MXLA}$ for 60 day rolling windows using the total sample period between 2/02/2005 and 31/08/2011. Where R_{MXLA} = Aggregate daily returns, R_{sp} = daily returns of the S&P500, $\alpha_{Aggregate}$ = constant, and $e_{Aggregate}$ = an error term. The $\mu_{idiocol}$ and the μ_{syscol} are obtained discomposing β_{MXLA} using the relationships in equations (2.5) and (2.6).



Panel B
DCC GJR-GARCH-Time varying

Note: The time-varying β_{MXLA} statistics are calculated using the DCC system specified in equation (2.3) in the following form:

$$h_{sp} = \alpha_{0sp} + \alpha_{1sp}\varepsilon^2_{sp_{t-1}} + \lambda_{1sp} I_{sp_{t-1}} \varepsilon^2_{sp_{t-1}} + \eta_{1sp} h_{sp_{t-1}}$$

$$h_{sp,mxla} = \alpha_{0sp,mxla} + \alpha_{1sp,mxla}\varepsilon_{sp_{t-1}}\varepsilon_{mxla_{t-1}} + \lambda_{1sp,mxla} I_{sp_{t-1}} \varepsilon_{sp_{t-1}} I_{mxla_{t-1}} \varepsilon_{mxla_{t-1}} + \eta_{1sp,mxla} h_{sp_{t-1},mxla_{t-1}}$$

$$h_{mxla} = \alpha_{0mxla} + \alpha_{1mxla}\varepsilon^2_{mxla_{t-1}} + \lambda_{1mxla} I_{mxla_{t-1}} \varepsilon^2_{mxla_{t-1}} + \eta_{1mxla} h_{mxla_{t-1}}$$

where: h_{sp} = the estimated conditional daily variance of the S&P, h_{mxla} = the estimated conditional daily variance of aggregate and $h_{sp,mxla}$ = the estimated conditional covariance of S&P and MXLA using the DCC model as explained in section 2.5. The β_{MXLA}, uniquemxla and systematicmxla are obtained by rearranging the estimated conditional daily variances and covariances by the relationships explained in equations (2.4), (2.5) and (2.6).

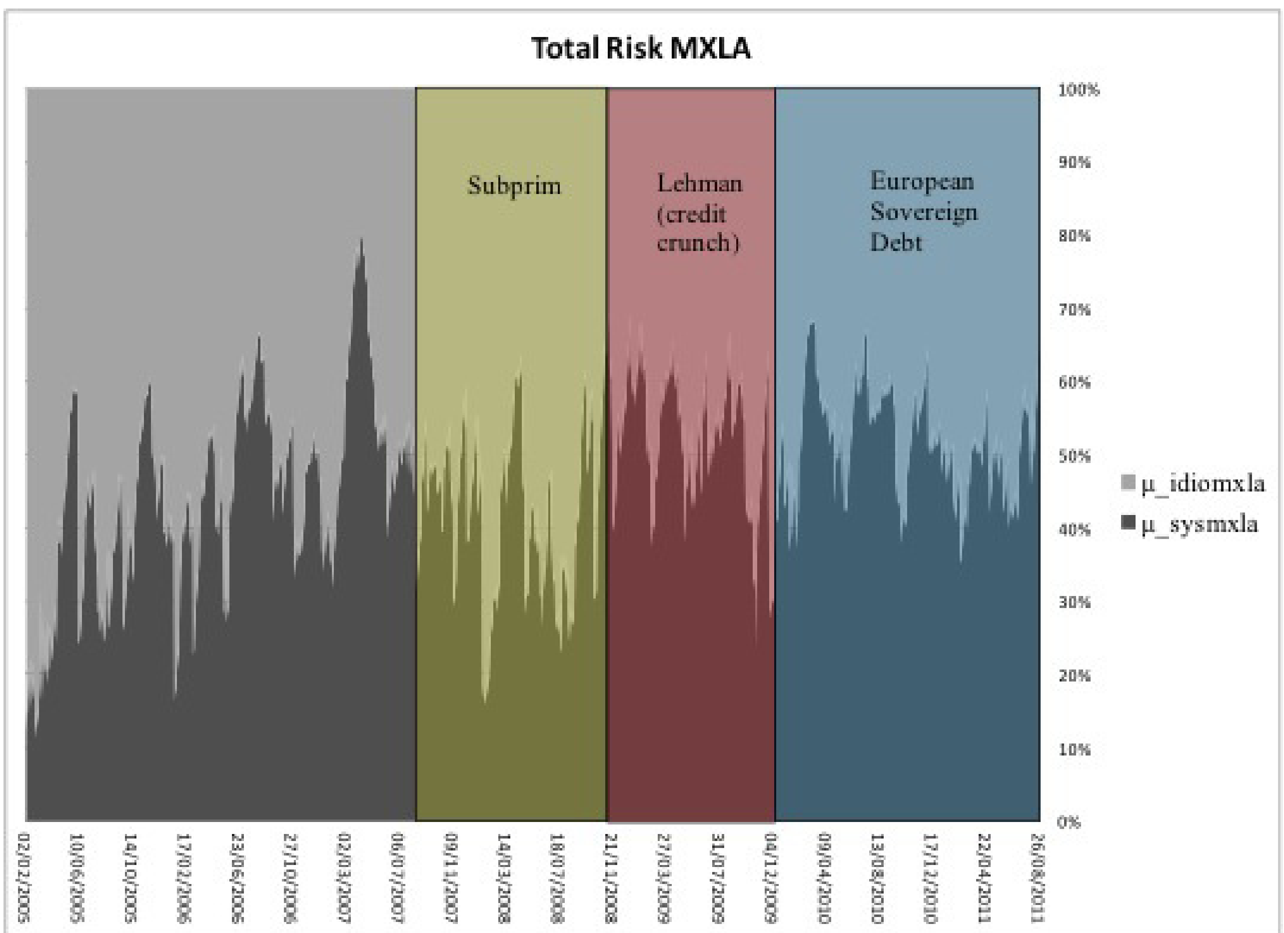


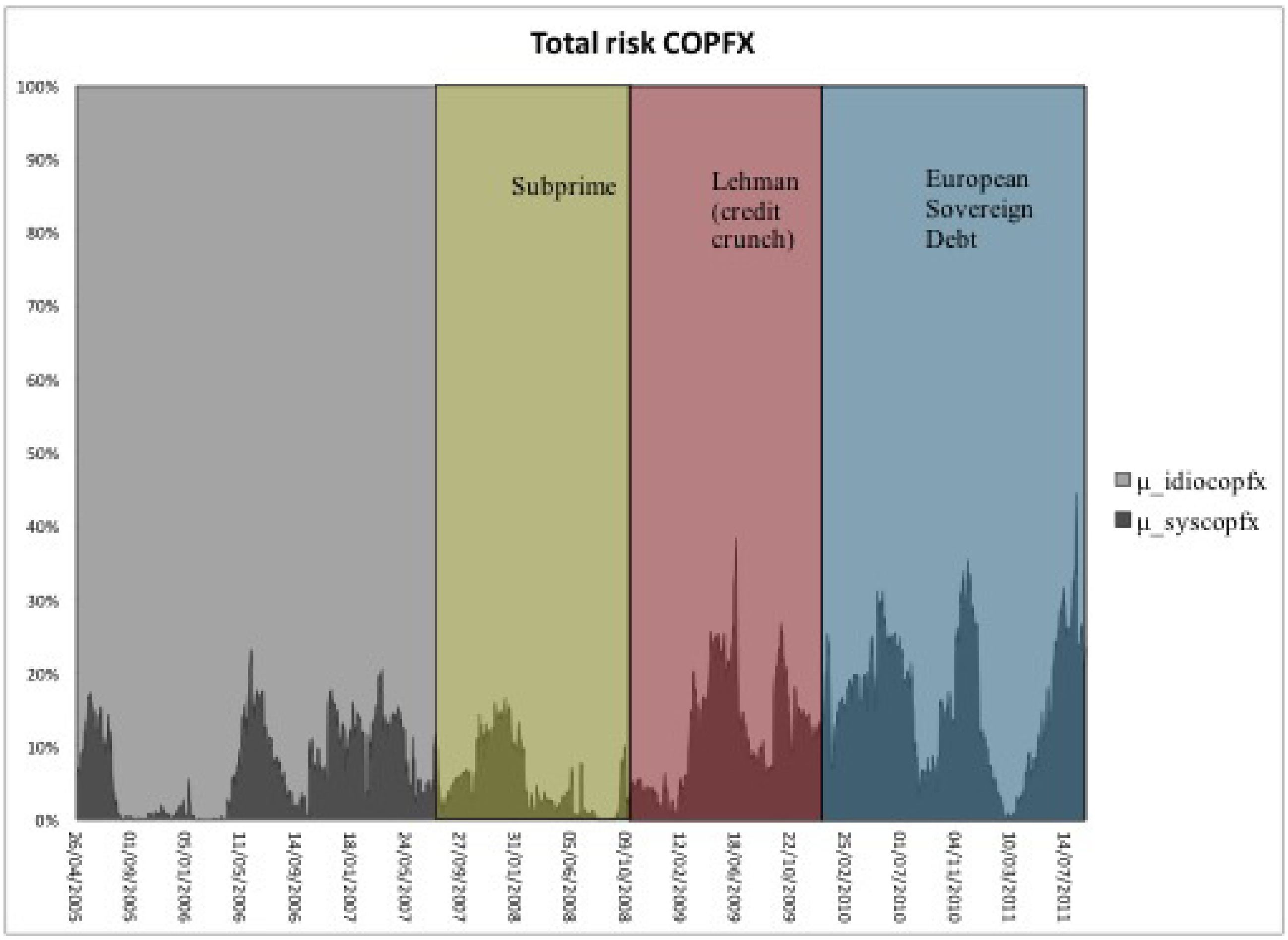
Figure 8

Conditional and time varying beta decomposition for S&P and COPFX

Panel A

60 day rolling window

Note: The β_{COPFX} statistics are the estimated linear regression coefficients of the single index model specification $E(R_{COPFX}) = \alpha_{COPFX} + \beta_{COPFX} R_{sp} + e_{COPFX}$ for 60 day rolling windows using the total sample period between 2/02/2005 and 31/08/2011. Where R_{COPFX} = Aggregate daily returns, R_{sp} = daily returns of the S&P500, α_{COPFX} = constant, and e_{COPFX} = an error term. The $\mu_{idiocol}$ and the μ_{syscol} are obtained discomposing β_{COPFX} using the relationships in equations (2.5) and (2.6).



Panel B
DCC-GJR-GARCH-Time varying

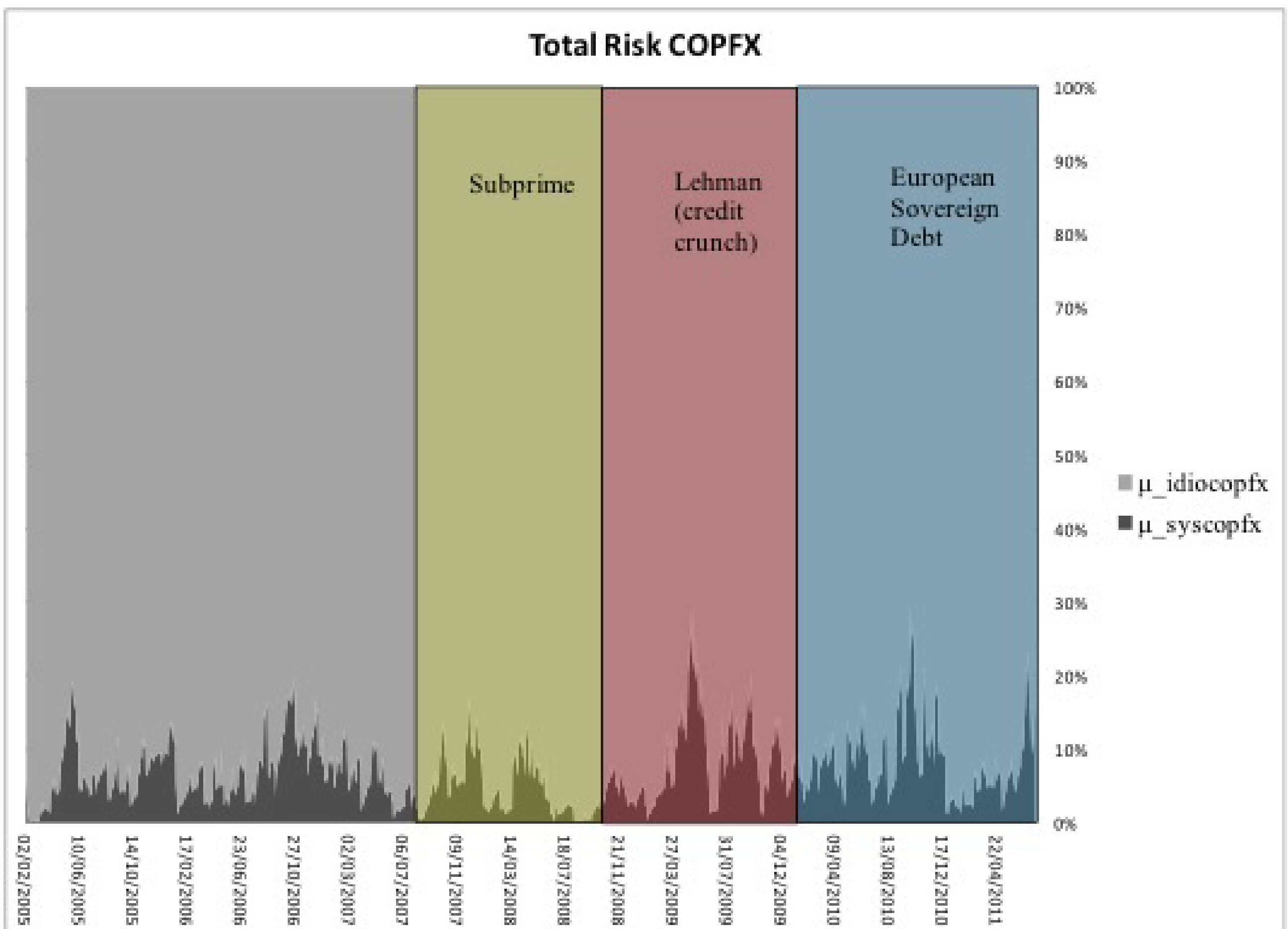
Note: The time-varying β_{COPFX} statistics are calculated using the DCC system specified in equation (2.3) in the following form:

$$h_{sp} = \alpha_{0sp} + \alpha_{1sp}\varepsilon^2_{sp_{t-1}} + \lambda_{1sp} I_{sp_{t-1}} \varepsilon^2_{sp_{t-1}} + \eta_{1sp} h_{sp_{t-1}}$$

$$h_{sp,copfx} = \alpha_{0sp,copfx} + \alpha_{1sp,copfx}\varepsilon_{sp_{t-1}}\varepsilon_{copfx_{t-1}} + \lambda_{1sp,copfx} I_{sp_{t-1}}\varepsilon_{sp_{t-1}} I_{copfx_{t-1}}\varepsilon_{copfx_{t-1}} + \eta_{1sp,copfx} h_{sp_{t-1},copfx_{t-1}}$$

$$h_{copfx} = \alpha_{0copfx} + \alpha_{1copfx}\varepsilon^2_{copfx_{t-1}} + \lambda_{1copfx} I_{copfx_{t-1}} \varepsilon^2_{copfx_{t-1}} + \eta_{1copfx} h_{copfx_{t-1}}$$

where: h_{sp} = the estimated conditional daily variance of the SP, h_{copfx} = the estimated conditional daily variance of aggregate and $h_{sp,copfx}$ = the estimated conditional covariance of S&P and Aggregate using the DCC model as explained in section 5. The β_{COPFX} , uniquecopfx and systematiccopfx are obtained by rearranging the estimated conditional daily variances and covariances by the relationships explained in equations (2.4), (2.5) and (2.6).



From Figure 6, and in the specific case of AGGREGATE and the rolling window betas, we can observe how the systematic risk increases at the beginning of the subprime crisis, decreases during the CCC, and then it begins to suddenly increase during the ESD crisis, but due to the smoothing effect persistent in the series this dampening effect occurs slowly. Interestingly, when we allow for time varying betas in order to correct for this smoothing effect, we can observe a sudden increase of systematic risk at the beginning and in the middle of the subprime crisis. In the case of the CCC we can observe these systematic peaks at the beginning of the crisis, but this effect dampens out quickly through the end of the crisis. Finally, in the case of ESD we can observe an increase of systematic risk relative to the two previous periods. This in turn, can lead us to believe that there is evidence in support of the decoupling/recoupling hypothesis as investors see that the impact of the news of the subprime and the CCC are not directly related to the fundamentals affecting the performance of AGGREGATE as opposed to the case of ESD in which the effects of the news may have a direct impact in the increase of systematic risk.

On the other hand, the observed behavior of COPFX rolling windows systemic risk in Figure 8 shows a dampening effect during the subprime crisis and a sudden increase towards the end of the CCC, and this trend is maintained throughout the ESD crisis. However, when we allow for dynamic correlation this increase in systemic risk is less pronounced than the one obtained by using the rolling windows method. Finally, it is worth pointing out the increase in systematic risk during mid-2006 for both AGGREGATE and COPFX before the crises. This is explained by three consecutive interest hikes of the Federal Reserve between March and June of 2006 which had a huge effect in Latin American markets. According to Ocampo (2009) these hikes had a direct effect in the cost of financing for the Latin America region that had enjoyed a period of stability since 2003. The effect of three consecutive hikes in such a short period of time caused a turbulence as the cost of financing adjusted to new levels and capital flows to the region diminished for this short period when foreign borrowers reassessed their investments.

