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ESSAYS ON FINANCIAL CONTAGION IN EMERGING MARKET ECONOMIES

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I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

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ABSTRACT

Since the collapse of the Bretton Woods system the integration of national financial markets grew steadily, to reach unprecedented levels. At the same time, episodes of extreme financial instability became more frequent. The latter were often extremely contagious, in the sense that country-specific episodes had hugely disruptive effects on financial markets across the globe. The literature on Financial Contagion investigates the channels through which that instability is propagated. This thesis deals with the two most recurring questions in the literature:

1) What are the channels of macroeconomic instability propagation?

A theoretical model of instability propagation in presence of currency mismatches is presented. The model shows that when domestic agents' liabilities are denominated in foreign currency, exchange rate volatility raises credit costs, with negative real effects. Currency mismatches therefore create a channel through which external disturbances causing exchange rate volatility affect negatively the domestic supply.

Several reasons why currency mismatches might magnify the effect of foreign disturbances have been identified by the theoretical literature on the issue. The empirical relevance of the magnification hypothesis is tested by investigating whether the degree of domestic output's sensitivity to foreign output fluctuations is higher in countries where currency mismatches are widespread than in countries able to borrow abroad in domestic currency. The analysis gives strong support to the hypothesis: currency mismatches magnify the real effects of foreign disturbances. The analysis also highlights the presence of asymmetry of propagation: negative shocks have proportionally stronger real effects than positive ones in currency-mismatches-prone countries.

2) Is the financial shocks propagation mechanism altered by major events such as banking or currency crises?

The intensity of propagation of the crises in the '90s led researchers to ask whether the linkages between countries grew stronger during these turbulent times or were instead as strong before. Various tests of the instability of the propagation mechanism have been proposed since. These can be divided in two families: correlation-based and extreme-event-based tests. I propose a new approach, based on the Quantile Regression technique. It is argued that this approach retains the appealing features of the two families of test while avoiding some of their limitations. The new approach is then applied to stock market returns, finding strong evidence of instability of the propagation mechanism.

CHAPTER 1 – INTRODUCTION

1.1   Why study contagion

During the two centuries passed since financial intermediation became a crucial sector of the economic organization of societies, financial instability has been a common experience. Whether one uses this term to describe a Balance of Payment crisis with a devaluation of the currency, a banking crisis in which a country experiences bankruptcy of financial institutions or a mix of these two events, these have pointed the economic history of modern world (Bordo et al. 2001, Allen-Gale 2007, ch. 1, Reinhard and Rogoff 2009).

Nonetheless, the frequency of these varied significantly among different époques. Banking panics leading to runs and eventually bankruptcies have plagued Europe and the United States throughout the nineteenth century. The creation of central banks was aimed directly to the containment of these panics, and it succeeded in doing this. In Europe, England's Central Bank learned how to prevent nationwide banking crises and the last such episode took place in 1866. Panics affecting single banking institutions did not happen for over a century, until the demise of Northern Rock in 2007. A central banks system with power and coordination comparable to nowadays standards was instead established later in the US, specifically after the trauma of the Great Depression. The introduction of central banks effectively curtailed the diffusion of economy-wide bank crises in Europe and the States. This historical experience influenced strongly the interpretation of these episodes. Especially after the Great Depression, banking crises were seen as a market failure, to be avoided at all costs (Kindleberger 1978, Diamond and Dybvig 1983). This frame of mind was dominant in 1948, when the Bretton Woods system was created. It is the unsurprising that   the latter entailed extensive regulation of the financial system. As a consequence, banking crises (of even a much smaller severity than the 19th century ones) virtually disappeared.

From the beginning of the '70s it became clear that the elimination of banking crises came with a cost. This was in the form of slow development and deepening of credit markets due to excessive regulation, leading to scarcity and inefficiency of banks' investment allocation and ultimately lower growth (King and Levine 1993).

Calls for deregulation became usual. Banking crises ceased to be seen as pure market failures, driven by the irrationality of depositors. Instead an alternative interpretation of crises as an integral part of the business cycle gained popularity (Gorton 1988). This approach highlighted the intrinsic weakness of the banking system during economic downturns. Holding illiquid assets and liquid liabilities, banks cannot satisfy the liquidity demand depositors show when they predict low assets' returns. Depositors are therefore rational in their running, because they predict correctly that bank's revenues will not be enough to pay all depositors' claims. The factor causing banking crises is then aggregate risk on asset returns, not depositors' irrationality. It follows that runs are rational and, as long as central banks intervention allows troubled banks to avoid a premature sell of their illiquid assets, optimal too. Government intervention is thus seen as necessary, but only to manage the failure of financial institutions in an orderly way. As these considerations gained popularity, the financial sector underwent a substantial deregulation in most of OECD countries, and banking crises reappeared.

Currency crises had, on the other hand, a more constant distribution throughout the 19th and 20th centuries, quite irrespective to the dominant policy environment in that moment. Since the reappearance of banking crises in the late '70s, the latter have been often followed by Balance of Payment distress and eventually crises. This phenomenon attracted the attention of economists, as the recent development of "twin crises" models testifies (Kaminsky and Reinhart 1999).

Financial instability has then featured prominently in the economic history of the world in the last two centuries. Just as much as its frequency, its costs make it an important topic of research. Bordo et al. (2001) estimate the costs of financial crises as the difference between the cumulative drop in output during normal recessions (from the peak of the business cycle until the year when growth returns to its pre-crisis level) and during recessions accompanied by financial crises. The estimated output losses are sizeable. Over a period of 120 years, the sample of twenty-one middle to high-income countries lost an average of 9% of GDP per crisis. Since the probability of a random country in the sample incurring in a crisis is 8% per year, rough calculations suggest that the countries in the sample lost 1 percentage point of annual growth due to financial crises. This is a huge number: a 1% higher growth increases incomes by a third in 25 years. Hoggarth et al (2002) focus on banking crises and find the latter to be even costlier, causing an average output loss of 15 to

20% annual GDP per crisis. Dobson and Hufbauer (2001) focus on emerging markets in the 1980s and 1990s and again find estimates higher than those of Bordo et al (2001). According to them, Latin American countries lost 2.2% of annual growth in the '80s decade while Asia lost 1.4% of annual growth in the '90s decade. Other studies estimate the output loss caused by a crisis per year of duration, rather than the cumulative costs. Caprio and Klingebiel (1996) estimate that banking crises cost 2.4% of GDP per year of duration. Goldstein et al. (2000) estimate currency crises to cost 3% per year of duration in low-inflation countries, and 6% in high inflation ones.

These estimates are big by any standard, yet the social consequences of financial crises can be easily underestimated by looking at GDP statistics only. Chen and Ravallion (2001) estimate that, if the pre-1997-crisis pace of poverty reduction would have been sustained, the poverty incidence in East Asia would have been 4% lower in 1998. This suggests that the crisis increased the number of poor in the region (excluding China) by 22 million people in one year. Lee (2004) provides social indicators for post-crisis Korea. Reported crimes, drug addicts and suicides grew by respectively 46.2, 15.8 and 49.1 percent in the 1996-1998 period. Frankenberg and Thomas (2004) use household data to assess the impact of the crisis on Indonesia. They demonstrate that in the first year of the crisis poverty rose by between 50 and 100 percent, real wages declined by 40 percent and household per capita consumption declined by 15 percent. Financial instability has therefore a direct and disruptive effect on the lives of millions, which gives a reason for trying to understand what cause it, *and how it spreads*.

In fact, the deregulation of financial sectors, the progress of information technology and the overall increased interdependence of real sectors in different economies around the world due to the rise in world trade generated an international financial market whose integration was unknown before. What is now called "globalisation" poses new issues in the financial crises theory. Up until the early '90s these events were treated as mainly national, for they were mostly caused by domestic macroeconomic imbalances. The '90s crises had instead a distinct international nature. Country-specific events such as the Mexico, Thailand and Russia devaluations and/or defaults in 1995, 1997 and 1998 generated an outstanding way of turbulence, felt all the way through financial markets thousand of miles away. Certainly the '90s were not the first time financial crises exerted their effects well beyond national boundaries, nonetheless the speed and the strength of their international transmission

seemed of a higher degree, and the links between originating and affected countries often looser. It is no coincidence that theories of financial instability propagation across borders saw the light in the mid '90s, and at the end of the decade were one of the most researched topics in economics. The result is a rich body of literature, which is reviewed in chapter 2.

The propagation of financial instability across borders is a very complex, multi-faceted phenomenon. It is for this reason that the literature studying it provides at least three definitions of "contagion" (see Dornbusch and Claessens 2000 and Kodres and Pritsker 1999 for a detailed treatment of the issue of contagion definitions). The first is "propagation of macroeconomic instability across borders", the second is "propagation of macroeconomic instability unexplained by fundamentals across borders" and the last is "increased/strengthened propagation of macroeconomic instability across borders during crises". Clearly, the first one is the broadest, it includes the other two: the fact that a macroeconomic shock originating in one country affects another one constitutes contagion, whether or not the propagation is explained by fundamentals, whether or not the correlation among macroeconomic indicators in the two countries increases. The other two definitions highlight instead two different aspects of the propagation mechanism: that the propagation can be detached by any macroeconomic linkage (bilateral trade, competition for trade with a 3rd country, common lender to name the most recurring) and that it can become stronger during turbulent times. These two aspects are equally important in the study of shocks propagation, for they shed light on key aspects of international economics theory as well as on policy recommendations. For example, whether shocks propagate through macro channels or not helps explaining what are these channels, their relative importance and the importance of investors' sentiment shifts in contagion episodes. This in turn has relevant policy implications as the presence of sentiment shifts uncorrelated with macroeconomic considerations might give a rationale for introducing capital controls for example. Whether shocks propagate more strongly during crises is also an issue with relevant theoretical and policy implications. It is a test of the relevance of crisis-contingent versus non-crisis-contingent contagion models, as well assessing the scope for portfolio diversification and the measurability of systemic risk (see Chapter 5 for a detailed discussion of the issue). Both definitions are helpful in shedding light on key aspect of international interdependence of financial markets. There is thus no reason to choose one over the other. It seems more

reasonable to call "contagion" without any further specification the propagation of macroeconomic shocks across borders, "unexplained-by-fundamentals contagion" the propagation of macroeconomic shocks across borders *over and above that explained by macroeconomic fundamentals* and "shift contagion" the *increase* in the strength of propagation of macroeconomic shocks across borders during turbulent times. This will be the terminology used throughout the thesis.

The two most recurring questions in the contagion literature are:

1) what are the channels of contagion? and:

2) is contagion mechanism altered by major events such as banking or currency crises? In other words, is there evidence of shift contagion?

This thesis addresses both questions.

1.2   What are the channels of contagion?

Recent work has emphasized the prevalence of currency mismatches (i.e. the different currency composition of agents' assets and liabilities) in the financial systems of emerging markets economies as a key source of financial instability in those countries (see the literature review in Chapter 2 and references therein). Models investigating currency mismatches and the propagation of external disturbances to the domestic economies have been put forward. Chapter 3 reviews briefly this literature and expands it by providing a theoretical model of financial instability propagation driven by the presence of currency mismatches and credit markets imperfections. The model shows that when domestic agents' liabilities are denominated in foreign currency exchange rate volatility raises credit costs, with negative effects on production. Currency mismatches therefore create a channel of contagion: financial crises abroad generate uncertainty about the future exchange rate, this in turn increases the cost of credit for domestic firms, therefore reducing production. Crucially, the channel of contagion may link countries with no direct trade or financial linkages, thereby generating unexplained-by-fundamentals contagion.

Where trade linkages are present, theoretical models suggested that currency mismatches might magnify the effects of trade shocks (see, among others, Cespedes et al. 2004). Trade has been identified as the major source of output co-movements

across countries from both the literature on optimal currency area and financial contagion. Currency mismatches' magnification of trade shocks' real effects could then explain the higher observed output volatility in emerging market economies. Notwithstanding this, a systematic study of the way currency mismatches affect the propagation of trade shocks is not present in the literature. Chapter 4 fills this gap by empirically investigating three related hypotheses: a) that currency mismatches magnify the real effects of negative trade shocks, b) that currency mismatches magnify trade-related output volatility (i.e. that they magnify the real effects of trade shocks of either sign) and c) that currency mismatches generate asymmetric trade shocks propagation (i.e. that negative trade shocks propagate more strongly than positive ones in presence of currency mismatches).

1.3 Is the contagion mechanism altered by major events such as banking or currency crises?

The speed, intensity and pervasiveness of the turbulence caused by the '90s crises led researchers to ask whether the linkages between countries grew stronger during these turbulent times or were instead already as strong before. Various tests of the instability of the propagation mechanism (i.e. of shift contagion) have been proposed since. A review of these tests, provided in chapter 5, shows that the latter can be divided in two families: correlation-based and extreme-event-based tests. A new approach, based on the Quantile Regression technique, is proposed in the same chapter. It is argued that this approach retains the appealing features of the two families of tests while avoiding some of their limitations. The new approach is then applied to stock market returns, finding strong evidence of shift contagion.

The conclusions of the thesis are presented in Chapter 6.

CHAPTER 2 - CURRENCY MISMATCHES AND CONTAGION: A LITERATURE REVIEW

2.1 Theoretical models of contagion

2.1.1 Limitations of financial crisis models and the birth of contagion theory

The financial crises of the '90s featured country-specific events triggering speculative attacks in several different countries across the globe. This event was a challenge for the theory of currency crises dominant at the time. The latter, so-called "first generation", consisted of models linking the collapse of a peg with the inconsistency between monetary and fiscal policies pursued and a stable exchange rate (see Krugman 1979, Flood and Garber 1984). In these models the growth of domestic credit forces the central bank to offset it by using foreign reserves in order to maintain a fixed exchange rate. With finite reserves, this would lead to reserve exhaustion. Agents with perfect foresight will anticipate this and attack the currency when the amount of reserves is just enough to maintain the current exchange rate so that no arbitrage possibility is there. After the attack, reserves are exhausted and the exchange rate is let free to float.

Since excessive domestic credit growth is causing the exhaustion of the central bank reserves, currency crises have a purely domestic reason in such a framework. A crisis elsewhere cannot cause a crisis domestically. This framework could not explain the time-proximity of speculative attacks characterizing the crisis episodes in the '90s. To do so, it would have required budget deficits and/or expanding domestic credit in both the crisis and the affected country determining a similar path of central bank reserves exhaustion. Only in this way reserves would have fallen under the critical level triggering the attack in the same period of time.

The experience of European currencies in the 1992-93 turmoil clearly challenged this theory: after the floating of the Finnish Marrka in September 1992, the Swedish and the Norwegian Krona came under intense speculative pressure that eventually led to the floating of the Swedish currency. This notwithstanding the relatively strong fiscal position of the two countries and their moderate credit growth up to then. Similarly, the devaluation of the Italian Lira triggered a wave of sales of the British

Pound and the French Franc, forcing the former out of the ERM band. Again, neither of the two countries showed evident signs of growing monetized government debt nor credit growth inconsistent with a peg. The same is true for Argentina after the Mexican devaluation in 1994, when after years of moderate credit growth and fiscal discipline a speculative attack on the peso was repelled only at the costs of extreme monetary tightening and a painful recession.

2.1.2   Fundamental-based contagion models

By showing that devaluations tended to trigger speculative attacks in trade partners and that credit growth could hardly be the reason behind it, the experiences of European currencies and Argentina led to the development of the first formal models of contagion. These applied the logic of the first-generation crisis models to a multi-country setting. Crises were still seen as the moment of exhaustion of central banks reserves, excluding the possibility of a voluntary abandon of the peg, and reserves exhaustion was still seen as depending from the inconsistency of pursued macroeconomic policies and a stable exchange rate. However, foreign disturbances that speed up the exhaustion process were introduced. In this way, the framework was able to explain the time-proximity of speculative attacks.

An example is Gerlach and Smets (1995), which is essentially a two-country version of the Flood-Garber model with one difference: the policy inconsistency leading to reserve exhaustion is arising from capital outflows generated by the current account deficit rather than by expanding domestic credit. To offset such outflows the central bank uses foreign reserves. The time proximity of speculative attacks is explained via the "competitive devaluation" argument: a devaluation in a trade-competing country reduces domestic net exports therefore increasing the capital outflows and speeding up the process of reserves exhaustion. After a devaluation in a trade partner, rational investors will then attack the domestic currency sooner: the time of the attack is then interdependent in trade-competing countries. This model could better describe the European contagion episode, where the devaluations caused speculative pressures on trade partners showing current account deficits (see Gerlach and Smets op. cit.), and the Mexican one, where countries with relevant current account deficit and real exchange rate overvaluation were found to be the most affected (see Sachs et al. (1996)). It also provides a plausible explanation of the time

clustering of speculative attacks. Notice that, since the trade partner's devaluation speeds up the reserves exhaustion process, the speculative attack is rational, based on the deteriorating fundamentals of the affected economy. Contagion is therefore rational and fundamental-based in this model.

The Gerlach-Smets approach lost much of its appeal after the East Asian 1997 regional meltdown. Countries such as Malaysia, Indonesia, Korea were hugely affected even if coming from years of fiscal, current account surpluses and moderate credit growth. A predictable path of reserves exhaustion was very hard to conceive, even accepting that the Thai devaluation could have caused a loss of competitiveness in neighbouring countries. In fact, inside and outside academia, the "Asian tigers" were hold as examples of a successful economic development and of safe emerging markets.

Less than a year later, in August 1998, Russia defaulted on its debt and as a consequence of this too, the Long Term Capital Management (LTCM) hedge fund suffered immense losses and would have filed for bankruptcy if a consortium of American banks (following a warm invitation from the Fed) would not have agreed to bail it out. These two events together generated an outstanding wave of instability that eventually forced Brazil to abandon its peg. The fact that a shock coming from such a small financial market like Russia could spread so strongly to countries with no evident macroeconomic imbalances or trade/financial linkages with it was even harder than the Asian contagion to reconcile with the fundamental-based contagion theory. If the East Asian contagion put the latter into question, the Russian-Brazilian episode definitely shifted the consensus away from it. Policy inconsistencies and trade linkages alone could not explain the timing and the strength of speculative attacks triggered by the Thai devaluation and the Russian default. Meanwhile, various weaknesses in emerging financial markets, in the banking sector particularly, had been identified as key players in the propagation of the crises. It was then natural to introduce financial market imperfections in contagion models. Researchers' explanations pointed in two main directions: multiple equilibria models and investor behaviour/financial sector weaknesses models.

2.1.2 Multiple Equilibria models

The new line of thought abandoned the fundamental-based setting and saw the East Asian experience as a Multiple Equilibria story in which the Thai devaluation determined a jump towards the bad equilibrium in the neighbouring countries (see, for example, Masson 1998). This model starts from the Krugman-Flood-Garber crisis theory by assuming that a speculative attack takes place when the reserves are just enough to maintain the current level of the peg. Defining this critical level of reserves as $\overline{R}$, we have that the probability of an attack and thus of a devaluation is $\Pr\left(R < \overline{R}\right)$ where R is the amount of international reserves available to the central bank. The latter are given by: $R_t = R_{t-1} + TB_t - DS_t$, respectively the reserves accumulated in the past plus the trade balance minus the cost of debt servicing. Perfect capital mobility and perfect foresight are assumed, so that uncovered interest parity holds. Agents will then request a domestic interest rate equal to the world risk-free rate plus a premium for the expected depreciation. This is where the multiple equilibria arise: the interest rate paid on the debt is a function of the expected depreciation. Therefore, the more expected is a devaluation, the higher the interest rate required by investors to hold domestic debt, and thus the higher the cost of debt servicing. This is turn makes a devaluation more likely, closing the circle and generating the possibility of multiple equilibria. The cost of debt servicing is indeed given by $DS_t = Dr = D\left(r^* + \pi\delta\right)$, where D is the external debt accumulated, r and r^* the domestic and world interest rates respectively, π the probability of a devaluation and δ the exchange rate jump taking place in case of a devaluation. If agents consider a devaluation likely, they will request a high interest rate. Debt servicing will then be high, available reserves low and the probability of a devaluation high. If agents consider a devaluation unlikely, the opposite will be true and a devaluation will indeed be unlikely. There are multiple equilibria.

The East Asian contagion is interpreted under this light: the Thai devaluation increased markedly the perceived probability of other regional currencies devaluating. Investors shied away from those currencies, therefore increasing the cost of debt servicing for those countries to unsustainable levels and causing a chain of devaluations.

This would imply that the overall macroeconomic situation in the affected countries (not Thailand) was not unavoidably inconsistent with a stable exchange rate. However, the Thai crash eroded investor confidence, triggering speculations on neighbouring countries. The macroeconomic situation was not totally consistent with a stable exchange rate either (otherwise the attacks could have been repelled and rational investors, knowing it, would have not attacked). Nevertheless, it would have been consistent, had the Thai market not collapsed and investors' confidence faded in a typical self-fulfilling prophecy of doom.

In light of this, a crisis is not solely caused by the inconsistency of fundamentals with a peg. The departure from the fundamental-based contagion approach consists in this. It is however important to notice that this view does not deny the role of fundamentals (i.e. the amount of reserves) in triggering a crisis: the model specifies a range of reserve levels within which there exists more than one equilibrium. Outside that range, a unique good or bad equilibrium is possible. Intuitively, if the reserve cushion $R - \overline{R}$ is bigger than the additional cost of debt servicing caused by a devaluation even if the latter is sure (i.e. if $\pi = 1$), then a speculative attack is always repelled by the central bank. Agents know this and thus don't attack. The only equilibrium possible is the one with $\pi = 0$ and the peg is stable. The contrary is true if the reserve cushion is zero; the only possible equilibrium is an attack and the collapse of the fixed exchange rate. The level of reserves is then crucial in determining the possibility of multiple equilibria. A common critique to multiple equilibria models is that they absolve policy makers from any blame for the crises in their countries by denying the role of weak fundamentals in such episodes. In light of these considerations, the critique seems here misplaced.

The crucial element in any multiple equilibria model of contagion is the self-fulfilment of the devaluation prophecy. If investors get convinced a devaluation will take place, they pull out of the market, thereby making the peg unsustainable. This element is present in various other models. All generate the possibility of multiple equilibria, and they model contagion as a shift from the stable peg to the devaluation equilibrium caused by a crisis abroad. These models can be divided in two broad categories:

a) Macroeconomic feedback models

Obstfeld (1994) provides an alternative take on the contagion as jump between multiple equilibria theory. In his setting increased expectations of devaluation raise the interest rate required by investor to hold domestic debt. To hold the peg, the central bank must keep higher interest rates, thus causing unemployment to rise. This tilts the cost-benefit analysis of maintaining the peg faced by the monetary authorities towards the red. Since the costs exceed the benefits, the peg is abandoned. The difference from Masson's model is that in that model the turning of investor expectations towards the bad triggers the attack that exhausts all reserves. In Obstfeld model the peg is instead *voluntarily* abandoned by the monetary authorities because the costs of maintaining it exceed the benefits. Reserves are not necessarily exhausted.

b) Liquidity shocks/Bank runs models

These are models of multiple equilibria-based banking crises. As in Diamond and Dybvig (1983), the decision of any agent depends on the expected decision of other agents. An adverse external shock acts as a sunspot and coordinates agents' decision towards the bad equilibrium: each investor pulls out.

Sachs (1994) applies this idea to international banking. There are *n* creditor banks with borrowers located in a foreign country. If any bank believes other banks will stop providing credit to borrowers, thus making them go bankrupt, all banks will stop lending, fulfilling the prophecy. A crisis elsewhere convinces banks that the other banks will cut credit lines. All banks cut the credit lines and precipitate the crisis.

Chang and Velasco (1998) provide a model of twin (currency and banking) crisis in a multiple equilibria fashion. An adverse external shock leads to an interest rise. This in turn might trigger a run on banks. The central bank, in order to save the banking sector, is forced to intervene with a sterilised money intervention. Even if it succeeds, the intervention causes a loss of reserves and then the speeding up of the reserves exhaustion process. In the best case, a currency crises follows, in the worst case, the central bank's intervention is not enough to save the banking sector and a twin crisis follows suit.

Some authors proposed models in which the time-proximity of crises is explained by shifts in investors' behaviour caused by a crisis somewhere but without the circular logic generating multiple equilibria. In this models the possible equilibrium is always one only. However, this equilibrium does depend on factors detached from the fundamentals of the country. Common feature of these models is the presence of a shock propagation channel that causes a crisis to have repercussions on assets whose expected returns are not affected by it. The underlying idea is that when a crisis hits market A, investors active in that market have incentives or obligations to alter their portfolio, regardless of whether the expected return on their other assets changed. The crisis therefore triggers trades of assets in market B. The trades are not caused by a change in market B's assets' *absolute* expected returns. It is the change in their expected returns *relative* to the other assets in the investors' portfolio causing the trades. The price of assets whose returns are totally unrelated with the those of the assets hit by the crisis might therefore be affected as well. A country can thus be affected whatever its fundamentals, as long as domestic investors are active in the crisis market too.

An example of such framework is Schinasi and Smith (1999), which shows how standard portfolio management rules such as the return-benchmark, the trade off and the value-at-risk approaches can generate correlation of assets holdings even when these have uncorrelated returns. Schinasi and Smith describe a simplified portfolio design problem in which an agent has to allocate his wealth between two risky assets. The agent can also borrow in order to finance investment. They show how, under all three portfolio-management rules, a capital loss generated by the drop of one asset's price will cause a net purchase of both assets if the agent is not leveraged and a net sale if she is. Being the assets uncorrelated and being their conditional distribution unaltered by the price shock, the co-movement of assets' holding is not justified by any correlation in the expected returns of the two, it is caused by the portfolio management rule only.

Schinasi and Smith focus on the role of leverage: if the investor is leveraged, the capital loss will cause a sale of both assets. The reason is that the capital loss generated an over-borrowing for the investor. If indeed the ratio of debt to assets (i.e.

the leverage ratio) was optimal before the loss, it is excessive now, since the value of assets has fallen by the value of the debt did not. It is therefore optimal to reduce this latter in proportion of the capital loss, which can happen only by disinvesting. Thus, the degree of leverage amplifies the reduction of total investment generated by a capital loss. Relatively small drops in wealth can then generate big unrelated-to-expected-returns sales of both assets and thus full-blown unrelated-to-expected-returns contagion when hit investors are leveraged enough.

The model is not able to predict how the sales will affect assets prices. The price fall causing the initial capital loss is indeed assumed to be the only price variation. The relationship between domestic and foreign asset prices is not defined. The model does nevertheless derive a relationship between the foreign asset price shock and the reduction in domestic asset *demand*. Whether this translates in correlated price movements is a question that can be formally answered by a full price-determination model only.

This is provided by Calvo (1999), a model of contagion based on liquidity shocks and asymmetric information. Investors in country *x* (the crisis country) suffer capital losses due to the fall of *x*'s assets' value. The reduced assets value puts them on margin calls or similar. As a consequence, they need liquidity, which they raise by selling assets in other (liquid) markets. They will transmit the shock to the country *y*, whose fundamentals have not been changed by the crisis. Therefore, there is a price movement unexplained by fundamentals.

The liquidity shock works once and for all, so that the movement in *y*'s price should be quickly reversed. Moreover, other investors, knowing that *y*'s fundamentals are not changed, should be happy to buy *y* at the pre-shock price. In a world of perfectly informed investors, liquidity shocks should therefore have no effect on *y*'s price. If, on the other hand, both informed and uninformed investor are present in the market, Calvo shows that liquidity shocks generate unexplained-by-fundamentals and time-persistent price movements.

The core structure of the model is borrowed from Grossman and Stiglitz (1980). There are two type of investors, informed and uninformed. The former observe a signal of the future expected return of each asset *s*. On this basis they choose their optimal portfolio allocation. However, when suffering a capital loss, they are forced

to liquidate some of their assets, thus departing unwillingly form their optimal allocation.

Uninformed investors observe informed investors' trading decisions only. As a consequence, their are not able to distinguish whether informed investors' trades are dictated by shifts in *s* or by liquidity shocks. In other words, uninformed investors can infer $E(s)$ from the actions of other investors, but with some noise generated by the liquidity trading of informed investors. Liquidity shocks are at least partly interpreted as movement in *s* by uninformed investors and their trades move the asset prices in a way that is partly unrelated to expected returns. In this context contagion arises when a crisis in country *x* generates significant capital losses to investors which are forced to liquidate some assets in country *y*. These sales trigger a misguided lowering of the expected return in *y*'s assets by uninformed investors and therefore a sale in the *y* market. As a consequence, prices of *y*'s assets fall, even though their expected returns are unaffected by the events in *x*. Furthermore, the fall in *y*'s price reduces $E(s)$, so that informed investor *as well* will lower the price they are willing to pay for *y*. The price movement caused by the uninformed investors is then not reversed. The liquidity shocks produce persistent, unexplained-by-fundamentals price movements.

Kodres and Pritsker (2002) propose a model of contagion based on cross-market portfolio rebalancing that shares the main features of Calvo's model, even if in a very different setting. The driving force behind contagion is, again, the presence of uninformed investors that are unable to interpret the informational content of the transactions they observe. The novelty in the Kodres-Pritsker setting is that informed investors can trade because a price change altered the composition of their portfolio and it is therefore optimal to alter the weights given to each asset in the portfolio. If the price of asset A changes, informed traders rebalance their portfolio by altering their positions on asset B. Differently from Calvo's setting, liquidity needs do not play any role here. However, similarly to Calvo (1999), uninformed investors are unable to understand whether informed investors traded asset B because of voluntary portfolio rebalancing or the acquisition of private information on the asset value. They therefore alter their expected returns on B in ways partly unrelated to the asset's fundamentals. Voluntary portfolio rebalancing introduces noise in the price formation process just as liquidity trading did in the Calvo model.

The key question is then why are uninformed investors there? Calvo and Mendoza (2000) give two possible explanations. First, performance-based managers' wages in an incomplete information setting. If managers receive wages based on the difference between their fund performance and the market average performance, their optimal strategy is choosing the same portfolio as the market does. Following the herd, the manager does not risk anything. If he made the wrong decision, everybody did as well. If instead he did not follow the herd and the decision turned out to be wrong, his remuneration is reduced. Of course, if the expected pay back of not following the herd is high enough, following his own information might be the optimal strategy too. This possibility is ruled out with the assumption that the marginal cost of performing worse than the market is higher than the marginal benefit of doing better. The second explanation is the simultaneous presence of fixed costs of information, limits to short selling and what they call globalisation (the expansion of investment opportunities through the opening of new markets). The benefit of acquiring information is to know which assets have higher expected returns and lower variance. When investment opportunities increase due to globalisation, investors can diversify, thus reducing their portfolio variance. Therefore, the second benefit of acquiring information (lower variance) diminishes with globalisation. The other benefit (knowing which markets have higher expected returns) remains. However, limits to short selling limit the benefits one can reap knowing the highest-return assets. Calvo and Mendoza show that a critical number of markets above which the benefits of acquiring information are lower than the (fixed) costs can be reached, therefore making it rational to be uninformed investors. In other words, the possibility of diversification offered by the ever-increasing investment opportunities would reduce the rationale for acquiring costly information about the fundamentals.