From Figure 7, we can appreciate that in the case of MXLA both, the rolling window betas and the DCC betas, show an abnormal increase of systemic risk before the subprime crisis, and then dampen during the crisis due to the same reasons as above. This result can be intriguing at first sight, but it can be explained in part by the high positive correlation between the S&P500 and the MXLA (see Table 2.5). Another explanation can be that there is some evidence of decoupling in time of crisis, in line with the results obtained by Wang and Moore (2012) in the sense that the degree of integration between markets during the crisis was higher among developed countries than emerging ones. In the case of the CCC and ESD periods, the systematic risk is higher than in the subprime, but lower than the period before the subprime crisis. Even though, in the case of MXLA the systemic risk is lower on average in time of crisis than in the pre-crisis period, the total average systemic risk observed for the whole sample is higher than the observed ones for AGGREGATE and MXLA due to its high correlation with the SP.

In order to test if there is evidence of contagion among the time varying statistics, we conducted the test described in equation (2.11) for each of the u_{sys} *(%Systematic)* and time varying β_i respectively using Ordinary Least Squares (OLS). The results are summarized in Tables 2.8, 2.9 and 2.10:

Table 2.8
Test for evidence of contagion AGGREGATE

The results reported in this table are the estimated coefficients obtained from running the following OLS regression: $S_{i,t} = \alpha_{0,i} + \alpha S_{i,t-1} + \phi D_{i,t} + e_{i,t}$ where $S_{i,t}$ = the corresponding statistic (μ_{syscol} *(%Systematic risk AGGREGATE)* and $\beta_{AGGREGATE}$) for AGGREGATE, $D_{i,t}$ = a dummy variable that denotes the respective crisis dates and $\alpha_{0,i}$, $\alpha_{1,i}$, ϕ , $e_{i,t}$ are the respective coefficients from the OLS regression. $S_{i,t-1}$ is just the AR(1) of the corresponding statistic *(* μ_{syscol} *(%Systematic risk AGGREGATE)* and $\beta_{AGGREGATE}$) for AGGREGATE. The total sample period and the dummy crisis dates for each one of the six (6) regressions are the same as the ones presented in Tables 2.6, 2.7 and 2.8 for the subprime (ϕ_{Subprime}), CCC (ϕ_{CCC}) and ESD (ϕ_{ESD}) crises.
***1%; **5%; and *10% significance.

Dependent variables									
%Systematic Risk AGGREGATE					*Time varying Beta AGGREGATE*				
	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*		*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
$\phi_{Subprime}$	0.001	0.002	0.290	0.772	$\phi_{Subprime}$	(.001)	0.001	(1.174)	0.241
ϕ_{CCC}	0.000	0.002	0.117	0.907	ϕ_{CCC}	(.001)	0.001	(.997)	0.319
ϕ_{ESD}	0.005	0.002	2.743***	**0.006**	ϕ_{ESD}	0.001	0.001	1.628	0.104
AR(1)	0.962	0.007	136.496	0.000	AR(1)	0.976	0.005	183.524	0.000
R-squared	0.931				R-squared	0.965			
Adjusted R-squared	0.930				Adjusted R-squared	0.965			
S.E. of regression	0.029				S.E. of regression	0.013			

Table 2.9
Test for evidence of contagion MXLA

The results reported in this table are the estimated coefficients obtained from running the following OLS regression: $S_{i,t} = \alpha_{0,i} + \alpha S_{i,t-1} + \phi D_{i,t} + e_{i,t}$ where $S_{i,t}$ = the corresponding statistic ($\mu_{sysmxla}$ (*%Systematic risk MXLA*) and β) for MXLA, $D_{i,t}$ = a dummy variable that denotes the respective crisis dates, and $\alpha_{0,i}$, α , ϕ , $e_{i,t}$ are the respective coefficients from the OLS regression. $S_{i,t-1}$ is just the AR(1) of the corresponding statistic ($\mu_{sysmxla}$ (*%Systematic risk MXLA*) and β_{MXLA}) for MXLA. The total sample period and the dummy crisis dates for each one of the six (6) regressions are the same as the ones presented in Tables 2.6, 2.7 and 2.8 for the subprime ($\phi_{Subprime}$), CCC (ϕ_{CCC}) and ESD (ϕ_{ESD}) crises.
***1%; **5%; and *10% significance.

Dependent variables									
%Systematic Risk MXLA					*Time varying Beta MXLA*				
	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*		*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
$\phi_{Subprime}$	(.002)	0.002	(.934)	0.350	$\phi_{Subprime}$	(.019)	0.006	(2.95)***	**0.003**
ϕ_{CCC}	0.003	0.002	1.1869	0.235	ϕ_{CCC}	(.02)	0.006	(3.19)***	**0.002**
ϕ_{ESD}	0.003	0.002	1.5146	0.130	ϕ_{ESD}	(.013)	0.005	(2.52)**	**0.012**
AR(1)	0.954	0.007	133.9796	0.000	AR(1)	0.949	0.008	126.505	0.000
R-squared	0.001				R-squared	0.929			
Adjusted R-squared	0.976				Adjusted R-squared	0.929			
S.E. of regression	0.002				S.E. of regression	0.081			

Table 2.10
Test for evidence of contagion COPFX

The results reported in this table are the estimated coefficients obtained from running the following OLS regression: $S_{i,t} = \alpha_{0,i} + \alpha S_{i,t-1} + \phi D_{i,t} + e_{i,t}$, where $S_{i,t}$ = the corresponding statistic ($\mu_{syscopfx}$ (*%Systematic risk COPFX*) and β_{COPFX}) for COPFX, $D_{i,t}$ = a dummy variable that denotes the respective crisis dates, and $\alpha_{0,i}$, α , ϕ , $e_{i,t}$ are the respective coefficients from the OLS regression. $S_{i,t-1}$ is just the AR(1) of the corresponding statistic ($\mu_{syscopfx}$ (*%Systematic risk COPFX*) and β_{MXLA}) for COPFX. The total sample period and the dummy crisis dates for each one of the six (6) regressions are the same as the ones presented in Tables 2.6, 2.7 and 2.8 for the subprime ($\phi_{Subprime}$), CCC (ϕ_{CCC}) and ESD (ϕ_{ESD}) crises.
***1%; **5%; and *10% significance.

Dependent variables									
%Systematic Risk COPFX					Time varying Beta COPFX				
	Coefficient	Std. Error	t-Statistic	Prob.		Coefficient	Std. Error	t-Statistic	Prob.
$\phi_{Subprime}$	(.001)	0.001	(1.15)	0.251	$\phi_{Subprime}$	0.0024	0.002	1.204	0.229
ϕ_{CCC}	0.001	0.001	0.725	0.469	ϕ_{CCC}	(.001)	0.002	(.287)	0.774
ϕ_{ESD}	0.001	0.001	1.078	0.281	ϕ_{ESD}	0.0001	0.002	0.036	0.971
AR(1)	0.938	0.008	112.293	0.000	AR(1)	0.9553	0.007	136.682	0.000
R-squared	0.888				R-squared	0.919			
Adjusted R-squared	0.888				Adjusted R-squared	0.919			
S.E. of regression	0.016				S.E. of regression	0.028			

From Table 2.8 we can corroborate that, in the case of AGGREGATE, the only significant coefficients for %Systematic Risk are the ones related to the ESD, in all other cases we fail to reject the null of no contagion. These results are similar to the ones obtained using the FR-test statistic, in which we fail to reject the null of no contagion for the subprime and CCC, and reject it in the case of ESD for the reasons explained in section 2.6. In the case of Table 2.9, we obtain some conflicting results in the sense that when we test for contagion using the β_{MXLA} variable we corroborate the results obtained using the FR test, but when we use u_{sys} %Systematic Risk MXLA as the dependent variable we fail to reject the null of contagion in all three cases. One plausible explanation could be the higher variability of β_{MXLA} time series in contrast to the lower variability of the time series of u_{sys} (%Systematic). Finally from table 2.10 we corroborate the results obtained with the variation form of the FR test as we fail to reject the null of no contagion for β_{COPFX} and %Systematic Risk COPFX is rejected in all three crises using the total sample period.

2.7.2 .Contagion as volatility spillover

In tables 2.11, 2.12 and 2.13, we show the results for the significance of the dates of the crises and the volatility spillover from the US market at the univariate level using the GJR-GARCH model as specified in equation (2.8) scaled by a 100:

Table 2.11

Evidence of date and volatility spillover effect of the crises at the univariate level for AGGREGATE

The results reported in this table are the coefficients obtained from running the GJR-GARCH model in equation (2.8): $h_t = \alpha_0 + \alpha_1\varepsilon^2_{i_{t-1}} + \lambda_1 I_{t-1}\varepsilon^2_{i_{t-1}} + \eta_1 h_{t-1} + \gamma_0 X_t + \gamma_1 I_L X_t + \sum_{C=2}^{4}\gamma_C D_C \varepsilon^2_{S\&P_{t-1}} + \sum_{L=5}^{7}\gamma_L D_C I_L \varepsilon^2_{S\&P_{t-1}}$ where h_t = the conditional variance of AGGREGATE under scrutiny, ε^2_{t-1} are the squared returns of AGGREGATE filtered by an ARMA(1,2) process to account for partial autocorrelation, I_{t-1} is a dummy variable that takes either the value of 0 or 1 when $\varepsilon^2_{t-1} < 0$ or $0 > \varepsilon^2_{t-1}$, and h_{t-1} is the conditional variance from the previous period, $\varepsilon^2_{S\&P_{t-1}}$ denotes the squared lagged returns of the S&P, D_C = denotes a dummy variable where 0 denotes the dates of the pre crisis period and 1 the dates in which the crisis period occurs, I_L is a dummy variable that measures the effect of negative returns on the S&P and takes either the value of 0 or 1 when $\varepsilon_{S\&P_{t-1}} < 0$ or $0 > \varepsilon_{S\&P_{t-1}}$. The coefficients γ_0, γ_1, γ_C and γ_L are the coefficients of each variable estimated by maximum likelihood assuming normal innovations that is why we obtain a Z-statistic instead of a T-statistic. The total sample period and the dummy crisis dates for each one of the three (3) models are the same as the ones presented in Table 2.6 for the Subprime, CCC and ESD crises. ***1%; **5%; and *10% significance.

Dependent Variable-Variance equation				
RETURNS AGGREGATE				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
$\alpha_{0,\ \text{CONSTANT}}$	0.002	0.000	5.904	0.000
$\alpha_{1,\ \text{ARCH}}$	0.113	0.021	5.273	0.000
$\lambda_{1,\ \text{I(AGGREGATE)}}$	0.119	0.026	4.568***	0.000
$\eta_{1,\ \text{GARCH}}$	0.786	0.018	44.000	0.000
$\gamma_{0,\ \text{S\&P}^2\text{(-1)}}$	(.002)	0.001	(2.468)**	0.014
$\gamma_{1,\ \text{S\&P}^2\text{(-1)*I(S\&P)}}$	0.000	0.001	0.207	0.836
$\gamma_{\text{Subprime, S\&P}^2\text{(-1)}}$	0.001	0.001	2.302**	0.021
$\gamma_{\text{CCC, S\&P}^2\text{(-1)}}$	0.002	0.001	2.490**	0.013
$\gamma_{\text{ESD, S\&P}^2\text{(-1)}}$	0.009	0.002	4.388***	0.000
$\gamma_{\text{Subprime, S\&P}^2\text{(-1)*I(S\&P)}}$	(.0003)	0.001	(.276)	0.782
$\gamma_{\text{CCC, S\&P}^2\text{(-1)*I(S\&P)}}$	(.0003)	0.001	(.257)	0.797
$\gamma_{\text{ESD, S\&P}^2\text{(-1)*I(S\&P)}}$	(.009)	0.004	(2.389)**	0.017
R-squared	0.030			
Adjusted R-squared	0.028			
S.E. of regression	0.247			

Table 2.12

Evidence of date and volatility spillover effect of the crises at the univariate level for MXLA

The results reported in this table are the coefficients obtained from running the GJR-GARCH model in equation (2.8): $h_t = \alpha_0 + \alpha_1\varepsilon_{i_{t-1}}^2 + \lambda_1 I_{t-1}\varepsilon_{i_{t-1}}^2 + \eta_1 h_{t-1} + \gamma_0 X_t + \gamma_1 I_L X_t + \sum_{C=2}^{4}\gamma_C D_C \varepsilon_{S\&P_{t-1}}^2 + \sum_{L=5}^{7}\gamma_L D_C I_L \varepsilon_{S\&P_{t-1}}^2$ where h_t = the conditional variance of MXLA under scrutiny, ε_{t-1}^2 are the squared returns of MXLA filtered by an ARMA(1,2) process to account for partial auto-correlation, I_{t-1} is a dummy variable that takes either the value of 0 or 1 when $\varepsilon_{t-1}^2 < 0$ or $0 > \varepsilon_{t-1}^2$, and h_{t-1} is the conditional variance from the previous period, $\varepsilon_{S\&P_{t-1}}^2$ denotes the squared lagged returns of the S&P, D_C = denotes a dummy variable where 0 denotes the dates of the pre crisis period and 1 the dates in which the crisis period occurs, I_L is a dummy variable that measures the effect of negative returns on the S&P and takes either the value of 0 or 1 when $\varepsilon_{S\&P_{t-1}} < 0$ or $0 > \varepsilon_{S\&P_{t-1}}$. The coefficients γ_0, γ_1, γ_C and γ_L are the coefficients of each variable estimated by maximum likelihood that is why we obtain a Z-statistic instead of a T-statistic. The total sample period and the dummy crisis dates for each one of the three (3) models are the same as the ones presented in Table 2.6 for the Subprime, CCC and ESD crises. ***1%; **5%; and *10% significance.

Dependent Variable-Variance equation				
RETURNS MXLA				
	Coefficient	Std. Error	z-Statistic	Prob.
$\alpha_{0,\ \text{CONSTANT}}$	0.164	0.023	7.286	0.000
$\alpha_{1,\ \text{ARCH}}$	(.054)	0.014	(4.008)	0.000
$\lambda_{1,\ \text{I(MXLA)}}$	0.200	0.021	9.688***	0.000
$\eta_{1,\ \text{GARCH}}$	0.867	0.018	47.190	0.000
$\gamma_{0,\ \text{S\&P}^2(-1)}$	(.089)	0.050	(1.776)	0.076
$\gamma_{1,\ \text{S\&P}^2(-1)\text{*I(S\&P)}}$	0.334	0.127	2.639***	0.008
$\gamma_{\text{Subprime, S\&P}^2(-1)}$	0.218	0.091	2.391**	0.017
$\gamma_{\text{CCC, S\&P}^2(-1)}$	0.172	0.073	2.353**	0.019
$\gamma_{\text{ESD, S\&P}^2(-1)}$	(.042)	0.048	(.864)	0.388
$\gamma_{\text{Subprime, S\&P}^2(-1)\text{*I(S\&P)}}$	(.364)	0.190	(1.914)*	0.056
$\gamma_{\text{CCC, S\&P}^2(-1)\text{*I(S\&P)}}$	(.212)	0.151	(1.411)	0.158
$\gamma_{\text{ESD, S\&P}^2(-1)\text{*I(S\&P)}}$	(.087)	0.126	(.693)	0.489
R-squared	0.004			
Adjusted R-squared	0.003			
S.E. of regression	2.126			

Table 2.13

Evidence of date and volatility spillover effect of the crises at the univariate level for COPFX

The results reported in this table are the coefficients obtained from running the GJR-GARCH model in equation (2.8): $h_t = \alpha_0 + \alpha_1\varepsilon^2_{i_{t-1}} + \lambda_1 I_{t-1}\varepsilon^2_{i_{t-1}} + \eta_1 h_{t-1} + \gamma_0 X_t + \gamma_1 I_L X_t + \sum_{C=2}^{4}\gamma_C D_C \varepsilon^2_{S\&P_{t-1}} + \sum_{L=5}^{7}\gamma_L D_C I_L \varepsilon^2_{S\&P_{t-1}}$ where h_t = the conditional variance of COPFX under scrutiny, ε^2_{t-1} are the squared returns of COPFX filtered by an ARMA(1,2) process to account for partial auto-correlation, I_{t-1} is a dummy variable that takes either the value of 0 or 1 when $\varepsilon^2_{t-1} < 0$ or $0 > \varepsilon^2_{t-1}$, and h_{t-1} is the conditional variance from the previous period, $\varepsilon^2_{S\&P_{t-1}}$ denotes the squared lagged returns of the S&P, D_C= denotes a dummy variable where 0 denotes the dates of the pre crisis period and 1 the dates in which the crisis period occurs, I_L is a dummy variable that measures the effect of negative returns on the S&P and takes either the value of 0 or 1 when $\varepsilon_{S\&P_{t-1}} < 0$ or $0 > \varepsilon_{S\&P_{t-1}}$. The coefficients γ_0, γ_1, γ_C and γ_L are the coefficients of each variable estimated by maximum likelihood that is why we obtain a Z-statistic instead of a T-statistic. The total sample period and the dummy crisis dates for each one of the three (3) models are the same as the ones presented in Table 2.6 for the Subprime, CCC and ESD crises. ***1%; **5%; and *10% significance.

Dependent Variable-Variance equation				
RETURNS COPFX				
	Coefficient	Std. Error	z-Statistic	Prob.
$\alpha_{0,\ \mathrm{CONSTANT}}$	0.007	0.002	4.368	0.000
$\alpha_{1,\ \mathrm{ARCH}}$	0.192	0.019	10.359	0.000
$\lambda_{1,\ \mathrm{I(COPFX)}}$	(.07)	0.020	(3.495)***	**0.001**
$\eta_{1,\ \mathrm{GARCH}}$	0.833	0.013	63.063	0.000
$\gamma_{0,\ \mathrm{S\&P}^2(-1)}$	(.004)	0.003	(1.136)	0.256
$\gamma_{1,\ \mathrm{S\&P}^2(-1)*\mathrm{I(S\&P)}}$	0.012	0.006	2.195**	**0.028**
$\gamma_{\mathrm{Subprime,\ S\&P}^2(-1)}$	0.033	0.009	3.668	**0.000**
$\gamma_{\mathrm{CCC,\ S\&P}^2(-1)}$	0.015	0.007	2.162**	**0.031**
$\gamma_{\mathrm{ESD,\ S\&P}^2(-1)}$	(.004)	0.004	(1.025)	0.305
$\gamma_{\mathrm{Subprime,\ S\&P}^2(-1)*\mathrm{I(S\&P)}}$	(.051)	0.014	(3.628)***	**0.000**
$\gamma_{\mathrm{CCC,\ S\&P}^2(-1)*\mathrm{I(S\&P)}}$	(.026)	0.013	(2.088)**	**0.037**
$\gamma_{\mathrm{ESD,\ S\&P}^2(-1)*\mathrm{I(S\&P)}}$	0.004	0.008	0.526	0.599
R-squared	0.002			
Adjusted R-squared	0.001			
S.E. of regression	0.809			

From the previous tables we can observe that in the specific case of AGGREGATE there is asymmetry effect from its negative returns as well as spillovers from the S&P500 for the whole period, but no asymmetry effect from the negative returns from the S&P500. An additional volatility spillover effect is significant for all crises dates, but the asymmetry effect is significant only for the ESD.

In the case of MXLA there is an asymmetry effect from its own negative returns, but the spill-overs from the S&P500 are not separately significant although the asymmetric volatility spillover is strong. The additional crisis volatility spillover effect is significant for the subprime and CCC, but not for the ESD period. Also, the negative returns from the S&P500 are significant for the Subprime crisis. In the case of COPFX there is an asymmetric effect from its negative returns and the negative returns from the S&P but not from the S&P for the whole period. The volatility spillover effect and negative returns from the S&P are significant for the subprime and CCC, but not for the ESD crisis.

These results are in conflict with those obtained by applying the FR test in the sense that from the perspective of volatility spillovers there is contagion in all cases with the exception of the ESD period for COPFX and MXLA. The results obtained reinforce the validity of the S&P as a common channel of contagion for all three cases.

2.7.3. Robustness Checks Alternative fixed income factors

In order to check for robustness regarding the S&P500 as a common factor in the case of AGGREGATE, we used the EMBI global and the EFFA fixed income indices. There are large investments in Colombian local government debt in AGGREGATE, and fixed interest shocks may be more relevant. The results are summarized in Table 2.14.

Table 2.14
Evidence of date and volatility spillover
effect of the crises at the univariate level for EMBI and EFFA

The results reported in this table are the coefficients obtained from running the GJR-GARCH model in equation (2.8) using the specification described in Table 2.11 in which the lagged squared returns of the S&P are replaced by the lagged squared returns of the EMBI and EFFA for robustness check. ***1%; **5%; and *10% significance.

Dependent Variable-Variance equation									
RETURNS AGGREGATE (EMBI)					RETURNS AGGREGATE (EFFA)				
	Coefficient	Std. Error	z-Statistic	Prob.		Coefficient	Std. Error	z-Statistic	Prob.
$\alpha_{0,\ \mathrm{CONSTANT}}$	0.002	0.000	6.249	0.000	$\alpha_{0,\ \mathrm{CONSTANT}}$	0.0022	0.000	5.180	0.000
$\alpha_{1,\ \mathrm{ARCH}}$	0.107	0.022	4.935	0.000	$\alpha_{1,\ \mathrm{ARCH}}$	0.1112	0.023	4.915	0.000
$\lambda_{1,\ \mathrm{I(AGGREGATE)}}$	0.125	0.027	4.670***	**0.000**	$\lambda_{1,\ \mathrm{I(AGGREGATE)}}$	0.1282	0.028	4.604***	**0.000**
$\eta_{1,\ \mathrm{GARCH}}$	0.780	0.018	43.232	0.000	$\eta_{1,\ \mathrm{GARCH}}$	0.7687	0.020	37.548	0.000
$\gamma_{0,\ \mathrm{EMBI}}{}^{2}(-1)$	(.0098)	0.004	(2.27)**	**0.023**	$\gamma_{0,\mathrm{EEFA}}{}^{2}(-1)$	(.005)	0.014	(.381)	0.703
$\gamma_{1,\ \mathrm{EMBI}}{}^{2}(-1)*I(\mathrm{EMBI})$	0.004	0.005	0.798	0.425	$\gamma_{1,\mathrm{EEFA}}{}^{2}(-1)*I(\mathrm{EEFA})$	(.013)	0.015	-0.821	0.412
$\gamma_{\mathrm{Subprime,\ EMBI2(-1)}}$	0.002	0.008	0.253	0.800	$\gamma_{\mathrm{Subprime,EEFA}}{}^{2}(-1)$	0.012	0.015	0.757	0.449
$\gamma_{\mathrm{CCC,\ EMBI}}{}^{2}(-1)$	0.011	0.005	2.287**	**0.022**	$\gamma_{\mathrm{CCC,EEFA}}{}^{2}(-1)$	0.022	0.019	1.169	0.243
$\gamma_{\mathrm{ESD,\ EMBI}}{}^{2}(-1)$	0.077	0.024	3.203***	**0.001**	$\gamma_{\mathrm{ESD,EEFA}}{}^{2}(-1)$	0.238	0.060	3.961***	**0.000**
$\gamma_{\mathrm{Subprime,\ EMBI}}{}^{2}(-1)*I(\mathrm{EMBI})$	0.011	0.021	0.5428	0.587	$\gamma_{\mathrm{Subprime,EEFA}}{}^{2}(-1)*I(\mathrm{EEFA})$	(.013)	0.022	(.583)	0.560
$\gamma_{\mathrm{CCC,\ EMBI}}{}^{2}(-1)*I(\mathrm{EMBI})$	(.0009)	0.006	(.151)	0.880	$\gamma_{\mathrm{CCC,EEFA}}{}^{2}(-1)*I(\mathrm{EEFA})$	0.004	0.030	0.128	0.898
$\gamma_{\mathrm{ESD,\ EMBI2(-1)}*I(\mathrm{EMBI})}$	0.028	0.050	0.55	0.580	$\gamma_{\mathrm{ESD,EEFA}}{}^{2}(-1)*I(\mathrm{EEFA})$	(.223)	0.105	(2.115)**	**0.034**
R-squared	0.030				R-squared	0.030			
Adjusted R-squared	0.028				Adjusted R-squared	0.028			
S.E. of regression	0.247				S.E. of regression	0.247			

We can observe that when we use either the EMBI or the EFFA as the common factor for AGGREGATE we only obtain a marginal improvement in the R^2 statistic. In the case of the EMBI, we find a significant spillover effect but not an asymmetry effect which is important because it represents the impact of negative returns during the crisis period. There is also evidence of contagious spillovers from the EMBI in the subprime and CCC but not in the ESD crisis, nevertheless no asymmetry effect. The negative returns of the EMBI are not significant during the crises periods.

In the case of the EFFA we find neither a spillover effect nor an asymmetry effect. There is, however, evidence of spillovers from the EFFA in the ESD crisis but not in the Subprime and CCC periods. There are two reasons as to why the EMBI is more significant than the EFFA in terms of explaining volatility spillovers in AGGREGATE: 1) The EMBI is computed from emerging market issuers (Greece included) with similar weights, and since Colombia is also a small component of the EMBI this may lead to endogeneity issues, and 2) The EFFA is a market weighted index for the whole Eurozone, so the effect of volatility of the countries in crisis is mitigated by the larger and more stable countries in the index. However, it is important to mention that when we use the EMBI or the EFFA as the common factor in the case of AGGREGATE, the results are more in line with those obtained by previous tests.

Overall we find that, with the exception of the MXLA during the ESD crisis, all the other periods and assets under scrutiny exhibited some form of contagion from the S&P500. However, when the crisis dates are taken into account the only results that converge with those obtained by the FR test and the basic OLS procedure using time varying statistics for AGGREGATE are those that take the effect of negative returns into account. In tables 2.15, 2.16 and 2.17 there is a summary of results for the three tests and the additional choice of common factor for aggregate:

Table 2.15

Summary of contagion tests and variance contribution test for AGGREGATE

	Summary tests for AGGREGATE (Y=CONTAGION, N= NO CONTAGION)									
	FR	DFGM-FR	BHN		GJR-GARCH variance regressor					
Crisis			Beta	Systematic	Crisis Date S&P	Crisis Date EMBI	Crisis Date EFFA	Leverage S&P	Leverage EMBI	Leverage EFFA
SUBPRIME	Y	Y	N	N	Y	N	N	N	N	N
LEHMAN-CCC	N	Y	N	N	Y	Y	N	N	N	N
ESD	Y	Y	N	Y	Y	Y	Y	N	Y	Y

Additional GRJ-GARCH whole equation results	
S&P significant:	YES
Leverage (Negative returns from S&P) significant:	NO
EMBJ significant:	YES
Leverage (Negative returns from EMBI) significant:	NO
EFFA significant:	NO
Leverage (Negative returns from EFFA) significant:	NO

Table 2.16

Summary of contagion tests and variance contribution test for MXLA

	Summary tests for MXLA (Y=CONTAGION, N= NO CONTAGION)					
	FR	DFGM-FR	BHN		GJR-GARCH variance regressor	
					Crisis Date	
Crisis			Beta	Systematic	S&P	Leverage
SUBPRIME	Y	Y	Y	N	Y	Y
LEHMAN-CCC	Y	N	Y	N	Y	N
ESD	Y	Y	Y	N	N	N

Additional GRJ-GARCH whole equation results

S&P significant:	NO
Leverage (Negative returns from S&P) significant:	YES

Table 2.17

Summary of contagion tests and variance contribution test for COPFX

	Sumary tests for COPFX (Y=CONTAGION, N= NO CONTAGION)					
	FR	DfGM-FR	BHN		GJR-GARCH variance regressor	
					Crisis Date	
Crisis			Beta	Systematic	S&P	Leverage
SUBPRIME	Y	N	N	N	Y	Y
LEHMAN-CCC	Y	N	N	N	Y	Y
ESC	Y	N	N	N	N	N

Additional GRJ-GARCH whole equation results

S&P significant:	NO
Leverage (Negative returns from S&P) significant:	YES

From the summary tables we can compare the results obtained by the different methodologies. In the case of COPFX, the results obtained for the DFGM adjusted FR statistic and BHN give the same results when we measure contagion either by the Beta statistic or the degree of systematic risk. Furthermore, in the case of AGGREGATE, when we measure the effect of the volatility contagion (GJR-GARCH model) the S&P is significant in all crises dates converging with the results obtained using the DFGM adjusted FR statistic. However, when we take the leverage (negative returns) effect of the S&P there is not a significant contribution to variance in all the specified crises dates. On the other hand, when we use the EMBI and the EFFA as common factor there is no evidence of spillovers in the subprime crisis and the only significant asymmetry effect (negative returns) is the one of the ESD crisis.

In the case of MXLA the results obtained for the FR and the BHN in the beta case are the same with the exception of the ESD crisis, but when we conduct the BHN test using systematic risk the result changes to no contagion in all three cases. Furthermore, when we test for the significance of the variance regressors in the GRJ-GARCH equation for the whole period, we observe that there is evidence from volatility spillovers from the negative returns of the S&P in all three cases. Finally, when we test for the significance of the crisis dates in their contribution to variance, and we obtain mixed results for MXLA and AGGREGATE, with the only exception being COPFX where both the effects of the S&P and its leverage is the same for all the crises periods. Finally, it is important to mention that with the exception of MXLA, all the coefficients of the S&P and crises dates although significant are very close to zero for AGGREGATE under the univariate GRJ-GARCH specification.

2.7.4. Robustness Checks for non normality

In order to check for robustness regarding the observed differences among models of contagion, our model of choice was a quantile autoregression model as described in Appendix C given the asymmetric nature of our data. The QAR(1) when applied to the time varying statistics from the BHN model offer a framework that provides further economic intuition to the testing of contagion[25]. By dividing the observed statistics into quantiles (25, 50 and 75%), and allowing an AR(1) term to correct for auto-correlation, we can isolate the significance of the crisis period. The logic behind the specification is that if indeed there is contagion during the defined crisis period, one should observe a higher com-

25. According to Baur (2013), by estimating over the extreme quantiles we can observe the (asymmetric) structure of dependence in the tails of the distribution in the direct context of a factor model. This is why in the context of this chapter quantile regression becomes a handy tool to check the robustness of the results obtained using the BHN model.

ponent of systematic risk during the defined dates than in other periods. Therefore, if the crisis periods coincide with the higher periods of systematic risk observed from the common factor (S&P), we can test for contagion if highest quantile (75% or above) coefficients are significant. In Tables 2.18, 2.19 and 2.20 we summarize the results:

Table 2.18
Summary statistics of the QAR(1) model-AGGREGATE

The results reported in this table are the coefficients obtained from running the following quantile regression: $F^{-1}(q|S_{i,t}) = \alpha_{q,i} + \alpha_{1q,i}S_{iq,t-1} + \phi D_{iq,t} + F_{\varepsilon}^{-1}(q|S_{i,t})$ where $F^{-1}(q|S_{i,t})$ = are the conditional quantiles of (μ_{syscol} (*%Systematic risk AGGREGATE*), $D_{i,t}$ = a dummy variable that denotes the respective crisis dates and $\alpha_{0,i}$, $\alpha_{1,i}$, ϕ , $F_{\varepsilon}^{-1}(q|S_{i,t})$ are the respective coefficients from the quantile regression for the respective quantiles (in our case 0.25, 0.5, 0.75 and 0.90). $S_{i,t-1}$ is just the AR(1) of the corresponding statistic. The total sample period and the dummy crisis dates for each one of the four (4) regressions are the same as the ones presented in Tables 2.6, 2.7 and 2.8 for the subprime ($\phi_{Subprime}$), CCC (ϕ_{CCC}) and ESD (ϕ_{ESD}) crises.

Dependent Variable-%Systematic Risk AGGREGATE									
	Quantile 25%					*Quantile 50%*			
	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*		*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
$\phi_{Subprime}$	(.001)	0.001	(.547)	0.585	$\phi_{Subprime}$	0.000	0.001	0.019	0.985
ϕ_{CCC}	(.003)	0.001	(2.441)	0.015	ϕ_{CCC}	0.000	0.001	0.077	0.939
ϕ_{ESD}	0.002	0.001	1.735*	**0.083**	ϕ_{ESD}	0.002	0.001	3.102***	0.**002**
AR(1)	0.923	0.013	69.006	0.000	AR(1)	1.014	0.006	177.502	0.000
	Quantile 75%					*Quantile 90%*			
$\phi_{Subprime}$	0.000	0.001	0.205	0.838	$\phi_{Subprime}$	0.006	0.004	1.625	0.104
ϕ_{CCC}	0.000	0.001	0.443	0.658	ϕ_{CCC}	0.002	0.003	0.746	0.456
ϕ_{ESD}	0.003	0.001	3.273***	**0.001**	ϕ_{ESD}	0.007	0.003	2.261**	**0.024**
AR(1)	1.055	0.005	233.258	0.000	AR(1)	1.044	0.010	107.910	0.000

Table 2.19
Summary statistics of the QAR(1) model-MXLA

The results reported in this table are the coefficients obtained from running the following quantile regression: $F^{-1}(q|S_{i,t}) = \alpha_{q,i} + \alpha_{1q,i}S_{iq,t-1} + \phi D_{iq,t} + F_{\varepsilon}^{-1}(q|S_{i,t})$ where $F^{-1}(q|S_{i,t})$ = are the conditional quantiles of ($\mu_{sysmxla}$ (*%Systematic risk MXLA*), $D_{i,t}$ = a dummy variable that denotes the respective crisis dates and $\alpha_{0,i}$, $\alpha_{1,i}$, ϕ , $F^{-1}(q|S_{i,t})$ are the respective coefficients from the quantile regression for the respective quantiles (in our case 0.25, 0.5, 0.75 and 0.90). $S_{i,t-1}$ is just the AR(1) of the corresponding statistic. The total sample period and the dummy crisis dates for each one of the four (4) regressions are the same as the ones presented in Tables 2.6, 2.7 and 2.8 for the subprime ($\phi_{Subprime}$), CCC (ϕ_{CCC}) and ESD (ϕ_{ESD}) crises. ***1%; **5%; and *10% significance.