Even if it is optimal for agents to acquire costly information rather than stay uninformed, the associated costs will influence the working of the financial market and might generate contagion. This is the case in Romer-type intermediation models based on asymmetric information such as Agenor and Aizenmann (1998). Two agents are present in this model: banks that borrow abroad and lend to domestic firms. The latter can default, in which case banks can force the firm's liquidation and recover part of the credit, undergoing some costs of state verification (Townsend 1979). These costs arise from the fact that the bank does not know the value of the firm's

assets and therefore how much of its credit can be recovered. Firms have an obvious incentive to underreport their asset value, reason for which a verification of the firms' book value is necessary. This verification is costly for the bank. It follows that the possibility of default introduces agency costs in the intermediation process. These agency costs are internalised by banks by raising the lending rate charged to firms.

Deteriorating economic conditions increase agency costs because they reduce the firm's net worth and increase the probability of the firm's defaulting (a sort of Bernanke-Gertler effect, although the fall in firms' net worth provokes an increase in credit costs rather than its rationing). The assumed deterioration in economic conditions is an increase in the volatility of the firm's profits due to increased turbulence in international financial markets. This increases the probability of default, agency costs and thus the lending rate. Facing higher costs of credit, firms reduce production and employment. Notice that firms' expected profits did *not* change. If that would be the case, the fact that firms reduce employment would not be particularly interesting and would not need any financial market imperfection to arise. It is the fact that only the variance of the expected profits' increased that makes the model interesting. With costly-state-verification, turbulence *itself* has negative real effects.

Some models of capital market imperfections other than agency costs derive similar conclusions. An example is given by Caballero and Krishnamuthy (1999). Here the imperfection is given by the scarcity of internationally accepted collateral in the domestic financial market. As a consequence of this, the supply of credit might be just enough to satisfy domestic firms' credit demand. In such a situation, major shocks (such as financial crises abroad or terms-of-trade shocks) reduce the quality and/or the quantity of domestic collaterals, thus pushing the supply of credit under the demand level. Therefore, domestic firms are forced to costly liquidate illiquid assets, generating a fire sale. Assets prices drop and all firms' profits are transferred to collateral holders. Shocks in foreign prices generating a fall in the domestic credit supply level underneath demand level provoke domestic prices collapse. This is the contagion channel highlighted. The authors then show why the obvious incentive to increase collateral holding given by the firms' profit transfer to collateral-holders might be insufficient.

Caballero (2000a,b) presents extensive evidence showing how, due to weak links with the international market, Latin American financial markets (namely the ones of Argentina, Chile and Mexico) face constraints in the supply of credit. According to Caballero, this suggests that in Latin American credit markets major external shocks might push the supply level under the minimum demand level necessary to conclude the productive cycle, thus forcing firms to costly liquidate their illiquid assets as described by the model. This would explain the chronic instability of financial markets in that continent.

Finally, Allen and Gale (1998) provides an application of a similar idea on the inter-bank lending markets. They focus on the structure of interbank lending markets, describing a situation in which linkages between banks are "incomplete". If the interbank market is complete (i.e. each bank has liquid deposits in all other banks) any liquidity demand shock can be accommodated. The excess demand of credit in the market hit by the liquidity shock is satisfied by inter-bank lending and default is avoided. If instead banks are linked in an incomplete way (i.e. each bank has liquid deposit in a subset of banks only), banks hit by unexpected liquidity shocks might not be able to satisfy the withdrawals and default.

Allen and Gale give this example: assume the interbank lending system is a loop, in which any bank borrows from the previous one only and lends to the following one only. When a liquidity shock hits one market, the excess demand in that market can be satisfied only if the previous bank (the one lending to the one hit by the shock) has an excess supply of liquidity. Otherwise, this latter won't lend and the bank hit by the shock will have to default. Contagion is then modelled as a liquidity shock to a bank (a price shock generating a capital loss) that triggers the domino effect on the bank located downstream in another country.

Reviewing the contagion models developed in the last fifteen years has hopefully shown the variety of explanations given to the phenomenon. Empirically assessing their relative importance is not easy. This is a recurring problem in the theory of contagion. For example, the fact that countries with relevant current account deficits were found to be the most affected by the Mexican crisis tells only that trade imbalances made these countries more vulnerable. Whether this happened because of the reserve exhaustion argument at the basis of the Gerlach-Smets approach or instead

because concerns about the current account deficit co-ordinated investors expectations toward a bad equilibrium in a multiple equilibria fashion is very hard to assess. In general, trade is found to be a very important (if not the most important) channel of propagation of financial instability across emerging markets (see, to name just a few, Eichengreen et al. (1996), Glick and Rose (1998), De Gregorio and Valdez (1997), Forbes (2001)). However, this tells only that financial instability tends to spread towards trade partners. Whether this happens via a rational speculative attack à la Flood and Garber or by a jump between equilibria or other channels detached from fundamentals is hard to establish.

For this reason, when trying to assess the relevance of competing contagion models, researchers tended to focus on the crisis-contingent vs. non-crisis-contingent dichotomy rather than on one particular theory against the other. Multiple equilibria models and in general models based on a shift in investor behaviour during crises imply a break in the shocks' propagation mechanism. They are crisis-contingent models, as opposed to, for example, the Gerlach-Smets model. According to the latter, the propagation of shocks should indeed be stable during normal and crisis times, since trade shocks would cause the same path of reserves exhaustion in a trade partner irrespective of the turbulence in the markets. A necessary condition for crisis-contingent models to be relevant is then the observation of a break in the propagation mechanism during crises. This can be assessed by comparing the degree of correlation among financial markets during normal and crisis times. The relevance of alternative contagion models has then been assessed testing the stability of such correlation. This empirical literature is reviewed in chapter 5.

Empirically testing the relevance of theoretical models is certainly important. However, as noticed by Allen and Gale (2007), financial contagion is a complex phenomenon in which a multitude of factors are interplaying to generate the final outcome. In this light, looking for *the* theory of contagion does not seem a fruitful approach. Different models all highlight important channels of financial instability propagation.

2.2   *Currency mismatches in emerging market economies*

This literature review showed how real world events shifted the consensus of economists towards a new view of financial contagion. This view includes a bigger role assigned to investor behaviour or financial market weaknesses in transmitting shocks across borders and a wider set of fundamentals, both macro- and microeconomic (banking sector health, the quality of market regulatory bodies, maturity composition of the debt to name a few) considered determinant for the resilience of domestic financial markets to external shocks.

In this light, one feature of emerging markets received much attention in recent times: the currency composition of public and private debt. As stated by Eichengreen and Hausmann. (1999), "essentially all non-OECD countries have virtually no external debt denominated in their own currency". They called this phenomenon the "Original Sin" of emerging markets, to suggest that these are unable to borrow abroad for reasons related to their past and beyond their control. According to them, emerging market economies (EMEs henceforth) cannot borrow abroad because of their history of inflation, devaluations and default. This view contrasts with the moral-hazard view according to which the virtual non-existence of local-currency denominated debt in EMEs derives from credible pegs and implicit bailout guarantees from central banks. These would let borrowers and lenders discharge currency risks onto the central bank and the taxpayer, thus promoting excessive unhedged foreign-currency borrowing. The pervasiveness of foreign-currency-denominated debt would then be a voluntary choice of domestic borrowers, rather than an unavoidable risk for them.

Whatever the reason behind it, foreign-currency-denominated debt is a global phenomenon. Hausmann and Panizza (2003) provide detailed measures of the currency composition of internationally traded bonded debt: 97% of the latter is issued in five currencies (USD, EUR, YEN, GBP, CHF). On the other hand, the countries printing the five currencies issue only 83% of it. The rest of the world issue the remaining 17%, but only 3% is denominated in local currencies. This has two important implications: first, EMEs are almost completely unable to issue debt in their own currency, second, the five major currencies issuers have the opportunity to hedge against currency risk by swapping their credit with debt emitted elsewhere in their own currency. Agents in EMEs are then exposing themselves to currency risks

by borrowing in foreign currencies while typically earning in local currencies. In other words, they present relevant "currency mismatches" in their balance sheets. This is made clear by the regional index of currency mismatches proposed by Eichengreen et al. (2003), the OSIN3 index[1]. This is defined as *1* minus the ratio of the value of securities issued in currency *i* over the value of securities issued in country *i*. By considering total debt issued in currency *i* (rather than debt issued in currency *i* by country *i*), the index takes into consideration the hedging opportunities offered by bonds issued abroad in the country's own currency. The results for the years 1999-2001 show enormous differences between financial centres and EMEs: Latin America, Asia-Pacific and Eastern Europe have an OSIN3 index of, respectively, 1.00, 0.94 and 0.84. The index for financial centres is instead 0.08. This means that the latter can hedge 92% of their debt by swapping with debt issued elsewhere in their own currency. On the other hand, Latin American countries cannot hedge any of their external debt, while the other EMEs are close to it. Also, another index (the OSIN1) shows that financial centres issue 42% of their debt in own currencies, while the same figure is around 1% for EMEs.

Goldstein and Turner (2004) point out that the OSIN indexes are defective on four grounds. First, they consider the currency composition of liabilities only, not assets. Clearly, if a country has a trade surplus covering all its foreign-currency denominated debt, its exposure to currency risk is lower than if its trade balance is negative. This is also true regarding international reserves, an important issue considering the immense amount of reserves stashed by EMEs in recent years. Second, the OSIN indexes neglect the disaggregated side of currency mismatches. Who actually holds the foreign-currency-denominated debt within the economy? Are they exporting firms, earning in dollars, or local businesses invoicing in local currency? This has a crucial impact on exposure to currency risk, and it is neglected by looking at the aggregate side only. Third, domestic financial markets are now a relevant (in fact the biggest) source of credit in various EMEs and they tend to trade credit in local currency. Finally, the development of derivatives markets extended significantly the hedging opportunities available to agents in EMEs. Focusing on bonded debt only neglects that hedging opportunity.

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[1] For a detailed discussion of the OSIN indexes see Chapter 4.

Goldstein and Turner develop a more sophisticated index of currency mismatches that takes on boards these considerations, the AECM. This and the OSIN indexes are described in greater detail in Chapter 4, the interested reader is redirected there. Using their more sophisticated index, Goldstein and Turner are able to distinguish more subtly among EMEs, and find that not all of them are completely unable to avoid currency risk. However, also according to the AECM index, most EMEs that experienced financial crises and/or contagion in the '90s (namely Argentina, Brazil, Mexico, Indonesia, Korea, Thailand and Turkey) appear to have substantial currency mismatches in the years leading to the crisis/contagion, and often afterwards as well.

Whatever method of assessment is used, the inability to borrow in domestic currency appears then to be a prominent feature of financial markets in EMEs. Furthermore, currency mismatches provide the most convincing explanation of the recurrence of strongly contractionary devaluations in those countries. To show this, a brief review of the contractionary devaluation literature is here presented, with particular reference to aspects regarding EMEs.

2.3   Currency mismatches and contractionary devaluations in Emerging Market Economies

The fact that most of the devaluations taking place in EMEs in the last fifteen years were associated with sizeable drops in economic activity is hardly reconcilable with standard open economy macroeconomics, where devaluations are thought to increase aggregate demand via increased competitiveness, thus fostering rather than hindering economic activity. Some authors (notably Radelet and Sachs 1998) explain this conundrum by blaming the excessive reliance on monetary and fiscal tightening as stabilizing factors as the ultimate cause of such downturns. In this view, devaluations would not cause recessions, rather it would be the policy response to them. However, as pointed out by Frankel (2005), these policies might exacerbate the contractionary effects of a devaluation, but they hardly can be their origin. If devaluations have expansionary effects, then an optimal combination of exchange and interest rate interventions that allows achieving external balance without causing a recession should exist. Frankel's argument is that with openness to trade, the expenditure-reducing effect of a rise in interest rates can be offset by a devaluation, which increases net demand for domestic goods. Thus, full employment can be always guaranteed moving the two rates in the same direction. On the other hand

capital mobility and trade openness imply that both exchange and interest rates improve the balance of payments, so that it is always possible to maintain the latter balanced trading off the two rates. Because exchange and interest rates are two independent instruments, any combination of them can be chosen. Therefore, there must be one combination giving current account balance and full employment. It is then unclear why EMEs government, having the tools to fix current account imbalances while avoiding politically damning recessions, would systematically fail to do so. Frankel concludes that a more appealing explanation is that devaluations have intrinsically contractionary effects in EMEs. In this case, current account imbalances can be levelled only through a fall in output.

Frankel's argument is nested in the traditional Mundell-Fleming approach to exchange rate determination. Investors' sentiment shifts and other capital markets imperfections are not considered relevant in the dynamics of recent currency crashes. This is certainly a strong assumption when applying the approach to the EMEs crises of the '90s, since a large evidence of investor "flight to quality" and other shifts in investor behaviour have been documented in those events (among others: Ahluwalia 2000, Basu 2002, Kumar and Persaud 2001, Favero and Giavazzi 2002, Kamin and Von Kleist (1999), Eichengreen and Mody (1998), Eichengreen et al. 2000). It seems that instead of restoring trust in the stability of the macroeconomic environment, devaluations unleashed fears of further troubles in financial markets, slides of the exchange rate and in general of poor economic performance, thus triggering huge capital outflows. In this view, the "natural" expansionary effects of devaluations would be dwarfed by the havoc in the domestic financial sector caused by the sharp credit crunch. This eventuality cannot be ruled out a priori. However, contractionary devaluations *and* sentiment shifts are not mutually exclusive. They could well interact with each other in a crisis episode.

But why might devaluations be contractionary? Since the 1963 paper of Diaz-Alejandro, a good amount of research has been dedicated to answer this question. To date, ten channels through which a devaluation might affect negatively output have been identified:

1) Devaluations boost profits of producers operating in the tradable sector as a consequence of higher tradable-goods prices in domestic currency. In the meantime, if wages are sticky, real wages are falling. Therefore a

redistribution of income from wages to profits is taking place and, being the latter's propensity to save higher, the aggregate demand shrinks (Diaz-Alejandro 1963). With foreign ownership of capital, the negative effect will take place irrespective of agents' marginal propensity to save. In this case the income redistributed towards profit will simply leak to the rest of the world (Barbone and Rivera-Batiz 1987).

2) Countries usually devalue when they have a trade deficit, so when imports value in local currency is higher than exports value. A devaluation will initially increase this discrepancy as the value of imports increase. If the discrepancy was sizeable for start, then the elasticities of demand of import and export can be not high enough to fill the gap in the aggregate demand, even if the Marshall-Lerner condition is satisfied (Krugman and Taylor 1978).

3) The rise in imported goods prices causes inflation and reduces real balances, pushing domestic expenditure down. In presence of non-tradable goods with sticky prices the excess supply is not immediately corrected (Williamson 1991).

4) When debt is predominantly denominated in foreign currency, a devaluation increases debt and debt service payments in local currency, worsening banks' and firms' balance sheets and draining resources that could be used in spending and production (Cooper 1971, Gylfason and Risager 1984, van Wijnbergen 1986).

5) Speculative buying of durable goods. With high inflation and underdeveloped financial markets, the purchase of durable goods might be the only investment available to households. Expecting a devaluation and subsequent rise in inflation, households would anticipate the purchase of such goods. Aggregate demand would then increase before the devaluation, and then fall, since the rationale for the purchase is not there anymore (Dornbusch 1985).

6) Ad valorem taxes on imports represent a relevant source of government revenues in EMEs. A devaluation increases the value and thus the tax levied on imported goods, thus representing a tax increase. If the government don't spend the additional revenue, a fiscal contraction takes place and aggregate demand falls (Krugman and Taylor 1978).

All the above models highlighted potential negative effects of devaluations on the aggregate demand. Others have instead focused on the supply side of the story. Under this approach, some costs of production are in foreign currency (imported production inputs) or indexed to inflation (wages), so that a devaluation worsen firms' profitability and thus reduces supply.

7) imported production inputs: when a substantial part of raw materials, intermediate inputs and capital goods are imported the devaluation increases the cost of production per unit, thus reducing the firm's profitability (Hanson 1983, van Wijnbergen 1986)

8) when wages are indexed to inflation, a devaluation causes them to rise via a rise in domestic prices. The effect is similar to that of point 7) (Hanson 1983, van Wijnbergen 1986)

9) The reduction in real balances highlighted in point 3) might affect the supply side as well via rises in interest rates. In EMEs, firms are often relying on external finance for their working capital needs. With higher interest rates working capital becomes costlier, with a depressing effect on firm's profitability. (Bruno 1979, van Wijnbergen 1986)

As Frankel et al. (2005) point out, all the explanations apart from the balance sheet effect in point 4) share one feature: the contractionary effect involves a rise in domestic prices. If these channels are to explain the sharp drop in output that followed the 1990s devaluations, we should then observe a strong "pass-through" effect in EMEs. Yet, Frankel et al. (2005) provide evidence of the contrary. Estimating the pass-through of exchange rate movements to prices of eight narrowly defined retail imports to 76 countries, they find that the pass-through coefficient fell significantly along the 1990s. Such a fall was particularly strong in developing countries. So much so that, if those countries' coefficient was 0.8 in 1990, it dropped to 0.29 in 2001, compared with 0.05 for high-income countries. According to these estimates, developing countries had at the end of the 1990s pass-through coefficients similar to those of high-income countries a decade earlier. Yet this fact did not protect those who experienced a devaluation from massive downturns in economic activity. On the other hand, substantial evidence showed that devaluations in high-income countries tend to be expansionary (see, among others, Ahmed et al. 2002). Why then rich countries that devalued during the ERM crisis in 1992 (Sweden, the UK, Italy)

did not suffer sharp recessions whereas the Mexico, Southeast Asian countries, Brazil, Russia and Argentina all did? As the Frankel et al. (2005) study rules out differences in the pass-through coefficients, the most plausible explanation is the Balance Sheet effect. Contrary to the "rich" devaluing countries of 1992, at the end of the decade EMEs had sizeable foreign currency denominated debt. In these countries the expansionary effect on exports might have been more than offset by the negative real effect brought by the worsening of banks' and firms' balance sheets experienced after the devaluation. Supporting this view, there is ample evidence that after a devaluation countries with high levels of liability dollarization experience sharper drops in output and slower recovery than those with debt mainly denominated in national currency (see Roca and Priale 1987, Nunnenkamp and Schweickert 1990, Cavallo et al. 2002, Guidotti et al 2004, Cespedes 2004).

Theoretical models and empirical evidence suggest therefore that currency mismatches are a key source of financial instability and recessions in EMEs. The relevance of this argument is witnessed by various researches' statements. For example, Calvo and Reinhardt (2000) coin the term "fear of floating" to describe the fact that countries stating they allow their exchange rate to float mostly do not. The main reason behind such fear is, according to them, the fact that "in EMEs devaluations (…) tend to be associated with recessions -not the kind of benign outcome stressed in standard textbooks. This is hardly surprising *in light of the fact that in EMEs there is pervasive liability dollarization*" (the italic is mine). Obstfeld et al. (2008) identify three forces behind the recent unprecedented accumulation of foreign reserves by central banks in EMEs. One of them is "a continuing desire to maintain a policy of fixed or tightly managed exchange rates (…) possibly to avert destabilizing balance sheet shocks when liabilities are dollarized". Goldstein and Turner (2004) notice in their book's preface "currency mismatches have been present in virtually every major financial crisis in emerging economies over the past decade" and "the countries that have experienced the largest currency mismatches have typically been the ones that have suffered the largest output losses during crises". Finally, Furman and Stiglitz (1998) affirm "the ability of this variable (foreign-currency denominated debt), by itself, to predict the crises of 1997 is remarkable". Notwithstanding this, very few papers have been dedicated to the theoretical analysis of the role of currency mismatches in the propagation of external disturbances. The

next chapter briefly reviews this literature and expands it by investigating a previously neglected issue: the joint effect of variance shocks (i.e. increases in the exchange rate variance) and currency mismatches on the propagation of financial instability.

CHAPTER 3 – EXCHANGE RATE VOLATILITY AND CONTAGION IN PRESENCE OF CURRENCY MISMATCHES

3.1   Introduction

The literature summarized in the previous chapter highlighted the pervasiveness of foreign currency denominated borrowing in *EMEs*. It was argued that this gives a plausible and evidence-backed explanation of the recurrence of contractionary devaluations in those economies. A number of studies have investigated the link between currency mismatches and macroeconomic instability in *EMEs*. Some authors developed *DSGE* models that extended the Bernanke-Gertler approach (in which domestic firms' access to credit depends on their net worth) to a setting in which firms' net worth depends on exchange rate levels since firms' debt is denominated in foreign currency (see Cespedes et al. (2002), Devereuax et al. (2003), Gertler et al. (2002)). These studies show how currency mismatches generate a financial accelerator: negative shocks to the trade balance cause depreciation, this in turn reduces firms' net worth therefore increasing their costs of funding. The effect of foreign disturbances on firms' output is in this way magnified by the presence of currency mismatches. The focus is on the magnification of *level* shocks (i.e. shocks to the level of net exports). This work investigates instead the real effects of *volatility* shocks (i.e. increases in the macroeconomic volatility impinging on the economy, e.g. increases in the volatility of net exports) on countries with substantial currency mismatches. These shocks are a recurring feature of financial crises, during which EMEs' volatility of exports, production, inflation, and financial variables such as stocks, bonds prices and exchange rates prices all tend to increase markedly. Just to give an idea of the magnitude of the phenomenon, in the months following the major crises of the 1990s the exchange rate variance of EMEs increased by 15% to 30% in the EMEs present in our sample (discussed below). Notwithstanding this, to my knowledge no formal analysis of the real effects of exchange rate volatility hikes in presence of currency mismatches have been carried out.

Variance shocks are investigated developing a model of financial intermediation with domestic banks and producers where the latter borrow in foreign currency but

earn revenues in domestic currency. The currency risk renders firms' profit (and therefore their ability to repay the debt) dependent on the exchange rate. When the exchange rate depreciates enough to wipe out all profits, firms default and the bank can recover the full value of the credit only incurring in a costly enforcement process. Banks will then internalise the expected enforcement costs by charging a risk premium on the rate at which they borrow. It is shown that the risk premium is a positive function of the exchange rate volatility. Higher volatility increases the probability of both extreme appreciations and depreciations. However, while higher probability of extreme appreciations do not increase banks' expected revenues (for any level of exchange rate below that allowing firms to repay the full debt firms' repayment to banks will not increase), higher probability of extreme depreciations reduces banks' revenues as firms will be unable to repay the debt more often. Ceteris paribus, higher exchange rate volatility translates therefore in bigger risk premia. Default is costly for firms too, since they are sold piecemeal to find the additional resources needed to repay the debt, thereby loosing some of their value. Numerical computations show that, by raising default costs for both banks and firms, exchange rate volatility causes a drop in both the demand and the supply of loans and pushes production and employment down.

In such a setting, shocks causing an increase in the exchange rate variance (e.g. an increase in the variance of foreign output) depress the aggregate supply and employment. Financial contagion events can be explained by these supply-side shocks: when a crisis renders the future performance of a trade partner less predictable its output volatility increases. This translates into higher volatility of the domestic trade balance and exchange rate. This in turn depresses domestic production. The framework thus provides a model of contagion driven by currency mismatches and volatility shocks.

The model extends the literature on currency mismatches in two ways: first by showing that the negative effects of currency mismatches during financial turmoil may go beyond the much studied balance sheet effects. These consist of a deterioration of the balance sheet due to a level shock (exchange rate depreciation). A necessary condition for the negative real effects to materialize is the presence of foreign currency denominated debt. Without it, exchange rate fluctuations do not affect the balance sheet and thus the net worth of agents. The model presented below shows instead that a variance shock could negatively affect also firms with no foreign

currency denominated debt if these are dependent on foreign currency denominated credit. This will indeed become more expensive as a result of increased variance, reducing firms' margin. Shifting the attention on variance shocks, the analysis shows that, even if they do not affect the balance sheet of a firm, variance shocks can affect supply negatively.

The second contribution is related to the issue of contagion. The analysis shows that currency mismatches may generate a channel of contagion among countries with no direct trade or financial linkages. It is enough that a financial turmoil abroad increases uncertainty about the domestic economy's exchange rate developments for domestic output and employment to be negatively affected.

3.2   *The bank loans market*

3.2.1   *The Agenor-Aizenmann model*

The bank loans market is modelled introducing currency mismatches in the theoretical framework developed by Agenor and Aizenmann (1998) (*AA* henceforth), a model that was sketched in the literature review. In the *AA* model there is uncertainty regarding the future productivity of firms. The latter borrow from banks to cover their labour costs and once the production is completed they can either repay the debt or default. In this second case banks can seize a part of the firm's output as compensation, after paying a fixed amount for legal expenses and contract enforcement costs. The costs arise from the fact that firms have an obvious incentive to underreport the value of their output in order to reduce the amount seized by banks. These can however observe the true value of the firm's output, but only through a costly legal process. Firms' are heterogeneous (i.e. they have different productivity levels). However their productivity has a common component, influencing all firms' productivity. When this common component is low, average firms' productivity is low and the output that banks can seize from defaulting firms is lower than the amount owed by the latter for many firms. For all these firms, it is profitable to default. When instead productivity is high it is convenient for fewer firms to default. Thus, the probability of default (and the expected losses for banks) is negatively correlated with expected productivity. Banks internalise this by charging higher interest rates when expected productivity is low. Notice the similarity with the

Bernanke-Gertler financial accelerator argument: here too economic downturns (drops in productivity) are amplified by the increase in agency costs. In fact, both models depart from the neo-classical Modigliani-Miller theory of investment by introducing Costly State Verification agency costs (Townsend (1979)).

The volatility of aggregate shocks impinging on the economy (in the form of productivity shocks) plays an important role in this chapter. The asymmetric effect of extreme events on banks' expected profits described in the introduction of this model are present here too. An increase in the probability of extreme hikes in productivity levels do not increase banks' expected revenues while that of extreme drops increase banks' expected verification costs. These react charging a higher risk premium, widening the spread between deposit and lending interest rate. Firms face a higher cost of funding and as a consequence reduce production. Volatility has thus a negative effect on the supply side of the economy.

The *AA* setting gives a useful framework to analyse the issue of volatility in the financial intermediation process. I use it to investigate the effect of exchange rate rather than productivity fluctuations. To do so, the model presented here departs from the *AA* structure in two aspects. First, there is no uncertainty regarding firms' productivity, which is instead constant, equal for all firms and known to all agents. Secondly, banks' loans to firms are denominated in foreign currency. The domestic currency will be the "peso" and the foreign the "dollar". Since firms borrow in dollars and earn in pesos, exchange rate movements affect their profits. In such a setting a rise in exchange rate volatility causes a drop in firms' employment since it increases their costs of funding and expected losses related to the event of defaulting. To see this, let us look at the model in detail.

3.2.2   *The Agenor-Aizenmann model revisited*

There are two agents operating in this economy: producers (firms) and commercial banks. The latter borrow in dollars on the world markets and lend in dollars to firms. In period 0 firms must borrow from banks in order to cover their labour costs and start production; in period 1 production is completed, the output is sold and the debt repaid or defaulted. We therefore have the following time-line:

0	*1*

- Production levels set
- Loans contracted
- Wages paid

- Production completed
- Output sold
- Loans repaid or defaulted
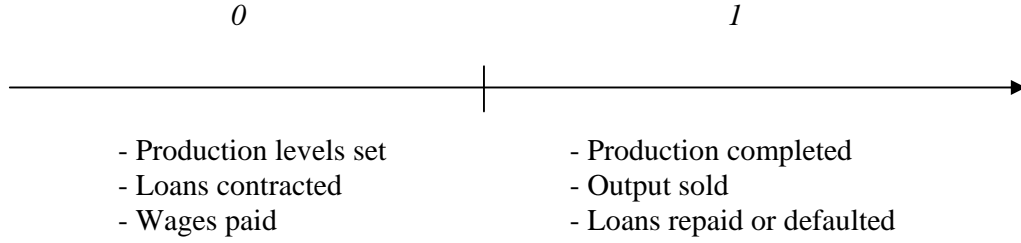
All firms are identical, and the representative producer faces a production function of the type:

$$y = n^b \qquad (3.1)$$

y and n are, respectively, the output and employment levels of the representative producer; b is the share of labour in production and it is assumed smaller than one, implying diminishing marginal labour productivity. Capital is assumed fixed and normalized to one. Before starting the production, firms need to borrow from banks in order to pay employees a fixed peso wage w. It is assumed that banks lend to firms in dollars only. Firms borrow in dollars at the contractual interest rate r. They do so when the exchange rate is s_0 and must repay in the next period when the exchange rate is s_1. The exchange rate is expressed as the cost of one dollar in pesos, so that its increase represents a depreciation of the peso.

The representative firm's costs of funding to be repaid in time *1* (called *F* henceforth) are equivalent to the peso value of its debt. This in turn is the wage bill times one plus the lending rate adjusted for the exchange rate movement:

$$F = wn(1+r)\frac{s_1}{s_0} \qquad (3.2)$$

The firm can default its obligations, but in this case the bank is able to force the liquidation of its assets to recover its credit. I assume that loans are fully collateralised and thus banks can always recover the full value of their loans. Since firms are borrowing to cover their labour cost only, it is reasonable to assume that the value of the firm's total assets is always enough to cover the full amount lent.

Knowing that the bank is always able to recover its full credit, the firm has no incentive to default and will do so only if it cannot do otherwise. The default represents the end of the firm, as all its assets are liquidated in order to repay its obligations. The liquidation process is assumed costly for the owners. The firm is dismembered and its assets are sold piecemeal, thus losing part of their value. In other words, there is a difference between the going concern and the liquidation value of the firm, and this difference is the cost of default borne by the owners. For this reason, although firms repay the full amount owed to banks whether they default or not, they will try to avoid it if possible.

I therefore use an "ability to pay" approach in which firms always pay if they have resources enough to do so. This contrasts with the "willingness to pay" approach followed in *AA* in which firms default if the part of their revenues recoverable by banks (assumed less than 100%) is smaller than the value of their debt. In that approach firms' default decisions are based on the present costs and benefits of defaulting only. In the next period, a firm that defaulted has the same access to credit than one that did not. This is an uncomfortable assumption. The "ability to pay" approach is preferable because it better captures the fact that, after defaulting, a firm at the very least cannot borrow easily and thus it tries to avoid it in any possible way.

Firms will repay unless their revenues are not enough to repay the debt. The default condition in pesos is then essentially a negative profits condition:

$$n^b < wn(1+r)\frac{s_1}{s_0} \tag{3.3}$$

The term on the left hand side is the firm's total revenues (i.e. the units of good produced times the good's price, which is assumed fixed and normalized to one). The fact that revenues are in pesos while costs are in dollar is what generates currency risk and renders firm's profit dependent on s_1. This is the only stochastic element in (3.3), so that expectations on the probability of default and thus on banks' expected profits are based on expectations on the future exchange rate. Banks' and firms' profits are then both dependent on s_1.

Setting (3.3) as equivalence gives s_1^*, the exchange rate at which firms' revenues are just enough to repay the debt:

$$s_1^* = \frac{n^{b-1}s_0}{(1+r)w} \qquad (3.4)$$

For any exchange rate level higher than s_1^*, the firm will have to default. Agents are able to predict the exchange rate in the next period with an error e, so that:

$$s_1 = s_e + e \qquad (3.5)$$

where s_e is the exchange rate that agents in $t=0$ predict will prevail in $t=1$. Substituting (3.5) for s_1 in (3.4) and rearranging we obtain the highest forecast error e^* still allowing the firm to repay its debt, given the expected rate s_e:

$$e^* = \frac{n^{b-1}s_0}{(1+r)w} - s_e \qquad (3.6)$$

Given the expected exchange rate, e^* is the maximum error that leaves the firm able to repay its debt. Above it, it will have to default its debt, starting the liquidation process.

The bank is always able to fully recover its credit. However, the liquidation procedure implies some costs c. The latter can be thought of as legal expenses. These are assumed to be proportional to the amount lent, since it is thought that overseeing the liquidation process of a big firm is more expensive that the one of a family business, for example. Since wn represents the peso value of the amount lent by the bank, cwn is the proportion of amount lent that must be spent in order to recover the credit, in case of default. Also, taking into consideration the fact that professionals tend to be paid in foreign currency in *EMEs*, it is assumed that the recovering costs are indexed to the dollar. In other words, recovery costs are assumed to vary in line with the exchange rate. The recovery costs A expressed in pesos are thus *cwn* times the depreciation between periods 0 and 1:

$$A = cwn\left(\frac{s_1}{s_0}\right) \tag{3.7}$$

The bank's expected return from a loan is the expected value of the credit minus the expected recovering costs:

$$\left(\frac{s_e}{s_0}\right)(1+r)wn - cwn\left(\frac{s_e}{s_0}\right)\Pr(d) \tag{3.8}$$

where $\Pr(d)$ represents the probability of the firm defaulting. For each peso lent (i.e. dividing (3.8) by $\left(\frac{s_e}{s_0}\right)wn$), the bank expected returns are thus:

$$(1+r) - c\Pr(d) \tag{3.9}$$

Banks must borrow at the interest rate r_B in the international money markets. Free entry makes the banking sector perfectly competitive, so that banks make zero profits. Therefore, we must have that expected costs and return for each peso lent are equal:

$$(1 + r_B) = (1+r) - c\Pr(d) \tag{3.10}$$

Or:

$$r - r_B = c\Pr(d) \tag{3.11}$$

Eq. (3.11) states that the spread between borrowing and lending rate is set by the bank so as to cover the expected costs of recovering defaulted loans. Given the international borrowing rate, the lending rate is then determined by the probability of default. The latter is the probability of the exchange rate forecast error being higher than e^*, forcing firms to default. We thus have that:

$$\Pr(d) \equiv \Pr(e > e^*) = 1 - \Phi(e^*) \tag{3.12}$$

where $\Phi(e)$ is the cumulative distribution function of e. Substituting it in (3.11) we get:

$$r - r_B = c(1 - \Phi(e^*)) \tag{3.13}$$

Finally, substituting (3.6) into the latter we get:

$$r - r_B = c\left(1 - \Phi\left(\frac{n^{b-1} s_0}{(1+r)w} - s_e\right)\right) \tag{3.14}$$

Eq. (3.14) contains all the pairs (n, r) ensuring that the bank's expected profits are zero. In other words, it gives the interest rate the bank will charge in order to lend any amount of money to the firms. It is therefore the funds supply function, henceforth called S. The latter states that banks supply funds at the borrowing rate r_B plus a premium to cover their expected enforcement costs in case of default.

Turning to the demand of funds, this is determined by the firm's production decisions. These in turn are taken so as to maximize the firm's expected value, which is given by the expected value of the firms' fixed capital plus profits. There is no investment nor capital depreciation in this economy, so that the only element affecting the value of the fixed capital is a default event. As seen above, if the firm defaults and it is therefore forced into liquidation, the total value of the fixed capital sold piecemeal will fall by a certain amount, assumed equal to x. We thus have that the expected value of the firm is:

$$E(v) = Q + E(\pi) - \Pr(d)x \tag{3.15}$$

Q represents the total value of the fixed capital in period 0, $E(\pi)$ expected profits and $\Pr(d)x$ the expected costs of default.

Expected profits are given by revenues minus expected costs. Recall that prices are normalized to 1, so that revenues U are equal to the value of output:

$$U = pn^b = n^b \qquad (3.16)$$

Expected costs of funding are given by the expected repayment to banks, which is the amount borrowed times the interest rate and the expected depreciation:

$$E(F) = wn(1+r)\frac{s_e}{s_0} \qquad (3.17)$$

Recall that firms always repay their debt, whether they default or not. For this reason, $\Pr(d)$ does not appear in the costs of funding expression.

Putting together the last three expressions we obtain the firm's expected value:

$$E(v) = Q + n^b - \frac{s_e}{s_0}(1+r)wn - \Pr(d)x \qquad (3.18)$$

The value-maximizing level of employment is given by the first order condition:

$$bn^{b-1} - \frac{s_e}{s_0}(1+r)w - xf(e^*)\frac{(1-b)n^{b-2}s_0}{(1+r)w} = 0 \qquad (3.19)$$

where $f(e)$ is the probability distribution function of e. (3.19) is essentially a profit maximization condition with the addition of the marginal effect of the marginal worker on the probability (and thus costs) of default. The latter is identified by the last term in (3.19). This is obtained by differentiating the last term in (3.18) w.r.t n and noticing that:

$$\frac{\partial \Pr(d)}{\partial n} = \frac{\partial \Pr(d)}{\partial e^*}\frac{\partial e^*}{\partial n}$$

$$= \left(-f\left(e^*\right)\right)\frac{(b-1)n^{b-2}s_0}{(1+r)w}$$

$$= f\left(e^*\right)\frac{(1-b)n^{b-2}s_0}{(1+b)w} \tag{3.20}$$

I define the last term in (3.19) the "marginal costs of default" and, as we will see later, these costs play a key role in the determination of the equilibrium levels of n and r.

Eq. (3.19), together with the concavity of the expected value function, gives the value-maximizing level of employment. It therefore gives the amount firms will borrow at any lending rate level. It represents the funds' demand function, henceforth called D.

The equilibrium in loans market is described in the following with numerical computations of the two equations of the supply and demand for funds. The computations are then used to do some comparative statics in order to get insight on the effects of exchange rate depreciations and volatility on the equilibrium levels of employment and interest rate.

3.3   Numerical Computations

3.3.1   Model parametrization

This section presents the calibration of the model, which is summarized in Table 3.1. Most of the parameters values are taken from previous literature, the others are obtained from financial data as described in the following.

Consistent with the *DSGE* literature on the topic (see for example Cespedes et al. 2004 and Elekdag and Tchakarov 2007), the labour intensity of domestic goods represented by the parameter b is set equal to 0.65.

The exchange rate in time 0 is normalized to 1. To investigate the effect of expected depreciations on the equilibrium, the expected time 1 exchange rate s_e is set to different levels. The assumed maturity of the loans is a key issue to establish what levels of exchange rate depreciation (i.e. what levels of s_e) to use in the

computations. If the firm's debt is due to repayment in one month, the one-month exchange rate movement is what affects the debt value and thus s_e should be the exchange rate one month ahead. If the loan matures in a year, the relevant s_e is instead the exchange rate in a year time. If we want to use the average depreciation after a crisis as the level of s_e in the computations, we need to decide the time-span over which the average depreciation is computed. The Survey of Terms of Business Lending provides information concerning the terms of commercial and industrial loans made to U.S. non-financial businesses by commercial banks. According to it, the average maturity of a loan with purpose "general corporate purposes/working capital" is of 9.6 months. Data for emerging markets are very scarce, but a recent study on Bolivia found the average maturity to be 11 months (Ioannidu et al. 2008). We then set the average maturity of working capital loans at 11 months. Accordingly, s_e must be the expected exchange rate in eleven months time. Then we estimate the average 11-months exchange rate movement following a major crisis event in a sample of 40 *EMEs* in the period January 1995 – December 2005[2]. The inter-quantile range of the exchange rate movement is +0.098 to +0.2. In other words, the exchange rate depreciated between 9.7 and 20 percent in the 11 months following a major crisis in the 50% of cases at the centre of the distribution (or alternatively, in the lowest 25% of cases the exchange rate depreciated less than 9.8% or appreciated and in the highest 25% of cases it depreciated by more than 20%). We run two computations with s_e equal to 1.1 and 1.2, therefore representing a 10% and 20% expected depreciation. We interpret these as the boundaries of the average exchange rate pressure felt by an EME after a crisis.

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[2] The major crisis events are: the East Asian (start point Jul-97), the Russian-Brazilian (Aug-98), the Turkish-Argentinean (Feb-01), considered one only event as the proximity of the two makes it impossible to distinguish them.

Table 3.1
Computations parameters values

parameter	description	value	source
b	Share of Labour in production	0.65	*DGSE* literature (Cespedes et al 2004, …)
p	Price levels	1.00	normalized to 1
s_0	Exchange rate in 0	1.00	normalized to 1
s_e	Exchange rate in 1	various	
w	annual / productive cycle workers' wage	0.60	wn/y=0.65, labour's share in production
c	enforcement costs as % of loan	0.18	Djankov et al. (2004)
r_B	international interest rate	0.04	average 6-months LIBOR Jan1995-Dec2005
σ	Exchange rate forecast error st. dev.	0.22	Sample average exchange rate volatility, Jan1995-Dec2005
B	Bankruptcy costs as % of firm's value	0.192	Thorburn (2000)
T	Price-to-Sales ratio	3.61	Computed from Damodaran's database (var. years)

Assuming a perfectly competitive labour market, labour's share in the revenues should be roughly equal to the labour's share in production. Wages levels are thus set so that the wage bill over total revenues (i.e. labour's revenues share) is equal to the labour productivity share (i.e. *b*). In other words, *w* are set so that $\frac{wn}{n^b} = b$, giving a value of *w=0.60*.

Djankov et al. (2004) provide data on the estimated cost of debt enforcement proceedings as a percentage of the value of the debt for the claimant in 88 countries. Costs include court/bankruptcy authority costs, attorney fees, bankruptcy administrations fees, accountant fees and other associated costs. The average for *EMEs* (lower- and middle-income countries in the World Bank classification used in the study) is 18% of the loan. Accordingly, the value of *c* is set to 0.18.

The international borrowing rate is computed as the average six-months LIBOR rate (i.e. the average LIBOR for a six month deposit in US Dollars on the last business day of the previous month) in the period January 1995 – December 2005, which gives a value of 4%.

The exchange rate volatility is calculated as the average eleven-months volatility of the exchange rate vis-à-vis the US Dollar. The figure is obtained with a three-

stages procedure: first the eleven-months volatility for each country's exchange rate is computed as the variance of an eleven-observations rolling sample of monthly exchange rate levels and the country-specific average is calculated. Then each country-specific average standard error is transformed into percentage change from the mean exchange rate in order to make standard errors comparable across countries. Finally the transformed standard errors for all 40 countries are summed up and the simple average taken. The procedure gives an exchange rate standard error of 0.22. The forecast error e is assumed to be normally distributed with mean 0. The figure above implies therefore that agents are able to forecast the exchange rate in 11 months time with less than 22% error on both sides roughly two-thirds of the times. To analyse the effect of variance shocks on the equilibrium, the latter is also computed for $\sigma = 0.253$ and $\sigma = 0.286$ (i.e. for a 14% and 30% standard error increase). These values represent the average increase in the exchange rate variance after main crisis episodes, computed in the same way as the average depreciation. Specifically, we consider the values at the borders of the interquantile range of increases in exchange rate variance in the eleven months after a crisis (i.e. $\sigma = 0.253$ and $\sigma = 0.286$ are the 25th and 75th percentile of the variance increases after a crisis).

When the firm defaults on its debt, the bank can force its liquidation and recover the full amount lent. The liquidation causes a monetary loss to the firm, equal to x. To calibrate this parameter, estimates of the cost of bankruptcy/liquidation for the firm's owners are needed. These have been estimated for listed companied by a number of researchers. The most quoted study (Altman 1984) estimates bankruptcy-related costs to be around 16.7% of US firms' value in the year before bankruptcy. More recently, Thorburn (2000) finds an estimate of 19.2% for Swedish and Russian companies. Bankruptcy costs as a percentage of the firm's value are thus set equal to 0.192. To estimate the representative firm's value, I use data on the Price-to-Sales ratio. This is the ratio of the market capitalization of a firm over its revenues in the past 12 months. Knowing the value of revenues U and the Price-to-Sales ratio T one can compute the representative firm's value as: $v = U * T$. Average revenues $\overline{U}$ are obtained by computing the equilibrium with all parameters (expected depreciation included) at their average value and computing $\overline{U} = \overline{n}^b$, where $\overline{n}$ is the equilibrium employment level for all parameters equal to their mean. The Price-to-Sales ratio is instead based on the dataset of Damodaran of the Stern business school (see

www.damodaranonline.com). This provides the ratio of roughly 8000 firms listed in emerging stock markets in the 2002-2007 period, with an average Price-to-Sales ratio of 3.61. Assuming that listed firms' are representative of all firms in *EMEs* so that the former' and the latter' bankruptcy costs and *PSR* are similar we can compute the costs of default *x* as follows:

$$x = B * v = B * (\overline{U} * T)$$

$$= 0.192 * (\overline{n}^{0.65} * 3.61) = 0.521$$

3.3.2 *Numerical Computations*

With the above parameters values and no expected depreciation (i.e. setting $s^e = 1$), the computed demand and supply for funds are as depicted in Figure 3.1. Figure 3.2 shows the enlarged detail of the equilibrium, from which one can see that the latter is given by r=0.04 and n=1.04.

Figure 3.1
**Equilibrium in the loans market
with no expected depreciation**
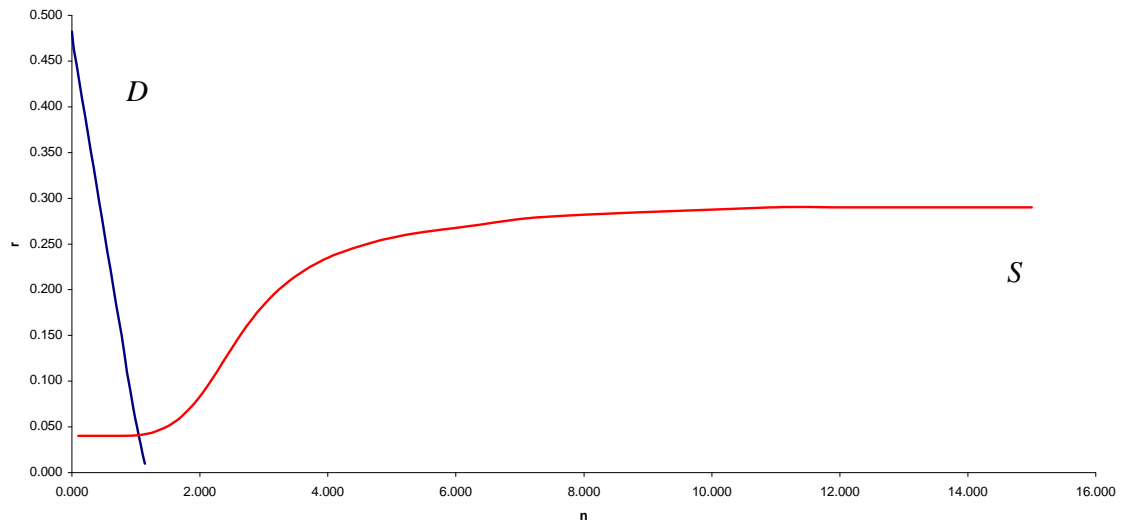
The most interesting part of the analysis is the supply curve. Recall that banks charge a premium proportional to the probability of default over the borrowing rate.

The probability of default is in turn a positive function of the amount lent: because of diminishing marginal productivity of labour, an additional worker (i.e. one more wage to pay and thus a bigger amount borrowed) increases firms' revenues by less than it increases its debt. Profits per worker fall and the depreciation necessary to wipe out all profits and force the firm to default is lowered. It follows that an additional worker increases $\Pr(d)$ and lowers banks' expected profits.

Figure 3.2
Detail of the equilibrium
with no expected depreciation
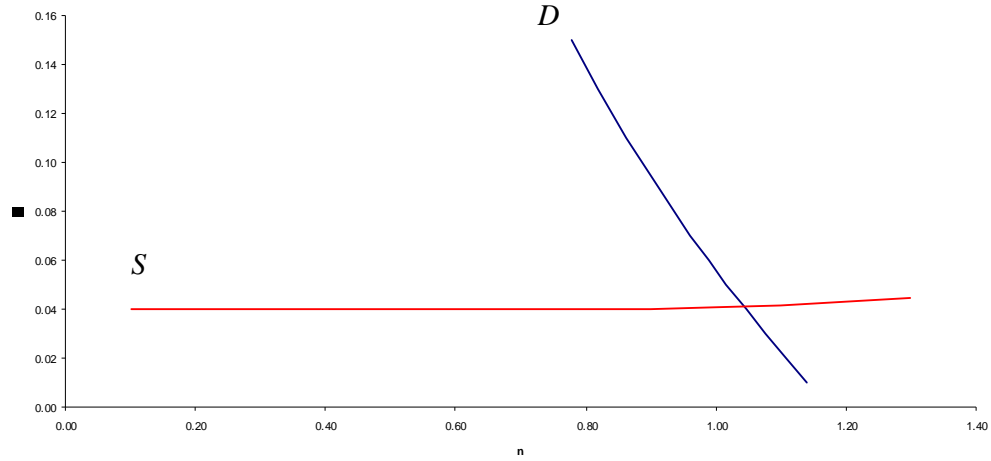
This can be seen differentiating the supply equation (3.14) with respect to employment:

$$S_n \equiv \frac{\partial S}{\partial n} = -c\frac{\partial \Pr(d)}{\partial e^*}\frac{\partial e^*}{\partial n} = -cf\left(e^*\right)\frac{(1-b)n^{b-2}s_0}{(1+r)w} < 0 \qquad (3.21)$$

The derivative is negative for any value of n and r. Another representation of the phenomenon is provided by Figure 3.3, plotting the probability of default as a function of n and r. We can see that, given r, an increase in n pushes $\Pr(d)$ up.

Low values of n are thus associated with low probability of default and low lending rate as banks charge a negligible premium: the supply is roughly flat at the borrowing rate. Given a borrowing rate of 4%, $\Pr(d) \approx 0$ for all values of n below 1 and as a consequence the supply is flat at $r=0.04$ (see Figure 3.2).

As *n* increases, it raises the probability of default above zero and thus reduces banks' expected profits. These react charging a higher premium and the lending rate *r* rises.

Notice however that the interest rate has two contrasting effects on the supply, as can be seen differentiating the latter w.r.t. *r*:

$$S_r \equiv \frac{\partial S}{\partial r} = 1 - c \frac{\partial \Pr(d)}{\partial e^*} \frac{\partial e^*}{\partial r} = 1 - cf(e^*) \frac{n^{b-1} s_0}{(1+r)^2 w} \qquad (3.22)$$

On one hand, an increase in *r* raises the amount due to the bank per dollar lent, on the other it increases the probability of default since it raises the firm's debt. The first effect (identified by 1 in 3.22) increases banks' expected repayments while the second (last term in 3.22) decreases it; the final effect on expected repayment and thus on banks' profits is then theoretically ambiguous. For the values used in the computations we have however that (3.22) is positive: a marginal increase in *r* raises banks' expected profits. It follows that banks offset the fall in expected profits due to the increase in *n* by increasing *r*: the supply is positively sloped.

It is interesting to analyse why, starting from low levels of *n* and increasing, the supply gets steeper first and then gradually flattens until it is flat again at *r=0.29*. The key behind this is $f(e^*)$, which can be interpreted as the joint marginal effect of *n* and *r* on the probability of default and thus on banks' profits. We have already seen that the probability of default is zero for low enough levels of *n* and *r*. For these values, since the forecast error *e* is normally distributed, $f(e^*)$ is also zero: a marginal increase in *n* does not increase the probability of default nor reduces banks' expected profits (see 3.21, giving $S_n = 0$ for $f(e^*) = 0$). $f(e^*)$ equal to zero also implies that an increase in *r* translates one to one in higher expected profits for banks (i.e $S_r = 1$ for $f(e^*) = 0$, see 3.22). This is because higher rates cause no increase in $\Pr(d)$ and thus increase banks' expected revenues one to one. For low enough levels of *n* and *r* we thus have that the supply slope $-\frac{S_n}{S_r} = \frac{0}{1} = 0$: the supply is flat.

Given r, as the amount lent increases so does the probability of default and $f(e^*)$. Eventually, S_n will turn negative while S_r will become smaller than one: the supply will turn positive. At this point $f(e^*) > 0$ and an increase in n will have to be offset by an increase in r in order for the bank to break even.

With an upward sloping supply curve, as n increases, so does the level of r guaranteeing banks' breakeven. This in turn pushes $f(e^*)$ up, further reducing both S_n and S_r and thus steepening the supply curve. This has a clear interpretation: in a world with Gaussian forecast errors, as default becomes more and more likely, the same increase in n will cause a bigger increase in banks' costs and the same increase in r will have a smaller effect on banks' profits. This process continues until $\Pr(d) = 0.5$. At this point e^* is at the mean of the error distribution and $f(e^*)$ is at its maximum: the marginal effect of n on banks' costs is maximum and the marginal effect of r on banks' profit minimum. Any further increase in n and r will now decrease $f(e^*)$ and thus the opposite process takes place: the supply flattens. Once $\Pr(d) = 1$, an increase in n and r will not have any effect on banks' profits: the supply returns flat. This happens at the interest rate level $r = r_B + c = 0.04 + 0.25 = 0.29$, which is indeed the supply equation (3.14) with $\Pr(d) = 1$.

Figure 3.3
The Probability of default
as a function of N and R
no expected depreciation
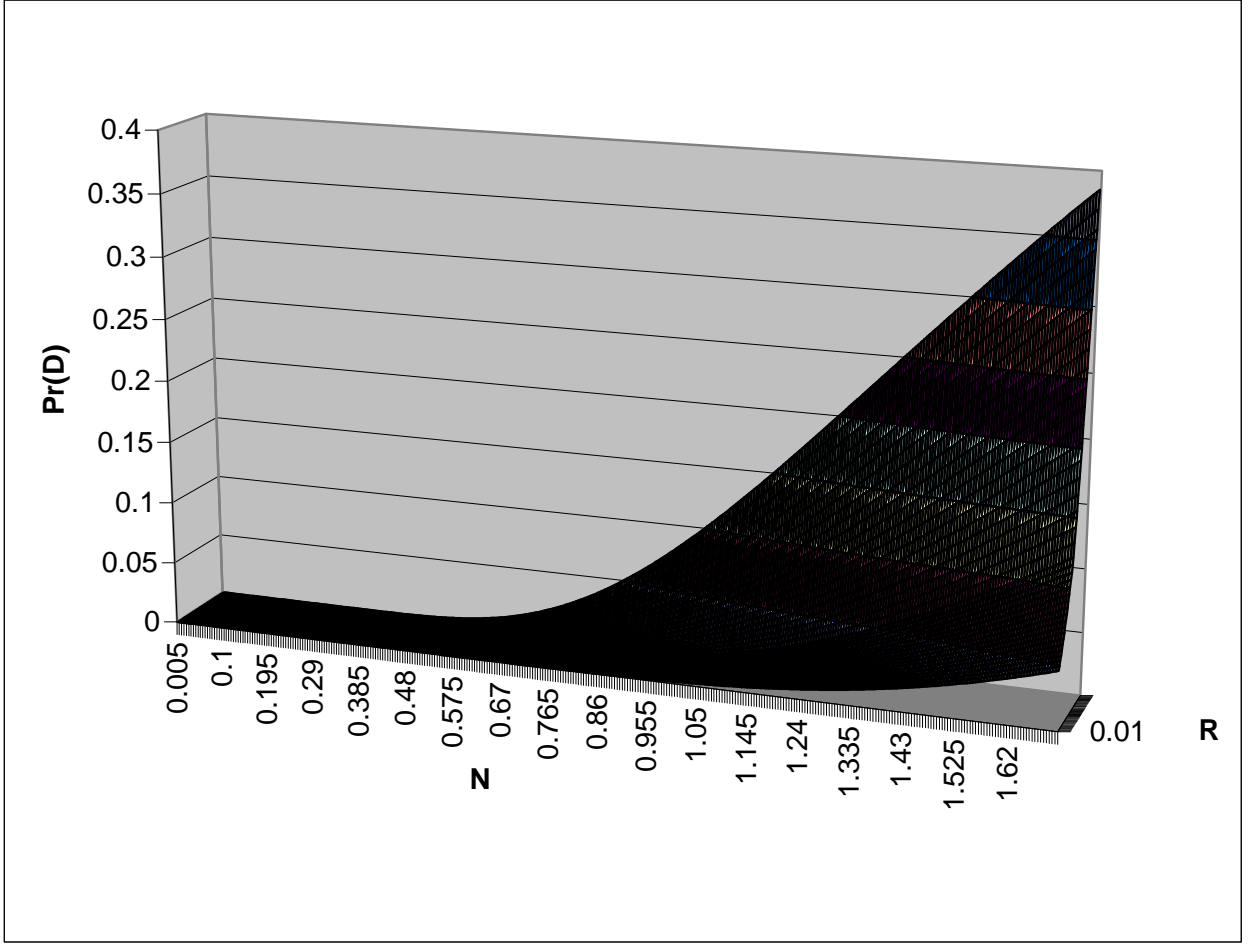
Turning to the demand, its key derivatives are:

$$D_n \equiv \frac{\partial D}{\partial n} = b(b-1)n^{b-2} - x\left[\frac{\partial f(e^*)}{\partial n}\frac{(1-b)n^{b-2}s_0}{(1+r)w} - f(e^*)\frac{(1-b)(2-b)n^{b-3}s_0}{(1+r)w}\right] \quad (3.23)$$

$$D_r \equiv \frac{\partial D}{\partial r} = -\frac{s_e}{s_0}w - x\left[\frac{\partial f(e^*)}{\partial r}\frac{(1-b)n^{b-2}s_0}{(1+r)w} - f(e^*)\frac{(1-b)n^{b-2}s_0}{(1+r)^2 w}\right] \quad (3.24)$$

The first terms of the two equations' left-hand side represent standard effects of employment and the interest rate on the firm's marginal revenues and costs. The terms in parenthesis represent the effects of n and r on the marginal costs of default. Depending on the level of $f(e^*)$ or, in other words, depending on the level of n and r,

the terms in parenthesis can be positive or negative. However, the computations show that $\Pr(d) \approx 0$ along the whole range of values of n and r consistent with firms' profit maximization, so that $f(e^*) \approx \dfrac{\partial f(e^*)}{\partial n} \approx \dfrac{\partial f(e^*)}{\partial r} \approx 0$. The effect of employment and interest rate levels on the marginal costs of default is close to zero. The terms in parenthesis are then negligible and we are left with a standard downward sloping demand for funds. Falling labour productivity implies that marginal revenues fall as employment expands: the term $b(b-1)n^{b-2}$ in (3.23) is negative since $b<1$. Higher interest rates increase marginal costs: $-\dfrac{s_e}{s_0}w$ is negative. The standard negative D_r and D_n generate a standard downward sloping demand for funds, as shown in figures 3.1 and 3.2.

Comparative Statics I: level shocks

We want to investigate the effect of increases in the level and variance of the exchange rate on the equilibrium levels of employment and interest rate. Let us focus on level shocks first. To see the effect of a 10% and 20% expected depreciation the equilibrium is computed for $s^e = 1.1$ (Figure 3.4) and $s^e = 1.2$ (Figure 3.5). The dotted lines represent post-shock demand and supply while the solid lines reproduce the pre-shock ones.

Expected depreciations increase firms' expected costs of funding and thus the probability of default. Looking at (3.6) we can indeed see that an increase in s_e reduces e^*. The reason is simple: since a higher depreciation is expected, a lower forecast error is now enough to wipe out firm's profits and force them to default. As a consequence, the default risk premium charged by banks rises. The difference between the dotted and solid supply curves D' and D represents that increase. Regarding the demand, the increase in s_e has a double negative impact: it increases both the firm's marginal costs of funding and the marginal costs of default (see the first order condition (3.19), second and third term respectively). The economic sense of the first effect is the following: borrowing in dollars, a higher depreciation translates into higher expected marginal costs of funding. The second negative

impact is caused by the marginal costs of default increase highlighted above: an increase in s_e means higher $f(e^*)$ so that an additional worker increases $\Pr(d)$ by more. Expected depreciations therefore increase the negative effects of the marginal workers on the firm's value. As a consequence, the demand falls for any value of r as firms find it optimal to reduce the scale of operations: the demand shifts to D'.

Expected depreciations reduce banks' expected profits and increase firms' marginal costs: both the supply and demand for funds shrink, bringing down the level of production. The 10% (20%) expected depreciation reduces the equilibrium level of employment to 0.81 (0.64) while the interest rate remains unchanged (see Figures 3.4 and 3.5).