Dependent Variable-%Systematic Risk MXLA									
	Quantile 25%					*Quantile 50%*			
	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*		*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
$\phi_{Subprime}$	(.006)	0.003	(1.999)**	**0.046**	$\phi_{Subprime}$	0.000	0.001	0.419	0.676
ϕ_{CCC}	(.003)	0.003	(1.18)	0.238	ϕ_{CCC}	0.003	0.001	2.964***	**0.003**
ϕ_{ESD}	0.002	0.002	1.065	0.287	ϕ_{ESD}	0.001	0.001	0.964	0.335
AR(1)	0.962	0.006	158.114	0.000	AR(1)	0.979	0.003	341.180	0.000
	Quantile 75%					*Quantile 90%*			
$\phi_{Subprime}$	0.002	0.001	1.960**	**0.050**	$\phi_{Subprime}$	0.004	0.002	1.522	0.128
ϕ_{CCC}	0.004	0.001	4.634***	**0.000**	ϕ_{CCC}	0.004	0.001	3.619***	**0.000**
ϕ_{ESD}	0.000	0.001	0.451	0.652	ϕ_{ESD}	(.0003)	0.001	-0.237	0.813
AR(1)	0.989	0.003	343.699	0.000	AR(1)	0.969	0.007	144.836	0.000

Table 2.20
Summary statistics of the QAR(1) model-COPFX

The results reported on this table are the coefficients obtained from running the following quantile regression: $F^{-1}(q|S_{i,t}) = \alpha_{q,i} + \alpha_{1q,i}S_{iq,t-1} + \phi D_{iq,t} + F_{\varepsilon}^{-1}(q|S_{i,t})$ where $F^{-1}(q|S_{i,t})$ = are the conditional quantiles of ($\mu_{syscopfx}$ (*%Systematic risk COPFX*), $D_{i,t}$ = a dummy variable that denotes the respective crisis dates and $\alpha_{0,i}$, $\alpha_{1,i}$, ϕ , $F_{\varepsilon}^{-1}(q|S_{i,t})$ are the respective coefficients from the quantile regression for the respective quantiles (in our case 0.25, 0.5, 0.75 and 0.90). $S_{i,t-1}$ is just the AR(1) of the corresponding statistic. The total sample period and the dummy crisis dates for each one of the four (4) regressions are the same as the ones presented in Tables 2.6, 2.7 and 2.8 for the subprime ($\phi_{Subprime}$), CCC (ϕ_{CCC}) and ESD (ϕ_{ESD}) crises.

Dependent Variable-%Systematic Risk COPFX									
	Quantile 25%					*Quantile 50%*			
	Coefficient	Std. Error	t-Statistic	Prob.		Coefficient	Std. Error	t-Statistic	Prob.
ϕSubprime	(.003)	0.001	(4.689)***	**0.000**	ϕSubprime	(.002)	0.001	(3.378)***	**0.001**
ϕCCC	(.002)	0.001	(2.615)***	**0.009**	ϕCCC	(.001)	0.001	(1.833)*	0.067
ϕESD	(.001)	0.001	(1.282)	0.200	ϕESD	0.000	0.000	0.285	0.775
AR(1)	0.893	0.011	82.958	0.000	AR(1)	0.996	0.008	118.681	0.000
	Quantile 75%					*Quantile 90%*			
ϕSubprime	0.000	0.000	0.112	0.911	ϕSubprime	(.001)	0.001	(1.154)	0.2488
ϕCCC	0.001	0.001	2.061**	**0.040**	ϕCCC	0.004	0.002	1.625	0.104
ϕESD	0.001	0.000	1.544	0.123	ϕESD	0.002	0.002	1.379	0.168
AR(1)	1.041	0.004	244.281	0.000	AR(1)	1.066	0.016	65.498	0.000

Observing the results obtained from the previous tables, we can notice that in the case of AGGREGATE there is evidence of contagion just for the ESD crisis in line with the results of BHN but not the FR. This is important since in the case of AGGREGATE there is evidence of negative skewness and high positive kurtosis which indicate the presence of heavy tails; by using the QAR(1) specification we can observe the exact behavior of the extreme values and correct the bias generated by tests based on OLS procedures. In the case of MXLA, there is contagion just in the case of the CCC as opposed to the OLS test in table 2.9, that lead to no contagion in all three cases using the same statistic. Finally, for the COPFX we find that there is no evidence of contagion at the highest quantile for all of the periods.

2.8. Conclusion

Using a time-varying framework we were able to analyze the behavior of a particularly isolated (autarchic) asset during the GFC. In this particular case, we argue that the Colombian private pension funds can be seen as autarchic assets due to their particular regulatory constrains regarding their portfolio holdings. Even though this “quantitative restrictions” can limit the risk/return potential of the autarchic portfolio, this same restrictions can limit the potential losses in time of crisis as seen by the higher Sharpe ratios of AGGREGATE against regional and global benchmarks during the crisis period.

Furthermore, our time varying framework allows us to decompose risk into its systematic and idiosyncratic components by assuming that all shocks are transmitted through a common factor, which in our case was the S&P500 index and a couple of bond indices, in order for further test contagion by asset type in the case of the Colombian private pension funds. Using this decomposition approach, we were able to test for contagion in the context of its two broader definitions: 1) As the notion that contagion creates additional linkages in market co-movement, and 2) As the notion that contagion creates additional volatility spillover from one market to another. Although the proposed models for testing contagion are commonly used in the literature on the subject, our contribution is that, by allowing the models to capture the significance of the effect of negative returns in a financial contagion framework, new insights can be gain into the nature and the magnitude of contagion in asset returns. Additionally, by using quantile autoregression to test the significance of crisis dates using time varying systemic risk is possible to overcome some of the limitations and biases generated by asymmetric data.

Our results using the first notion found evidence that in the case of the Colombian funds there was no evidence of contagion during the first two episodes of the GFC when we allowed for time varying volatilities and different common factors. However, during the ESD crisis episode there is strong evidence of contagion in all tests, including the robustness QAR(1) case, even when we allow for different channels of transmission such as the EMBI and the EFFA indices. In the case of the MXLA index the results of the robustness test show that there was contagion only during the CCC episode as opposed to the OLS that tested negative contagion during the three crises. In the specific case of the Colombian exchange rate, the results were mixed in the sense that, although there was no significant statistical effect for the dates of the crisis, there was still a clear interdependency from the S&P and the robustness test shows no evidence of contagion at the higher quantile. Indeed, another question for future research is regarding the impact of floating exchanges regimes in the volatility of stocks and bonds in emerging countries. Finally, the GJR-GARCH specification for testing the second notion led us to a set of different results where there was contagion for all assets under scrutiny for the exception of the ESD crisis period for COPX and the MXLA. However, when we allow for the leverage effect of negative returns, the results tend to be more in line than those obtained using the first notion.

Our findings are similar to the ones of Dooley and Hutchison (2009), in the sense that a first sight there is a strong evidence of decoupling during the year 2007. Our results are also in line with the finding of Boyer et al. (2006) that, using a different methodology, have found that the interdependence among accessible assets was greater than the inaccessible (autarchic) assets. Although there was evidence of decoupling in regard to the Colombian funds, our findings in the case of the MXLA index also show a strong evidence of recoupling in line with those of Frank & Hesse (2009) in their study of the EMBI. Finally, and most importantly, we hope that by analyzing the effect of government regulation in emerging markets there can be some lessons to be learned in regard to what special kind of assets can help to mitigate the effects of contagion.

Chapter 3

The performance of State Owned Enterprises in BRIC countries during the GFC

3.1. Introduction

In recent years there has been a change in paradigm regarding foreign direct investment (FDI) in emerging markets as these countries are shifting from being recipients to becoming investors in their own right. UNCTAD (2012) estimates that, for the first time, in 2010 developing countries received more than 50% of total global FDI and that 30% of global FDI is coming directly from emerging markets. It is in this context that emerging markets State Owned Enterprises (SOEs) have become increasingly important agents for fostering economic growth and developing functional capital markets in their countries of origin. Although SOEs multinationals represent just 1% of the total multinational companies by market capitalization around the world, they account for at least 11% of total FDI, due in part to the increasing trend of national governments of taking an active role in promoting economic growth, and with an estimated USD 5 trillion of assets under management their share of global FDI will continue to increase (UNCTAD, 2012). Therefore, it is an important research question for both, academics and policy makers, to analyze the real effects of government ownership on the financial performance of SOEs as these companies become publicly traded companies through partial privatization processes around the world.

Most of the literature concerning the behavior of returns of SOEs is focused on the issue of government versus private ownership and its effect on performance. Hart et al. (1997) and Shleifer (1998) argue that, from a contractual perspective, a government should be indifferent between either class of ownership since it can use its regulatory power to draft optimal contracts in order to force a private supplier to deliver exactly what it wants, and in those cases private ownership should be superior to government ownership as it implies an increase of efficiency derived from the profit-maximizing objective of the private agent. Even in extreme cases where non-contractible quality (represented by social welfare) is an issue, e.g. public schooling, Shleifer (1998) argues that private ownership can lead to superior results if the government knows exactly what it wants, drafts the optimal contract and enforces it through regulation. However, previous theoretical work by Shapiro and Willing (1990) suggests exactly the opposite and argues that, when non-contractible quality is an issue, public ownership is preferred since the cost of drafting, implementing and monitoring effective regulation that maximizes social welfare will outweigh the benefits of privatization. Finally, Sappington and Stiglitz (1987) argue that, depending on the kind of service or good required by the government, the choice of public versus private ownership is not dichotomous, and that in most cases a public-private partnership should be the optimal solution for the cost-regulation dilemma.

Based on these opposing theoretical views, there are a significant number of empirical studies that used different models to test the comparative performance of state versus private ownership. Most of these studies used data from the privatization processes of SOEs around the globe that took place during the last three decades (Bortolotti and Perotti, 2007). The first empirical studies on the subject tested relative performance using a set of accounting variables of privatized SOEs against the same variables from the pre-privatization period; they found that for both developed and developing countries privatization had led to statistically meaningful increases in sales, operating efficiency, and profitability (see: Boubakri and Cosset, 1998; D'Souza and Megginson, 1999; Megginson et al., 1994). Also, using a comprehensive dataset of privatized Mexican SOEs, La Porta and Lopez-de-Silanes (1999) found that privatized SOEs exhibited superior financial performance in the post privatization period, but that a significant portion in the increase of profits was explained by savings from layoffs. Dewenter and Malatesta (2001) using a dataset composed of the largest global SOEs found evidence that profitability increased in the immediate three years after privatization. La Porta and Lopez-de-Silanes (1999) find that labor intensity decreased significantly after privatization. On the other hand, Estrin et al. (2009) showed that for the specific case of Eastern Europe and former soviet countries private ownership of former SOEs contributed positively to total factor productivity.

Other studies on the subject of privatization of SOEs focused on the development of capital markets. For example, Subrahmanyam and Titman (1999) hypothesized that privatizing SOEs via the public capital markets helps to develop the capital market in question by creating a snowballing effect attracting new investors. This hypothesis was in line with later findings by Megginson et al. (2004) that used a global sample of 2.547 privatized SOEs, and found evidence that in less developed markets a Share Issue Privatization (SIP) was the preferred vehicle for privatization in order to develop local capital markets, as opposed to developed countries where direct sales to small groups of private investors was usually the norm. Bortolotti et al. (2004), using a comprehensive dataset that encompassed both developed and emerging markets, found evidence that privatization was more likely to occur in wealthy democracies with high public debt and where common law was the norm.

In summary, most of these studies gave evidence in support of privatization, one possible explanation as to why government ownership tended to underperform private ownership is patronage (Shleifer, 1998; Shleifer and Vishny, 1994). According to Shleifer and Vishny (1994), patronage occurs when a government uses its dominant position in SOEs to provide benefits to political supporters in the form of above-market wages or in the form of transfer payments through bribes and corruption. La Porta et al. (2002) concluded that state ownership of the financial sector tends to fail as an instrument for promoting economic growth due mainly to politicization. Furthermore, by isolating political influence as a factor, Dinç (2005) concludes that government owned banks tend to increase lending during election years as opposed to private competitors. In the case of Vietnam, Nguyen and Van Dijk (2012) found that patronage was less harmful for SOEs than for private firms, but that in either case it hindered economic growth. There is empirical evidence that publicly traded politically connected firms tend to be twice as likely to be bailed out by their respective governments in time of crisis than non-connected firms (Faccio et al., 2006). In a later study, Faccio (2010) found evidence that privatized firms with political connections have more access to external financing, but have poorer performance than non-connected peers. In the case of India, Dinc and Gupta (2011) found that government firms located in the ruling minister's home district were never privatized, the authors suggested patronage as a possible explanation. However, McGuinness (2012) argued that, in the case of the Chinese SOE Initial Public Offerings (IPOs), there was no convincing evidence of underpricing due to an investor perception of higher risk or that politically connected "cornerstone" investors made superior returns during these IPOs. Firth et al. (2010) hypothesized that political connections could be a reason why local Chinese mutual funds tended to quickly agree with the SOE management position in matters that affected the shareholders.

During the GFC the role of state ownership has been revisited given the fact that Western governments (the US included) had to take huge ownership stakes in previously privately owned banks in order to avoid a collapse of the financial sector (Borisova and Megginson, 2011). The fact that governments were there to bailout the banking sector was primarily due to the misconception by the general public that government guarantees were in place to cover non performing investments (Acharya and Franks, 2009). In a comparative study of the cost of debt, Borisova and Megginson (2011) observed that the cost of financing was lower for state-owned enterprises than for partially privatized or private enterprises due to the implicit belief by lenders of a government guarantee. The effect of government ownership on the capital structure of the firm can be beneficial, and when this effect is taken into account, the differences in performance between private and government owned become statistically insignificant (Knyazeva et al., 2009). However, there is evidence that partial privatization can enhance operating performance, even if the government retains control of the firm (Gupta, 2005). The theoretical argument in favor of partial privatization is that politicization is in itself an agency problem that can be alleviated by the increasing demands of credible financial information from minority shareholders that trade in the public stock market (E. F. Fama, 1980; Holmstrom and Tirole, 1993). Chen et al. (2009) argue that in the specific case of China the partially privatized SOEs where the central government is the major shareholder exhibited better operating performance than other forms of ownership such as state management bureaus, local governments and private companies. Li et al. (2011) argue that big government firms in China provide better safeguards for shareholder wealth protection than their private counterparts.

In the case of the financial sector in the Asia Pacific region there is evidence that government ownership reduces losses in crisis periods but also hinders growth in normal periods (Hossain et al., 2013). For example, Liu and Siu (2011) provided evidence that SOEs valued capital investments at a much lower discount rate than partially privatized SOEs and private firms in order to foster growth according to the central government directives.

Unlike previous work on the subject of privatization, this chapter focuses on the comparative return performance of the largest SOEs in Brazil, Russia, India and China which are commonly known as the BRIC countries against industry competitors in the US during the GFC, and what we can learn from the performance of SOEs stocks during the GFC. In this chapter, as opposed to the previous one, our main objective is to test for evidence of financial contagion in the context of SOE portfolio performance. Since the GFC originated from the US, in this chapter we assume that the returns of the SOEs and the comparable US industries can be explained by the Fama and French three factor model plus momentum, usually known as the Carhart model (Carhart, 1997; Fama and French, 1993, 1998). For the purposes of this chapter we assume that the US factors are the common drivers for the SOEs stocks during the GFC in order to avoid possible endogeneity issues. Also, since we know that the US market was the originator of the GFC it is not counterintuitive to hypothesize that US factors act as contagion carriers to emerging markets[26]. Our hypothesis is that if indeed government ownership is beneficial in partially privatized companies in times of crisis, SOEs should experience less severe losses than private competitors. In other words, we expect government ownership to act like a "cushion" during crisis periods. On the other hand, we expect that SOEs exhibit smaller returns in growth periods than their private counterparts. The reason being that SOEs are companies where bankruptcy risks are mitigated by having stable dividend policies, and taking a more conservative approach toward investment opportunities than private companies during economic "boom" periods (He et al., 2012).

26. For examples of recent studies of the US as carrier of contagion see: (Beirne et al., 2008; Bekaert, Ehrmann, et al., 2011; Bekaert, Harvey, et al., 2011; Dooley and Hutchison, 2009; Dufrénot et al., 2011; Dungey et al., 2010; Fazio, 2007; Felices and Wieladek, 2012; Korkmaz et al., 2012).

We contribute to the literature by accounting for industry sectors and finding a meaningful mechanism for benchmarking SOEs performance. Also, we argue that by using quantile regression we can observe the changes of factor loadings attributable to tail dependence during crisis periods, and the effect of contagion during those periods.

The remainder of the book is organized as follows: in Section 3.2 we describe the data and sources; in Section 3.3 we describe in detail our model of choice for measuring the performance of our proxy for state ownership, and how the use of quantile regressions can provide additional information in time of crisis; in Section 3.4 we discuss the results obtained from the linear, quantile and cross sectional regression models, and in Section 3.5 we conclude.

3.2. Data

In order to compile our publicly traded state owned enterprises dataset and avoid liquidity issues, we selected only SOEs that are components of their national stock market indexes[27], and where the majority of the company shares are controlled by the central government or any other form of government agency[28]. For all the companies in our study, with the exception of the consumer staple sector in Brazil, the state holds majority control (50% or more). In the specific case of the consumer staple sector in Brazil the state holdings add up to only 40%, but these holdings are still larger than the ones held by private shareholders; therefore one can argue that still in this case the state can exert considerable control in the companies that compose this sector. In the case of the US comparables, we used the stocks that comprised the S&P 500 Global Industry Classification Standard (GICS) level 1 indices using the respective SOEs GICS code in order to identify their US private counterparts. All of the previous datasets were extracted from Bloomberg for the period between 03/01/2000 and 31/04/2012. The Fama and French (FF) factors plus momentum were downloaded from the Kenneth French website. In Table 3.1 we summarize the number of SOEs stocks and comparables by industry sector.

27. In the case of Brazil we used the BOVESPA, India the BSE 30 index, and Russia the RTS Index. In the case of China we used the CSISOE, which is a special index that comprises the 40 largest state owned enterprises in Mainland China.

28. For example, state asset management bureaus or development banks.

Table 3.1
Number of SOEs and comparables by GICS industry sector

		State Owned Enterprises					
GICS	Sector	Brazil	Russia	India	China	Total	Comparables
25	Consumer discretionary				1	1	80
30	Consumer Staples	3			3	6	39
10	Energy	1	1	2	7	11	43
40	Financials	1	1	3	15	20	80
20	Industrials	2	1	1	6	10	61
45	Information technology				1	1	69
15	Materials	1			4	5	31
50	Telecommunication services	1			3	4	8
55	Utilities	4	4	3	1	12	30
	Total	**13**	**7**	**9**	**41**	**70**	**441**

All the data for this study, with the exception of some of the FF factors, was collected as daily data using the closing price for each market. In order to avoid fluctuations due to the exchange rate, all series were converted to US dollars at the corresponding exchange rate. We use short term (weekly) and medium term (monthly) holding periods to compute portfolio returns. The idea behind using two time periods is to account for the time varying nature of the observed betas. Additionally, we use log returns to obtain the weekly and monthly returns for each stock. Therefore, our equally weighted portfolio time-series samples contain an average of 649 weekly and 148 monthly observations respectively. The only exception is the consumer discretionary sector that includes one Chinese SOE that began to publicly trade in the mid-2000s with 337 weekly and 77 monthly observations.

3.3. Model

Using the same model that Hong and Kacperczyk (2009) proposed to value the performance of sin stocks, we create a dependent variable for each industry sector as follows ($SECSOE_t$-$COMPSEC_t$) where $SECSOE_t$ is an equally weighted portfolio of the SOEs stocks that represents the sector net of the risk free rate, minus an equally weighted portfolio of US comparables ($COMPSEC_t$) in that sector net of the risk free rate[29].

29. We use the One Month US Treasury Bill as a proxy for this rate.

The dependent variable aims to capture the component of the return that is due to the stake of the government ("state"). If the difference between the SOE return and the comparable firm that is not state-owned is positive, the SOE outperforms the comparable firms. If the difference is negative the SOE underperforms the comparables.

The independent variables are the FF factors[30] and momentum: 1) $MKTPREM_t$ which is the excess market return of a portfolio of firms listed in the NYSE, AMEX and NASDAQ stock exchanges over the risk free rate; 2) SMB_t which is known as the small minus big factor and is constructed to measure the size premium, so that a positive coefficient means that small capitalization stocks outperform large capitalization and vice versa; 3) HML_t, or high minus low, is constructed to measure the premium in investing in companies with a high book-to-market ratio, therefore a positive coefficient means that "value" outperforms "growth" companies in a given observation period, and 4) MOM_t or momentum is constructed by building portfolios that are long on stocks with the highest returns and short on stocks with the lowest returns during the last 2 to 12 months, therefore a positive coefficient means that past winners outperformed past losers and vice versa (Daniel et al., 2012; Gutierrez and Gaglianone, 2008).

Also, in order to observe the effect of changing regimes during the GFC, we divided the GFC in three phases denoted by indicator variables which take the value of one during the specific crisis phases and zero otherwise. The first phase 'subprime' crisis (D_{Sub}) begins July 26th 2007, which was the day the Dow Jones recorded a large loss in response to bad news from mortgage lender Country Wide Financial. At this point, the market processed news of "difficult conditions" in the subprime market following Country Wide Financial Corporation's SEC filing on the 24th of July. The beginning of the Credit Crunch Crisis (D_{Lehman}) is generally dated from the time when Lehman Brothers filed for bankruptcy on 15 September 2008. We date the ESD crisis (D_{ESD}) from 22 October 2009 when Fitch first downgraded and reported a negative outlook for Greek sovereign debt. The turbulence in European debt markets was continuing at the end of our sample, 31 April 2012[31]. All standard errors are adjusted using the Newey-West correction for serial correlation. Therefore, the conditional mean equation for the four factor model is:

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30. For detailed information on how to construct the factors, please refer to the Kenneth R. French website.

31. The key dates for the Subprime and CCC were taken from the financial turmoil timeline chart from The Federal Reserve Bank of St Louis [http://timeline.stlouisfed.org/pdf/CrisisTimeline.pdf], and for the ESD crisis from the credit rating function in Bloomberg. There are other studies that use similar dates for the CCC, and place the subprime around the same period, including Frank and Hesse (2009), Dooley and Hutchison (2009), and Felices and Wieladek (2012).

$$(SECSOE_t - COMPSEC_t) = \alpha_t + \beta_1 MKTPREM_t + \beta_2 SMB_t + \beta_3 HML_{i,t}$$
$$+\beta_4 MOM_t + \gamma_1 D_{Sub} + \gamma_2 D_{Lehman} + \gamma_3 D_{ESD} + \varepsilon_t \tag{3.1}$$

If the SOE firms perform better (worse) than their comparables, after controlling for the four factors and the crisis terms, the coefficient α will be positive (negative). However, the aim of this study is not on the average performance of SOEs but on their performance during crisis periods. If SOEs outperform their comparables during a financial crisis the government's stake in the firm is assumed to act like a cushion for the state-owned enterprise and thus protects the value of the firm to some degree. The economic rationale for this "cushion" effect is that the stake of the government is either so large that the firm is fully protected from general market conditions, or that investors in state-owned firms know that the government provides a certain degree of protection and thus are more reluctant to sell the shares despite the crisis conditions.

If SOEs outperform their comparables during the entire crisis period, all three gamma coefficients in equation (3.1) will be positive. If the outperformance and thus the cushion effect is only evident in one of the three crisis periods, it will show in a positive gamma coefficient representing that specific crisis period. Obviously, if the SOEs perform worse in the crisis period, the gamma coefficients are negative. Since we do not test whether the correlation between the SOEs and the comparables or the market has changed as is a premise in the contagion literature, the model given by equation (3.1) is not a test of contagion. It is primarily a test of a cushion effect. Additionally, by using tail dependence we can test for differences in the explanatory power of the factors in the presence of abnormal returns during regime changes as observed by the sing of significant beta (β_t) coefficients. In this case our test of the cushion effect can be more closely related to regression-based tests of contagion, where contagion is defined as a significant increase in the loadings of a standard factor model during the crisis periods (Bekaert et al., 2005), and is not related to the most common adjusted pairwise correlation based test, whose main purpose is to correct the possible biases in pairwise correlations attributable to the change in regimes (Forbes and Rigobon, 2002).

One problem of the conditional return model of equation (3.1) is the presence of outliers during the crises periods. We implement a quantile regression model as proposed by (Koenker and Bassett Jr, 1978) in order to observe if there are structural breaks due to the presence of extreme values during crisis periods. We generalize equation (1) and allow the coefficients to be quantile dependent:

$$F^{-1}(\tau | SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau) MKTPREM_t + \beta_2(\tau) SMB_t$$
$$+\beta_3(\tau) HML_{i,t} + \beta_4(\tau) MOM_t + \gamma_1(\tau) D_{Sub} + \gamma_2(\tau) D_{Lehman} + \gamma_3(\tau) D_{ESD} + F_\varepsilon^{-1}(\tau | SECSOE_t - COMPSEC_t) \tag{3.2}$$

where τ represents the 1, 5, 50, 95, and 99% quantiles for the weekly[32] and 3, 5, 50, 95, and 97% quantiles for the monthly observations. By estimating over the extreme quantiles we can observe the (asymmetric) structure of dependence in the tails of the distribution (Baur, 2013). In the context of contagion in emerging markets, Rodriguez (2007) argues that breaks in the structure of tail dependence and asymmetry was significant in the case of the Asian crisis of 1997, but irrelevant in the Mexican crisis of 1994. By analyzing the gamma coefficients across quantiles and thus the structure of dependence, we can test if indeed certain SOE industry sectors exhibit a "cushion" effect not only on average, i.e. in the mean, but also in the tails, specifically in the left tails of the distribution.

Finally, we run a cross-sectional regression model to assess the performance of SOEs against comparables and account for fixed effects. Using a similar model as the one proposed by Hong and Kacperczyk (2009)[33], as they did in the case of sin stocks, we use two explanatory variables to proxy the FF factors that account for size and value in the case of the SOEs and all other stocks in our sample. We use the reported cross sectional averages for each stock during the observation period. In our case these two variables are the average change in market-to-book[34] value (AVGBK), and the average change in market capitalization (AVGCAP) lagged by one period. In order to correct for serial correlation we use Newey-West robust standard errors and we include a cross-sectional autoregressive term using the average excess returns (AVGER) for each stock in the sample. Therefore, our conditional excess return specification is:

32. In the case of the Energy and Discretionary SOEs sectors, the weekly and monthly quantiles are: 3, 5, 10, 50, 95, and 97%; and 5, 8, 25, 50, 75, 92%, respectively, since there are not enough data points to compute higher quantiles.

33. The main idea behind the cross sectional regression is to test, whether or not country of origin, if state ownership and sector characteristics have a positive or negative effect in performance. In other words, when c_4 is significant and greater than 0, then a particular characteristic in vector D_{it} has a positive effect on returns, and if c_4 is less than 0 otherwise.

34. In this specific case we use the inverse of the book-to-market ratio as reported by Bloomberg.

$$AVGER_{it} = c_0 + c_1 AVGER_{it-1} + c_2 AVGCAP_{it-1} + c_3 AVGBK_{it-1} + \mathbf{c_4 D_{it}} + \varepsilon_{it},\ i = 1,....n \tag{3.3}$$

In this case the coefficient of interest is (c_4) which is the vector of loadings on dummy variables (D_{it}) that account for all possible combinations of fixed effects for both comparables and SOEs industry classification as well as the SOEs country of origin (see Table 3.12). The next section describes the results.

3.4. Results

3.4.1. Results of the four factor model linear regression

In Table 3.2. we summarize the results of the four factor linear weekly regressions for all the sectors, and the main results of the Carhart model for all industry sector. From this table we can see that the traditional CAPM (MKTPREM) based on the US market index is significant in all but the industrial and material sectors. The coefficients are time varying depending on the length of the holding period, which in our case is weekly (short term) and monthly (medium term). Also, with the exception of the financial SOEs sector, there are no alphas (α) statistically different than zero indicating that in some cases the factors do a good job explaining excess returns.

Table 3.2

Results of the four factor linear regression model

The results are the estimated coefficients obtained from the following OLS regression:

$$(SECSOE_t - COMPSEC_t) = \alpha_t + \beta_1 MKTPREM_t + \beta_2 SMB_t + \beta_3 HML_{i,t} + \beta_4 MOM_t + \gamma_1 D_{Sub} + \gamma_2 D_{Lehman} + \gamma_3 D_{ESD} + \varepsilon_t$$

Where $(SECSOE_t - COMPSEC_t) =$ an equally weighted portfolio of the corresponding SOE sector stocks than compose the sector net of the interest risk free rate minus an equally weighted portfolio of US sector comparable stocks net of the risk free interest rate for the period between 2000 and 2012 in a weekly and monthly basis. MKTPREM, SMB, HML and MOM are the US explanatory factors downloaded on a weekly and monthly basis from the Kenneth R. French website. D_{Sub}, L_{ehman}, and D_{ESD} are dummy variables that take the value of 0 or 1 for our specified crisis periods as defined in section 3.3. All standard errors are adjusted using the Newey-West correction for serial correlation. ***1%; **5%; and *10% significance.

WEEKLY (2000-2012)					
SOE	**ALPHA**	**MKTPREM**	**SMB**	**HML**	**MOM**
DISCRETIONARY p-value	0.0089 (0.1905)	0.2998 (0.1120)	-0.5350 **(0.0997)** *	-0.2779 (0.4389)	0.3320 **(0.0767)** *
STAPLES p-value	0.0022 (0.5071)	0.4112 **(0.0002)** ***	0.5309 **(0.0044)** ***	0.0679 (0.5864)	-0.0271 (0.8001)
ENERGY p-value	-0.0004 (0.8614)	-0.3240 **(0.0000)** ***	0.1717 (0.2957)	-0.2753 **(0.0286)** **	-0.2497 **(0.0036)** ***
FINANCIAL p-value	0.0032 (0.1183)	-0.3180 **(0.0013)** ***	0.2728 (0.0542)	-0.6574 **(0.0000)** ***	0.1711 **(0.0776)** *
INDUSTRIAL p-value	0.0001 (0.9313)	-0.1103 (0.1512)	0.1788 (0.1389)	-0.0883 (0.2861)	-0.0169 (0.8021)
INFORMATION p-value	-0.0062 (0.1113)	-0.3916 **(0.0105)** **	0.1123 (0.6575)	0.7851 **(0.0009)** ***	0.1299 (0.3488)
MATERIALS p-value	0.0005 (0.9015)	-0.0282 (0.8175)	0.6662 **(0.0011)** ***	-0.0415 (0.8449)	0.0315 (0.7597)
TELECOMMUNI- CATIONS p-value	0.0012 (0.6449)	-0.0393 (0.6562)	0.2829 **(0.0978)** *	-0.3475 **(0.0374)** **	0.2362 **(0.0112)** **
UTILITIES p-value	0.0005 (0.8492)	0.2667 **(0.0157)** **	0.7164 **(0.0001)** ***	-0.2648 (0.1596)	-0.0798 (0.5276)

MONTHLY (2000-2012)					
SOE	**ALPHA**	**MKTPREM**	**SMB**	**HML**	**MOM**
DISCRETIONARY p-value	0.0328 (0.4813)	1.0507 **(0.0013)** ***	-1.2557 (0.1052)	-1.9255 **(0.0005)** ***	-0.4902 **(0.0253)** **
STAPLES p-value	0.0163 (0.1979)	1.2321 **(0.0000)** ***	0.4282 (0.3421)	-0.8414 **(0.0500)** **	0.4567 (0.1186)
ENERGY p-value	-0.0029 (0.7884)	0.0342 (0.8536)	0.0790 (0.7993)	-0.2796 (0.2128)	0.0048 (0.9747)
FINANCIAL p-value	0.0169 **(0.0245)** **	0.3682 **(0.0342)** **	0.0837 (0.7258)	-0.9923 **(0.0008)** ***	0.2847 **(0.0315)** **
INDUSTRIAL p-value	0.0039 (0.5367)	0.1852 (0.1878)	0.0807 (0.6187)	-0.4821 **(0.0020)** ***	0.1313 (0.2540)
INFORMATION p-value	-0.0182 (0.3720)	-0.2437 (0.6071)	0.1890 (0.7806)	0.2979 (0.6032)	0.2374 (0.5257)
MATERIALS p-value	0.0082 (0.6693)	0.6843 **(0.0091)** *	0.2879 (0.2611)	-0.7109 **(0.0169)** **	0.2244 (0.2017)
TELECOMMUNI- CATIONS p-value	0.0094 (0.3438)	0.4450 **(0.0571)** *	0.1365 (0.5788)	-0.6594 **(0.0220)** **	0.1921 (0.2799)

UTILITIES	0.0068	0.8678	0.3606	-0.5999	-0.0066
p-value	(0.4329)	**(0.0007)** ***	(0.2028)	**(0.0037)** ***	(0.9712)

In the case of the discretionary SOEs sector the most significant short term factors are the SMB and MOM. In the case of the SMB and MOM the respective negative and positive coefficients indicates that at least for the short term in this specific SOE large cap and past winning US stocks are good descriptors of this sector. In the medium term holding period, the most meaningful factors are the US market index, HML and MOM, these last two exhibit negative coefficients which means that in the medium term the SOE discretionary sector excess returns can be explained to comparables US growth (low book to market ratio) stocks and a contrarian strategy (negative momentum). In the consumer staples sector for the short and medium term the MKTPREM is significant, but for the short term a positive SMB indicates small cap US stocks do a god job in explaining SOEs excess returns and that in the medium term US growth stocks (negative HML coefficient) are more significant.

The energy SOEs sector is an interesting one given its countercyclical nature, and for the short period its relevant factors are the MKTPREM, HML, and MOM, all with negative coefficients in which the sector is inversely related with the market and its excess returns are explained by US growth stocks and a contrarian strategy. However, for the medium term holding period none of the factors is correlated with the energy SOEs sector excess returns. The financial SOEs sector is of special interest since its US counterparts were the originators of the GFC. In the short term, the MKTPREM exhibit a negative coefficient (inversely correlated with the US market), and is the only sector where all the four factors are significant, at least in the short term. US small caps (positive SMB), US growth stocks (negative HML) and momentum are very significant in explaining excess returns in the short term. In the medium term, the financial SOEs sector exhibits a significant positive (α), which means that in this case a fraction of the excess returns is explained by the fact that the companies are SOEs. Also, in the medium term MKTPREM, US growth stocks (negative HML) and momentum are significant in explaining excess returns in the SOEs financial sector.

In the short term the industrial SOEs sector has no correlation with the US factors, and in the medium term the only relevant factor is HML (negative coefficient), which means that SOEs excess returns in the industrial sector are related to US growth stocks. The information technology SOE sector appears to have some countercyclical property as it has a negative MKTPREM coefficient, and the sector excess returns are correlated to US value stocks, but in the medium term the sector has no correlation with any of the factors. In the short term the materials SOEs sector excess returns are correlated to US small capitalization stocks, and in the medium term to the excess return US market index (positive MKTPREM) and US growth stocks (negative HML). In the short term the telecommunications SOEs sector excess returns are explained by US small caps (positive SMB), US growth stocks (negative HML) and momentum (positive MOM). In the medium term this sector excess returns seem to be explained by the US market index and US growth stocks. Finally, in the short term the utilities SOEs sector excess are explained to the US stock index (positive MKTPREM) and US small capitalization stocks, and in the medium term by the US stock index and US growth stocks.