Figure 3.4
Equilibrium in the loans market
with 10% expected depreciation
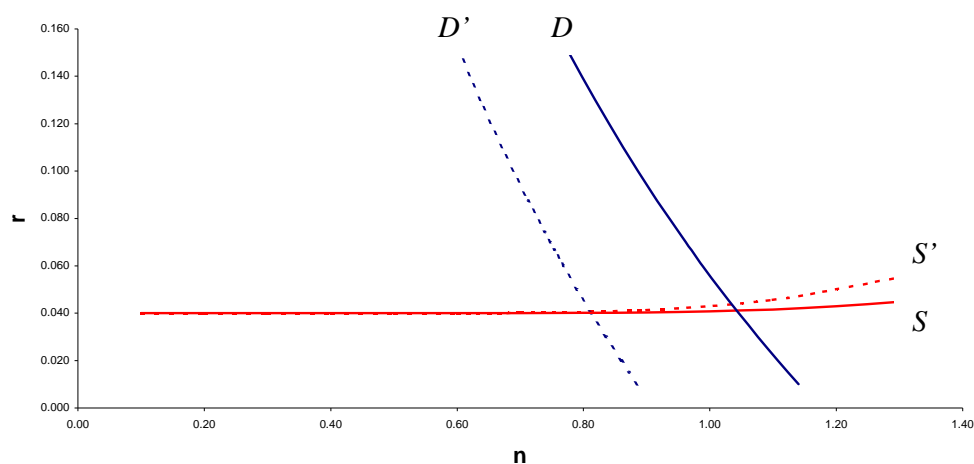
Figure 3.5
Equilibrium in the loans market
with 20% expected depreciation
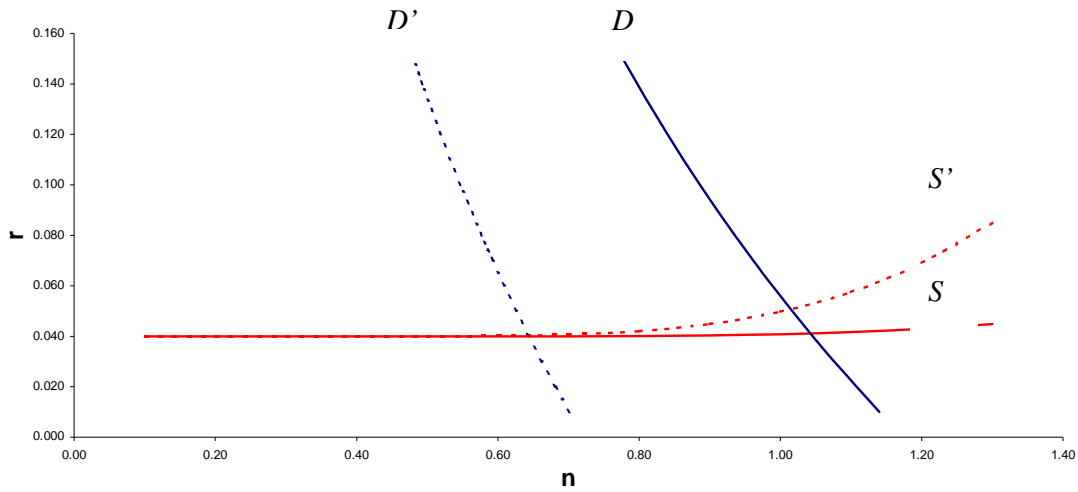
Comparative Statics II: volatility shocks

Figures 3.6 and 3.7 show the equilibrium shifts for a 14% and 30% increase in the pre-shock levels of the exchange rate variance σ. Again, the dotted lines represent the post-shock demand and supply while the solid lines pre-shock schedules. The computations for variance shocks give results similar to those for expected depreciations: both the demand and supply shrink and the equilibrium employment levels fall.

This can be explained as follows: ceteris paribus, an increase in the exchange rate variance σ increases the probability of default. This is because extremely positive values of the forecast error e (i.e. extreme unexpected depreciations) become more likely. Firms will therefore be forced to default more often as their debt value will exceed their revenues[3]. Thus, an increase in the error variance pushes $\Pr(d)$ up and raises the risk premium charged by banks just as depreciations did. The premium widening is identified by the wedge between the dotted and the solid supply curves *S'* and *S*.

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[3] Of course, extreme unexpected appreciations also become more likely. However, for values of the actual exchange rate lower than expected (i.e. for any negative value of e) the firms must be already able to repay its debt. The equilibrium probability of default is indeed smaller than 50%, reason for which e^* must be positive. Any negative value of e is thus associated with full debt repayment. Thus, the variance increase leaves banks' expected profit unaffected.

The variance shock also increases firms' marginal costs of default (the last term in (3.19)), thereby reducing the funds demand. This is because an increase in variance shifts probability mass from the mean towards the tails of the error distribution and pushes $f(e^*)$ up. Recall indeed that the pre-shock level of $\Pr(d)$ is close to zero and e^* is at the upper tail of the distribution. As σ increases, the tail of the normally distributed error becomes fatter. Therefore, with higher volatility an additional worker increases the probability of default by more: the marginal costs of defaults are higher.

We can see this formally by differentiating the expression for the normal probability density function (with mean zero and standard deviation σ) with respect to σ and evaluating the resulting expression in e^*:

$$\frac{\partial f(e^*)}{\partial \sigma} = \frac{f(e^*)}{\sigma}\left(\frac{1}{2}\left(\frac{e^*}{\sigma}\right)^2 - 1\right) \qquad (3.25)$$

The parenthesis on the right hand side of (3.25) can be positive or negative, depending on the level of e^*. An increase in variance can therefore increase or decrease $f(e^*)$, depending on the value of e^*. For values of e^* close to zero[4] (i.e. close to its mean), the effect of a variance increase on $f(e^*)$ is negative, for "big" values (i.e. on the tails of e's distribution) the effect is positive. This is intuitive, an increase in variance shifts probability mass from the mean towards the tails of the Gaussian bell. Central points (i.e. small absolute values of e) will lose probability density as they become less likely and tail points (i.e. big absolute values of e) will gain density as they become more likely.

In our computations the pre-shock levels of $\Pr(d)$ are close to zero, e^* is at the positive tail of the distribution, (3.25) is positive and an increase in the error variance pushes $f(e^*)$ up. Therefore, the variance shock causes the marginal worker to increase the probability of default by more: labour becomes costlier and as a consequence the demand shifts in. Variance shocks act just as level ones: they increase marginal costs for firms and reduce banks' expected profits: the funds'

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[4] More precisely for any value of e^* smaller than $\sqrt{2}$ standard deviations in absolute terms, a variance increase reduces $f(e^*)$.

demand falls, the supply shifts up and the equilibrium employment levels fall. Pure risk has then a negative effect on firms' output.

Figure 3.6
Equilibrium in the loans market
with 14% increase in volatility
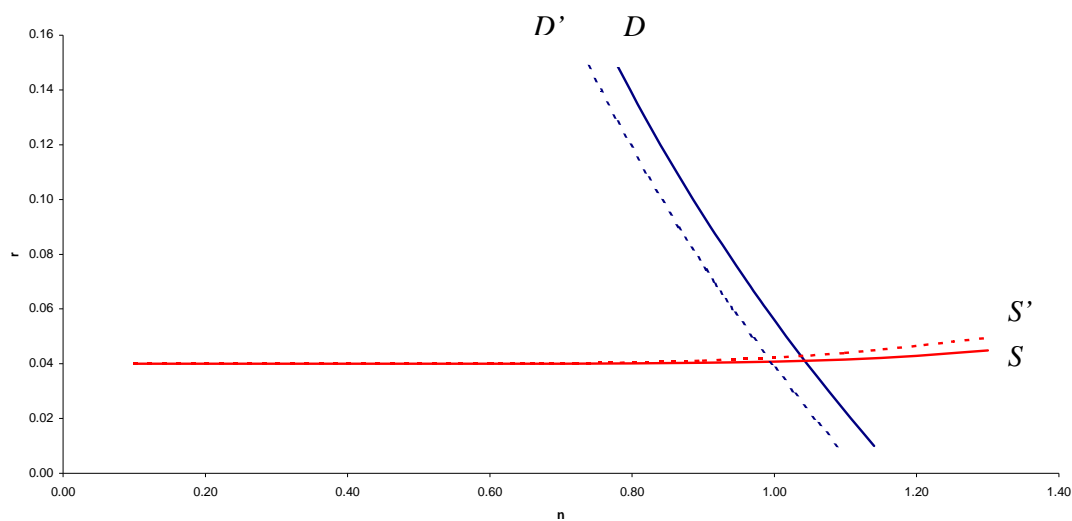
Figure 3.7
Equilibrium in the loans market
with 30% increase in volatility
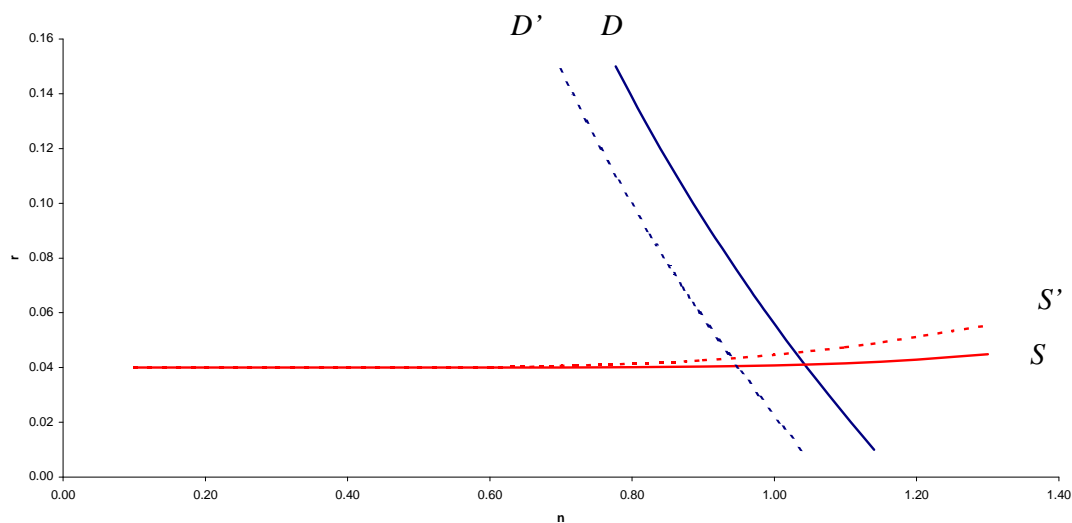
Level and variance shocks negatively affect both the supply and the demand for funds. They do so for two different reasons: because they increase the *level* of the probability of default (with negative effect on the supply) and the *rate* at which the probability of default increases for an additional worker (with negative effect on the demand).

Introducing default costs for both banks *and* firms, expected depreciations and variance increases do not necessarily cause a widening in the borrowing-lending spread. This is a key difference between this and the Agenor-Aizenmann model. In that framework higher probability of default is associated with lower costs of funding for firms since in case of default the debt is only partially recovered by banks. Therefore, default is detrimental only for banks. In such a setting an exogenous shock increasing the probability of default reduces banks' profits *and* firms' marginal costs. It thus translates into lower supply and higher demand for funds. The result is higher interest rates, higher $\Pr(d)$ and a wider borrowing-lending spread. Differently, in our framework default is detrimental for both banks and firms so that an exogenous shock pushing $\Pr(d)$ up causes a contraction of both demand and supply, with strong negative effects on employment and uncertain effects on the interest rate. The computations show that the interest is indeed unaffected by shocks to the level of the exchange rate and only slightly by variance shocks (see Table 3.2). Most of the adjustment weights on employment levels, which fall dramatically. This in turn keeps the equilibrium probability of default low. The computations describe then a realistic picture in which firms and banks find it optimal to keep the probability of default close to zero (see Table 3.2, last column). In normal times, *EMEs* bank non-performing loans are indeed typically in the range of 0-3% of the total (see BIS 2009), suggesting that the probability of a loan being defaulted should be in a similar range. This is consistent with our computations where the computed equilibrium $\Pr(d)$ levels are between 0 and 1%.

The fact that firms and banks adjust to expected changes in the exchange rate level and variance to keep the equilibrium $\Pr(d)$ low also highlights the key distinction between expected and unexpected exchange rate movements. When these are expected, they are less disruptive on the productive sector as both banks and firms adjust and avoid default. It is instead unexpected shocks that cause default and thus

the liquidation of firms. Inserting such a framework in a dynamic setting in which the number of existing firms is negatively affected by default, one may show that expected exchange rate movements have only temporary effect on the country's potential output as firms avoid default by reducing their operation in time while unexpected shocks reduce persistently potential output by forcing firms into liquidation thus reducing the capital stock of the country. Such a model is however beyond the scope of this work.

The models sketched at the beginning of this chapter identified balance sheet effects caused by currency mismatches as a key driver behind financial instability in *EMEs*. Analysing the effects of level shocks (exchange rate depreciations) on the financial intermediation process between banks and firms and through this on production they showed that in a Bernanke-Gertler world with currency mismatches a depreciation worsen firms' net worth, thus impairing their ability to borrow. The analysis presented in this chapter shifts the attention on variance shocks. Leaving the exchange rate level unchanged, these do not affect the balance sheet of a firm but they increase firms' costs of funding through the channel highlighted above. It follows that financial turbulence (in the form of exchange rate variance) has negative effects on firms' production even in absence of foreign currency-denominated debt. This suggests that, although the size and the currency composition of agents' stock of debt is an important factor determining the vulnerability of a country to external shocks, the currency composition of capital flows might be another, more neglected one. Thus, the negative effects of currency mismatches might go beyond the much studied balance sheet effects.

Table 3.2
Simulated Equilibria

n	r	s_e	σ	$\Pr(d)$
1.05	0.04	1	0.22	0.007
0.81	0.04	1.1	0.22	0.005
0.64	0.04	1.2	0.22	0.002
0.99	0.042	1	0.253	0.008
0.92	0.045	1	0.286	0.011

3.3   *Volatility shocks and financial contagion*

Variance shocks can also help explain the contagiousness of financial crises among EMEs. In a setting such as the one described by our analysis, shocks causing an increase in the volatility of the exchange rate translate into higher costs for both banks and firms, thus depressing aggregate supply. There are a number of ways under which a financial crisis abroad can generate an increase in domestic exchange rate volatility, thus creating a channel of contagion working through the supply side of the economy. If a country has trade or financial linkages with a country running into financial troubles, the uncertainty regarding the crisis country's future output will translate into higher uncertainty about the domestic country trade balance and/or capital account: the crisis will then cause exchange rate volatility and the supply shock identified by the model. However, the same linkages between crisis and domestic country generate contagion under standard level shocks: the crisis country falls into recession, its imports plummet or its collapsing banking sector cuts funding to the domestic country. As a consequence, domestic output falls. These standard demand-side contagion channels, where drops in domestic production are caused by a sudden stop of capital inflows and worsening trade balance, have been extensively documented. What is interesting of our analysis is that variance shocks can generate contagion among countries with *no* direct trade or financial linkages. In presence of currency mismatches, if a crisis abroad increases uncertainty about the domestic trade balance and exchange rate, it will represent a negative supply shock. This may happen because a crisis abroad increases uncertainty about the future output of the domestic country's trade partners. Trade has however not to be necessarily the channel of contagion. Major events such as debt restructuring/defaults or banking crises in an EME tend to cause flight-to-quality phenomena in which risk aversion jumps and capitals desert any asset perceived to be risky. If this happens, EMEs bonds, stock and currency markets are the first to suffer. By raising the possibility of flight-to-quality phenomena, a crisis in an EME increases the volatility of other EMEs' exchange rates, regardless of the trade/financial linkages between the crisis country and the others. This alone is enough to depress production in our model. This can then generate unexplained-by-fundamentals contagion, a phenomenon widely documented in the major crisis episodes of the '90s. Currency mismatches are critical. If firms could borrow in domestic currency, increases in exchange rate volatility

would not affect their expected profits and output. Financial instability would in this case propagate only to countries sharing direct linkages with the crisis country.

The main features of our model, liability dollarization and weak regulatory systems (implying high enforcement costs) are widespread in EMEs. The model can then provide a useful framework for interpreting the recurrence of sharp recessions and depreciations experienced during turbulent times by emerging markets without clear linkages with the crisis country. The key is the increased uncertainty about the domestic country's prospects caused by the crisis. This reminds one of the events occurred in Brazil during the Russian-LCTM crisis in 1998. The latter caused a marked increase in the volatility of Latin America financial markets. Notwithstanding the non-existence of direct trade or financial linkages between Brazil and Russia, the former suffered a sharp widening of the deposit-lending spread, was forced to abandon its dollar peg and the economy went into a painful recession. These events are consistent with our theory. Brazil had indeed a sizable part of public and private sector debt denominated in foreign currency and was highly dependent on foreign-currency denominated funding (see Baig and Goldfajn 2000). It also ranked very low in measures of business regulations and their enforcement such as the Doing Business index complied by the World Bank (129th out of 183, the lowest of all major Latin American economies). Indeed, Baig and Goldfajn gave a similar interpretation of the Brazilian episode, based on investors' sentiment shifts. They pointed out that foreign investors' withdrawal from Brazilian financial markets immediately after the Russian default played a crucial role in precipitating the crisis, suggesting that foreign investors panicked after the Russian crisis and speculated against the Real, even if the Brazilian economy did not show evident signs of macroeconomic disequilibrium. The authors therefore suggest that investors flew to more secure assets without a careful assessment of the situation, following a self-fulfilling prophecy of doom for Brazil.

According to them, foreign investors' flight to quality increased markedly the interest rate domestic financial institutions had to pay to raise capital abroad, while increased perceived exchange rate volatility (in the form of a reduced credibility of the existing crawling peg) increased the borrowing-lending spread charged by domestic financial institutions. These factors together caused a surge in the firms' costs of funding and a drop in economic activity. Our analysis is consistent with Bajg and Goldfain's interpretation: both highlight imperfections in the financial markets

that created interdependence between Brazil and Russia beyond that explained by macroeconomic fundamentals and point to the key role played by increased exchange rate variance.

Beyond the Brazilian case, the very different performances of Eastern European EMEs in the 2008-9 global financial crisis suggest that currency mismatches are still a key factor determining the likelihood and severity of contagion. Slovakia adopted the Euro, the Czech Republic strongly reduced its currency mismatches in the years before the crisis. On the other hand, Romania and Hungary borrowed heavily in Euros betting on future accession and convergence to the Euro Zone. This has been quoted as a key factor explaining the stronger contraction felt by the latter countries (IMF 2010). Investigating the link between currency mismatches and macroeconomic volatility seems still a worth exercise.

CHAPTER 4 - CURRENCY MISMATCHES AND THE PROPAGATION OF TRADE SHOCKS

4.1   *Introduction*

Developing countries tend to be more volatile than industrial countries in the sense that they have a more unstable rate of GDP growth. Eichengreen et al. (1999) show that in the 1980-1999 period the standard deviation of developing countries' annual GDP growth has been more than double than that of industrial countries: 5.8 percent instead of 2.7. As the authors show, a relevant part of the difference is explained by the presence of currency mismatches in developing countries. Regressing output volatility on a series of controls and a measure of currency mismatches, they estimate that the latter are significantly associated with relatively high levels of output volatility and account for a third of the difference in output volatility between developed and developing countries.

They give a three-folded explanation of such phenomenon: first, the presence of currency mismatches limits the scope and effectiveness of countercyclical monetary policies because of the negative effects of expansionary policies on the exchange rate and thus on domestic agents' balance sheets. This point is also made by many others (see for example, Aghion et al. (2000), Calvo and Reinhardt (1999) and Obstfeld et al. (2005)) who highlight the catch-22 situation EMEs' central banks are in when negative shocks hit: if they allow a depreciation they hurt agents' balance sheets, if the rise interest rate to defend the currency they hurt agents' ability to repay their debts. The latter tend indeed to be short-term for the same reasons causing currency mismatches (i.e. domestic financial markets underdevelopment). Second, foreign-currency liabilities reduce central banks' control over the amount of liquidity in domestic financial markets, thus reducing their ability to avert liquidity crises in their role as lenders of last resort. Third, dollar-denominated debts and real exchange rate interact to create uncertainty over the cost of dollar debt service, thus lowering credit ratings and making capital flows more volatile.

The above arguments suggest that the effects of foreign shocks on the domestic output should be magnified by the presence of currency mismatches. A major (if not

the principal) source of foreign shocks is trade. Research on the optimal currency area found a strong positive link between trade intensity and business cycle synchronization (see, among others, Frankel and Rose 1996, Baxter and Kouparitsas 2004, Gruben et al. 2002, Imbs 2004, Calderon et al. 2007, Inklaar et al 2008). This result is robust to a vast array of estimation techniques, definition of the relevant variables and choice of countries included in the sample. There is then strong evidence that trade shocks affect domestic output significantly.

If the above considerations are correct, trade shocks should therefore cause stronger output fluctuations in currency-mismatches-prone countries because they hit an environment of more volatile capital flows and constrained and less effective monetary policy. This is the conclusion of DSGE models on the issue (see, for example, Cespedes et al. (2004)) where liability dollarization is found to magnify the effect of foreign disturbances on domestic output. The analysis carried out in the previous chapter also suggests that currency mismatches magnify the strength of trade shocks. Chapter 3 showed that, trade shocks cause exchange rate fluctuations impacting on firms' costs of funding and thus on their production levels. In this setting trade shocks affect output levels in two ways: through the standard effect on the foreign component of aggregate demand and through the effect on firms' costs of funding that affects the aggregate supply. The second effect is there only in presence of currency mismatches. However, the framework developed in chapter 3 describes only the functioning of the loans market. To formally assess the real effects of trade shocks with and without currency mismatches, one would need to insert it into a general equilibrium framework where prices, interest and exchange rates and output are simultaneously determined. The model identifies however a propagation channel of trade-related output fluctuations generated by currency mismatches, additional to the standard AD channel, thereby suggesting a magnification effect of currency mismatches.

In the presence of currency mismatches, trade shocks might then have stronger repercussions on firms' production decisions, cause higher capital volatility and be less counter-balanceable by monetary policy. Altogether, this suggests that the output of currency-mismatches-prone countries should be more sensitive to trade shocks than that of countries where currency mismatches are negligible. This hypothesis is tested in the following.

Estimating the effect of currency mismatches on the sensitivity to foreign output fluctuations, *of either sign*, is a way of assessing the empirical relevance of the above discussion. However, of particular interest is the sensitivity to negative trade shocks (i.e. drops in the economic activity of trade partners). As Goldstein and Turner (2004) notice in their book's preface "currency mismatches have been present in virtually every major financial crisis in emerging economies over the past decade" and "the countries that have experienced the largest currency mismatches have typically been the ones that have suffered the largest output losses during crises". This view is supported by ample evidence. It is widely recognized that short-term foreign-currency denominated debt was a key factor in the East Asian episode (see Table 2.1 in Goldstein-Turner 2004). Furman and Stiglitz (1998) affirm "the ability of this variable (foreign-currency denominated debt), by itself, to predict the crises of 1997 is remarkable". The same is true for foreign-currency indexed tesobonos in the Mexican 1994 crisis, as documented by Calvo and Goldstein (1996). Finally, the large literature on the leading indicators of currency and banking crises generalized this result for emerging market economies in the last three decades: the ratio of short-term external (mainly denominated in foreign currency) debt to international reserves and the ratio of bank and corporate external debt to exports are among the most powerful predictors of a crisis (Sachs et al. (1996), Kaminsky and Reinhardt (1999), Berg and Patillo (1998)). Therefore, ample evidence suggests a key role played by currency mismatches in crisis episodes. Some of these episodes, notably the Argentinean difficulties in 1995, the Korean, Malaysian and Indonesian troubles in 1997 had a clear contagious nature, in the sense that the crises in those countries were imported from the original crisis country rather than caused by domestic macroeconomic imbalances. It is then important to assess the role of currency mismatches in the propagation of crises, in particular after the observations on trade-related shocks put forward above. Notwithstanding this, to my knowledge a systematic study of the effect of currency mismatches on the propagation of negative trade shocks is not present in the literature. This chapter fills this gap by investigating whether negative trade shocks are felt more strongly in countries where agents are exposed to currency mismatches.

The chapter also tests for asymmetries in the propagation of trade shocks (i.e. whether negative trade shocks affect the domestic output proportionally more than positive shocks) in both countries with and without a substantial degree of currency

mismatches. These asymmetries can arise if for example asymmetric reactions to productivity shocks such as the ones described by Bernanke and Gertler (1989) are present. In their renowned paper the authors show that the real effects of productivity shocks can be asymmetric: negative ones can reduce firms' net worth below a threshold, making borrowing unprofitable and thus having a negative effect on investment while positive ones might not alter the profitability of borrowing and thus the level of investment. In such a setting, negative productivity shocks have stronger absolute real effects than positive ones. If trade shocks translate into productivity shocks (because exporting firms reduce their capacity utilization following negative trade shocks and increase it following positive ones) these might have an asymmetric effect on domestic output, with negative shocks being felt more strongly than positive ones.

Trade shocks might then propagate asymmetrically, regardless of the presence of currency mismatches. On top of this, the latter may introduce an additional element generating asymmetric shock propagation. If firms are exposed to currency mismatches, their net worth is dependent on the exchange rate. The logic behind the Bernanke-Gertler effect can then apply to a context of liability dollarization as well: negative trade shocks cause depreciations that might push firms' net worth below the critical level and thus cause a rationing of credit, while positive shocks might not have that effect. Therefore, we might have that currency mismatches generate asymmetries if these are not there, or magnify them if instead they are there already. Asymmetries in trade shocks' propagation could then arise in both countries with and without pervasive currency mismatches: the following analysis investigates both hypotheses.

4.2 Testing the link between currency mismatches and trade-related contagion

4.2.1 The tests

Aim of the chapter is thus to test:

a) whether the output of currency-mismatches-prone countries is more sensitive to negative trade shocks than the output of currency-mismatches-free countries (*negative hypothesis* henceforth)

b) whether the output of currency-mismatches-prone countries is more sensitive to trade shocks of either sign than the output of currency-mismatches-free countries (*higher sensitivity hypothesis* henceforth)

c) whether negative trade shocks propagate more strongly than positive trade shocks of the same size, in both countries with and without a substantial degree of currency mismatches (*asymmetry hypothesis* henceforth)

Note that point b) implies point a) and is a more general test of the magnification effect of currency mismatches on trade-related output volatility. Point c) is a test of asymmetric shock propagation. It asks whether there is such asymmetry, and whether is confined to currency-mismatches countries or instead is a general phenomenon. All tests can be carried out with a single model estimation, as shown now.

Before carrying on it is worth recalling the definition of contagion used: "propagation of macroeconomic instability". Focusing on output, contagion is synonymous with output shocks propagation and output interdependence. In this light, the first two hypotheses investigate the role of currency mismatches in magnifying contagion while the third focuses on its role in generating asymmetric contagion. The acceptance of the hypotheses would only prove that currency mismatches increase output interdependence and/or render it asymmetric. It would not prove that currency mismatches generate shift- or unexplained-by-fundamentals contagion.

There are four possible trade shock regimes: positive shock to a currency-mismatches-free country (financial centre or *FC* henceforth), positive shock to a currency-mismatches-prone country (Original Sin country or *OS* henceforth, for

reasons explained below), negative shock to an *FC*, and finally negative shock to an *OS*.

Estimating a regression such as (4.1) below, we can estimate the effect of each of the four shock regimes on the output of country *i*:

$$\Delta y_{it} = \alpha + \beta_0 C_{it} + \beta_1 C_{it} * Pos_{it} * OS_i + \beta_2 C_{it} * Neg_{it} + \beta_3 C_{it} * Neg_{it} * OS_i + \gamma X_{it} \quad (4.1)$$

where:

Δy_{it} is the percentage change in country *i*'s output in period *t*

C_{it} is the contagion proxy, the sum of the percentage changes in foreign countries' output in period *t*. These changes are weighted for the relevance of any country *j* as a trade partner of country *i*.

Pos_{it} is a dummy variable assuming value *1* when $C_{it} \geq 0$ and zero otherwise

Neg_{it} is a dummy variable assuming value *1* when $C_{it} < 0$ and zero otherwise

OS_i is the "Original Sin" dummy variable, assuming value *0* if country *i* is a financial centre, able to borrow abroad in domestic currency and *1* otherwise. The definition of Original Sin and Financial Centre countries is based on Eichengreen et al (1999). The issue is discussed at length below. See Appendix A for an explanation of the dummies specification chosen.

X_{it} is a set of control variables.

The estimated effect of each of the four types of trade shock on the domestic output is given by the linear combinations listed in Table 4.1:

Table 4.1
The four regimes

Regime	Estimated effect
positive shock to FC	β_0
positive shock to OS	$\beta_0 + \beta_1$
negative shock to FC	$\beta_0 + \beta_2$
negative shock to OS	$\beta_0 + \beta_2 + \beta_3$

Testing the hypotheses above amounts therefore to test the statistical significance of the differences between the linear combinations in Table 4.1. Subtracting the last row of the table from the second last we see that the difference between the estimated real effect of a negative shock in an *OS* and in an *FC* is given by β_3. This parameter therefore identifies the reaction of *OS* countries to negative shocks *over and above the reaction of FC*s. If negative shocks affect the former more than the latter, β_3 must be positive. Therefore, testing the *negative hypothesis* is equivalent to test the hypothesis $\beta_3 > 0$.

Similarly, subtracting the second row from the first we find that the difference between the estimated real effect of a positive shock in an *OS* and in an *FC* is given by β_1. This parameter identifies the reaction of *OS* countries to positive shocks *over and above the reaction of FC*s. If positive shocks affect the former more than the latter, β_1 must be positive. Therefore, if *OS* countries are more sensitive than *FC*s to trade shocks of either sign, we should have both β_1 and β_3 positive. The *higher sensitivity hypothesis* is then a test of the joint hypothesis $\beta_1 > 0$ and $\beta_3 > 0$.

Subtracting the first row from the third we get the difference between the estimated reaction of *FC*s' output to negative and positive shocks. If the former are felt more strongly than the latter we must have that $\beta_2 > 0$. This parameter thus identifies the asymmetry in the propagation of trade shocks to *FCs* and the hypothesis $\beta_2 > 0$ is the one tested to investigate the *Asymmetry to FC hypothesis*. The estimated asymmetry of propagation in *OS* countries is instead found subtracting the second row from the last. This gives $\beta_2 + \beta_3 - \beta_1$ so that testing the *Asymmetry to OS hypothesis* is equivalent to test $\beta_1 < \beta_2 + \beta_3$.

Table 4.2 sums up and describes the hypotheses tested.

Table 4.2
The four tests

Hypothesis	Description	Test
Negative	negative shocks more affecting in OS countries	$\beta_3 > 0$
Higher sensitivity	shocks of either sign more affecting in OS countries	$\beta_1 > 0$ and $\beta_3 > 0$
Asymmetry in FC	negative shocks more affecting than positive ones in FC countries	$\beta_2 > 0$
Asymmetry in OS	negative shocks more affecting than positive ones in OS countries	$\beta_1 < \beta_2 + \beta_3$

4.2.2   *Data*

The following analysis exploits data from three main sources: the International Financial Statistics (*IFS*) and the Directorate of Trade Statistics (*DOTS*) complied by the *IMF* and the World Development Indicators (*WDI*) compiled by the World Bank. All three databases have been accessed via the *ESDS* system based at the University of Manchester.

All data used in the analysis apart from those on exports are taken by the *IFS* database. This provides national-level data on a wide range of economic aggregates from interest rates to exchange rate vis-à-vis major currencies, price and production indexes, government spending and national accounts, international transactions and money, banking and financial sector indicators. Monthly and quarterly data are available. Both monthly and quarterly data present advantages and disadvantages. Monthly data are preferable for two reasons: a) given the speed at which macroeconomic fluctuations are transmitted across borders, quarterly and annually data would probably lose some of the dynamics by averaging out higher frequency oscillations and b) higher frequency gives more observations in the same time span. Since complete data for all variables needed started to be compiled only recently, this has a relevant effect on the degrees of freedom available to the estimation process. On the other side, it might take more than a month for the effects of output fluctuations in trade partners on the domestic economy to fully manifest themselves. Importing firms located in the trade partner will see their orders or sales change, they will revise their own orders to domestic firms that will in turn reset their production levels accordingly. The process is likely to take more than a month, so that the monthly analysis may not be able to identify the correlation. One can control for this using lags in the monthly analysis or instead carrying it out with quarterly data. I tried both and the former gave very unstable and unreliable results, both in terms of statistical and economic significance. For this reason, I chose to include in this chapter only the results from the quarterly analysis.