The effect of the different episodes of the GFC in the Carhart model is summarized in Table 3.3, in which none of the SOEs sectors seem affected by the subprime crisis. However, during the Lehman bankruptcy, just the dummy in the financial SOEs sector for the short term holding period is significant, but with a positive coefficient indicating superior performance during those dates relative to the US comparables. Finally, during the ESD episode all the sectors affected by contagion exhibit negative coefficients, with the exception of the information technology SOE sector in the short term that exhibits a positive effect. In the financial SOEs and consumer staples sectors the effect is significant, and has a negative effect in the short and medium terms during the ESD. For the industrials, materials and utilities SOEs sector the effect seem more relevant in the medium term that in the short term, and the telecommunication services SOEs sector seem immune to the GFC at least at the conditional mean return level.

Table 3.3
Crisis effect by sector

The results are the estimated coefficients obtained from the following OLS regression:

$$(SECSOE_t - COMPSEC_t) = \alpha_t + \beta_1 MKTPREM_t + \beta_2 SMB_t + \beta_3 HML_{i,t} + \beta_4 MOM_t + \gamma_1 D_{Sub} + \gamma_2 D_{Lehman} + \gamma_3 D_{ESD} + \varepsilon_t$$

Where $(SECSOE_t - COMPSEC_t) =$ an equally weighted portfolio of the corresponding SOE sector stocks than compose the sector net of the interest risk free rate, minus an equally weighted portfolio of US sector comparable stocks net of the risk free interest rate for the period between 2000 and 2012 in a weekly and monthly basis. MKTPREM, SMB, HML and MOM are the US explanatory factors downloaded on a weekly and monthly basis from the Kenneth R. French website. D_{Sub}, L_{ehman}, and D_{ESD} are dummy variables that take the value of 0 or 1 for our specified crisis periods as defined in section 3.3. All standard errors are adjusted using the Newey-West correction for serial correlation. ***1%; **5%; and *10% significance

	Discretionary		Staples		Energy		Financials	
	Weekly	*Monthly*	*Weekly*	*Monthly*	*Weekly*	*Monthly*	*Weekly*	*Monthly*
(D_{sub})	-0.0129	-0.0099	-0.0040	-0.0062	-0.0044	-0.0048	-0.0065	-0.0071
p-value	(0.2616)	(0.8579)	(0.5540)	(0.7962)	(0.5158)	(0.7486)	(0.2939)	(0.6705)
(L_{ehman})	0.0152	0.0284	0.0035	0.0154	0.0047	0.0238	0.0110	0.0319
p-value	(0.1379)	(0.6098)	(0.6120)	(0.6219)	(0.4348)	(0.3136)	**(0.0184)** **	(0.1688)
(D_{ESD})	-0.0101	-0.0427	-0.0077	-0.0520	-0.0008	-0.0100	-0.0069	-0.0371
p-value	(0.2154)	(0.4016)	**(0.0817)** *	**(0.0083)** ***	(0.8127)	(0.7449)	**(0.0351)** **	**(0.0016)** ***

	Industrials		Infotec		Materials		Telco	
	Weekly	*Monthly*	*Weekly*	*Monthly*	*Weekly*	*Monthly*	*Weekly*	*Monthly*
(D_{sub})	-0.0056	-0.0175	0.0054	0.0259	-0.0090	-0.0192	0.0019	0.0162
p-value	(0.3198)	(0.4309)	(0.5839)	(0.3430)	(0.3359)	(0.5998)	(0.7835)	(0.5929)
(L_{ehman})	0.0037	0.0117	0.0096	0.0158	0.0080	0.0221	-0.0027	0.0014
p-value	(0.4617)	(0.6548)	(0.4197)	(0.8571)	(0.2072)	(0.3762)	(0.4752)	(0.9581)
(D_{ESD})	-0.0048	-0.0280	0.0093	0.0050	-0.0076	-0.0474	0.0053	-0.0161
p-value	(0.1218)	**(0.0224)** **	**(0.0928)** *	(0.9118)	(0.0833)	**(0.0300)** **	(0.4540)	(0.2931)

	Utilities	
	Weekly	*Monthly*
(D_{sub})	0.0011	0.0180
p-value	(0.8711)	(0.1725)
(L_{ehman})	0.0034	0.0008
p-value	(0.6885)	(0.9811)
(D_{ESD})	-0.0045	-0.0297
p-value	(0.1595)	**(0.0154)** **

3.4.2. Results of the four factor model quantile regressions

By using a quantile regression approach it is possible to observe the behavior of the common factors in periods of excessive positive/negative returns, and infer the possible effect of the crisis on the behavior of returns as well as the explanatory power of the factors. The higher and lower quantiles describe extreme positive and negative returns respectively, being for example 99% an abnormal positive excess return and 1% an abnormal negative excess return. The 50% quantile can be described as the median quantile where the upper 25% and lower 25% observations are trimmed in order to watch the behavior of returns without the presence of outliers. From Tables 3.4 to 3.7 we use quantile regressions to observe the significance and behaviour of the Carhart factors coefficients as explanatory factors of extreme negative and positive excess returns. From Tables 3.8 to 3.10 we observe if there is evidence of our hypothesized "cushion" effect during the crisis periods by observing the sign and significance of the dummy coefficients that denotes these periods, and their explanatory power in elucidating the behaviour of extreme and negative excess returns by industry sector. Below each table we discuss in depth the economic rationale.

From Table 3.4 we can observe that in the short term the CAPM (MKTPREM) is significant at different quantiles in the majority of the sectors, with the exception of the SOE telecommunication sector. In the medium term, the number of sectors in which the CAPM is significant decreases, while the industrials, information technology, and energy SOEs sectors become insignificant. In the short term most of the significant coefficients, with the exception of the material SOE sector, have values of less than one, which is a common sign of a portfolio that bears less risk than the market in general. In the case of the financials, industrial and energy sectors the sign of the coefficients is negative, which can be interpreted as a sign of negative correlation with the US stock market. In the short term the CAPM is significant in explaining part of the variation in large negative and positive excess returns in the consumer staples, financials, materials, energy, and industrial (large positive returns only) SOEs sectors. In the medium term the CAPM is significant explaining large negative excess returns in the consumer staples, utilities and telecommunication SOEs sector and positive excess returns in the staples, materials and consumer discretionary sectors.

Table 3.4
Quantile Regression Estimates for weekly and monthly holding periods-CAPM (MKTPREM)

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau | SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau) MKTPREM_t + \beta_2(\tau) SMB_t + \beta_3(\tau) HML_{i,t} + \beta_4(\tau) MOM_t + \gamma_1(\tau) D_{Sub} + \gamma_2(\tau) D_{Lehman} + \gamma_3(\tau) D_{ESD} + F_\varepsilon^{-1}(\tau | SECSOE_t - COMPSEC_t)$$

where $(\tau)=$ the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations. The CAPM is significant in explaining part of the variation in large negative and positive excess returns in the consumer staples, financials, materials, energy, and industrial (large positive returns only) SOEs sectors at the weekly level. At the monthly level, the CAPM is significant explaining large negative excess returns in the consumer staples, utilities and telecommunication SOEs sector, and positive excess returns in the staples, materials and consumer discretionary sectors.

MKTPREM COEFFICIENTS-WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
1%	0.3842**	-0.2040	0.3288	-0.4539	1.0903***	0.0935	0.0973	0.3848	-0.3739*
5%	0.5589***	-0.3614**	-0.0681	0.0017	1.1395***	0.0024	0.1083	0.3558	-0.3853*
50%	0.3860***	-0.3239***	-0.1947***	-0.3048***	1.1538***	-0.0918	0.2700***	0.3235*	-0.3094***
95%	0.4231***	-0.4021***	-0.2956**	-0.5177	0.9957***	-0.0432	0.2538	0.2190	-0.3644***
99%	0.4842**	-0.5812***	-0.0145	-1.1036	0.8251***	0.0412	0.0587	0.0700	-0.3046**

MKTPREM COEFFICIENTS-MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	1.2418***	-0.1728	-0.2850	-1.6818	0.5621	0.7264	0.8245**	0.1895	0.2215
5%	1.2533***	0.2060	-0.1386	-0.2751	0.3201	1.1180**	1.0071**	0.2912	0.3644
50%	0.7502**	0.4848**	0.1380	-0.2437	0.4522*	0.2237	1.4116***	1.0614**	-0.0177
95%	1.0577	0.2879	-0.2032	0.3256	1.0531	0.4977	0.4082	1.6849***	-0.0788
97%	1.4870**	0.2802	-0.2239	0.7541	2.0795**	0.9587	0.5191	1.3834***	-0.0592

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors.***1%; **5%; and *10% significance.

In the case of the SMB factor, and from Table 3.5, in the short term we find significant coefficients at different quantiles in the consumer staples, financials, industrials, telecommunication services and utilities SOEs sector. In the medium term this factor is significant at different quantiles in the information technology, materials, utilities and discretionary SOEs sector. In the short term all of the significant SMB coefficients independent of the sector display a positive sign which is an indication that part of the variation of these sectors returns are explained by US small capitalization firms. In the short term the SMB coefficients that are significant are associated for those quantiles with large and negative excess returns, especially for the staples, financials, and telecommunication services SOEs sector. In the case of the utilities sector US small capitalization utilities companies seem to explain a significant portion of excess returns for all quantiles levels. In the medium term the only significant coefficients are associated with large negative excess returns in the information technology and material SOEs sector, and with large positive excess returns in the discretionary sector. It is important to mention that in the specific case of the discretionary SOE sector the sign of the SMB coefficient is negative which can be interpreted that for this sector part of the variation in returns are explained by US large capitalization comparables.

Table 3.5

Quantile Regression Estimates for weekly and monthly holding periods-Small minus Big factor (SMB)

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau | SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau) MKTPREM_t + \beta_2(\tau) SMB_t + \beta_3(\tau) HML_{i,t} + \beta_4(\tau) MOM_t + \gamma_1(\tau) D_{Sub} + \gamma_2(\tau) D_{Lehman} + \gamma_3(\tau) D_{ESD} + F_\varepsilon^{-1}(\tau | SECSOE_t - COMPSEC_t)$$

where (τ) = the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations. The SMB factor is significant in explaining part of the variation in large negative and positive excess returns in the consumer staples, financials, utilities and telecommunication services (large negative returns only) SOEs sectors at the weekly level. At the monthly level, the SMB factor is significant in explaining large negative excess returns in the information technology and materials SOEs sector, and positive excess returns in the consumer discretionary sector. A negative coefficient like in the discretionary sector means that large capitalization firms from the US can explain part of the variation in returns.

SMB COEFFICIENTS-WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
1%	1.6089***	1.2574***	0.5450	0.0057	0.0007	0.7876*	1.6096***	-0.0808	0.3769
5%	1.1619***	0.5371**	0.3974	-0.1707	0.0696	-0.0007	1.0673***	-0.3182	0.5171
50%	0.2351	0.0641	0.1114	-0.1012	0.0937	0.1296	0.5760***	-0.2915	0.1411
95%	0.5052	0.3297	0.2221	1.1065	-0.0302	0.1596	0.8387**	-0.7580	0.1429
99%	1.1033*	0.8056**	0.0911	1.6645	0.0093	-0.0300	0.3761	-0.6229	-0.0465

SMB COEFFICIENTS-MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	-0.4947	-0.0670	0.9716	4.8511*	1.3094	0.0091	0.5647	-0.8626	0.2729
5%	-0.3941	0.1450	0.2405	1.4180	1.2331*	-0.1752	0.1654	-0.2841	0.3268
50%	0.1710	0.2182	-0.0469	0.1890	0.2087	-0.1152	0.1367	-1.7586*	-0.2555
95%	0.7513	0.0656	-0.0600	0.3418	-0.6069	0.3376	0.1793	-0.3579	0.4425
97%	1.3314	0.0271	-0.1153	0.1562	-0.4700	0.5136	0.5729	-2.4097**	0.4306

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors. *** 1%; ** 5%; and * 10% significance.

From Table 3.6 we can observe that for both, the short and medium term, the HML factor coefficients are significant in most of the SOEs sectors, with the exception of consumer staples and energy. In the case of the financial SOEs sector both, the short and medium terms, the HML factor coefficients have negative signs which imply that US growth stocks explain part of the variation of excess returns. Also in the short term, negative HML coefficients are observable in the telecommunication services, utilities and discretionary sectors. In the short term the information technology and material SOEs sector have positive HML coefficients, which imply that US value stocks in comparable sector explain part of the variation in excess returns for all quantile levels. In the medium term, only the information technology sector has a positive HML significant coefficient at a very low quantile associated with extreme negative excess returns. Also, in the medium term higher quantiles with large excess positive returns are associated with US growth stocks (negative HML coefficients) in comparable sectors in the industrial, telecommunication services, and discretionary SOEs sectors.

Table 3.6
Quantile Regression Estimates for weekly and monthly holding periods-High minus Low factor (HML)

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau | SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau) MKTPREM_t + \beta_2(\tau) SMB_t + \beta_3(\tau) HML_{i,t} + \beta_4(\tau) MOM_t + \gamma_1(\tau) D_{Sub} + \gamma_2(\tau) D_{Lehman} + \gamma_3(\tau) D_{ESD} + F_\varepsilon^{-1}(\tau | SECSOE_t - COMPSEC_t)$$

where (τ) = the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations The HML factor is significant in explaining part of the variation in large negative and positive excess returns in the financials, information technology, and materials at the weekly level. In the case of telecommunication services, utilities and consumer discretionary, the factor explains part of the variation associated with large positive excess returns. At the monthly level, the HML factor is significant in explaining large negative excess returns in the information technology and materials SOEs sector, and positive excess returns in the consumer discretionary, industrials and telecommunication services sector. A negative coefficient like the one in the financial sector means that growth firms from the US can explain part of the variation in returns.

HML COEFFICIENTS-WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
1%	-0.0333	-0.4828	0.6410	2.1905***	0.5025*	0.2868	0.2544	-0.1905	-0.3823
5%	-0.1673	-0.7550***	0.0975	1.1924*	0.6812***	-0.4006	0.0643	-0.4318	-0.1511
50%	-0.0345	-0.6112***	-0.1286	0.7097***	0.5480***	-0.2897*	-0.3389*	-0.0513	-0.2050
95%	-0.0712	-0.6536**	0.0332	0.4709	0.8249***	-0.6477**	-0.2803	-1.2947*	-0.0880
99%	0.0244	-0.6199**	-0.2162	2.6846**	0.6745***	-0.5134	-0.6619*	-1.7998**	-0.1658

HML COEFFICIENTS-MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	-0.7035	-0.8624	0.2850	2.2237**	-0.6470	-0.4980	-0.4964	0.2015	-0.7377
5%	-0.5146	-0.6252	-0.3168	0.4505	-1.0741**	-0.6276	-0.8406	-0.6799	-0.6871
50%	-0.5250	-1.3345***	-0.4439*	0.2979	-0.6533*	-0.4987	-0.3871	-2.1925***	-0.5094
95%	-0.9738	-0.8481	-0.8242**	0.3248	-0.2601	-1.3414**	-0.5512	-2.9834***	-0.0147
97%	-1.8206	-0.6850	-0.8496**	0.4698	-1.0990	-1.4585**	-0.4902	-0.1314	-0.0068

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors. *** 1%; ** 5%; and * 10% significance.

The coefficient significance of the momentum factor at different quantile levels is summarized in table 3.7. In the short term momentum coefficients are significant for all sectors at different quantile levels with the exception of consumer staples and financials. In the medium term momentum coefficients are significant at different quantile levels for the financials, telecommunication services and discretionary SOEs sectors only. A positive MOM coefficient means that the strategy of buying past US winners and shorting past US losers (momentum) seems to explain part of the variation of large negative excess returns in the financials, materials, telecommunication services and discretionary SOEs sectors in the short term. Also in the medium term, momentum (positive MOM coefficient) explains part of the variation of large negative excess returns in telecommunications services SOE sector. On the other hand, a contrarian strategy of buying past losers and selling past winners (negative MOM coefficient) tend to explain part of the variation of extreme negative movements in the short term for the industrials, utility and energy SOEs sectors and the discretionary SOE sector in the medium term.

Table 3.7
Quantile Regression Estimates for weekly and monthly holding periods- Momentum factor (MOM)

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau|SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau)MKTPREM_t + \beta_2(\tau)SMB_t + \beta_3(\tau)HML_{i,t} + \beta_4(\tau)MOM_t + \gamma_1(\tau)D_{Sub} + \gamma_2(\tau)D_{Lehman} + \gamma_3(\tau)D_{ESD} + F_\varepsilon^{-1}(\tau|SECSOE_t - COMPSEC_t)$$

where (τ) = the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations. The MOM factor is significant in explaining part of the variation in large negative and positive excess returns in the telecommunication services sector. In the case of the utilities, consumer discretionary and energy sectors, the factor explains part of the variation associated with large positive excess returns. At the monthly level, the MOM factor is significant in explaining large positive excess returns in the telecommunication services and consumer discretionary sectors. A negative coefficient like the one in the energy sector means that a contrarian strategy of buying past losers and selling past winners from comparable companies in the US can explain part of the variation in returns.