Data on exports disaggregated for country of destination is taken from the *DOTS* database, while data on exports' share of *GDP* is provided by the *WDI* database. The latter are provided at yearly frequency and they are transformed in quarterly data by assigning the same value to all quarters of the same year.

The data covers 23 countries from January 1995 to December 2005, giving 44 quarterly observations for each country, for a total of 1012 observations. Due to the inclusion of lagged variables, the number of observations used in the estimation is however smaller: 897. Exports data from the 1993-94 period are used in calculating the weighting, as it will be explained below. The countries included in the sample are: Austria, Brazil, Canada, Czech Republic, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Mexico, the Netherlands, Norway, Poland, Portugal, Slovak Republic, Spain, Turkey and the United Kingdom.

Summary statistics are given in Tables 4.3 and 4.4.

4.2.3   *The estimated model*

The estimated model is equation 4.1 with six control variables and one lagged dependent variables (*LDV* henceforth) for reasons that will be explained below:

$$\Delta y_{it} = \alpha + \beta_0 C_{it} + \beta_1 C_{it} * Pos_{it} * OS_i + \beta_2 C_{it} * Neg_{it} + \beta_3 C_{it} * Neg_{it} * OS_i +$$
$$+ \gamma_0 \Delta i_{it} + \gamma_1 \Delta e_{it} + \gamma_2 \Delta ius_t + \gamma_3 \Delta oil_t + \delta_0 \Delta y_{it-1} + u_t$$
$$(4.2)$$

where the four control variables are:

Δi_{it}: the change in country *i*'s discount rate from the end of quarter *t-1* to the end of quarter *t*.

Δe_{it}: the percentage change in country *i*'s average exchange rate vis-à-vis the *US dollar* in quarter *t*.

Δius_t: the change in the Federal Reserve's discount rate from the end of quarter *t-1* to the end of quarter *t*.

Δoil_t: the percentage change in the average crude oil price during quarter *t*.

and finally, Δy_{it-1} is a lagged dependent variable, the percentage change in country *i*'s output in quarter *t-1*. See Appendix A for an explanation of the dummies specification chosen.

As a proxy for the output level I use the quarterly Index of Industrial Production (*IIP*). This is preferred to *GDP* because it is more widely available at a quarter

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frequency, especially for developing countries. This clearly comes at the cost of neglecting fluctuations in non-industrial production. On the other side, the advantages of higher frequency data (more observations and the identification of short-term fluctuations lost in the annual average) outweigh such costs. The base of the index number varies across countries, but this is not a problem since the *IIP* appears in the estimated equation as percentage change over the previous quarter. I firstly used both seasonally adjusted *IIP* series as well as non-adjusted. This provided a larger sample of countries (37). However, the quality of the estimation, both in terms of the coefficients signs and asymptotic variances, increased notably when restricting the sample to seasonally adjusted series only. This makes sense, since the intrinsic autocorrelation in the non-adjusted series is clear at first sight (e.g. production in July and January drops markedly in all northern-hemisphere countries). This creates a spurious correlation between fluctuations across countries. The results presented here are for the 23-countries adjusted-*IIP* sample only.

The Contagion index

The key variable is the contagion index *C*. This is intended to measure the intensity of the trade shocks by summing up the quarterly percentage changes of foreign countries' *IIP*. How intense a shock for the domestic economy is a trade partner's output fluctuation depends on two main factors. One is the openness to trade of the domestic country. If most of the *AD* is represented by absorption, foreign output fluctuations will be felt much less than if exports represent most of the *AD*. The other factor is the importance of the country where the shock originated as an importer of domestic goods: an economic boom in a major importer of domestic goods will have a stronger impact on the domestic *AD* than a boom in a country with which the domestic one has no trade linkages. Therefore, the intensity of a trade shock depends on both the openness to trade of the domestic economy and the relevance of the originating country as a trade partner. To take these two factors into consideration the foreign output fluctuations summed up in the contagion proxy *C* are weighted for the share of domestic exports to each country over total domestic exports $\frac{EX_{12t}}{TOTEX_{1t}},....,\frac{EX_{1nt}}{TOTEX_{1t}}$ and the sum is then multiplied by the exports' share of

GDP, $\dfrac{TOTEX_{1t}}{GDP_{1t}}$. These two measures are intended to capture respectively the openness to trade of the domestic country and the relative importance of each foreign country as a trade partner. Notice that, since total exports appear both in the denominator of the measures of bilateral trade intensity and in the numerator of the exports' share of *GDP*, total exports cancel out so that the weights are actually the share of bilateral trade over *GDP* $\dfrac{EX_{12t}}{GDP_{1t}},...,\dfrac{EX_{1nt}}{GDP_{1t}}$. This measure of trade intensity is preferred to bilateral over total trade because it takes into consideration both the closeness of the trade linkage and the importance of trade on the overall economy, while bilateral over total trade only the first. This point is made, for example, by Calderòn et al (2006).

A three-countries example might clarify matters. The Contagion proxy for country *1* in quarter *t* is:

$$C_{1t} = M_{1t}^{'} * \Delta c_{1t} \tag{4.3}$$

where:

$$M_{1t}^{'} \equiv \left[\dfrac{EX_{12t}}{GDP_{1t}} \quad \dfrac{EX_{13t}}{GDP_{1t}} \right] \tag{4.4}$$

is the (*1x2*) weighting vector composed by the value of exports from country *1* to countries *2* and *3* in quarter *t* over GDP_{1t}, country *1*'s *GDP* in *t*, all in *US* dollars millions.

$\Delta c_{1t} \equiv \left[\begin{array}{c} \Delta y_{2t} \\ \Delta y_{3t} \end{array} \right]$ is the (*2x1*) vector of percentage *IIP* changes in countries *2* and *3*.

The Contagion index for country *1* is then:

$$C_{1t} = \left(\dfrac{EX_{12t}}{GDP_{1t}} * \Delta y_{2t} \right) + \left(\dfrac{EX_{13t}}{GDP_{1t}} * \Delta y_{3t} \right)$$

$$= \dfrac{1}{GDP_{1t}} \left[(EX_{12t} * \Delta y_{2t}) + (EX_{13t} * \Delta y_{3t}) \right]$$

It is the sum of the fluctuations in the *IIP* of country *2* weighted for country *1*'s exports to country *2* and the fluctuations in the *IIP* of country *3* weighted for country *1*'s exports to country *3,* all divided by country *1*'s *GDP*.

The contagion proxy for country *2* and *3* are respectively:

$$C_{2t} = \frac{1}{GDP_{2t}} \left[\left(EX_{21t} * \Delta y_{1t} \right) + \left(EX_{23t} * \Delta y_{3t} \right) \right]$$

$$C_{3t} = \frac{1}{GDP_{3t}} \left[\left(EX_{31t} * \Delta y_{1t} \right) + \left(EX_{32t} * \Delta y_{2t} \right) \right]$$

The fact that output fluctuations in country *j* influence the exports from country *i* to country *j* may generate a misleading correlation between Δc and the weights *M*. If for example a recession hits country *2*, this will cause exports from *1* to *2* to fall. So *both* Δy_{2t} *and* EX_{12t} will fall simultaneously. The latter is the weight assigned to Δy_{2t}. Therefore, whenever Δy_{2t} is negative, the weight assigned to it falls. Conversely, whenever Δy_{2t} is positive the weight assigned to it increases, since an increase in country *2*'s production pushes exports from *1* to *2* (i.e. EX_{12t}) up. The way is calculated, the contagion index would then assign more weight to positive trade shocks than to negative ones.

An example might help. Suppose we are in the three-country world just described and in quarter *t* country *1* exports 50% of its total exports to country *2* and 50% to country *3*. The two weights assigned to the *IIP* fluctuations of countries *2* and *3* will then be equal. Now suppose that in quarter *t+1* a crisis hits country *2* and as a consequence exports from *1* to *2* drop to zero in one quarter. Now country *1* exports 100% of its exports to country *3* and zero to country *1*. As a consequence, the weight assigned to the fluctuations of country *2*'s output in quarter *t+1* is zero. The drop in country *2*'s output will thus not show up in the contagion index of country *1*, which will not vary since country *3*'s output did not vary. However, the drop had a significant impact on country *1*'s aggregate demand, since 50% of its exports have been wiped out by it.

The pro-ciclycality (with the trade partner's cycle) of the weights would then lead to systematic under-weighting of negative trade shocks and over-weighting of

positive ones in the contagion index *C*. For this reason, instead of the simple share of trade to *j* on *GDP*, the last three years average of that magnitude is used as a weight. In other words, the weights used are the three-year average exports of country *i* to country *j*, proxying the long-term average share of country *i*'s aggregate demand represented by exports to country *j*. Short-term output fluctuations should then not affect the weight assigned to them. The weights used for 1995 are then the average exports' shares in the 1993-1995 period, so that the contagion index for country *1* is:

$$C_{1t} = \frac{1}{\overline{GDP}_{1t}} \left[\left(\overline{EX}_{12t} * \Delta y_{2t} \right) + \left(\overline{EX}_{13t} * \Delta y_{3t} \right) \right]$$

where the $\overline{GDP}_{1t}$, $\overline{EX}_{12t}$ and $\overline{EX}_{13t}$ are the three-year average up to quarter *t* of, respectively, GDP_{1t}, EX_{12t} and EX_{13t}.

The dummy variables and their interactions with the Contagion index

The contagion index is interacted with the three dummy variables *Pos*, *Neg* and *OS* in order to capture the different real effects of positive and negative trade shocks, in both *OS* and *FC* countries. *Neg* assumes value *1* when the contagion index is negative and *0* otherwise. *Pos* assumes value *1* when the contagion index is positive or zero and *0* otherwise and *OS* assumes value *1* when the country is categorized as an "Original Sin" country and *0* when it is categorized as a financial centre (*FC*). As shown above, the interaction *C*Neg* captures any effect of negative trade shocks to *FC*s additional to the effect of positive shocks captured by *C* itself while the interactions *C*Pos*OS* and *C*Neg*OS* capture the effect of, respectively, positive and negative trade shocks on *OS* countries' output over and above the effect of such shocks on *FC*s' output[5]. Appendix A justifies the dummies specification showing how this is equivalent to a standard three dummies specification as suggested by Wooldridge (2002).

The distinction between *OS* countries and *FC* is based on the work of Eichengreen et al (1999), where the authors analyse the problem of currency

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[5] Note that the sum of the interactions *C*Pos*OS* and *C*Neg*OS* gives *C*OS*. The latter is however not included in the equation so that there is no perfect multicollinearity and the two interactions can be included in the estimated model.

mismatches in emerging markets and develop some measures of it. They coined the term "Original Sin" to suggest that emerging markets are unable to borrow abroad for reasons related to their past and beyond their control. The currency mismatches measures proposed by the authors are presented in the following.

The first measure is one minus the ratio of the stock of securities issued by country i in its own currency to the total stock issued by country i:

$$OSIN1_i = 1 - \frac{B_i}{totB_i} \qquad (4.5)$$

A country able to raise money abroad in its own currency will issue most of its bonded debt in domestic currency and thus have an $OSIN1$ index close to zero. The closer the index to 1, the stronger the currency mismatches. As the authors recognize, this measure has two drawbacks: first it neglects any form of debt other than bonded debt and, second, it neglects the opportunities for hedging currency exposure through derivatives such as swaps. In order to tackle the second problem, they develop another measure:

$$OSIN3 = \max\left\{1 - \frac{B_{DCi}}{totB_i}; 0\right\} \qquad (4.6)$$

The first element in parenthesis, $1 - \frac{B_{DCi}}{totB_i}$, is one minus the ratio of the stock of securities issued *everywhere* in currency i to the stock of securities issued by country i. The idea behind this indicator is that if a country other than i issues securities in currency i it gives country i an opportunity to hedge its currency exposure via the swap market. Therefore the relevant measure is the stock of securities issued in currency i rather than issued by country i. Since there can be more debt issued in domestic currency than debt issued domestically, the ratio can be over 1 and the element turns negative. In order to avoid this, the $OSIN3$ is constrained to be weakly positive.

In order to tackle the other drawback of $OSIN1$ (i.e. the neglect of non-bonded debt) another measure is defined as the ratio of securities and cross-border loans

issued in country *i* in the five major currencies to the total stock of securities and cross-border loans issued in country *i*:

$$INDEXA = \frac{B_{\$i} + L_{\$i}}{totB_i + totL_i}$$ (4.7)

This gives country *i'*s proportion of internationally traded bonds and cross-border bank loans denominated in the five major currencies (USD, EUR, YEN, GBP, CHF). The closer the index to *1*, the stronger the currency mismatches. The reason why cross-border loans denominated in the five major currencies only are taken into consideration is simple: data are available for those currencies only. Notice that *INDEXA* is implicitly assuming that all debt non denominated in those five currencies is in domestic currency. *INDEXA* therefore overstates the domestic currency-denominated debt and understates the degree of currency mismatch. It might be a good approximation for countries able to issue a non-negligible part of their debt in domestic currency. However, if this is the case, then is should be reflected in *OSIN3* because domestic or foreign agents are then able to issue debt in domestic currency. Otherwise, the index provides information about the likelihood of a bank loan being denominated in a foreign currency other than one of the five major. For this reason the last index proposed by Eichengreen et al. is:

$$OSIN2 = \max\{INDEXA; OSIN3\}$$ (4.8)

Table 4.5 gives the average *OSIN* indexes for the countries in the sample across two periods: pre- and post-*ECU* introduction. As expected, countries issuing major currencies present the lowest indexes. This "major-currency effect" is noticeable in the Euro area, where all countries experience a major reduction is their currency mismatches after the introduction of the *ECU* in January 1999. Original Sin seems affecting all *EMEs* equally: all countries but major-currencies-issuers present higher indexes than the latter's, and close to 1. Various *EMEs* show indexes values equal to 1, meaning that they are completely unable to access international credit in domestic currency.

The *OSIN* indexes and in general the Original Sin approach has been recently criticized by Goldstein and Turner (2004). Their critiques can be summarized in three points:

a) The Original Sin approach neglects the asset side of the story. Consider two countries with identical shares of foreign currency-denominated debt. One has a twice as high ratio of exports to *GDP* than the other. Clearly, they do not have the same exposure to currency risk. Yet, the *OSIN* indexes will miss this difference. The same reasoning applies to reserve holdings and foreign currency-denominated assets in general. These are neglected by the *OSIN* indexes.

b) By taking into consideration the currency denomination of internationally traded bonds and banking flows only, the Original Sin approach neglects the role of domestic bonds markets and banking sectors as sources of credit. Newly available data quoted by the authors shows that local bond markets in *EME*s (see Burger and Warnock 2002, quoted in Goldstein and Turner, 2004) amount to between 30 and 60% of *GDP*. Although still far from *OECD* levels (being around 100%), local bond markets are now the single largest source of domestic and international funding to *EMEs*. Crucially, the currency composition of such bonds is similar to that in *OECD* countries. For example, in emerging Asian economies, the share of locally traded, domestic-currency-denominated bonds is 88% of the locally traded total, higher than that in the *UK* (74%) and identical to that in the Euro Area (see Burger and Warnock 2002). Similarly, the domestic banking sector represents a sizeable part of funding in the *EMEs* and it is mainly domestic-currency-denominated. By considering only international bonds and banking flows, the *OSIN* indexes are therefore likely to overestimate the degree of currency risk to which *EMEs* are exposed. They are also likely to miss important differences in the degree of currency mismatches across *EMEs*. International bonds markets are indeed dominated by the five major currencies. Focusing on these only, all *EMEs* appear similarly exposed to currency mismatches. However,

there are important differences in the size and depth of their local bonds and credit markets in general.

c)   The Original Sin indexes, as any aggregate measures of currency mismatches, ignore the fundamental question of who within the economy actually bears the currency risk. If, for example, all foreign currency liabilities are held by exporting firms who earn in dollars the currency risk will be very different than if all those liabilities are in the hands of companies earning in domestic currency.

Goldstein and Turner propose an index of Aggregate Effective Currency Mismatch (*AECM*) that takes on board these considerations:

$$AECM = \frac{NFCA}{X} * FCD \tag{4.9}$$

where *NFCA* stands for Net Foreign Currency Assets and is the sum of the net foreign currency assets of monetary authorities, domestic deposit banks, non-banks (held with *BIS*-reporting banks) and international foreign currency-denominated bonds outstanding. Using *NFCA* instead of the sum of liabilities controls for both the liabilities and assets sides of the currency mismatch problem. With the same aim, the country's exports of goods and services *X* are included. Finally, the ratio is multiplied for *FCD*, the share of total debt denominated in foreign currency. The latter is computed as the ratio of banks' and non-banks' (cross-border) liabilities to *BIS*-reporting banks, domestic credit to the private sector and domestic and international outstanding bonds that is denominated in foreign currencies. Notice that both the international (cross-border) and domestic markets for bonds and loans are included in this index, therefore reflecting the considerations put forward in point b). A country is a net debtor in foreign currency if *NFCA* is negative. Thus, the more negative the index the stronger the currency mismatch.

The authors highlight that the index is computed assuming that all domestic bank and bonded credit is in domestic currency. However, recently available data show that this is not the case and that the share of foreign-currency-denominated domestic credit is not negligible (see Reinhardt, Rogoff and Savastano 2003). The *FCD*

measure in the *AECM* index would then underestimate the foreign currency share of debt. To avoid this problem, the authors incorporate the data from Reinhardt, Rogoff and Savastano (2003) in the index *AECM2*, using the estimated share of foreign currency-denominated loans and bonds traded in emerging domestic markets.

Table 4.6 provides the *AECM* and *AECM2* indexes alongside the *OSIN* ones. Unfortunately, Goldstein and Turner provide data for emerging markets only, so that a comparison in possible for these countries only. Nonetheless, we can see that by taking into consideration foreign currency asset holdings and the domestic financial markets, the *AECM* indexes distinguish more than the *OSIN* ones among *EME*s. For example, all countries for which the *AECMs* are available show an *OSIN1* index of *1* (apart from Poland, showing *0.97*). On the other side we can see that big differences are detected by the *AECMs*. Israel and Poland, for example, had a net asset position in foreign currency for the whole period covered. According to *OSIN1* they are not different from, say, Turkey, Mexico or Brazil, all of which had instead huge net liabilities and experienced sharp devaluations and recessions in the period considered. *OSIN2* and *OSIN3* fares slightly better, but still are missing important differences across *EMEs*. It is this consideration that makes Goldstein and Turner question the validity of the *OSIN* indexes and in general of the Original Sin hypothesis, which states that currency mismatches are an unavoidable feature, blighting all emerging markets equally.

The *AECM* indexes certainly fix some of the shortcomings of the *OSIN* ones, however, they have limitations themselves: first, they focus on net rather than gross positions, notwithstanding that balance sheet effects depend on gross positions rather than net ones. *OSIN* indexes are instead based on gross magnitudes (liabilities). Second, on a more practical level, the *AECM* indexes are available for a small number of *EMEs* only, so that a comparative study between financial centres and emerging markets as this one cannot be based on those indexes. For these reasons I define the *OS* dummies on the basis of the *OSIN* rather than the *AECM* indexes.

Among the *OSIN* indexes, *OSIN2* is the one with the broadest coverage and for this reason it is the chosen one. However, it has an obvious limitation: it considers loans denominated in the five major currencies as foreign currency loans. The index is then meaningless for those countries issuing the five major currencies. These issue debt in their own currency and still have high *OSIN2* indexes, as one can see

comparing *OSIN2* and *OSIN3* in table 4.6: Germany, Japan, the UK and the US all have *OSIN3* equal to zero, proving their ability to raise all the (bonded) credit they need in domestic currencies, yet their *OSIN2* are high because the loans denominated in their own currencies are considered foreign-currency loans by this index. In order to avoid this, the three major currencies issuers included in the sample (Germany and the Euro Area after 1999, Japan and the UK) are considered financial centres by definition.

The dummy variable *OS* is then assuming value *1* when the country is considered an *OS* country (i.e. heavily relying of foreign funding) and *0* otherwise. To render this definition operational, one has to decide a threshold above which a country is considered an *OS* one. In order to limit the arbitrariety of such choice, various dummies with different thresholds are defined and the estimation results are compared. Table 4.7 describes which countries and when are considered *OS* countries in each of the dummies' specification used. Very little changes between different specifications. Only 3 (2) countries "become" *OS* countries when the threshold is lowered from 80% to 60% in the 1993-1998 (1999-2005) period. A further lowering of the threshold would not change much since, apart from the major currency issuers, all countries but two are already considered *OS* countries by the 60% threshold dummy *OS2*.

Since the *OSIN* indexes are continuous variables, one could include them in the regression analysis without converting them to dummies. However, I prefer not to do so for two reasons. Firstly, the indexes are likely to have substantial measurement error. Secondly they show very little variation. As already noticed, most *OS*s have indexes equal to 1 across the whole period considered while most financial centres present values in the 0.4-0.5 range. The conversion to dummies is then eliminating the measurement error problem at the cost of very little variance lost.

The control variables

The domestic interest rate is included to control for monetary policy interventions. Since monetary policy is used also for counterbalancing the real effects of foreign shocks such as trade shocks, not controlling for it might generate a negative correlation between the contagion index and the error, therefore creating a negative bias in the betas. The end of period discount rate applied by the country's central

bank has been used for all countries apart from Mexico, Poland and the United Kingdom. For these, only the money market rate (the overnight interbank rate for Poland and the *UK*, the bankers' acceptances for Mexico) was available. An important issue in this discussion is the advent of the *ECU* first and the Euro subsequently. Various countries in the sample fixed their exchange rate to the *ECU* at its introduction in January 1999 and then adopted the Euro in the following years. For these countries, I have considered the domestic discount rate before the Euro accession and the European Central Bank's discount rate thereafter. Only the money market rate was available for France and Nederland until their accession to the Euro. For this reason, I have used their money market rates until their accession, and the *ECB* discount rate thereafter.

In order to control for the real effects of monetary authorities' intervention in the forex markets I include the period average exchange rate, defined as the cost of one dollar in domestic currency, so that an increase in the exchange rate represents a depreciation of the domestic currency. The justification for this is similar to that for the interest rates inclusion. If the monetary authorities react to trade shocks with forex interventions in order to smooth the fluctuations in domestic output, omitting exchange rate fluctuations could cause endogeneity. Again, for Euro Area countries, I consider their domestic rate until the accession to the Euro.

Notice that no control for the fiscal policy is included. I chose to do so because in the sample period (1995-2005) the use of fiscal policy as a short-term stabilization tool was not common. By including it, I would have introduced a potentially endogenous variable with scarce influence on the dependent variable. Losing degrees of freedom to instrument and estimate a scarcely relevant correlation seems not worthwhile. Of course, interest and exchange rates are also policy variables and endogenous. These are however included (and instrumented) because they are widely used as short-term stabilization tools.

Common shocks such as an increase in the price of oil are likely to affect both the target country and its trade partners. If neglected, this would then lead to overestimate the effect of trade and ultimately would give an inconsistent estimate of the betas. For this reason the quarterly change in the world average price of crude oil is included. The quarterly change of the Federal Reserve end-of-period base rate is also included as a proxy for the price of credit.

As explained in Appendix A, the two dummies *Neg* and *OS* and their interaction are included to control for the effects of trade shocks' sign and the presence of currency mismatches on the intercept. These controls do not tell anything about the changes in strength of trade shocks propagation caused by the sign of the shock and the currency mismatch degree (i.e. about the so-called slopes effects) so that they are not the focus of this study. However, leaving the two dummies and their interaction in the error could generate endogeneity of the other interactions.

Finally, one lagged dependent variable is included for reasons explained in the next section.

4.3   *Methodology and Econometric Issues*

4.3.1   *Simultaneity bias and instrumentation*

If output fluctuations are interdependent (i.e. if the true β's are positive), *C* determines Δy as well as the reverse. Movements in *u* affect other countries' fluctuations and therefore *C*. It follows that the error term is not independent from the latter. If the true β's are positive, *OLS* regressions will then give upward biased and inconsistent estimators, and the bias will be directly proportional to the interdependence of output fluctuations. This simultaneity bias might affect Δius as well. Imagine that a productivity shock common to various countries arises. This could be, for example, the discovery and diffusion of a new technology. This phenomenon would not be picked up by the variables included in the model and thus would be picked up by the error term. If the output fluctuations generated by the productivity shock are sizeable in various countries and affect *US* output, the Federal Reserve is likely to intervene to offset such fluctuations. The *US* discount rate would then be correlated with the errors as well. This could happen in a quarter, so that the problem can theoretically arise. Finally, monetary authorities intervention suggests that the exchange and interest rates are at least partly determined simultaneously with output fluctuations. Δi and Δe may thus be endogenous as well.

The econometric procedure needs to take into consideration the likely endogeneity present in the model. As usual, the tool used to overcome these problems is the instrumentation of potentially endogenous variables. This poses another

question: what instruments are likely to be relevant and valid? Relevance (i.e. the partial correlation of excluded instruments with the instrumented variables) can be achieved in this model exploiting the strong autocorrelation exhibited by C, Δius, Δi and Δe. The relevance of the lags as instruments is tested via Bound's partial-Rsquared, which will be provided and discussed in the results section below.

4.3.2   Autocorrelated errors and instrumentation

Having established the relevance of the instruments used, it is as important to understand their validity (i.e. their orthogonality with u): endogenous instruments would again give inconsistent estimates. If the error is autocorrelated, then the lags of endogenous variables used to instrument them could be endogenous themselves. To see this, first notice that:

$$\text{cov}\left(u_{it-1}\Delta y_{it-1}\right) \neq 0 \tag{4.10}$$

by definition. If the output fluctuations are interdependent so that $\beta > 0$ then (4.10) implies:

$$\text{cov}\left(u_{it-1}C_{it-1}\right) \neq 0. \tag{4.11}$$

If the error is autocorrelated, from (4.11) follows that:

$$\text{cov}\left(u_{it}C_{it-1}\right) \neq 0 \tag{4.12}$$

i.e.: the first lag of C is endogenous and is not a valid instrument. In presence of autocorrelated errors, extra caution must be then used in choosing the lags to use as instruments. Let us be more specific and assume that the error exhibits autocorrelation of degree one (henceforth $AR(1)$), so that we can write:

$$u_{it} = \rho u_{it-1} + \varepsilon_{it} \tag{4.13}$$

with ε_{it} white noise. Substituting (4.13) in (4.12) we get:

$$\text{cov}\left(u_{it}C_{it-1}\right) = \text{cov}\left(\rho u_{it-1}C_{it-1}\right) \tag{4.14}$$

Eq. (4.14) says that C_{it-1} may not be used as instrument for C_{it} since the former is correlated with the error itself. However, the size of the problem depends on the strength of the *AR* process. The stronger the latter (i.e. the closer ρ to one in absolute terms) the stronger the correlation between the lagged variable and the errors. If $\rho = 0.1$, the endogeneity of C might be negligible, not so with $\rho = 0.9$. In this second case C_{it-1} is certainly not a valid instrument. It is then natural to try older lags, such as for example C_{it-2}. The latter's correlation with the errors is given by:

$$\text{cov}\left(u_{it}C_{it-2}\right) = \text{cov}\left(\rho^2 u_{it-2}C_{it-2}\right) \tag{4.15}$$

With $\rho = 0.9$ we have that $\text{cov}\left(u_{it}C_{it-2}\right) = \text{cov}\left(0.81u_{it-2}C_{it-2}\right)$. The correlation might still be too strong and older lags must be used. Differently, with $\rho = 0.1$ we have that $\text{cov}\left(u_{it}C_{it-2}\right) = \text{cov}\left(0.01u_{it-2}C_{it-2}\right)$, in which case one can reasonably consider C_{it-2} a valid instrument.

This simple example shows that when instrumenting with lags, care must be given to the presence of *AR* and that, even with autocorrelated errors, lags can be valid instruments for the potentially endogenous variables as long as the *AR* process is not too strong. Clearly, the longer the lag used, the weaker its correlation with the autocorrelated error. However, longer lags are likely to be less correlated with the instrumented variable as well. There is therefore a trade off between relevance and validity of the instruments. The strategy I followed is thus to try limiting the *AR* in the error by defining a model that is as close as possible to dynamic completeness and then use as instruments the shortest lags that give a reasonable chance of exogeneity.

With quarterly data, the are various reasons to suspect the errors of eq. (4.2) to be autocorrelated. First, cycles of expansion and contraction of economic activity last typically more than a quarter, so that y is likely to follow longer-than-quarterly cycles. Breaking those cycles into quarterly observations causes the past observations to be correlated with the present one: Δy might be autocorrelated. If some of this

correlation is not explained by the included regressors, then the error in (4.2) will be autocorrelated. Formally:

$$\text{If} \quad L(\Delta y_t \mid X) \neq L(\Delta y_t \mid X, \Delta y_{t-1}) \quad \text{and} \quad \text{cov}(\Delta y_t \Delta y_{t-1}) \neq 0, \quad \text{then} \quad \text{cov}(u_t u_{t-1}) \neq 0$$
(4.16)

Where $L(\Delta y_t \mid X)$ is the linear projection of Δy_t onto X, the set of regressors included in (4.2) except the lagged dependent variable. Since we know that $\text{cov}(\Delta y_t \Delta y_{t-1}) \neq 0$, the chain of causation (4.16) is true if a part of the cycle characterizing Δy_t is not explained by X. This is not hard to imagine. If, for example, productivity shocks hitting the domestic economy increase the growth rate of industrial production for more than a quarter, this would generate autocorrelation in Δy_t that is not be picked up by the regressors. The error would then be autocorrelated.

However, preliminary estimations of (4.2) without the lagged dependent variable (with longer-than-two lags of instrumented variables as instruments) showed no substantial *AR* in the error. A standard *AR* test such as the one suggested by Wooldridge (2002, p.177) did not reject the null of no autocorrelation (not shown). It seems that autocorrelation is not an issue. However, since we cannot confirm a null hypothesis, we want to minimize the type II error by "maximising" its P-value. If (4.16) is the only source of autocorrelation in *u*, then the inclusion of lags of the dependent variable in the model should eliminate it. Therefore, I include one lagged dependent variable to see whether this increases the P-value of the null of no-*AR*. This is the case: the introduction of one lagged dependent variable (*LDV* henceforth) in the model raises the test's P-value from 0.3215 to 0.8929, high enough to comfortably believe in the absence of *AR* in the model. The introduction of one *LDV* seems then enough to eliminate any evidence of autocorrelation. For this reason I include one only *LDV* in the estimated model.

4.3.3   GMM

In presence of heteroskedasticity, a *GMM* estimator with optimal weighting matrix is the efficient estimator. As pointed out by Baum et al. (2007) the efficiency

gains from the traditional *2SLS* estimator derive from the use of the optimal weighting matrix, the overidentifying restrictions of the model and the relaxation of the i.i.d. assumption. Since heteroskedasticity is present in this panel dataset (shown below), the two-step *GMM* estimation with clusterized errors is implemented.

4.3.4 *Panel Time-Series issues 1: the dimension of choice*

In standard panel datasets the number of periods/observations per panel T is so small that it does not allow for an estimation of panel-by-panel regressions. Developed in micro-econometrics field, those panel datasets exploited the time dimension mainly to control for the heterogeneous intercepts. However, when T is big enough to allow a panel-by-panel estimation, the researcher has the choice of considering the dataset as a set of N time-series or of T cross-sections. This choice has deep implications for estimation, since, for example, in a Fixed Effect estimation the intercepts would identify time-invariant country-specific effects in the first case and time-specific country-invariant effects in the second case. The choice of dimension is based on the purpose of the investigation.

In our case, both interpretations would be informative. Considering our dataset a set of 132 cross-sections with 23 observations each and estimating a panel data model would focus the analysis on the heterogeneity of coefficients across time. It might well be that trade shocks have different repercussions on domestic production in periods of sustained world growth like the mid-to-late nineties than in moments of recession like the present one. Considering our dataset a set of 132 cross-sections with 23 observations and applying an estimator controlling for heterogeneous coefficients such as, for example, the Swamy estimator would then be able to treat and estimate such heterogeneity. However, estimation techniques for heterogeneous slopes panel data models such as the Swamy or Random Coefficient estimators do not allow for instrumentation, which is unavoidable in our setting. This avenue is then not viable and we cannot control for heterogeneous slopes.

Moreover, the fact that we are dealing with countries provides a rationale to treat the dataset as a set of 23 time-series. In fact, a country-effect is very likely to be there: simply some countries grew more than others for idiosyncratic reasons. The most common way of controlling for such heterogeneity is an *FE* or *FD* model applied to the 23 cross-sections. Applying those models to the 132 cross-sections

would instead control for a country-invariant time-effect making all countries grow more or less in a certain period. This country-invariant unobservable should however be controlled for by the common shock proxies. The first interpretation gives then a higher guarantee of consistency than the second one.

FE/FD models are however useful if the country effect is correlated with the regressors. Otherwise, a Random Effect model or other estimators taking into consideration the heteroskedastic structure of the errors are the efficient estimators. In our case, the country effect is likely to be scarcely correlated with the regressors, so that *FE/FD* might be superfluous. The idiosyncratic (unexplained) growth of a country might affect other countries' growth via trade, in which case the country-effect would be correlated with the contagion index. However, since the contagion index is a weighted average of 23 countries' output fluctuations, the correlation between the latter and the country effects is likely to be low. Apart for the biggest importers in the sample (Germany, Japan, the *UK*), it is hard to imagine that the idiosyncratic growth of a country could affect strongly the output levels of a diversified set of countries such as the ones in the sample (e.g. Brazil, Canada, Korea, Mexico, Turkey..). Since most countries in the sample are likely to affect with their import demand the economic activity of their main trade partners only, the contagion index is likely to be scarcely correlated with the country unobservable effects. Also, there is no reason to expect a strong correlation between the country effect and the other regressors. This hypothesis is confirmed by a standard *FE* test: the country effects are present but do not seem to be correlated at any relevant degree with the regressors. An *FE/FD* specification is thus unnecessary here: a pooled regression with relevant and valid instruments guarantees consistency while the *GMM* estimation clustered by country guarantees efficiency. This is therefore the chosen estimation technique. The dimension of choice is thus irrelevant to our analysis.

4.3.5   *Panel Time-Series issues 2: T-asymptotics vs. N-asymptotics*

This section explains why estimating eq. (4.2) with a *FE* of *FD* model might cause problems that the pooled estimation avoids. Since the last section showed that the rationale for an *FE/FD* estimation is likely not to be there, this section can be skipped unless interested.

Eq. (4.2) is an autoregressive model containing a *LDV*. As shown by Nickell (1981), the demeaning of variables in the *FE* estimator gives inconsistent estimators in presence of *LDV*. To see this (the following discussion is taken from Bond 2002) assume we want to estimate a structural equation with country-effects such as:

$$y_{it} = \alpha + \beta y_{it-1} + u_{it} \text{ with } u_{it} = \eta_i + v_{it} \tag{4.17}$$

The *FE*-transformed lagged dependent variable is:

$$y_{it-1} - \frac{1}{T-1}\left(y_{i1} + ... + y_{it} + ... + y_{i,T-1}\right) \tag{4.18}$$

and the transformed error is:

$$v_{it} - \frac{1}{T-1}\left(v_{i2} + ... + v_{it} + ... + v_{i,T}\right) \tag{4.19}$$

The component $\dfrac{-y_{it}}{T-1}$ in (4.18) is correlated with v_{it} in (4.19) and $\dfrac{-v_{it-1}}{T-1}$ in (4.19) is correlated with y_{it-1} in (4.18). Nickell (1981) showed that these two correlations are both negative and dominate positive correlations between the other components in the two parenthesis, so that the correlation between the transformed *LDV* and error term can be shown to be negative. This correlation does not vanish as the number of panels in the sample increases, so that the *FE* estimator is not consistent for *N* going to infinity.

However, it does vanish for *T* going to infinite, since the contribution of $\dfrac{-y_{it}}{T-1}$ and $\dfrac{-v_{it-1}}{T-1}$ to their respective averages becomes negligible. The *FE* estimator can then be shown to be *N*-inconsistent but *T*-consistent for dynamic autoregressive processes. This highlights the difference between *T*- and *N*-asymptotic theory and provides an important result: using an *FE* estimator we would be taking country-

averages with 132 observations each, and thus it seems we could consider the Nickell bias negligible and the *FE* a consistent estimator for (4.2).

This is however not the case, since in our setting matters are complicated by the instrumentation. We cannot use the lags of the transformed variables as instruments. To see this, assume we are estimating:

$$y_{it} = \alpha + \beta x_{it} + u_{it} \text{ with } u_{it} = \eta_i + v_{it} \tag{4.20}$$

and that $\text{cov}(x_{it} v_{it}) \neq 0$: x is endogenous. Notice that no *LDV* is included. This is for simplicity only: since the presence of an *LDV* is irrelevant in this problem I put it aside in this example. Assume we want to use an *FE*-estimator and instrument x with its own lags. In practice we would be running a *2SLS* procedure on:

$$\left(y_{it} - \bar{y}\right) = \alpha + \beta\left(x_{it} - \bar{x}\right) + \left(v_{it} - \bar{v}\right)$$

In such a setting $x_{it-1} - \bar{x}$ cannot be used as an instrument for $x_{it} - \bar{x}$. In fact $\text{cov}(x_{it} v_{it}) \neq 0$ implies $\text{cov}(\bar{x}\bar{v}) \neq 0$ and thus *any* lag of the transformed (demeaned) variable will be endogenous. Therefore, the transformed variable cannot be instrumented with its own lags. We would have to use the non-demeaned lagged variable x_{it-1} or find other instruments. Both these options are not viable, the first because the correlation of x_{it-1} with $\left(x_{it} - \bar{x}\right)$ is so low that the model is not identified, the second because other relevant instruments could not be found. Therefore, we could not estimate (4.2) with a *FE* estimator.

Estimating eq. (4.2) with an *FD* model would generate other potential problems because of the presence of an *LDV*. To see this, assume we estimate (4.17) with an *FD* technique. In practice, we would be regressing:

$$\left(y_{it} - y_{it-1}\right) = \alpha + \beta\left(y_{it-1} - y_{it-2}\right) + \left(u_{it} - u_{it-1}\right) \tag{4.21}$$

The *LDV* becomes endogenous by construction, reason for which it would have to be instrumented. This brings us back to the issue of what instruments to use. As for the instrumentation of *C*, we would need to use lags older than the autocorrelated lags

of the error. In other words, if the error is $AR(1)$ the newest lag we can use as instrument is y_{it-3}. If the error is $AR(2)$ we can use y_{it-4} and so on. This would force us to use longer lags, with the likely loss of relevance we discussed above.

Since both the *FE* and *FD* specification are likely to raise the problems discussed above and the benefit of using them are scarce (because scarce is the correlation between the country effects and the regressors), I preferred to apply the *GMM* technique on the pooled dataset.

4.3.6   Panel Time-Series issues 3: stationarity

One last issue arising from the time-series nature of the dataset is stationarity. For the analysis to be reliable, we need to ensure the stationarity of the series. However, since the variables enter the model as percentage changes, this should not be a problem. It is unlikely that, for example, industrial production grows at an ever-faster *rate*. This is indeed confirmed by Augmented Dickey-Fuller tests, which reject the unit-root null without any doubt for each variable (not shown).

4.4   Results and interpretation

Table 4.8 shows the results obtained from the estimation of the equation (4.2), here reproduced for ease of reference:

$$\Delta y_{it} = \alpha + \beta_0 C_{it} + \beta_1 C_{it} * Pos_{it} * OS_i + \beta_2 C_{it} * Neg_{it} + \beta_3 C_{it} * Neg_{it} * OS_i +$$

$$+ \gamma_0 \Delta i_{it} + \gamma_1 \Delta e_{it} + \gamma_2 \Delta ius_t + \gamma_3 \Delta oil_t + \gamma_4 Neg_{it} + \gamma_5 OS_i + \gamma_6 Neg_{it} * OS_i + \delta_0 \Delta y_{it-1} + u_t$$

$$(4.22)$$

The estimation technique is the two-step *GMM* procedure described above and implemented by the ivreg2 Stata routine. From a first look at the results (Table 4.8) one can notice the effects of the instrumentation on the key variable *C* and its interactions. As expected, the instrumentation reduces the size of the estimated coefficient associated with *C*. In the *OLS* specifications this is roughly twice as big than in the *GMM* ones. This suggests the existence of a positive simultaneity bias.

Since the positive effect of a trade shock (from C to Δy) feeds back into the originating country (from Δy to C), the *OLS* estimates of C are biased upward.

Different specifications of the *OS* dummy do not alter the results: the three *GMM* models' results are very similar. This is not surprising since the countries were categorized in similar ways by the different dummies.

In all three specifications all variables but the oil price change have signs in line with theoretical expectations (the positive effect of oil price on production could anyway be explained by the presence of oil-exporting countries such as Canada, Mexico and Norway in the sample). The expected sign on the exchange rate is ambiguous, since it is positive for *FC*s but might be negative for *OSs* due to the presence of currency mismatches and other factors highlighted by the literature on contractionary devaluations. The *US* base rate is found to be contractionary, while the domestic rate vaguely expansionary. The latter's coefficient is however not significantly different from zero. Domestic policy variables seem to have a much smaller (if any) effect on output than the Fed's base rate: the latter's coefficient is at roughly eight times bigger than the domestic rates' one, twice as big than the exchange rate's one and extremely more significant in all three specifications.

Turning to the key variables, C and its interactions, all four present positive and extremely significant coefficients (in all tables the interaction *CpOS* represents $C*Pos*OS$, *Cm* represents $C*Neg$ and *CmOS* represents $C*Neg*OS$). Output fluctuations are thus found to propagate among trade partners. In line with the literature on trade intensity and business cycle synchronization, trade is confirmed to be a relevant channel of shock propagation, both between financial centres and emerging markets. Clearly, the fact that trade partners' output is correlated does not necessarily imply that this is because of trade. However, the sensitivity analysis below will show that this is instead the case.

Estimating one coefficient for each regime (see Table 4.1), we are able to investigate whether the propagation mechanism is stronger when the shocks are negative, and whether the presence of currency mismatches plays a part in it. Table 4.9 provides estimates for the strength of propagation of trade shocks in the four regimes for the three *OS* dummies specifications. The first column gives the model's reference number. The second and third columns describe respectively the regime and

the linear combination of coefficients associated with it. The other columns give the estimated coefficient, P-value and 95% confidence interval associated with the linear combination.

The first two rows of each model give the estimated response to a unit increase in the contagion index in *FC*s and *OS*s, respectively. In all three specifications *OS* countries are found to be markedly more reactive. A unit increase in the contagion index pushes *OS* countries' output up by roughly 2.1% while the same increase pushes *FC*s' output up by only 0.8%, on average and ceteris paribus. A unit increase in the contagion index represents a 1% increase in the output of all countries in the sample. Therefore, a 1% increase in the output of all countries will cause an average 0.8% increase in the domestic output of *FC*s and an average 2.1% increase in the domestic output of *OS*s, ceteris paribus. Countries where currency mismatches are widespread are thus more than twice as sensitive to positive trade shocks. Notice that the confidence intervals of the two combinations do not overlap in the first and third specifications and do only slightly in the second. The different sensitivity is then likely to be statistically significant, as the tests carried out below will confirm.

The same is true for negative trade shocks: these as well affect *OS* countries much more than *FC*s. A unit decrease in the contagion index pushes the output of the former down by roughly 5%, compared to roughly 2.1% for the latter. Therefore, a 1% decrease in the output of all countries will cause an average 2.1% decrease in the domestic output of *FC*s and an average 5% decrease in the domestic output of *OS*s, ceteris paribus. Again, the confidence intervals are overlapping only slightly in the second specification, suggesting that the difference is statistically very significant. Since shocks of both signs are found to affect *OS* countries more than *FC*s, the former appear to be more sensitive to trade shocks. The *negative* and *higher sensitivity* hypotheses seem confirmed. It is also interesting to notice that negative shocks appear to propagate more strongly than positive ones in both *FC*s and *OS*s. The asymmetry hypothesis seems therefore confirmed in relationship to both type of countries.

The analysis so far seem to prove all tests we wanted to perform. Trade shocks propagate in a very different manner depending on the degree of currency mismatches and their sign. However, to give statistical significance to such claims we need to perform the tests described in Table 4.2. The results of such tests for the three *OS* dummies specifications are provided in Table 4.10. The second and third columns

provide the name of the hypothesis tested and the null associated with it. The third and fourth columns give the statistic and associated P-value for each hypothesis.

The results give extremely strong support to the hypotheses tested. The first, third and fourth tests all give P-values close to zero. Evidence gives doubtless support to the *negativity*, *higher sensitivity* and *asymmetry in OS* hypotheses. *OS* countries are more sensitive than *FC*s to trade shocks, be these positive or negative. Furthermore, negative shocks are felt in *OS*s more than positive ones. There is also support to the asymmetry in *FC*s hypothesis, although slightly less than for the other three, its P-value hovering around 7% in the first two models. Notice however that in the model with the dummy *OS2*, the null of symmetry of shocks propagation in *FC*s is rejected at 0.9% significance level.

The tests confirm without doubts the impression raised by the estimated responses to trade shocks: *OS* countries are markedly more sensitive than *FC*s to trade shocks of either sign. Also, negative shocks affect *OS* countries more than positive shocks. These two elements interact, so that the real effect of a negative shock to an *OS* (5%) is more than four times stronger than the real effect of a positive shock to a *FC* (0.8%). These are big differences to any standard. Asymmetry of shock propagation is found in *FC*s as well, although the evidence on this point is not as clear-cut.

Currency Mismatches magnify the real effects of trade shocks. It is then interesting to investigate whether they exacerbate the asymmetry of propagation as well. In other words, it is interesting to test whether the asymmetry is stronger in *OS* countries than in *FC*s. This can be tested by noticing that the estimated asymmetry (i.e. the difference between the estimated response to negative and positive shocks) is given by $\beta_2 + \beta_3 - \beta_1$ in *OS*s and by β_2 in *FC*s. Subtracting the latter from the former one obtains $\beta_3 - \beta_1$. This is then a measure of the difference in the degree of asymmetry of shocks propagation in *OS* and *FC* countries. A positive number would imply that currency mismatches widen the gap between the propagation strength of negative and positive trade shocks, rendering the former more powerful than the latter. The hypothesis $\beta_3 - \beta_1 = 0$ is tested for all three models. The statistics for the three models, distributed as a Chi-squared with 1 d.o.f., are respectively 10.97, 8.09 and 16.50 with associated P-values of 0.0009, 0.00044 and 0.0000. According to the data, the asymmetry is then doubtlessly stronger in *OS* countries. Therefore, not only

currency mismatches render a country more vulnerable to trade shocks, but they also increase the strength of negative shocks with respect to positive ones.

Substantial differences in the way shocks propagate to *OS*s and *FC*s have been found. I've interpreted this as a proof that currency mismatches magnify the real effects of trade shocks. However, for this to be true, the degree of currency mismatches must be the only element affecting one country's sensitivity to trade shocks being different between *OS* and *FC* countries. If instead some other factor increasing one country's sensitivity to trade shocks is systematically higher in *OS*s, we might overestimate the importance of currency mismatches. In this case, the *OS* dummies would pick up the effect of that other factor along with that of currency mismatches. It is thus important to ask what factors determine the sensitivity of a country's output to external output fluctuations and whether these factors might be systematically higher in *OS* countries. The literature on business cycle synchronization offers answers to the first question. It highlights three main factors determining the sensitivity of a country's output to a trade partner's output fluctuations: bilateral trade intensity, distance and the degree of similarity of the industrial structure of the two countries. Distance is found to be negatively correlated with the synchronization of the business cycles, while the other two are found to be positively correlated. If any of these factors is not controlled for in the estimated equation and are positively correlated with the degree of currency mismatches we could have a bias in the estimated betas. This is however hard to conceive: bilateral trade intensity is controlled for by the weights assigned to the contagion index, while it is unclear why the other two factors should be related to the degree of currency mismatches. Take distance. To have an upward bias in the coefficient, *OS* countries should have their trade partners closer than *FC*s do. If anything, the opposite is more likely: apart from Japan and the *US*, all *FC*s in the sample (Austria, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, the United Kingdom) are European countries. These have other European countries as their major trade partners. Therefore, the distance between them and their major trade partner is generally lower than that of the *OS* countries in the sample (Brazil, Canada, Czech Republic, Hungary, Israel, Korea, Mexico, Norway, Slovak Republic, Turkey), whose major trade partners are typically neighbouring countries *and* major economies such as the US, Japan, or Germany. Regarding the similarity of the industrial

structure, there is no reason why this should be higher among *OSs* than among *FCs*. It follows that, if anything, given the proximity of *FCs* to each other a downward rather than upward bias in the estimated coefficients of the *C* interactions could be there. The analysis is then genuinely identifying the crucial role of currency mismatches in the propagation of trade-related shocks.

In order to see how reliable these results are, one has to assess the quality of the instrumentation used. Table 4.11 shows the relevant statistics from the first stage regressions. Each column corresponds to a different *OS* dummy specification. For each instrumented variable the table provides the F-statistic and its P-value, as well as the Partial R-Squared of the excluded instruments.

The partial R-squared is high for all instrumented variables, in particular for the key variables *C* and its interactions. Their partial R-squared are between 23% and 40% in all three specifications, more than satisfactory. Unsurprisingly, the F-test statistics of all instrumented variables are extremely high, enough to reject the null of no partial correlation between instruments and instrumented variables at the 0.1% significance level. Again, the key variables *C* and its interactions show the highest statistics. We can therefore say confidently that the instruments are relevant and the model is identified. This is indeed consistent with the strong significance found for almost each coefficient of the instrumented variables in the second stages.

The instruments are also valid, as shown by the Hansen *J*-statistics appearing in the bottom rows of the table. The test's P-value is around 17-20% for the first two specifications and higher for the third where it reaches 33%. Since we cannot confirm a null hypothesis of exogeneity but only hope not to reject it, we would like to get a higher the P-value. 33% is however large enough to believe reasonably in the exogeneity of the instruments.

Finally, it is worthwhile recalling that with homoskedasticity the *GMM* estimator is consistent but not efficient, the efficient one being the standard *2SLS* estimator instead. If errors are homoskedastic, the precision of the estimation could then be improved applying *2SLS* rather than *GMM*. For this reason, I test the null of homoskedasticity for all three specification with the Pagan-Hall test that allows for instrumentation. This returns 43.645, 44.713 and 43.075 for the three models respectively. Being distributed as a Chi-squared with 21 d.o.f., the three statistics are

associated with P-values of 0.0026, 0.0019 and 0.0031 respectively. The null of homoskedasticity can then be rejected with confidence, proving that *GMM* is the correct estimator for this application. Of course, the efficiency of the *GMM* estimator is conditional on the optimality of the weighting matrix used. The latter is the inverse of an heteroskedastic var-cov matrix with clustered variance, the clusters being the countries in the sample. Intra-cluster autocorrelation is however allowed, so that the variance structure assumed is quite general.

4.5   *Sensitivity analysis*

The findings of analysis are interesting, since they isolate a key role played by currency mismatches in the propagation of output fluctuations. It is then worthwhile to check the robustness of such results to different specifications and assumptions underlying the estimated model. I will do so modifying the base-line model in the following ways:

a)   Different test for the higher sensitivity of *OS* countries. If the latter are more sensitive to trade shocks irrespective of their sign, then the interaction of *C* and the *OS2* dummy (named *COS2*) should identify that higher sensitivity. *CpOS2*, *Cm* and *CmOS2* are then substituted by *COS2* in order to see if the higher sensitivity hypothesis is confirmed even when distinction between negative and positive shocks is put aside. The first column of Table 4.12 gives the regression results for this model.

b)   Different autocorrelation (*AR*) in the error term. While autocorrelation tests cannot reject the null of no-*AR*, this is not a definitive proof of its absence. In presence of *AR*, instruments would be endogenous themselves, therefore invalidating the analysis. For this reason I re-estimate the model assuming autocorrelation of first and second degree in the error term. In other words, I use one- and two-periods older lags to instrument the variables suspected to be endogenous. The models corresponding to these specifications are *S2* and *S3* in Table 4.12.

c)   Different de-trending method. In the trade intensity and business cycle synchronization literature various de-trending methods are used, the two most

common being the use of first-differenced log-output and output deviations from a linear trend as dependent variables. The first method was implemented in the base-line estimations. I use the second in the model *S4*. First, each country's output levels are regressed on a linear trend, then the errors from such regressions are regressed on the same right-hand-side variables of the base-line model (apart from the *LDV* obviously, which is the lagged deviation from the linear trend). The estimated model is then identical to 4.22) apart from the dependent variable and the *LDV*, which are now the deviation from the estimated linear trend.

d) Different measure of trade intensity. Again, this is suggested by the literature just quoted. Instead of bilateral trade as a percentage of *GDP*, bilateral trade as a percentage of total trade is used. I used the former for the reasons explained in section 4.2.3, but I now check that the choice of either measure of trade intensity does not affect the results. These are presented in the column *S5*.

e) Unweighted contagion proxy. If output co-movements are generated by common shocks rather than trade-shocks propagation, the analysis above would not prove the non-linearity of trade-related shocks propagation. Common shocks are assumed to be controlled for by, among others, the oil price variable. This is however found positively signed and significant, casting doubts on its ability to effectively pick up the effects of common shocks. In order to see whether the contagion proxy and its interactions isolate the effect of trade shocks or instead pick up common shocks affecting the output of more countries, I re-estimate the model with unweighted contagion proxy and interactions. In other words, the output fluctuations of all countries in the sample are summed up in the *C* assigning them the same importance. If trade linkages are the transmission channel, output fluctuations of countries with no trade linkages with the target one should not affect the latter's output. The unweighted contagion proxy and its interactions should then lose significance and have coefficients close to zero. This hypothesis is tested in model *S6*.

f) The domestic monetary and exchange rate policy proxies (*di* and *de*) are found to be scarcely insignificant in the output fluctuations at a quarterly frequency. This can be either because they actually are not affecting output, or more likely because their instrumentation is weak enough to produce excessively large variances in their coefficients. Considering them exogenous and therefore not

instrument them can improve the quality of the estimation without affecting its consistency if *di* and *de* are only slightly correlated with output fluctuations in the present quarter. In other words, if *di* and *de* in *t* are set on the basis of *past* rather than the present quarter's economic performance (dy_{t-1} and older), then they are exogenous and we could then save the degrees of freedom used to instrument them. Model *S7* implement this line of thought by re-estimating the base-line model considering *di* and *de* exogenous.

g) As shown in Appendix A (footnote 2), the dummies' specification assumes no effect of the dummies on the intercept. In other words, the fact that a trade shock is negative is assumed to have no effect *per se* on the domestic output. Similarly, being an *OS* country is assumed to have no effect *per se*. These assumptions are justifiable on a number of grounds: first, it is hard to conceive why the fact that a trade shock is negative should magnify of the shock's strength (the slope effect) *and* reduce domestic output irrespective of the shock's size. Second, it's unclear why *OS* countries as a whole should have grown more or less than *FC*s, being the former a group of diverse countries such as Austria, Brazil, Canada, Korea and Poland to name a few. Finally, we are interested in detecting an eventual magnification of the propagation strength, which is identified by the slopes effects. However, if the intercept effects are significative and omitted, they may cause endogeneity, since they are correlated with the slope dummies by definition. For this reason, it is important to test the significance of the intercept effects. This is pursued in the model *S8*, which introduces the dummies *Neg*, *OS* and their interaction to see whether they are significant and whether their introduction alters the results on the hypotheses tested. For identification reasons (the number of clusters used in the robust errors must be bigger than the number of instruments), one has to drop one variable to include the three new ones. Since the interest rate has been found non-significant in all baseline estimations, I drop that one.

Since the different specifications of the *OS* dummies give almost identical results, I will apply the modifications just described on the model with the third *OS* dummy (i.e. *OS2* as opposed to *OS* and *OS1*) only. This specification is chosen because it gives the strongest results in terms coefficients' size and significance.

Furthermore, it shows the highest statistics in the tests for the relevance and validity of the instruments. The results of the regressions and the four hypotheses' tests are provided by Table 4.12 and 4.13 respectively.

Table 4.12 provides the estimates for the eight specifications just described. The key parameters, C and its interactions are substantially stable, apart from C. The latter's coefficient is negative in various specifications. Notice however that in most of these cases the coefficient is not significant, only slightly in $S4$. The OS dummies interactions are instead positive and extremely significant in most specifications. I particular $CmOS$, the interaction identifying the magnifying effects of negative shocks by currency mismatches is big and extremely significant in all specifications. The higher sensitivity of OS countries to all shocks and in particular negative ones seems robust to a vast array of specifications. Different specification of the OS dummy, de-trending method, trade weights, assumption about the exogeneity of policy variables and about intercept effects do not alter the main finding of the analysis: that OS countries seems to react more strongly than FCs to trade shocks. This will be proven by the tests' results below.

This seems not to be the case for the asymmetry hypothesis, at least when it comes to FCs. Cm, the interaction identifying asymmetries in FCs, is indeed insignificant in all specifications, while the asymmetry in OS receives some support, as the tests results presented below will show. The evidence of asymmetry seemed weaker than that of higher sensitivity in the main analysis already.

The importance of trade as a propagation mechanism is confirmed by the model estimated with the unweighted contagion index ($S5$). We can see that the estimated coefficients for C and its interactions decrease markedly and loose significance completely (as noted above, the coefficient on C turns even negative). Notice that this does not happen because of an increase in the coefficients' standard errors. It is rather the drop of their sizes that causes their insignificance. So it is the genuine lack of correlation rather than weaker instrumentation that makes the unweighted contagion proxies irrelevant. Bilateral trade is then a relevant channel of shocks propagation: weighting foreign output fluctuations for its intensity increases the size and significance of the contagion coefficients.

Assuming di and de exogenous does not alter substantially the results of the analysis: the coefficients' signs and size are similar to those in the baseline model. The feedback from output fluctuations to economic policies does not seem to work

within the lapse of a quarter. Moreover, saving degrees of freedom by instrumenting two variables less has a beneficial impact on the precision of the estimation. The standard errors of most coefficients decrease.

Finally, *S8* shows that assuming no intercept effects of the dummies is reasonable: the controls for such effects introduced in *S8* are completely non-significant. Furthermore, the effect of currency mismatches on the propagation mechanism found in the main analysis are confirmed fully, as the tests below will prove.

The main analysis supported the hypotheses tested, and in particular it gave strong evidence in favour of the higher sensitivity hypothesis. To assess the robustness of these results, the four hypotheses are re-tested for all the sensitivity models. The results are presented in Table 4.13.

The higher sensitivity hypothesis is confirmed in all models but *S2* and *S3*, the models using older lags as instruments. Leaving aside the distinction between negative and positive shocks and introducing one dummy interaction only for *OS* countries (*COS2*), one finds that the effect of a unit change of the contagion index in both direction causes a 1.1% movement in the output of an *FC* and a 2.3% movement in an *OS*. The difference between the two, identified by *COS2*, is significant at the 1% level (see Table 4.12, first column). Keeping the difference between positive and negative shocks, the higher sensitivity is confirmed with a different de-trending method (*S4*), trade weights (*S5*), different exogeneity assumptions for the policy variables (*S7*) and about intercept effects (*S8*). *S2* do not confirm the higher sensitivity hypothesis, while *S3* does so only at the 7% significance level. However, this is likely to depend on the weaker instrumentation implemented in these models. Indeed, *S2* and *S3* show first-stage statistics much worse than those of both the other sensitivity models and of the baseline ones. The partial R-squared of *C* and its interactions falls markedly: they hover around 17% in the main regressions and in the other sensitivity models while they are close to 2% in the *S2* and *S3* specifications. In the same line, the Anderson canonical correlation likelihood-ratio test statistic gives a P-value of around 16% for the baseline models and 66% for *S2* and *S3*. Recalling that the *LR* test's null hypothesis is the underidentification of the reduced form coefficients (i.e. the non-relevance of all instruments), the Anderson statistics suggests that the instruments used in *S2* and *S3* are much more likely to be scarcely

correlated with the instrumented variables. Since *S2* and *S3* use older lags than all other models, this makes intuitive sense.

The negative hypothesis is also confirmed by the sensitivity test, albeit more weakly. Out of the seven specifications where it is tested (*S2* to *S8*), the hypothesis is not confirmed only in the models assuming different *AR* (*S2* and *S3*) and unweighted contagion proxy *S6*. The former are however suffering of poor instrumentation, so that all results loose significance, while the latter is meant to give non-significant contagion coefficients since the proxy is unweighted. In *S4* (different trade weight), the hypothesis is confirmed marginally, since the null of no additional effect of negative shocks is rejected with an 8.85% P-value. In all other specifications, the null is rejected with a P-value of zero.

The sensitivity analysis provides evidence of asymmetry in the propagation mechanism to *OS*s but not to *FC*s. The third row in each model of Table 4.13 gives the statistic and P-value associated with the Asymmetry to *FC* test. As one can see, the null of no asymmetries in *FC*s is never rejected at standard levels of significance. The mild support given by the main analysis to the Asymmetry to *FC* hypothesis does not stand the sensitivity check. On the other side, evidence of asymmetries in *OS* countries is more robust: statistically significant asymmetries are found for *OS* countries in all models but the one with different de-trending (*S4*) (and *S6*, where one expects the test results to be non-significant since unweighted contagion proxies are used).

The main result of this analysis, that currency mismatches magnify the effects of trade shocks, is then robust to a vast array of assumptions regarding the regressors' endogeneity, intercept effects, the de-trending techniques and trade intensity measures used. Moreover, the sensitivity analysis in model *S5* proves that it is trade-related contagion and not common shocks that causes the output co-movements isolated by the contagion proxy *C* and its interactions. Negative trade shocks seem to interact in a particularly damaging way, as proven by the evidence of magnification of negative trade shocks and asymmetry caused by the presence of currency mismatches.