MOM COEFFICIENTS-WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary$^+$	Energy$^+$
1%	-0.4395	-0.4153	-0.1102	-0.2752	-0.0906	0.7500***	-0.3644**	0.6486*	-0.7555***
5%	-0.1985	-0.0206	-0.1867*	0.5414	-0.0862	0.3654***	-0.2054	0.5283	-0.5219***
50%	0.0001	0.1561	0.0281	0.2685**	0.1058**	0.2300*	-0.0225	0.2872	-0.1983**
95%	-0.0982	0.0190	0.0769	-0.1120	-0.0173	0.1836	0.0368	-0.2423	-0.2030
99%	0.0608	0.0677	-0.0198	-0.3805	0.0039	0.5655**	-0.1763	-0.1636	-0.1769

MOM COEFFICIENTS-MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	0.3077	-0.0137	0.0054	0.4354	0.2899	0.8529*	-0.5203	0.0558	-0.4545
5%	0.1960	0.2374	0.1773	0.1675	-0.0682	0.8170	-0.3435	-0.6999**	-0.3088
50%	0.1462	0.4138**	0.1422	0.2374	0.1980	-0.0654	0.3445	-0.4943	-0.0644
95%	0.8298	0.3535	0.1203	0.2237	-0.6753	0.2863	-0.1593	-0.3838	-0.0706
97%	1.0095	0.3897	0.0989	0.2936	-0.1654	0.2076	0.0205	0.0934	-0.0701

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors.***1%; **5%; and *10% significance

In Table 3.8 we can observe the effect of the subprime crisis at different quantile levels. In the short term, the coefficients of the subprime crisis are significant for the majority of sectors with the exception of the materials, information technology and utilities SOEs sector. In the medium term, the only significant coefficients are found in the financials, and utility SOEs sector. In the short term the subprime crisis is associated with large negative excess returns in the staples, industrials, and discretionary SOEs sectors. In the financial and energy SOEs sectors, the subprime crisis has a significant positive effect on large positive excess returns, and a negative one on large negative excess returns. In the information technology sector the subprime crisis significant coefficients are associated with positive excess returns. In the case of the telecommunication services sector the subprime crisis has a positive effect on large negative short term excess returns. In the medium term, for the financial SOE sector the subprime crisis has a negative effect on large negative returns, and in the case of the utilities sector the crisis has a positive effect on large negative excess returns.

Table 3.8
Quantile Regression Estimates for weekly and monthly holding periods- Subprime crisis

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau | SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau) MKTPREM_t + \beta_2(\tau) SMB_t + \beta_3(\tau) HML_{i,t} + \beta_4(\tau) MOM_t + \gamma_1(\tau) D_{Sub} + \gamma_2(\tau) D_{Lehman} + \gamma_3(\tau) D_{ESD} + F_{\varepsilon}^{-1}(\tau | SECSOE_t - COMPSEC_t)$$

where $(\tau) =$ the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations. In the telecommunication services (weekly) and utilities (monthly) we reject the null of no contagion since the lower quantiles are characterized by positive coefficients. This is evidence of a "cushion" effect against contagion and suggests that these sectors are immune or, at least, that there is a decoupling in the tails regarding extreme negative movements during the subprime crisis (positive coefficients associated with large negative returns at lower quantiles).

SUBPRIME COEFFICIENTS-WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
1%	-0.0282	-0.0613**	-0.0391*	0.0136	-0.0142	0.0375***	0.0023	-0.0164	0.0005
5%	-0.0372**	-0.0260	-0.0429***	-0.0215	-0.0088	0.0232**	0.0153	-0.0356*	-0.0045
50%	0.0012	-0.0068	-0.0087	0.0112	0.0034	-0.0030	0.0034	-0.0116	-0.0076
95%	0.0018	0.0217	0.0280**	0.0224	0.0053	-0.0117	-0.0003	0.0138	0.0086
99%	-0.0101	0.0835**	0.0238	-0.0275	0.0012	-0.0119	-0.0153	0.0296	0.0321*

SUBPRIME COEFFICIENTS-MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	0.0594	-0.0552*	0.0046	0.1573	0.0704	0.0540	0.1033**	-0.0905	0.0756
5%	0.0331	-0.0267	-0.0308	0.0845	0.0465	0.0299	0.1175***	-0.0105	0.0640
50%	-0.0091	-0.0368	-0.0299	0.0141	-0.0225	-0.0040	-0.0111	-0.0172	-0.0349
95%	-0.0205	0.0290	-0.0067	0.1392	0.0023	-0.0232	0.0170	0.0016	0.0292
97%	-0.1532	0.0176	-0.0095	0.1024	-0.1445	-0.0384	-0.0059	-0.0697	0.0288

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors.*** 1%; ** 5%; and * 10% significance

In Table 3.9 we can observe the effect of the credit crunch (Lehman) crisis at different quantile levels. In the short term, the coefficients of the CCC are significant for financials, industrials, materials and telecommunication services SOEs sectors. In the medium term, the only significant coefficients are found in the materials SOE sector. In the short term and in the financial and materials SOEs sectors, the subprime crisis has a significant positive effect on large positive excess returns, and a negative one on large negative excess returns. In the telecommunication services sector the CCC significant coefficients are associated with large positive excess returns. Also, in the case of the telecommunication services sector the CCC has a positive effect on large negative short term excess returns. In the medium term the CCC has a significant positive on large negative excess returns of the materials SOEs sector.

Table 3.9

Quantile Regression Estimates for weekly and monthly holding periods - Credit Crunch Crisis

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau | SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau) MKTPREM_t + \beta_2(\tau) SMB_t + \beta_3(\tau) HML_{i,t} + \beta_4(\tau) MOM_t + \gamma_1(\tau) D_{Sub} + \gamma_2(\tau) D_{Lehman} + \gamma_3(\tau) D_{ESD} + F_\varepsilon^{-1}(\tau | SECSOE_t - COMPSEC_t)$$

where $(\tau) =$ the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations. In the telecommunication services (weekly) and materials (monthly) we reject the null of no contagion but the lower quantiles are characterized by positive coefficients and upper quantiles by negative coefficients. This is evidence of a “cushion” effect against contagion, and suggests that these sectors are immune or, at least, that there is a decoupling in the tails regarding extreme negative movements during the CCC (positive coefficients associated with large negative returns at lower quantiles).

CREDIT CRUNCH LEHMAN COEFFICIENTS - WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
1%	0.0288	-0.1021*	-0.0524	-0.0144	-0.0572**	0.0429*	0.0112	0.0013	-0.0151
5%	0.0029	-0.0237	-0.0092	-0.0617	-0.0337**	-0.0050	0.0095	-0.0143	-0.0017
50%	0.0100	0.0141*	0.0068	0.0081	-0.0003	-0.0059	0.0020	0.0297**	0.0024
95%	-0.0051	0.0391**	0.0210*	0.0299	0.0114	0.0431*	0.0307	-0.0136	0.0086
99%	-0.0345	0.0240	0.0081	-0.0119	0.0490*	0.0516	0.0034	0.0146	0.0025

CREDIT CRUNCH LEHMAN COEFFICIENTS - MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	-0.1240	-0.0228	0.0244	-0.0248	0.1829***	0.0863	0.0273	0.1360	0.0874
5%	-0.1573	-0.0445	-0.0432	-0.0681	0.1519***	0.0418	-0.0103	-0.0132	0.0986
50%	0.0270	0.0533	-0.0005	0.0158	0.0184	-0.0251	-0.0190	0.0736	0.0392
95%	0.0804	0.0423	0.0866	0.1537	-0.0586	0.0465	0.1028	0.0222	-0.0017
97%	-0.0570	0.0316	0.0811	0.1188	-0.2119*	0.0765	0.0917	0.0763	-0.0025

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors. ***1%; **5%; and *10% significance.

In Table 3.10 we can observe the effect of the ESD crisis at different quantile levels. In the short term, the coefficients of the subprime crisis are significant for the majority of SOEs sectors with the exception of the discretionary sector. In the medium term all sectors have significant coefficients at different quantile levels. In the short term the ESD crisis has a negative effect in large positive returns in the staples, financials, and information technology SOEs sectors. In the telecommunication services, utilities and energy SOEs sectors, the ESD crisis has a significant negative effect on large positive excess returns, and a positive one on large negative excess returns. In the medium term for the industrials, materials, and discretionary SOE sectors the ESD crisis has a negative effect on large positive returns. In the case of the utilities sector the ESD crisis has a positive effect on large negative excess returns, and a negative effect on positive large medium term excess returns. In the case of the staples, financials and telecommunication services the ESD crisis has a negative effect on medium term excess returns at the median level.

Table 3.10
Quantile Regression Estimates for weekly and monthly holding periods - Sovereign Debt Crisis

By generalizing equation (3.1) in section 3.3 we obtain:

$$F^{-1}(\tau|SECSOE_t - COMPSEC_t) = \alpha_t(\tau) + \beta_1(\tau)MKTPREM_t + \beta_2(\tau)SMB_t + \beta_3(\tau)HML_{i,t} + \beta_4(\tau)MOM_t + \gamma_1(\tau)D_{Sub} + \gamma_2(\tau)D_{Lehman} + \gamma_3(\tau)D_{ESD} + F_{\varepsilon}^{-1}(\tau|SECSOE_t - COMPSEC_t)$$

where $(\tau) =$ the 1, 5, 50, 95, and 99% for the weekly, and 3, 5, 50, 95, and 97% for the monthly observations. In the materials, telecommunication services, utilities, and energy (weekly), and in the information technology and utilities (monthly) SOEs sector we reject the null of no contagion since the lower quantiles are characterized by positive coefficients and upper quantiles by negative coefficients. This is evidence of a "cushion" effect against contagion, and suggests that these sectors are immune or, at least, that there is a decoupling in the tails regarding extreme negative movements during the sovereign debt crisis (positive coefficients associated with large negative returns at lower quantiles).

ESD COEFFICIENTS-WEEKLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
1%	0.0278	0.0038	-0.0159	0.1290	0.0122	0.0501***	0.0637***	-0.0171	0.0317**
5%	0.0021	-0.0019	-0.0053	0.0455**	0.0080	0.0347***	0.0508***	-0.0264	0.0248**
50%	-0.0069*	-0.0086**	-0.0047	0.0003	-0.0008	-0.0069**	-0.0074*	-0.0031	-0.0016
95%	-0.0199**	-0.0150***	-0.0076	-0.0120	-0.0028	-0.0221**	-0.0404***	-0.0159	-0.0217**
99%	-0.0384	-0.0124	0.0015	-0.0712**	-0.0029	-0.0413**	-0.0811***	-0.0292	-0.0190**

ESD COEFFICIENTS-MONTHLY (2000-2012)									
Quantile	Staples	Financials	Industrials	Infotec	Materials	Telco	Utilities	Discretionary+	Energy+
3%	-0.0119	-0.0546	-0.0331	0.1662*	0.0551	0.0141	0.1157***	0.0826	0.0254
5%	-0.0207	-0.0259	-0.0047	0.0818	0.0582	-0.0168	0.0809*	-0.0549	0.0368
50%	-0.0437**	-0.0471**	-0.0253*	0.0259	-0.0331*	-0.0386***	-0.0575**	-0.0333	-0.0015
95%	-0.0868	-0.0295	-0.0663***	0.0273	-0.2053**	-0.0528	-0.0949***	-0.1157**	-0.0339
97%	-0.1599	-0.0057	-0.0661***	0.0788	-0.2780***	-0.0397	-0.0735**	-0.1257**	-0.0353

+ In the case of the Energy and Discretionary SOEs sectors the weekly and monthly quantiles should be interpreted as: 3, 5, 50, 95, and 97%, and 5, 8, 50, 75, and 92% respectively, since there are not enough data points to compute higher quantiles in these two sectors. ***1%; **5%; and *10% significance.

In summary, during the subprime crisis the SOEs sectors where we fail to reject the null of no contagion or tail dependence in the short term are materials and utilities, and in the medium term consumer staples, information technology, materials, telecommunication services, consumer discretionary and energy. In the consumer staples, financials, industrials, consumer discretionary and energy SOEs sectors we find evidence of contagion associated with short term large negative excess returns, and financials and industrials with medium term large negative excess returns. In the telecommunication services (short term) and utilities (medium term) we reject the null of no contagion, but the lower quantiles are characterized by positive coefficients. This is evidence of a “cushion” effect against contagion and suggests that these sectors are immune or, at least, that there is a decoupling in the tails regarding extreme negative movements during the subprime crisis.

In the CCC the SOEs sectors were we fail to reject the null of no contagion or tail dependence are the consumer staples, utilities and the energy sector. In the case of the industrial, information technology, and discretionary sectors we reject the null of no contagion in the short term only in the higher quantiles associated with large positive returns, and find no evidence supporting that contagion is correlated with large negative excess returns at the lower quantile levels. In the financial and materials SOEs sectors we find evidence of contagion associated with short term large negative excess returns. In the telecommunication services (short term) and materials (medium term) we reject the null of no contagion, but the lower quantiles are characterized by positive coefficients and upper quantiles by negative coefficients. This is evidence of a “cushion” effect against contagion, and suggests that these sectors are immune or, at least, there is a decoupling in the tails in different directions and strong evidence for asymmetry during the CCC.

Finally, in the ESD the only SOE sector were we fail to reject the null of no contagion or tail dependence is the consumer discretionary sector in the short term and energy in the medium term. In the case of the staples, financials, and industrials we reject the null of no contagion in the short term only in the higher quantiles associated with large positive returns, and find no evidence supporting that contagion is correlated with large negative excess returns at the lower quantile levels. In the medium term, and in the case of the staples, financials, industrials, materials, and discretionary we reject the null of no contagion in the higher quantiles associated with large positive returns, and find no evidence supporting that contagion is correlated with large negative excess returns at the lower quantile levels. In the short term materials, telecommunication services, utilities, and energy and in the medium term information technology and utilities we reject the null of no contagion but the lower quantiles are characterized by positive coefficients and upper quantiles by negative coefficients. This is evidence of a “cushion” effect against contagion, and suggests that these sectors are immune or, at least, there is a decoupling in the tails in different directions and strong evidence for asymmetry as with other sectors during the ESD.

3.4.3. Results of the cross sectional regression

In order to account for the cross sectional variation that is not captured in the longitudinal regressions, and to measure the predictive power of the factors we run a standard cross sectional regression. Also, the cross sectional regression allows us to see if indeed fixed effects, such as country of origin and industry classification, can provide additional information in explaining SOEs excess returns. The results of the cross sectional regressions of excess returns are summarized in Tables 3.11 and 3.12. In the short and medium term market capitalization is a significant variable with the expected positive sign. In the medium term the market to book ratio is significant, and with a positive sign as expected of a sample composed mainly by big firms. Most of the cross sectional variation is explained by incorporating country and industry fixed effects, while the alpha (α) coefficients becomes insignificant. For example, it seems that the only relevant fixed effects at the country level are for those SOEs located in Brazil and China. In the case of China the coefficient has the expected positive sign and in the case of Brazil is negative.

Once we allow for industry classification fixed effects we have clearer picture of the relative performance of US comparables against SOEs. In both, the short and the medium term, the SOEs sector that outperformed their US comparables were the financial, consumer discretionary, and consumer staples. In the remaining sectors for both, the short and medium term, there was no statistical evidence that SOEs outperformed their US comparables. Finally, the telecommunication services sector effect was insignificant in the short term, but outperformed its US comparables in the medium term.

Table 3.11

Cross sectional excess returns fixed effects weekly

The results are based on the estimated coefficients from time-series regressions in a cross sectional framework: $AVGER_{it} = c_0 + c_1 AVGER_{it-1} + c_2 AVGCAP_{it-1} + c_3 AVGBK_{it-1} + \mathbf{c_4 D_{it}} + \varepsilon_{it},\ i = 1,\dots n$ where $AVGER_{it}$ = the average weekly excess return net of the interest risk free rate for each SOE and comparable US stocks that composes our sample for the period between 2000 and 2012. $AVGCAP_{it-1}$ = Weekly average change in market capitalization lagged by one period, $AVGCAP_{it-1}$ =Weekly average change in market-to-book value lagged by one period, and $AVGCAP_{it-1}$ = $AVGER_{it}$ =lagged by one period. D_{it}= is a dummy variable that accounts for country of origin or industry classification fixed effects. Standard errors are adjusted using the Newey-West correction for serial correlation. ***1%; **5%; and *10% significance.

WEEKLY (2000-2012)	***SOE-CROSS SECTIONAL***	
	AVGER	AVGER
AVGER(-1)	0.0438	0.0312
p-value	(0.4199)	(0.5592)
AVGCAP(-1)	0.2373	0.2450
p-value	**(0.0000)*****	**(0.0000)** ***
AVGBK(-1)	-0.0094	-0.0026
p-value	(0.8352)	(0.9536)
SOE	0.00013	
p-value	(0.5698)	
CHINA		0.00055
p-value		**(0.0425)** **
BRAZIL		-0.00089
p-value		**(0.0595)** *
INDIA		-0.00004
p-value		(0.9567)
RUSIA		-0.00054
p-value		(0.1810)

WEEKLY (2000-2012)	***SOE-CROSS SECTIONAL***			
	FINANCIALS	FINANCIALSSOE	DISCRETIONARY	DISCRETIONARYSOE
AVGER	-0.0001	0.0008	0.0008	0.0024
p-value	(0.4967)	**(0.0286)** **	**(0.0000)** ***	**(0.0000)** ***
WEEKLY (2000-2012)				
	ENERGY	ENERGYSOE	INFOTEC	INFOTECSOE
AVGER	0.0015	0.0010	-0.0001	-0.0023
p-value	**(0.0000)** ***	(0.1459)	(0.5609)	**(0.0000)** ***
WEEKLY (2000-2012)				
	MATERIALS	MATERIALSSOE	STAPLES	STAPLESSOE
AVGER	0.0009	0.0001	0.0007	0.0008
p-value	**(0.0001)** ***	(0.8343)	**(0.0019)** ***	**(0.0523)** *
WEEKLY (2000-2012)				
	TELCO	TELCOSOE	UTILITIES	UTILITIESSOE
AVGER	-0.0011	-0.0002	0.0004	-0.0002
p-value	**(0.0036)** ***	(0.5358)	**(0.0191)** **	(0.5314)

Table 3.12
Cross sectional excess returns fixed effects monthly

The results are based on the estimated coefficients from time-series regressions in a cross sectional framework: $AVGER_{it} = c_0 + c_1 AVGER_{it-1} + c_2 AVGCAP_{it-1} + c_3 AVGBK_{it-1} + \mathbf{c_4 D_{it}} + \varepsilon_{it},\ i = 1,\ldots n$ where $AVGER_{it}$ = the average monthly excess return net of the interest risk free rate for each SOE and comparable US stocks that composes our sample for the period between 2000 and 2012. $AVGCAP_{it-1}$ = Monthly average change in market capitalization lagged by one period, $AVGCAP_{it-1}$ = Monthly average change in market-to-book value lagged by one period, and $AVGCAP_{it-1} = AVGER_{it}$ = lagged by one period. D_{it}= is a dummy variable that accounts for country of origin or industry classification fixed effects. Standard errors are adjusted using the Newey-West correction for serial correlation. ***1%; **5%; and *10% significance.