4.6   *Conclusions and Policy Implications*

Several reasons why currency mismatches might magnify the effect of foreign disturbances have been identified by the literature. These feature: balance sheet effects, increasing costs of funding for dollar-borrowing firms, higher capital flows sensitivity to real shocks and limited scope and effectiveness of central banks' counterbalancing intervention. Notwithstanding this, a formal test of currency mismatches' magnification effect have not been performed before. Using *GMM* to overcome endogeneity and heteroskedasticity issues, I tested the effects of trade partners' output fluctuations on the domestic output of a sample of 23 countries spanning from the first quarter of 1995 to the last of 2005. Some of these countries showed widespread currency mismatches while others did not. In such a setting, it was possible to assess the role of currency mismatches on various aspects of the propagation mechanism. Four hypotheses were tested, namely that currency mismatches: a) magnify the real effects of negative trade shocks, b) magnify the real effects of trade shocks irrespective of their sign (i.e. magnify trade-related output volatility), c) generate asymmetric trade shock propagation (i.e. make negative trade shocks more effective on domestic output than positive ones). It was also tested whether negative shocks are more effective than positive ones in countries where currency mismatches are not widespread (d).

The analysis gives strong support for the first three hypotheses: currency mismatches do magnify the effects of trade shocks, both positive and negative, on domestic output levels. The reaction of an average *OS* country to an external trade shock (i.e. the output fluctuation caused by the shock) is roughly double than the reaction of an *FC* country, whatever the sign of the shock. Currency mismatches also generate asymmetry in the propagation mechanism, with negative trade shocks being felt more strongly than positive ones. Some evidence of asymmetry is found in countries without currency mismatches as well, thus lending some support to the fourth hypothesis tested. This appears however weak. Sensitivity checks suggest that the asymmetry is not robust to different assumptions regarding the regressors' endogeneity, the de-trending method and trade intensity measures used.

The analysis' findings relate with the existing literature in various ways. Eichengreen, Hausmann, Turner and Goldstein's empirical works quoted above

showed that currency mismatches increase the likelihood and severity of financial crises. This chapter complements those results by showing that currency mismatches also magnify the propagation of trade shocks, in particular negative ones. Their result is also generalized by showing that currency mismatches magnify the detrimental effects of negative output shocks of all sizes, not only of major ones. In other words, currency mismatches increase the output losses caused by trade slumps in normal times as well as during crises. By reducing its degree of liabilities dollarization, a country might reduce its vulnerability not only to full-blown financial crises but also to minor recessions caused by ordinary negative trade shocks.

In line with the theoretical findings of the DSGE literature quoted above, the results confirm that currency mismatches increase domestic output's volatility caused by trade shocks. This point is interesting in relationship with the recent literature on volatility and growth. Ramey and Ramey (1995) find a strong negative relationship between the standard deviation and the mean of the rate of output growth on a cross-section of countries. Since output volatility appear to be detrimental to growth, not only do currency mismatches exacerbate output fluctuations, they might also reduce its growth. More recently, Aghion et al. (2004) showed that the negative correlation between output volatility and growth is stronger, the lower the degree of development of financial markets. Countries with less developed financial markets suffer the negative effects of output volatility more than countries where financial markets are more advanced. Since financial underdevelopment and liability dollarization tend to go together, the negative effect of currency mismatches on growth might work via this channel too. This chapter's findings are then consistent with those of Aghion et al.

Finally, the results show that the negative shocks' real effects are more magnified than positive ones, so that there is a substantial asymmetry of propagation of shocks to countries with currency mismatches, but not towards financial centres.

These results suggest an obvious goal for policymakers in Emerging Markets: reducing their countries' degree of currency mismatches. How to pursue this goal depends on the opinion on the origin of the currency mismatches problem one has.

Following the Eichengreen et al. approach, currency mismatches is an "original sin", a phenomenon common to all *EMEs* and beyond their control. It is an history of defaults and scarce commitment to price and exchange rate stability that makes

foreign investors unwilling to buy debt denominated in local currency. In order to change this, *EMEs* government should start "behaving well" and then wait for their reputation among international investors to improve. However, the wait might be too long, especially if in the meantime their countries are exposed to devastating contagion episodes like the ones seen in the '90s. For this reason Eichengreen et al. suggest drastic measures: countries where currency mismatches are extreme should dollarize their economies, even if this means giving up any independence in the monetary and exchange rate policy management. In the meantime, a composite currency including major *EMEs'* currencies should be created and the G8 governments should issue debt in this composite currency, in order to give *EMEs* an hedging opportunity.

Goldstein and Turner argue that the Eichengreen et al. approach is misled and oversees crucial differences running between *EMEs*. They argue that good domestic policies can instead make a difference and reduce the degree of currency mismatches. They put forward four areas of macroeconomic policies that *EMEs* governments should implement:

a) a better inflation performance that would reassure international investors that the government will not inflate its debt away,

b) a more flexible exchange rate regime that will make agent less complacent about currency risk,

c) stronger government's fiscal accounts that will reduce its incentive to devalue or inflate its debt away and

d) a better management (i.e. lower exposure to currency risk) of public debt, which represents the most part of outstanding debt in *EMEs*.

Also, they point three microeconomic policies that introduce incentive for agents to reduce their exposure to currency risk:

a) developing more liquid domestic bond markets that will give agents the opportunity to trade domestic-currency-denominated debt,

b) prudential oversight of financial institutions ensuring that regulatory capital requirements reflect the risk the bank is exposed to, that banks have appropriate systems in place to monitor and control such exposures and transparent reporting exposes reckless risk-taking,

c) regulation of banks in major lending centres, aimed at reducing large-scale short-term dollar-denominated lending.

Further research on the ultimate causes of the arising of currency mismatches in EMEs are needed to settle this dispute and understand what are the best policy options to reduce the negative effect currency mismatches have on macroeconomic stability.

Table 4.3
Summary Statistics: levels

Variable		Mean	Std. Dev.	Min	Max
Index of Industrial Production	overall	98.43145	12.01942	52.78083	140.314
	between		3.500087	94.1727	107.4462
	within		11.52109	51.78006	139.8014
Contagion Index *	overall	0.0024031	0.0043115	-0.0154399	0.0303775
	between		0.0012021	0.0008052	0.005094
	within		0.004148	-0.0165222	0.0283187
Average price of crude oil	overall	27.03983	11.4556	11.64333	59.96333
	between		0	27.03983	27.03983
	within		11.4556	11.64333	59.96333
US discount rate	overall	3.820684	1.521618	0.9433333	6
	between		0	3.820684	3.820684
	within		1.521618	0.9433333	6
domestic discount rate**	overall	9.165423	11.83732	0.1	67
	between		11.27718	0.3081197	53.88889
	within		4.282645	-18.39013	29.37368
Domestic exchange rate vis-à-vis the US dollar	overall	100.3885	297.0761	0.0764986	1792.263
	between		252.1935	0.6196773	1147.113
	within		165.3784	-370.1997	1421.303
Observations: 897; Countries: 23; Periods (quarters) 39. * sum of IIP in trade partners, weighted for relative importance ** Money market rate for Mexico, Nederland and the UK					

Table 4.4
Summary Statistics: percentage changes

Variable		Mean	Std. Dev.	Min	Max
Index of Industrial Production	overall	0.0085937	0.0214923	-0.0809721	0.1186505
	between		0.0066125	-0.0000381	0.0246829
	within		0.0204951	-0.0914282	0.1069855
Contagion Index *	overall	0.0024031	0.0043115	-0.0154399	0.0303775
	between		0.0012021	0.0008052	0.005094
	within		0.004148	-0.0165222	0.0283187
Average price of crude oil	overall	0.037124	0.1260378	-0.2482307	0.3767536
	between		0	0.037124	0.037124
	within		0.1260378	-0.2482307	0.3767536
US discount rate	overall	-0.0028205	0.4864304	-1.416667	1.306667
	between		0	-0.0028205	-0.0028205
	within		0.4864304	-1.416667	1.306667
domestic discount rate**	overall	-0.1945659	1.503434	-10.76667	17
	between		0.2262142	-0.8428206	0.0021368
	within		1.487047	-10.78768	17.41227
Domestic exchange rate	overall	0.0000921	0.1033776	-0.9994587	0.4849018
vis-à-vis the US dollar	between		0.0235572	-0.0251111	0.0865369
	within		0.1007746	-0.9784078	0.4543013

Observations: 897; Countries: 23;
Periods (quarters) 39.
* sum of IIP in trade partners, weighted
for relative importance
** Money market rate for Mexico,
Nederland and the UK

Table 4.5
OSIN indexes

	OSIN1	OSIN1	OSIN2	OSIN2	OSIN3	OSIN3
	1993-1998	1999-2001	1993-1998	1999-2001	1993-1998	1999-2001
Austria	0.95	0.7	0.9	0.69	0.9	0.69
Brazil	1	1	1	1	1	1
Canada	0.78	0.85	0.76	0.83	0.55	0.76
Czech Republic	1	1	0.88	0.84	0	0
Finland	0.98	0.65	0.96	0.62	0.96	0.62
France	0.59	0.35	0.52	0.42	0.23	0.12
Germany	0.69	0.37	0.67	0.48	0	0
Greece	0.99	0.78	0.93	0.6	0.93	0.6
Hungary	1	1	1	0.98	1	0.98
Ireland	0.98	0.6	0.94	0.59	0.94	0.59
Israel	1	1	1	1	1	1
Italy	0.86	0.37	0.65	0.51	0	0
Japan	0.64	0.53	0.25	0.35	0	0
Korea, Rep.	1	1	1	1	1	1
Mexico	1	1	1	1	1	1
Netherlands	0.76	0.51	0.64	0.48	0.64	0.47
Norway	0.99	0.99	0.98	0.89	0.98	0.89
Poland	0.97	0.99	0.95	0.89	0.82	0
Portugal	0.97	0.44	0.42	0.59	0.42	0.24
Slovak Republic	1	1	0.96	0.97	0.87	0.85
Spain	0.96	0.52	0.59	0.61	0.59	0.42
Turkey	1	1	1	1	1	1
United Kingdom	0.56	0.64	0.26	0.31	0.26	0.31
United States	0.3	0.17	0.65	0.44	0	0

Table 4.6
OSIN and AECM indexes

	OSIN1	OSIN1	OSIN2	OSIN2	OSIN3	OSIN3	AECM	AECM	AECM2	AECM2
	1993-1998	1999-2001	1993-1998	1999-2001	1993-1998	1999-2001	1994-1998	1999-2001	1994-1998	1999-2001
Austria	0.95	0.7	0.9	0.69	0.9	0.69				
Brazil	1	1	1	1	1	1	-2.964	-16.300	-4.636	-23.547
Canada	0.78	0.85	0.76	0.83	0.55	0.76				
Czech Republic	1	1	0.88	0.84	0	0	3.364	5.730	6.784	10.063
Finland	0.98	0.65	0.96	0.62	0.96	0.62				
France	0.59	0.35	0.52	0.42	0.23	0.12				
Germany	0.69	0.37	0.67	0.48	0	0				
Greece	0.99	0.78	0.93	0.6	0.93	0.6				
Hungary	1	1	1	0.98	1	0.98	-11.960	-4.260	-18.120	-5.767
Ireland	0.98	0.6	0.94	0.59	0.94	0.59				
Israel	1	1	1	1	1	1	1.130	2.377	3.838	5.963
Italy	0.86	0.37	0.65	0.51	0	0				
Japan	0.64	0.53	0.25	0.35	0	0				
Korea, Rep.	1	1	1	1	1	1	-4.208	3.043	-4.836	4.003
Mexico	1	1	1	1	1	1	-21.036	-7.537	-27.694	-9.267
Netherlands	0.76	0.51	0.64	0.48	0.64	0.47				
Norway	0.99	0.99	0.98	0.89	0.98	0.89				
Poland	0.97	0.99	0.95	0.89	0.82	0	4.502	5.260	9.350	9.617
Portugal	0.97	0.44	0.42	0.59	0.42	0.24				
Slovak Republic	1	1	0.96	0.97	0.87	0.85				
Spain	0.96	0.52	0.59	0.61	0.59	0.42				
Turkey	1	1	1	1	1	1	-12.268	-19.460	-19.768	-34.820
United Kingdom	0.56	0.64	0.26	0.31	0.26	0.31				
United States	0.3	0.17	0.65	0.44	0	0				

Table 4.7
OS dummies specifications

	OS	OS	OS1	OS1	OS2	OS2
	1993-1998	1999-2005	1993-1998	1999-2005	1993-1998	1999-2005
Austria	X		X		X	X
Brazil	X	X	X	X	X	X
Canada		X	X	X	X	X
Czech Republic	X	X	X	X	X	X
Finland	X		X		X	X
France						
Germany						
Greece	X		X		X	
Hungary	X	X	X	X	X	X
Ireland	X		X		X	
Israel	X	X	X	X	X	X
Italy					X	
Japan						
Korea, Rep.	X	X	X	X	X	X
Mexico	X	X	X	X	X	X
Netherlands					X	
Norway	X	X	X	X	X	X
Poland	X	X	X	X	X	X
Portugal						
Slovak Republic	X	X	X	X	X	X
Spain						X
Turkey	X	X	X	X	X	X
United Kingdom						
United States						
N. of OS countries	14	11	15	11	17	13
Threshold	80%	80%	70%	70%	60%	60%

Table 4.8
Estimation results
Baseline model

	OLS			GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
	OS	OS1	OS2	OS	OS1	OS2
C	1.753***	1.802***	1.748**	0.759**	0.927**	0.799**
	(0.587)	(0.628)	(0.782)	(0.370)	(0.416)	(0.382)
CpOS	0.308	0.237	0.280	1.490***	1.249***	1.340***
	(0.512)	(0.546)	(0.659)	(0.372)	(0.391)	(0.407)
Cm	0.0132	-0.0455	-0.281	1.321*	1.363*	1.342***
	(1.099)	(1.118)	(1.201)	(0.747)	(0.743)	(0.514)
CmOS	-0.502	-0.501	-0.0665	3.073***	2.770***	2.902***
	(0.793)	(0.790)	(0.719)	(0.819)	(0.886)	(0.691)
dius	0.00220	0.00220	0.00232	-0.00814***	-0.00833***	-0.00918***
	(0.00174)	(0.00174)	(0.00162)	(0.00153)	(0.00166)	(0.00177)
di	-0.00130**	-0.00131**	-0.00131**	0.00115	0.00113	0.00156
	(0.000576)	(0.000575)	(0.000569)	(0.00230)	(0.00237)	(0.00249)
de	-0.000786	-0.000809	-0.000603	0.0456*	0.0424	0.0492***
	(0.00683)	(0.00682)	(0.00673)	(0.0268)	(0.0266)	(0.0180)
doil	0.00242	0.00242	0.00245	0.0118***	0.0130***	0.0113***
	(0.00894)	(0.00910)	(0.00932)	(0.00322)	(0.00357)	(0.00322)
L.dy	0.0467	0.0473	0.0468	0.378***	0.397***	0.410***
	(0.0653)	(0.0652)	(0.0652)	(0.0634)	(0.0632)	(0.0599)
Constant	0.00295**	0.00290**	0.00287**	0.00244**	0.00202*	0.00240***
	(0.00120)	(0.00120)	(0.00121)	(0.000988)	(0.00104)	(0.000809)
Observations	897	897	897	897	897	897
R-squared	0.176	0.176	0.175	-0.094	-0.095	-0.128

*** p<0.01, ** p<0.05, * p<0.1
Standard errors are robust, clusterized by country

Table 4.9
Estimated responses

	Regime	Linear Combination	Coefficient	P-value	95%	C.I.
(4)	+VE to FC	C	0.759	0.040	0.034	1.484
	+VE to OS	C+CpOS	2.249	0.000	1.781	2.718
	-VE to FC	C+Cm	2.080	0.005	0.629	3.531
	-VE to OS	C+Cm+CmOS	5.152	0.000	3.863	6.442
(5)	+VE to FC	C	0.927	0.026	0.113	1.742
	+VE to OS	C+CpOS1	2.176	0.000	1.692	2.660
	-VE to FC	C+Cm	2.290	0.003	0.786	3.794
	-VE to OS	C+Cm+CmOS1	5.060	0.000	3.726	6.394
(6)	+VE to FC	C	0.799	0.036	0.050	1.548
	+VE to OS	C+CpOS2	2.139	0.000	1.638	2.641
	-VE to FC	C+Cm	2.141	0.000	0.963	3.320
	-VE to OS	C+Cm+CmOS2	5.043	0.000	3.661	6.425

Ho: coefficient/sum of coefficients=0

Table 4.10
Hypotheses tests

	Hypothesis	Ho	Statistic	P-value
(4)	Negative	CmOS=0	14.08	0.0002
	Higher sensitivity	CmOS=0 & CpOS=0	17.87	0.0001
	Asymmetry in FC	Cm=0	3.13	0.0769
	Asymmetry in OS	Cm+CmOS-CpOS=0	19.79	0.0000
(5)	Negative	CmOS1=0	9.76	0.0018
	Higher sensitivity	CmOS1=0 & CpOS1=0	11.50	0.0032
	Asymmetry in FC	Cm=0	3.36	0.0667
	Asymmetry in OS	Cm+CmOS1-CpOS1=0	18.38	0.0000
(6)	Negative	CmOS2=0	17.64	0.0000
	Higher sensitivity	CmOS2=0 & CpOS2=0	17.64	0.0001
	Asymmetry in FC	Cm=0	6.82	0.0090
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	20.32	0.0000

Notes: All tests but high sensitivity distributed as a Chi-squared with 1 d.o.f..

Higher sensitivity tests distributed as a Chi-squared with 2 d.o.f.

Table 4.11
First Stage Results:
Selected statistics

		(4) OS	(5) OS1	(6) OS2
C	F-stat	1241.49	295.01	1240.98
	F-stat p-value	0.0000	0.0000	0.0000
	partial R-squared	0.223	0.2315	0.2295
CpOS	F-stat	4371.05		
	F-stat p-value	0.0000		
	partial R-squared	0.4041		
CpOS1	F-stat		6263.54	
	F-stat p-value		0.0000	
	partial R-squared		0.4098	
CpOS2	F-stat			2621.46
	F-stat p-value			0.0000
	partial R-squared			0.3746
Cm	F-stat	1200.63	1223.23	839.62
	F-stat p-value	0.0000	0.0000	0.0000
	partial R-squared	0.2153	0.2181	0.2195
CmOS	F-stat	5426.11		
	F-stat p-value	0.0000		
	partial R-squared	0.2624		
CmOS1	F-stat		1674.17	
	F-stat p-value		0.0000	
	partial R-squared		0.2681	
CmOS2	F-stat			1050.42
	F-stat p-value			0.0000
	partial R-squared			0.2522
dius	F-stat	1241.63	1093.28	1416.43
	F-stat p-value	0.0000	0.0000	0.0000
	partial R-squared	0.2156	0.2164	0.2157
di	F-stat	210.46	107.85	111.59
	F-stat p-value	0.0000	0.0000	0.0000
	partial R-squared	0.0488	0.0483	0.0458
de	F-stat	126.3	147.09	487.03
	F-stat p-value	0.0000	0.0000	0.0000
	partial R-squared	0.03	0.0315	0.0287
l.dy	F-stat	25.28	24.99	23.05
	F-stat p-value	0.0000	0.0000	0.0000
	partial R-squared	0.1114	0.1114	0.1109
J-statistic*		15.918	16.544	13.341
J-stat p-value**		0.195	0.1676	0.3448

* Hansen overidentification test of all instruments
**H0: exogeneity of all instruments

Table 4.12
Sensitivity Analysis
Regressions results

	(S1)	(S2)	(S3)	(S4)	(S5)	(S6)	(S7)	(S8)
C	1.123**	-1.405	-4.099	-1.681*	-0.305		1.534***	2.669***
	(0.533)	(2.860)	(3.616)	(1.012)	(0.342)		(0.325)	(0.826)
CpOS2		3.016	5.604**	4.991***	1.044**		0.738***	-1.015
		(2.404)	(2.843)	(0.691)	(0.419)		(0.242)	(1.180)
Cm		2.360	2.439	0.113	0.319		0.988	-0.580
		(1.931)	(2.334)	(1.471)	(1.579)		(0.773)	(1.031)
CmOS2		6.306	10.10*	6.369***	3.212*		2.073***	3.824**
		(4.352)	(5.667)	(1.312)	(1.886)		(0.503)	(1.651)
dius	-0.00284	-0.0219***	-0.0207**	0.00360	-0.0101**	-0.00710	-0.00703***	-0.00664**
	(0.00251)	(0.00821)	(0.00888)	(0.00641)	(0.00510)	(0.00689)	(0.00205)	(0.00296)
di	0.000499	0.000302	-0.000485	-0.00115	-0.00107	0.000108	-0.00145***	
	(0.00257)	(0.00286)	(0.00434)	(0.00107)	(0.00166)	(0.00380)	(0.000481)	
de	0.0196	-0.0995***	-0.0861	0.0215	0.0711***	0.0959	-2.06e-05	-0.0291
	(0.0246)	(0.0354)	(0.0609)	(0.0362)	(0.0183)	(0.106)	(0.00351)	(0.0350)
L.dy	0.322***	0.749***	0.610*	0.165*	0.506**	0.892***	0.433***	0.406***
	(0.0599)	(0.273)	(0.339)	(0.0930)	(0.225)	(0.203)	(0.0513)	(0.0481)
doil	0.00885**	0.0289*	0.0313	0.00445	0.00686	0.0257	0.00350	0.00726**
	(0.00370)	(0.0156)	(0.0216)	(0.00692)	(0.00439)	(0.0181)	(0.00306)	(0.00362)
COS2	1.189**							
	(0.508)							
Cnw						0.0876		
						(0.169)		
CnwpOS2						0.0621		
						(0.0886)		
Cnwm						-1.535		
						(1.192)		
CnwmOS2						1.156		
						(0.936)		
OS2								0.00688
								(0.00488)
neg								-0.000667
								(0.00365)
negOS2								0.00723
								(0.00859)
Constant	0.000558	0.00221	0.00529	0.00471***	0.00429**	-0.00379	0.000433	-0.00338
	(0.00154)	(0.00334)	(0.00422)	(0.00167)	(0.00185)	(0.00429)	(0.000961)	(0.00279)
Observations	897	874	851	897	897	897	897	897
R-squared	0.055	-0.864	-0.918	-0.057	-0.348	-0.726	-0.031	-0.038

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

Table 4.13
Sensitivity Analysis
Hypotheses tests

	Hypothesis	Ho	Statistic	P-value
(S1)	Higher sensitivity	C + CmOS2 = 0	18.25	0.0000
(S2)	Negative	CmOS2=0	2.10	0.1473
	Higher sensitivity	CmOS2=0 & CpOS2=0	2.12	0.3464
	Asymmetry in FC	Cm=0	1.49	0.2218
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	3.22	0.0728
(S3)	Negative	CmOS2=0	3.18	0.0746
	Higher sensitivity	CmOS2=0 & CpOS2=0	3.90	0.1422
	Asymmetry in FC	Cm=0	1.09	0.2960
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	3.87	0.0491
(S4)	Negative	CmOS2=0	23.57	0.0000
	Higher sensitivity	CmOS2=0 & CpOS2=0	52.91	0.0000
	Asymmetry in FC	Cm=0	0.01	0.9388
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	0.83	0.3613
(S5)	Negative	CmOS2=0	2.90	0.0885
	Higher sensitivity	CmOS2=0 & CpOS2=0	8.56	0.0138
	Asymmetry in FC	Cm=0	0.04	0.8397
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	4.73	0.0297
(S6)	Negative	CnwmOS2=0	1.52	0.2170
	Higher sensitivity	CnwmOS2=0 & CnwpOS2=0	1.79	0.4091
	Asymmetry in FC	Cnwm=0	1.66	0.1979
	Asymmetry in OS	Cnwm+CnwmOS2-CnwpOS2=0	0.61	0.4340
(S7)	Negative	CmOS2=0	16.97	0.0000
	Higher sensitivity	CmOS2=0 & CpOS2=0	18.72	0.0001
	Asymmetry in FC	Cm=0	1.63	0.2014
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	9.68	0.0019
(S8)	Negative	CmOS2=0	5.36	0.0206
	Higher sensitivity	CmOS2=0 & CpOS2=0	27.82	0.0000
	Asymmetry in FC	Cm=0	0.32	0.5735
	Asymmetry in OS	Cm+CmOS2-CpOS2=0	7.07	0.0078

Notes: All tests but high sensitivity distributed as a Chi-squared with 1 d.o.f.
All higher sensitivity tests but the one in (1) distributed as a Chi-squared with 2 d.o.f.
Higher sensitivity test in (1) distributed as a Chi-squared with 1 d.o.f.

Appendix A

The model as a standard three-dummies specification

Focusing on *C* and its interactions only, the estimated model is:

$$\Delta y_{it} = \alpha + \beta_0 C_{it} + \beta_1 C_{it} * Pos_{it} * OS_i + \beta_2 C_{it} * Neg_{it} + \beta_3 C_{it} * Neg_{it} * OS_i + u_t$$
(A1)

or, rearranging it:

$$\Delta y_{it} = \alpha + \beta_0 C_{it} + \beta_2 C_{it} * Neg_{it} + \beta_3 C_{it} * Neg_{it} * OS_i + \beta_1 C_{it} * Pos_{it} * OS_i + u_t$$
(A2)

Defining:
$$x_1 \equiv C_{it}$$
$$x_2 \equiv Neg_{it}$$
$$x_3 \equiv OS_i$$
$$x_4 \equiv Pos_{it}$$

(A2) can be rewritten as:

$$\Delta y_{it} = \alpha + \beta_0 x_1 + \beta_2 (x_1 * x_2) + \beta_3 (x_1 * x_2 * x_3) + \beta_1 (x_1 * x_4 * x_3) + u_t \qquad \text{(A3)}$$

The standard specification of such a structural model is suggested by Wooldridge (2002) as a one-continuous-variable-two-dummy-structure:

$$\Delta y_{it} = \alpha + \beta_0 x_1 + \beta_2 (x_1 * x_2) + \beta_3 (x_1 * x_3) + \beta_1 (x_1 * x_2 * x_3) + u_t \qquad \text{(A4)}$$

with:

$$x_1 \equiv C_{it}$$
$$x_2 \equiv Neg_{it}$$
$$x_3 \equiv OS_i$$

In other words, the standard specification includes the continuous variable and its interactions with all dummies. In this way, the specification controls for all possible effects of the dummies on the slopes (i.e. the effects of the dummies on $\frac{\partial y}{\partial x_1}$)[6].

Comparing the standard specification (A4) with (A3), we can see that there is only one difference: in my specification $\beta_1(x_1 * x_4 * x_3)$ substitutes $\beta_3(x_1 * x_3)$. The latter is a control for the interaction between the continuous variable and the dummy x_3. This control is however present in my specification as well. Recall that $x_2 \equiv Neg_{it}$ and $x_4 \equiv Pos_{it}$, so that the last two terms of my specification $\beta_1(x_1 * x_4 * x_3)$ and $\beta_1(x_1 * x_2 * x_3)$ are equivalent to $\beta_3(x_1 * x_3)$ split between positive and negative observations of x_1. In other words, $\beta_1(x_1 * x_4 * x_3)$ and $\beta_1(x_1 * x_2 * x_3)$ control for the effect of $\beta_3(x_1 * x_3)$ and any asymmetries in its effect. It follows that my specification controls for all potential interactions of x_1 and the dummies just as the standard specification does[7].

My specification has however a desirable feature over the standard specification: its betas identify the different effects of trade shocks we want to test. The estimated effect of each of the four types of trade shock on the domestic output is indeed given by the linear combinations listed in Table 4.1 reproduced here:

---

[6]   Wooldridge   is   actually   proposing   a   structure   such   as   :
$\Delta y_{it} = \alpha + \beta_0 x_1 + \beta_4 x_2 + \beta_5 x_3 + \beta_6(x_2 * x_3) + \beta_2(x_1 * x_2) + \beta_3(x_1 * x_3) + \beta_1(x_1 * x_2 * x_3) + u_t$
which is (A4) plus three controls for the effects on the intercept of the dummies x_2 and x_3 and their interaction. This specification includes the continuous variable, the two dummies and all the possible interactions between the three. (A4) and my specification assume instead no intercept effects of the two dummmies (i.e. they assume: $\beta_4 = \beta_5 = \beta_6 = 0$). This hypothesis is tested in the sensitivity analysis (model $S8$) where the three controls for intercept effects of the dummies are introduced (see the sensitivity analysis section for details).
[7] As noticed in the chapter, the interactions $\beta_1(x_1 * x_2 * x_3)$ and $\beta_1(x_1 * x_4 * x_3)$ would generate perfect multicollinearity with $\beta_1(x_1 * x_3)$. The latter is however not included, so that the two interactions can coexist in the estimated model.

Table 4.1
The four regimes

Regime	Estimated effect
positive shock to FC	β_0
positive shock to OS	$\beta_0 + \beta_1$
negative shock to FC	$\beta_0 + \beta_2$
negative shock to OS	$\beta_0 + \beta_2 + \beta_3$

The difference in the real effect of a positive trade shock in an *OS* with respect of an *FC* is identified by β_1 (second row minus first), the difference in the real effect of a negative trade shock in an *OS* with respect of an *FC* is identified by β_3 (last row minus third), the asymmetry of shocks propagation in *FC* is identified by β_2 (third row minus first) and, finally, the asymmetry of shocks propagation in *OS* is identified by $\beta_2 + \beta_3 - \beta_1$ (last row minus second). Apart from the latter, all effects are identified by single parameters so that they are more evidently shown in regression outputs. This contrasts with the standard specification where linear combinations are always needed to identify the differences. For this reason, the specification in (A3) is preferred.

CHAPTER 5 - TESTING THE STABILITY OF THE PROPAGATION MECHANISM

5.1   Introduction: Contagion tests

In this chapter we focus on the second main question addressed in the contagion literature: whether or not the strength of the contagion channels is stable across time. The following literature review sets the background for the instability test presented below.

The speed, intensity and pervasiveness of the turbulence caused by the major crises in the 1990s led researchers to ask whether the linkages between financial markets in different countries grew stronger during these turbulent times or were instead already as strong before. As pointed out by Forbes and Rigobon (2001), this is an important question because it sheds light on at least three key aspects of financial and international economics:

a)   The effectiveness of international portfolio diversification in reducing risk. If cross-country correlations of assets returns shift during crises, portfolios designed based on correlations during tranquil times would exhibit different properties in crises, which could lead to larger than expected losses

b)   The effectiveness of microprudential bank regulation as standardized by the Basel II accord. The latter sets the levels of banks' capital adequacy ratios on the basis of their risk weighted assets portfolio. The portfolio risk is typically estimated using Value-at-Risk (VaR) measures. These in turn are based on historical measures of assets correlations. If the correlations increase during crises, the risk is underestimated and thus the capital adequacy ratios are insufficient.

c)   The empirical relevance of crisis-contingent versus non-crisis-contingent contagion models. Models based on a shift in investor behaviour during crises imply a break in the shocks' propagation mechanism. Therefore, a necessary condition for such models to be relevant is the observation of a break in the propagation mechanism during crises.