MONTHLY (2000-2012)	***SOE-CROSS SECTIONAL***	
	AVGER	AVGER
AVGER(-1)	0.0765	0.1379
p-value	(0.2518)	**(0.0005)** ***
AVGBK(-1)	-0.0283	0.0024
p-value	(0.5315)	**(0.0401)** **
AVGCAP(-1)	0.1740	0.0006
p-value	**(0.0024)** ***	(0.5189)
SOE	0.00116	
p-value	(0.2381)	
CHINA		0.00263
p-value		**(0.0164)** **
BRAZIL		-0.00410
p-value		**(0.0589)** *
INDIA		-0.00003
p-value		(0.9918)
RUSIA		-0.00281
p-value		(0.2049)

MONTHLY (2000-2012)	*SOE-CROSS SECTIONAL*			
	FINANCIALS	FINANCIALSSOE	DISCRETIONARY	DISCRETIONARYSOE
AVGER	-0.0004	0.0040	0.0038	0.0106
p-value	(0.6292)	**(0.0156)** **	**(0.0000)** ***	**(0.0000)** ***
MONTHLY (2000-2012)				
	ENERGY	ENERGYSOE	INFOTEC	INFOTECSOE
AVGER	0.0068	0.0048	-0.0008	-0.0097
p-value	**(0.0000)** ***	(0.1195)	(0.4467)	**(0.0000)** ***

MONTHLY (2000-2012)				
	MATERIALS	MATERIALSSOE	STAPLES	STAPLESSOE
AVGER	0.0041	0.0005	0.0036	0.0039
p-value	**(0.0000)** ***	(0.7734)	**(0.0008)** ***	**(0.0237)** **

MONTHLY (2000-2012)				
	TELCO	TELCOSOE	UTILITIES	UTILITIESSOE
AVGER	-0.0031	0.0015	0.0020	-0.0004
p-value	**(0.0137)** **	**(0.0937)** *	**(0.0102)** **	(0.6905)

3.5. Conclusion

By estimating four-factor quantile regression models to returns to BRIC economy SOEs, we study their performance during the financial crisis and recovery period. Our model benchmarks the SOEs against US market factors, including industry-sector indexes. From many countries and sectors the size and value-growth of US market are significant factors for excess returns of SOEs.

The US market premium is a significant factor for explaining excess SOEs returns for the majority of sectors, with exceptions in industrials, IT and energy. In the SMB factor case, US small capitalization stocks are significant in explaining part of the variation associated with extreme SOEs excess returns in the staples, financial, utilities, telecommunication services and industrials, and information technology. In the case of the discretionary SOE sector, excess returns seem to be driven by US large capitalization stocks in the medium term.

The book-to-market factor also explains part of the variation of short term extreme shocks in the financial SOE sector. Finally, momentum explains large negative excess returns in the financials, materials (short term), and telecommunication services; an opposite strategy explains part of the variation of short term excess SOEs returns in the industrials, utilities, energy and discretionary (medium term) SOEs sectors.

Additionally, by analyzing dependence at extreme quantiles during crisis episodes, we observe that, indeed, certain SOEs industry sectors were either more immune or more exposed to contagion than others. Our results show that there is evidence of a "cushion" effect against contagion in the telecommunication, utilities, materials, information technology, and energy SOEs sectors during different episodes of the crisis. In the staples and industrial sector we observe contagion in the subprime episode, no contagion in the CCC, and a significant effect in the ESD crisis episode, but just associated with high positive excess returns. One plausible explanation could be that the crisis in Europe acted as a catalyst in stock prices for these sectors as investors rebalanced their portfolios seeking growth opportunities elsewhere. In the discretionary SOE sector we find evidence of contagion during the subprime crisis episode, but fail to reject the null of no contagion in all subsequent episodes. In the financial SOE sector there is evidence of contagion for the subprime, credit crunch (short term), and in the ESD significant effects associated with high positive excess returns. Finally, when we account for cross sectional variation, country effects are significant and positive for China and negative for Brazil. Economically this means that, at the country level, Chinese SOEs companies were more likely to outperform their comparables competitors in the US than Brazilian SOEs, meanwhile for India and Russia the cross sectional variation was statistically insignificant. At the industry level the SOE sectors that outperformed their US comparables were the financial, consumer discretionary, and consumer staples sectors.

Our results are similar to those obtained in a recent study in the area of segmentation which says that there is a trend of reversal in global market integration at the industry and country level (see: Bekaert, Harvey, et al., 2011), especially the increase in segmentation in the industrial sectors of emerging markets during crisis periods. In the case of the financial sector, our results are similar to other studies that have found that global factors can act as carriers of contagion in the financial industry (Bagliano and Morana, 2012; Bekaert, Ehrmann, et al., 2011). Additionally, a recent study by Hossain, Jain and Mitra (2013) found similar results regarding the performance of the financial SOE sector versus competitors. Finally, this book has important implications for the literature concerning the role of government ownership and intervention, because it analyzes issues related to performance of partially privatized SOEs, and how the "partnership" between the state and private investors can be mutually beneficial during crisis periods, especially, due to the "cushion" effect or decoupling in the tails regarding extreme negative movements in certain economic sectors.

Future research in this area should take into account the different levels of government ownership and indirect intervention (subsidized loans, effect of government contracts, etc.) as well as the effects of "implicit" government guarantees on firm performance in both developed and emerging markets.

Chapter 4

Conclusion

The final conclusion for this thesis is that during certain phases of the GFC there is evidence that in the case of government sponsored or regulated assets there was resilience or decoupling, at least for the assets under study. In the case of the Colombian pension funds (Chapter 2), using a time-varying framework we were able to analyze the behavior of a particularly isolated (autarchic) asset during the GFC. Furthermore, our time varying framework allows us to decompose risk into its systematic and idiosyncratic components, by assuming that all shocks are transmitted through a common factor which, in our case, was the S&P500 index and a couple of bond indices, in order for further test contagion by asset type in the case of the Colombian private pension funds. Using this decomposition approach we were able to test for contagion in the context of its two broader definitions: 1) As the notion that contagion creates additional linkages in market co-movement, and 2) As the notion that contagion creates additional volatility spillover from one market to the other. Although the proposed models for testing contagion are commonly used in the literature on the subject, our contribution is that, by allowing the models to capture the effect of negative returns, new insights can be gain into the nature and the magnitude of contagion in asset returns. Additionally, by using quantile autoregression to test the significance of crisis dates using time varying systemic risk is possible to overcome some of the limitations and biases generated by asymmetric data. Our results using the first notion found that, in the case of the Colombian funds, there was no evidence of contagion during the first two episodes of the GFC when we allowed for time varying volatilities and different common factors. However, during the ESD crisis episode there is strong evidence of contagion in all tests including robustness checks.

In Chapter 3 we estimate several factor models of returns of BRIC economies SOEs, and study their performance during the financial crisis and recovery period. Our model benchmarks the SOEs against US market factors, including industry-sector indexes. To many countries and sectors the size and value-growth factors of US market are significant for excess returns of SOEs. Additionally, by analyzing dependence at extreme quantiles during crisis episodes, we observe that indeed certain SOEs industry sectors were either more immune or more exposed to contagion than others. Our results show that there is evidence of a “cushion” effect against contagion in the telecommunication, utilities, materials, information technology, and energy SOEs sectors during different episodes of the crisis. Our results are similar to those obtained in a recent study in the area of segmentation in the sense that there is a trend of reversal in global market integration at the industry and country level (see: Bekaert, Harvey, et al., 2011), especially the increase in segmentation in the industrial sectors of emerging markets during crisis periods. Finally, this book has important implications for the literature concerning the role of government ownership and intervention because it analyzes issues related to performance of partially privatized SOEs, and how the "partnership" between the state and private investors can be mutually beneficial during crisis periods, especially, due to the "cushion" effect or decoupling in the tails regarding extreme negative movements in certain economic sectors.

We hope that, analyzing the effect of government regulation in emerging markets, some lessons will be learned in regard to what special kind of assets can help to mitigate the effects of contagion, and the consequent loss of wealth that can have devastating effects in the case of emerging economies. In the case of Chapter 2, future research in this area should take into account the role of regulatory constrains regarding portfolio holdings. Even though this "quantitative restrictions" can limit the risk/return potential of the autarchic portfolio, also can limit potential losses in time of crisis. In the case of Chapter 3, future research could take into account the different levels of government ownership and indirect intervention (subsidized loans, effect of government contracts, etc.), as well as the effects that "implicit" government guarantees have on firm performance in both developed and emerging markets.

APPENDIX A

According to the guidelines set in the *Decreto 1592 de 2004*, articles 1 and 2, the formula is:

$$RM = 0.5(0.7RPS) + 0.5(w_1 * 0.7RRV + w_2 * 0.7RFE + w_3 * 0.7BM)$$

Where:

RM = Minimum guaranteed annual rate of return.

RPS = Weighted average rate of return of all the private pension funds that compose the system per annum.

RRV = Annual rate of return of the Colombian stock market index.

RFE = Annual rate of return of a global stock market chosen by the Colombian banking regulatory agency.

BM = Annual return of a benchmark portfolio chosen and calculated by the Colombian banking regulatory agency.

w_1 = The proportion of the assets of the fund invested in Colombian stocks

w_2 = The proportion of the assets of the fund invested in foreign stocks

w_3 = The proportion of the assets of the fund invested in other asset.

APPENDIX B

According to the guidelines set in the Chapter 12 of the *Circular Externa 036 de 2003*, article 1, pages 1 to 4, the value of a PPF and how is expressed in unit value should be reported daily and in unit values. The units should reflect the market value of the contributions of the affiliates, and their number represents the equity position of the affiliate in the fund. The daily variation in the unit value should reflect the return between the buy and sell dates (Superfinanciera, 2003).

The formulas for calculating the value of the fund and the values of the units are:

For the value of the fund:

VFC = VFI + AT - TR – RC - MP - RAV - DS - SP - CA - OC - FSPsl - FSPsbp - FSPsbaf - FGPM - RV - OR ± AN

Where:

VFC = Value of the fund at the closing of day (t) – before dividends and yields.

VFI = Value of the fund at the opening of day (t).

AT = Contributions and transfers received in day (t), includes deposits for severance fund subsidies. In the case of mandatory pension funds in the brute value of the deposit is all inclusive (commissions, insurance, commissions and all relevant subsidies or additional contributions set by the legislation).

TR = Value of the transfers to other private pension fund administrator by petition of the client at day (t).

RC = Value of payments of severance fund subsidies (partial or definitive) at day (t).

MP = Value of the pension allowances payed at day (t).

RAV = Value of payments related to cancellations of voluntary contribution plans at day (t).

DS = Value of reversals in outstanding balances to affiliates or pensioners of the private pension fund in day (t).

SP = Value of pension insurance payed at day (t).

CA = Value of the commission payable to the private pension fund administrator at day (t).

OC = Value of other commissions payable to the private pension fund administrator at day (t).

FSPsl = Value of the contributions to the solidarity fund, subaccount solidarity, at day (t).

FSPsbp = Value of the contributions to the solidarity fund, subaccount subsistence pensioners, at day (t).

FSPsbaf = Value of the contributions to the solidarity fund, subaccount affiliates, at day (t).

FGPM = Value of the contributions of the minimum guarantee pension fund at day (t).

RV = Value of balance transfers to insurance companies for pension payments under the perpetual rent scheme at day (t).

OR = Value other transfers/retirement at day (t).

AN = Value of cancelled operations at day (t).

For the number of units:

NUC = NUCI + NUAT - NUTR - NURC – NUMP - NURAV - NUDS - NUSP - NUCA - NUOC - NUFSPsl - NUFSPsbp - NUFSPsbaf - NUFGPM - NURV - NUOR ± NUAN.

Where:

NUC = Number of units of the fund at the closing of day (t), which must be the same number at the opening of the next day (t+1).

NUCI = Number of units of the fund at the opening of day (t).

NUAT = Number of units related to new contribution and incoming transfers at day (t).

NUTR = Number of units related to transfers of existing contributions to other private pension fund administrators at day (t).

NURC = Number of units of severance fund subsidies (partial or definitive) at day (t).

NUMP = Number of units related to the payment of pensions allowances payed at day (t).

NURAV = Number of units corresponding to the value of payments related to cancellations of voluntary contribution plans at day (t).

NUDS = Number of units corresponding to the value of reversals in outstanding balances to affiliates or pensioners of the private pension fund in day (t).

NUSP = Number of units corresponding to the value of pension insurance payed at day (t).

NUCA = Number of units corresponding to the value of the commission payable to the private pension fund administrator at day (t).

NUOC = Number of units corresponding to the value of other commissions payable to the private pension fund administrator at day (t).

NUFSPsl = Number of units corresponding to the value of the contributions to the solidarity fund, subaccount solidarity, at day (t).

NUFSPsbp = Number of units corresponding to the value of the contributions to the solidarity fund, subaccount subsistence pensioners, at day (t).

NUFSPsbaf = Number of units corresponding to the value of the contributions to the solidarity fund, subaccount affiliates, at day (t).

NUFGPM = Number of units corresponding to the value of the contributions of the minimum guarantee pension fund at day (t).

NURV = Number of units corresponding to the value of balance transfers to insurance companies for pension payments under the perpetual rent scheme at day (t).

NUOR = Number of units corresponding to the value of other transfers/retirement at day (t).

NUAN = Number of units corresponding to the value of cancelled operations at day (t).

For all purposes, when a new fund enters de market, the initial net asset value (NAV) is set at COP $10.000. The total value of the funds including dividends and coupon payments is equal to:

VFCR = VFC + INGt - GTSt

Where:

VFCR = Value of the fund at the closing of day (t) including yields from related investments which must be the same as the opening of the next day (t+1).

VFC = Value of the fund at the closing of day (t) – before dividends and yields.

INGt = Yields form investments in the fund at day (t).

GTSt = Expenses related to purchasing investments for the fund at day (t).

Finally the net asset value of the unit (VUC) at the end of day (t) is equal to VUC = VFCR/NUC.

APPENDIX C

Quantile autoregression, as proposed by Koenker and Xiao (2006). can be an extremely useful econometric tool when we are dealing with asymmetric series. Using Koenker and Xiao (2006) notation assume that (U_t) is a normal distributed variable that exhibits the following (n) autoregressive process where the parameters $\theta_{n's}$ are unknowns:

$$y_t = \theta_0(U_t) + \theta_1(U_t)y_{t-1} + \theta_2(U_t)y_{t-2} + ... + \theta_n(U_t)y_{t-n} \tag{1}$$

Furthermore, if y_t is a monotone increasing function of (U_t) and that τ is a conditional quantile function of y_t, then equation (1) can be rewritten as:

$$Q_{y_t}(\tau | y_{t-1} ... y_{t-n}) = \theta_0(\tau) + \theta_1(\tau)y_{t-1} + \theta_2(\tau)y_{t-2} + ... + \theta_n(\tau)y_{t-n} \tag{2}$$

In matrix form:

$$Q_{y_t}(\tau | F_{t-1}) = X_t^T \theta_0(\tau) \tag{3}$$

Where $X_t^T = (1, y_{t-1}, ...y_{t-n})^T$ and F_{t-1} is the sigma field generated by $\{y_s, s \leq t\}$. The intuition behind the quantile autoregression model is the fact that the autoregressive coefficients or (θ) are quantile dependent (τ) thus allowing for the coefficients to vary along the quantiles. Therefore a QAR(1) process can be defined as:

$$Q_{y_t}(\tau|F_{t-1}) = \theta_0(\tau) + \theta_1(\tau)_{y_{t-1}} \tag{4}$$

Where $\theta_0(\tau) = \sigma\phi^{-1}(\tau)$ and $\theta_1(\tau) = \min\{\gamma_0 + \gamma_1\tau, 1\}$ for $\gamma_0 \in (0,1)$, and γ_1 > 0. According to Koenker and Xiao (2006), if $U_t > (1-\gamma_0)/\gamma_1$ [35] then the model generates a non-sationary process, but for smaller values of U_t there is a mean reversion tendency. This means that even though the whole process of y_t can be globally stationary, but still can display asymmetric persistence in the presence of large shocks. Therefore, one of the interesting qualities of a QAR process is that it allows for some form of asymmetric behavior in some quantiles while maintaining stationarity in the long run.

35. This come from the fact that $Q_{g(U)^{(\tau)}} = g(Q_u(\tau)) = g(\tau)$ therefore U is a function of the quantile (see Koenker and Xiao, (2006, p. 981).

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