For these reasons, the issue of instability of the propagation mechanism or shift contagion (see the introduction of the thesis) has been studied in depth. To present it formally, I follow the approach of Dungey et al. (2004) and specify a model of interdependence of asset markets during non-crisis periods as a latent factor model of asset returns. The model has its origins in the arbitrage pricing theory, where asset returns are determined by a set of common factors and a set of idiosyncratic factors (Sharpe 1964, Ross 1976). This framework is useful to show how instability can be and has been empirically tested in the literature.

The model is here presented in a two-country fashion, but its generalization to N countries is straightforward. Assume there are two countries whose stock returns are given by:

$$\{x_{1t}, x_{2t}\} \tag{5.1}$$

where both returns are assumed to have zero means. During non-crisis times, the returns are assumed to be determined by the following factor model:

$$x_{1t} = \lambda_1 w_t + \gamma_1 u_{2t} + \delta_1 u_{1t} \tag{5.2}$$
$$x_{2t} = \lambda_2 w_t + \gamma_2 u_{1t} + \delta_2 u_{2t}$$

where w_t represents the common factor affecting all stock markets with loadings λ. This can be thought of as changes in investor risk aversion or risk perception, or changes in world endowment. w_t is often referred to as the world factor. It is assumed to be a latent stochastic process with zero mean and unit variance. u_{it} represents the idiosyncratic factor that is unique to market i, with loading δ. u_{it} is also assumed to be a latent stochastic process with zero mean and unit variance. Correlation among stock returns in country 1 and 2 can arise from two sources: the world factor and the direct effect of country 1's stock market on country 2 (and vice-versa). This second source of correlation, called "market interdependence" is represented by the elements $\gamma_i u_{jt}$. The strength of the interdependence is measured by the loadings γ. These identify the interdependence of markets in normal times.

Why should stock markets be interdependent? The most obvious cause is trade linkages. If companies listed in country *1*'s stock exchange export a relevant part of their output to country *2*, shocks affecting country *2*'s aggregate demand will affect the expected profits of companies in both countries, therefore affecting both stock indexes. Financial linkages such as common lenders operating in both financial markets are another potential source of interdependence.

Notice that (5.2) is the reduced form of:

$$x_{1t} = \left(\frac{\lambda_1 \delta_2 - \gamma_1 \lambda_2}{\delta_2} \right) w_t + \frac{\gamma_1}{\delta_2} x_{2t} + \left(\frac{\delta_1 \delta_2 - \gamma_1 \gamma_2}{\delta_2} \right) u_{1t} \qquad (5.3)$$

$$x_{2t} = \left(\frac{\lambda_2 \delta_1 - \gamma_2 \lambda_1}{\delta_1} \right) w_t + \frac{\gamma_2}{\delta_1} x_{1t} + \left(\frac{\delta_1 \delta_2 - \gamma_1 \gamma_2}{\delta_1} \right) u_{2t}$$

or:

$$x_{1t} = \alpha_1 w_t + \beta_1 x_{2t} + \varepsilon_t \qquad (5.4)$$

$$x_{2t} = \alpha_2 w_t + \beta_2 x_{1t} + \eta_t$$

where:

$$\alpha_1 \equiv \left(\frac{\lambda_1 \delta_2 - \gamma_1 \lambda_2}{\delta_2} \right)$$

$$\beta_1 \equiv \frac{\gamma_1}{\delta_2}$$

$$\varepsilon_t \equiv \left(\frac{\delta_1 \delta_2 - \gamma_1 \gamma_2}{\delta_2} \right) u_{1t}$$

$$\alpha_2 \equiv \left(\frac{\lambda_2 \delta_1 - \gamma_2 \lambda_1}{\delta_1} \right)$$

$$\beta_2 \equiv \frac{\gamma_2}{\delta_1}$$

$$\eta_t \equiv \left(\frac{\delta_1 \delta_2 - \gamma_1 \gamma_2}{\delta_1} \right) u_{2t}$$

Equation (5.4) gives an intuitive model of market interdependence in which the stock returns are determined by a common factor, an idiosyncratic factor and the effect of the foreign shocks.

Assuming all factors to be independent so that:

$$E[u_{1t} u_{2t}] = 0 \qquad \forall i \neq j \tag{5.5}$$

$$E[u_{1t} w_t] = 0 \qquad \forall i \tag{5.6}$$

we have that the covariance between the two stock markets during tranquil times is given by:

$$E[x_{1t} x_{2t}] = \lambda_1 \lambda_2 + \gamma_1 \delta_2 + \gamma_2 \delta_1 \tag{5.7}$$

The first term on the right hand side represents the world-factor-induced covariance while the other two the effect of direct stock markets interdependence.

Now assume that during crisis times the returns are instead determined by the following factor model:

$$x_{1t} = \lambda_1' w_t + \gamma_1' u_{2t} + \delta_1' u_{1t} \tag{5.8}$$

$$x_{2t} = \lambda_2' w_t + \gamma_2' u_{1t} + \delta_2' u_{2t}$$

and the markets' covariance is given by:

$$E[x_{1t} x_{2t}] = \lambda_1' \lambda_2' + \gamma_1' \delta_2' + \gamma_2' \delta_1' \tag{5.9}$$

Comparing (5.9) with (5.7) we find the change in covariance from tranquil to crisis period. If the world and the *own* idiosyncratic factors retain the same influence on the markets we have that their loadings are unchanged. In other words we have

that $\lambda_1' = \lambda_1$, $\lambda_2' = \lambda_2$, $\delta_1' = \delta_1$, $\delta_2' = \delta_2$. In this case, the change in covariance from tranquil to crisis times is given by:

$$E[x_{1t}x_{2t}]_{crisis} - E[x_{1t}x_{2t}]_{tranquil} = (\gamma_1' - \gamma_1)\delta_2 + (\gamma_2' - \gamma_2)\delta_1 \qquad (5.10)$$

If $\gamma_i' - \gamma_i > 0$, $i=1,2$, there is a positive break in the interdependence structure of the two markets. These are more interdependent during crises: foreign shocks have stronger repercussions on the domestic market. Notice that, since $\delta_i > 0$ by assumption, the increase in the γ's causes an increase in the returns' covariance. Therefore, increased interdependence translates into higher covariance.

Shifts in the parameters γ are thus identifying the instability of the propagation mechanism or shift contagion. The test for shift contagion is then a test of the hypothesis:

$$\gamma_i' = \gamma_i \qquad \forall i \qquad (5.11)$$

A rejection of hypothesis (5.11) means that a crisis alters the effect of foreign stock returns' fluctuations on domestic indexes. Therefore, a rejection of (5.11) is considered as a proof of shift contagion, the instability of the propagation mechanism. As we will see now, all common shift contagion tests can be shown to have reference to the test of hypothesis (5.11) in the context of the latent factor model presented above.

Recall that the variances of all factors are fixed at 1. Assuming the loadings λ and δ fixed as we did, we are implicitly assuming homoskedastic factors. In other words, the variance of the world and the idiosyncratic factors are not allowed to vary during crises. The model is however easily augmented, allowing for increases in the factors' variances (structural breaks henceforth). Autoregressive dynamics can be introduced as well, both in the form of autocorrelation and *GARCH* processes of the factors. The nature of the shift contagion test (5.11) would not be altered by the introduction of these features in the latent factor model.

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5.1.1 *Early tests*

The first application of the ideas presented above was that of King and Wadhwani (1990). In this paper the authors examined the correlation coefficient of London and New York's stock exchange indexes before and after the 1987 crash, in order to see whether the coefficient increased during the latter. The link with the shift contagion test summarized in (5.11) is immediate. The correlation coefficient is the covariance scaled by the standard errors of the two variables. If the correlation coefficient increases in presence of increasing standard errors, the covariance must increase even more. Since the variance of both stock markets increased after the crash, an increase of the correlation coefficient in the period following the crash would be a proof of increase of the covariance as well. It would therefore represent a rejection of the hypothesis (5.11). The sharp increase in the coefficient documented by King and Wadhwani seems then to suggest the presence of shift contagion in the New York and London stock exchanges following the 1987 crash. The same finding was subsequently documented by similar correlation studies on emerging markets (Calvo and Reinhardt (1996), Bordo and Mushid (2000) and Bajg and Goldfajn (1998)). The third of this studies found that correlation coefficients of markets situated in different continents increased too.

Early tests therefore suggested the presence of shift contagion. However, Forbes and Rigobon (1999) showed how these results are flawed by the presence of heteroskedasticity. Their argument is that the correlation coefficient is a biased measure of the actual correlation between two variables when these two are related in the way described in (5.4) and heteroskedastic. This is because an increase in the variance of the one variable will cause an increase in the correlation coefficient even if the propagation mechanism is unaltered (i.e. even if the β's in the system (5.4) are unchanged). Therefore, an increase in the correlation coefficient is not necessarily a proof of shift contagion.

To see their point formally, recall the system (5.4) and for simplicity assume there are no common shocks. $\{x_{1t}, x_{2t}\}$ are thus given by:

$$x_{1t} = \beta_1 x_{2t} + \varepsilon_t \tag{5.12}$$

$$x_{2t} = \beta_2 x_{1t} + \eta_t$$

Assume also that we have two periods: one of high volatility and one of low. In the period of high volatility there is a structural break, i.e. the variance of x_2 increases so that:

$$\frac{\sigma_H^2(x_2)}{\sigma_L^2(x_2)} = 1 + \phi \qquad (5.13)$$

where $\sigma_H^2(x_2)$ and $\sigma_L^2(x_2)$ represent the variance of x_2 in the high and low volatility periods respectively. If $E[x_{2t}, \varepsilon_t] = 0$, from (5.12) one can see that the variance of x_1 in the high volatility period is given by:

$$\sigma_H^2(x_1) = \beta_1^2 \sigma_H^2(x_2) + \sigma_\varepsilon^2 \qquad (5.14)$$

Substituting (5.13) in (5.14) and rearranging one can show that:

$$\sigma_H^2(x_1) = \left(1 + \phi\beta_1^2 \frac{\sigma_L^2(x_2)}{\sigma_L^2(x_1)}\right) \qquad (5.15)$$

From the standard formula of the correlation coefficient we have that:

$$\rho = \frac{\sigma(x_1 x_2)}{\sigma(x_1)\sigma(x_2)} = \beta_1 \frac{\sigma(x_2)}{\sigma(x_1)} \qquad (5.16)$$

where ρ is the correlation coefficient between x_1 and x_2.
Substituting (5.16) in (5.15) we have that:

$$\sigma_H^2(x_1) = \sigma_L^2(x_1)\left(1 + \phi\rho_L^2\right)$$

or:

$$\frac{\sigma_H^2(x_1)}{\sigma_L^2(x_1)} = 1 + \phi \rho_L^2 \tag{5.17}$$

where ρ_L is the correlation coefficient in the low volatility period. (5.17) gives the increase in the variance of x_1 between the two periods. Expectedly, this is a function of the increase in x_2's variance and the correlation between the two variables. Comparing the increase in the variances of x_1 and x_2 as given by (5.17) and (5.13) we have that:

$$\frac{\sigma_H^2(x_1)}{\sigma_L^2(x_1)} = 1 + \phi \rho_L^2 < 1 + \phi = \frac{\sigma_H^2(x_2)}{\sigma_L^2(x_2)} \tag{5.18}$$

Unless $\rho_L = 1$, the variance of x_2 increases more than the variance of x_1. Thus, unless there is perfect correlation between the two variables in the low volatility period, the variance of x_2 increases more than the variance of x_1.

Rearranging (5.18) one can show that the ratio of the variance of x_1 over that of x_2 increases in the high volatility period:

$$\frac{\sigma_H^2(x_2)}{\sigma_H^2(x_1)} > \frac{\sigma_L^2(x_2)}{\sigma_L^2(x_1)} \tag{5.19}$$

from which follows that:

$$\rho_H = \beta_1 \frac{\sigma_H(x_2)}{\sigma_H(x_1)} > \beta_1 \frac{\sigma_L(x_2)}{\sigma_L(x_1)} = \rho_L \tag{5.20}$$

The correlation coefficient between x_1 and x_2 has increased in the high volatility period even if the actual correlation between the two variables (measured by β_1) has not. It is the increase in the variance of x_2 that caused such increase. This makes intuitive sense: the variance of x_1 is given by the variance of an idiosyncratic element (ε) and the variance of x_2. If x_2 becomes more volatile while ε does not, x_2 will

generate relatively more of the variation of x_1 than before, even if the two variables' correlation has not increased. The idiosyncratic element ε looses importance in favour of x_2 as a determinant of x_1's variance and the correlation coefficient picks this up increasing.

Since in periods of turbulence the variance of stock markets indexes tend to increase, Forbes and Rigobon argue that the increased correlation among stock markets found by previous studies is likely to be generated by the phenomenon just described rather than by a genuine increase in the correlation among stock markets. Forbes and Rigobon (1999) thus propose a corrected correlation coefficient v:

$$v = \frac{\rho_H}{\sqrt{1 + \left(\frac{\sigma_H^2(x_2) - \sigma_L^2(x_2)}{\sigma_L^2(x_2)}\right)(1 - \rho_H)}} \tag{5.21}$$

which is the standard correlation coefficient between the two stock markets during crisis times (ρ_H) discounted for the effect of the increase in $\sigma^2(x_2)$. The comparison between the adjusted crisis-time coefficient v and the tranquil-times unadjusted correlation coefficient ρ_L is then the basis of their shift contagion test. If $v > \rho_L$, the increase in the correlation coefficient is not completely attributable to the structural break in country 2 and thus it must be interpreted as a proof of shift contagion. If instead $v = \rho_L$ there is no shift contagion. Computing the corrected coefficient (called *FR* test henceforth), Forbes and Rigobon conclude for the second case: according to their test, no correlation increase has taken place in recent crises apart from East Asian one. They conclude that the quick spreading of crises across border is the effect of the high degree of interdependence that characterises financial markets in both tranquil and turbulent times (i.e. the high value of the β's), rather than shift contagion (i.e. a shift in the β's).

The corrected coefficient is however based on the assumption that:

$$E[x_{2t}, \varepsilon_t] = 0 \tag{5.22}$$

in (5.12). This is true only if $\beta_2 = 0$ in both periods. Thus, during tranquil *and* crisis times country *2* stock returns affect country *1*'s ones but not the reverse. Forbes and Rigobon assume that shocks originating in country *2* propagate towards country *1*, "with negligible feedback from *1* to *2*". This is equivalent to rule out by assumption the intrinsic endogeneity in the equations system (5.12). It is however hard to justify. It is not clear why, for example, swings in the Argentinean stock exchange should affect the Brazilian stock exchange but not vice-versa. Forbes and Rigobon are well aware of these limitations, but they rule them out a priori. The coefficient correction is thus based on a very unpleasant assumption.

5.1.2 The DCC test

Rigobon (2003) acknowledges the limitations of the *FR* test and affirms that its results are unreliable. He thus proposes a technique that should instead be able to test for parameter stability in presence of heteroskedasticity and endogeneity. Borrowing his words, the essence of the procedure can be described as "identification through heteroskedasticity". A graph might help intuition on the subject.

Figure 5.1
The simultaneous determination of stock returns
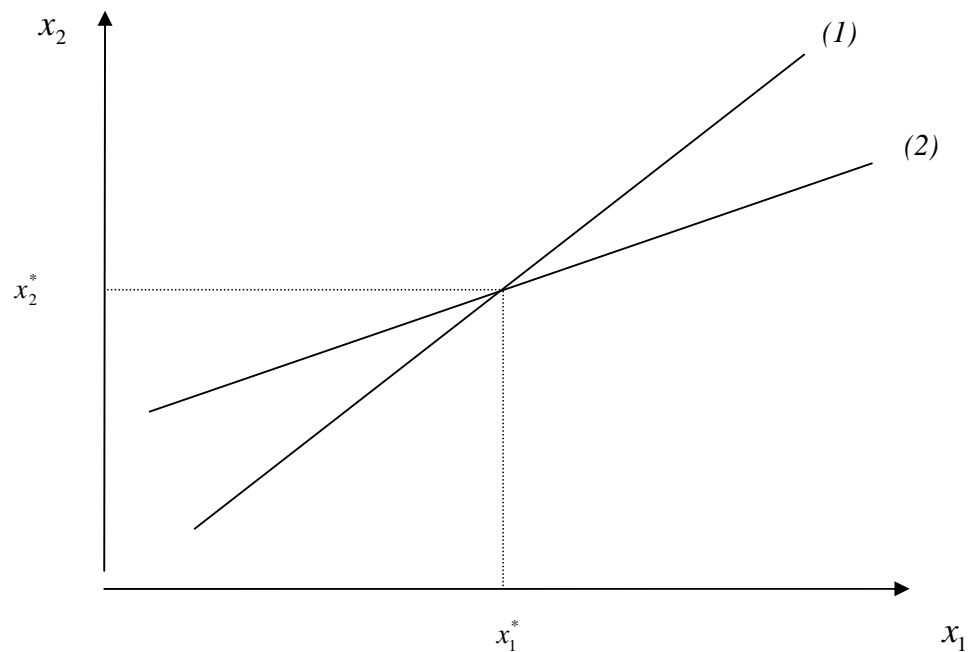
The two lines (*1*) and (*2*) in the figure represent the relationships between country *1* and *2* stock returns as given by the two equations in the non-reduced form system (5.4). If (*1*) represents the first equation in the system and (*2*) the second, we have that their slope is respectively $\frac{1}{\beta_1} = \frac{\delta_2}{\gamma_1}$ and $\beta_2 = \frac{\gamma_2}{\delta_1}$. Clearly, we do not observe the lines themselves, but only the equilibrium stock returns x_1^* and x_2^*. If we have a dataset of stock returns, what we observe is therefore a cloud of points, each one representing an observed pair of equilibrium returns ($x_1^*$; x_2^*). We cannot identify (*1*) and (*2*), to do so an instrument is needed. Rigobon argues that a structural break (i.e. the increase in the variance of one idiosyncratic element) provides such an instrument and gives a way of identifying the two schedules.

An example might help, Figure 5.2 below, taken from Rigobon (2000) describes graphically the "identification through heteroskedasticity" argument for a standard demand, supply and prices representation.

The top panel represents the pre-structural break set of observed equilibrium prices generated by the underlying demand and supply relationships. The cloud of points is evenly distributed around the lines' crossing. The bottom panel represents the post-break set. The break is an increase in the supply's variance. This causes the set of observed equilibrium points to align along the demand. It is this alignment that allows identification.

This example is useful in explaining the use of a structural break as an instrument. However, to apply this line of thought to the stock markets correlation issue one more step is needed. In fact, contrary to the demand and supply in the example, the two stock markets whose correlation is studied are interdependent. Therefore the increase in the variance of one stock's idiosyncratic factor will necessarily cause an increase in the other stock market's variance. Therefore, a structural break in one stock market will make both lines in figure 5.1 more volatile.

Figure 5.2
Identification through heteroskedasticity
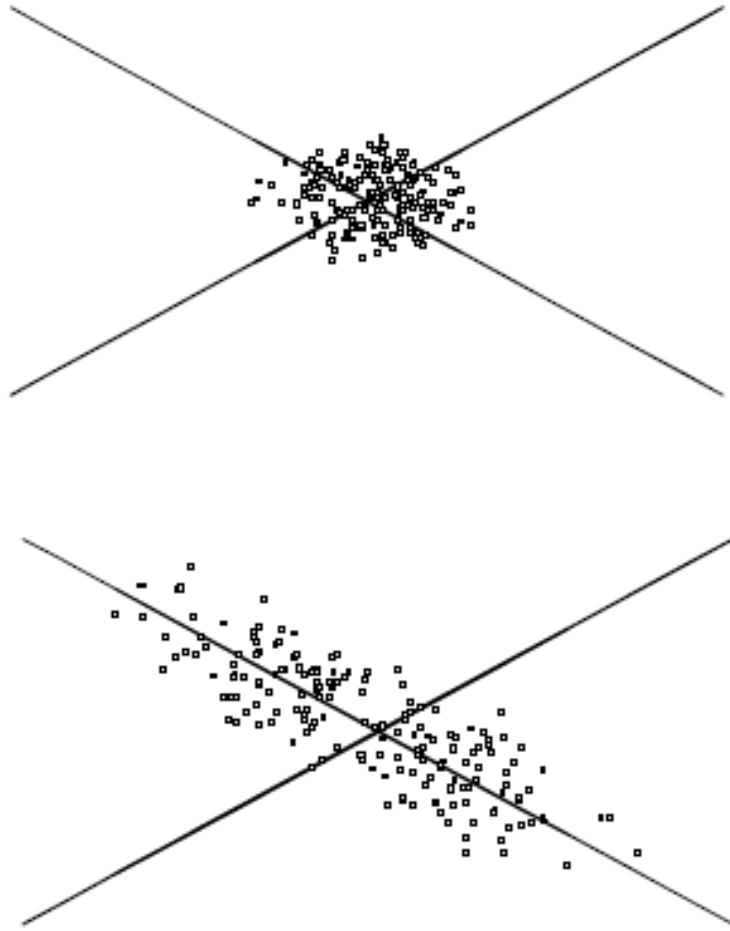
Rather than align the cloud of equilibrium points along one line, the break will then spread the cloud in both directions. Identification is however still possible: the key is that, under some assumptions, the increase in the variances of the two stock markets will be equal to a certain ratio. In other words, if the only shock to the system (5.4) is the increase in the variance of ε, the ratio of the increases in the variance of x_{1t} and x_{2t} is known. Therefore, one can estimate the increases in the variance of x_{1t} and x_{2t}, calculate their ratio and compare it to that known value. If the ratio is equal to that value, the increase in the variance of ε has been the only change in the system parameters. Otherwise, some other parameter, (the β 's) must have changed: there has been shift contagion.

The argument is formally expressed starting again from the system (5.4). Assuming $Cov(\varepsilon, w) = Cov(\eta, w) = Cov(\varepsilon, \eta) = 0$, the Variance-Covariance matrix of x_{1t} and x_{2t} is given by:

$$\Omega_t = \frac{1}{(1-\beta_1\beta_2)^2} \begin{bmatrix} (\alpha_1 + \alpha_2\beta_1)^2 \sigma_{w,t}^2 + \beta_1^2 \sigma_{\eta,t}^2 + \sigma_{\varepsilon,t}^2 & (\alpha_1 + \alpha_2\beta_1)(\alpha_1\beta_2 + \alpha_2)\sigma_{w,t}^2 + \beta_1 \sigma_{\eta,t}^2 + \beta_2 \sigma_{\varepsilon,t}^2 \\ \bullet & (\alpha_1\beta_2 + \alpha_2)^2 \sigma_{w,t}^2 + \sigma_{\eta,t}^2 + \beta_2^2 \sigma_{\varepsilon,t}^2 \end{bmatrix}$$

(5.23)

where $\sigma_{w,t}^2, \sigma_{\eta,t}^2, \sigma_{\varepsilon,t}^2$ are the variance of, respectively, w, η and ε at time t. A crisis is modelled as a one-shot increase in $\sigma_{\eta,t}^2$, the variance of the country 2's idiosyncratic element. In particular, it is assumed that:

$$\Delta\sigma_{\eta,t}^2 \equiv \sigma_{\eta,t+1}^2 - \sigma_{\eta,t}^2 = k\sigma_{\eta,t}^2 \qquad (5.24)$$

It is also assumed that:

$$\Delta\sigma_{\varepsilon,t}^2 = \Delta\sigma_{w,t}^2 = 0 \qquad (5.25)$$

Conditions (5.24) and (5.25) state that only *one* idiosyncratic shock experiences a variance increase, the other idiosyncratic and the world factors do not. These crucial assumptions can be summarized by the assumed matrix of changes in the variance-covariance matrix of the errors ε and η:

$$\Delta\Omega_t^\varepsilon = \begin{bmatrix} 0 & 0 \\ 0 & k\sigma_{\eta,t}^2 \end{bmatrix} \qquad (5.26)$$

From (5.24) follows that the post-shock level of η's variance is $\sigma_{\eta,t+1}^2 = (1+k)\sigma_{\eta,t}^2$. Substituting this in (5.23) one finds the post-break variance-covariance matrix of x_{1t} and x_{2t}. Subtracting the pre-shock matrix (5.23) from the

post-shock one, one obtains the changes in the variance-covariance matrix of x_{1t} and x_{2t} generated by the structural break:

$$\Delta\Omega_t \equiv \Omega_{t+1} - \Omega_t = \frac{k\sigma_{\eta,t}^2}{\left(1 - \beta_1\beta_2\right)^2}\begin{bmatrix} \beta_1^2 & \beta_1 \\ \beta_1 & 1 \end{bmatrix} \tag{5.27}$$

Notice that the covariance and the variances of both stock markets have increased after the break. However, they did so in known proportions. This is the key point, highlighted earlier: the ratios of the changes in the variance-covariance matrix are known. In particular, they are so that the determinant of the matrix $\Delta\Omega_t$ is equal to zero, irrespective of the value of all parameters. This can be easily seen looking at the squared parenthesis' elements, whose determinant is clearly zero. This result is the core of the Rigobon's test, which is indeed called the Determinant of the Change in the Covariance matrix (*DCC*) test. If only one idiosyncratic element increases its variance and the interdependence parameters (i.e the β 's) are stable, the determinant of the changes' matrix will be zero. Rigobon affirms that in order to test the stability of the parameters β it is then sufficient to estimate $\left|\Delta\Omega_t\right|$ and test whether this is different from zero. Formally, the *DCC* test states that if two markets are related in a manner reducible to eqs. (5.4), and one idiosyncratic structural break only hits the system, then $\Delta\Omega_t \neq 0$ if and only if $\Delta\beta_i \neq 0$ for some *i*. It follows that $\left|\Delta\Omega_t\right| = 0$ implies the stability of the β 's and thus the stability of the propagation mechanism. In other words, $\left|\Delta\Omega_t\right| = 0$ implies $\gamma_i' = \gamma_i$, $\forall i$ in the latent factor model (5.2); It means no shift contagion (see hypothesis 5.11).

Rigobon (2003) applies the *DCC* test to a multivariate version of eq. (5.4), expanded to include constant terms, lagged values of the *x*'s and the Fed discount rate as a proxy for the unobservable common factors w_t. He tests the change in the var-cov matrix during three recent crises: the Mexican, Asian and Russian-Brazilian one. The sample is of *36* countries, both *OECD* and not, for a period ranging from January 1993 to December 1998. The procedure is implemented as follows: first, the multivariate expanded system (5.4) is estimated for each crisis episode separately and ε_t is obtained. Second, "low" and "high" variance windows are defined for each

crisis. Third, the ε_t are split in two according to the defined windows. Once obtained the low and high variance ε_t, their variance-covariance matrix is estimated and the determinant of the change $\left|\Delta\Omega_t^\varepsilon\right|$ computed. Finally, to test the shift contagion hypothesis, $\left|\Delta\Omega_t^\varepsilon\right|$'s distribution is estimated by bootstrap. If the actual value of $\left|\Delta\Omega_t^\varepsilon\right|$ lies outside the 5-95% range of its bootstrapped distribution with zero mean, the null hypothesis of $\left|\Delta\Omega_t^\varepsilon\right|=0$ is rejected and one concludes for parameter instability. Note that this procedure is testing $\left|\Delta\Omega_t^\varepsilon\right|=0$. However, this is equivalent to test $\left|\Delta\Omega_t\right|=0$, as shown by Rigobon (2003) in its Appendix B.

In order to take into account the role of various events on the path of the unfolding of each crisis (e.g.: the Russian default and the *LTCM* near-collapse in the Russian-Brazilian episode), different windows definitions are implemented for each crisis. The test is performed separately on four different regions: *OECD*, East Asia, Latin America and others (India, Russia and South Africa) In other words, excluding the "other countries" group, it is a test for within-region parameter stability.

The results are notable: regarding Latin America, parameters stability is rejected only in 2 out of 5 windows definitions during the East Asian crisis and in 1 out of 4 during the Russian one. The same happens in the Other Countries group. Parameter stability is instead never rejected for the *OECD* and the East Asian group. These results suggest that a shift in the mechanism of financial shocks propagation never took place in the two latter groups. However, statistically significant shifts took place within Latin America and within India, Russia and South Africa during the East Asian and Russian Crises. These results are interpreted by Rigobon as a proof of substantial stability of the propagation mechanism, especially in more developed financial markets such as the *OECD* and East Asian ones, where parameter stability is never rejected.

A closer look to the DCC's assumptions

The *DCC* seemed to provide a way of testing parameters stability in models with simultaneous heteroskedasticity and endogeneity problems such as those describing financial markets' returns. However, a closer look to the set of assumptions on which

the test is based reveals some unappealing features. The crucial assumption is the diagonality and non-full-rankness of the matrix of changes in the variance covariance matrix of the idiosyncratic elements ε and η:

$$\Delta\Omega_t^\varepsilon = \begin{bmatrix} 0 & 0 \\ 0 & k\sigma_{\eta,t}^2 \end{bmatrix} \tag{5.26'}$$

It is the diagonality assumption that is most uncomfortable. To see why, recall the model depicted in eqs. (5.4): ε and η represent all the domestic factors influencing stock returns. They can be thought as a mix of country-specific macroeconomic (fundamentals such as the amount of money in circulation, easiness of credit, *GDP* growth, prevailing interest rates) and microeconomic factors, idiosyncratic to the companies listed in the indexes (think, for example, at the quality of the firm's management). Crucially, in the relationship between the macro and micro fundamentals and the stock returns a key element is the interpretation of such elements by the investors (i.e. the way investors determine the expected value of the asset from the analysis of the fundamentals). Therefore, investor behaviour is also part of ε and η. It is another determinant of the stock returns that is not foreign stock returns or common factors.

By assuming Ω_ε^t and $\Delta\Omega_\varepsilon^t$ diagonal, the *DCC* test assumes ε and η to be uncorrelated and stably so (i.e. they are assumed uncorrelated during tranquil and crisis times). This means that all domestic elements affecting country *1* stock index (ε), *investor behaviour included*, cannot be affected by shocks originating in country *2*'s market (η). Therefore, an extraordinary value of η (e.g. a stock market crash in country *2*) cannot affect the behaviour of country *1*'s investors (i.e. the way investors establish their ask and bid prices starting from country *1*'s fundamentals). Any shift in the way investors assess, analyse and interpret the fundamentals caused by foreign shocks would indeed affect domestic stock returns without implying a change in the linear correlation between the levels of x_{1t} and x_{2t} (i.e. without implying a change in the β's). Any such shift would then imply a movement of ε caused by a movement in η. In this case the shift in investor behaviour caused by foreign shocks would

generate correlation among the idiosyncratic factors ε and η. The change in the variance-covariance matrix of the idiosyncratic errors would be:

$$\Delta\Omega_t^\varepsilon = \begin{bmatrix} m & c \\ c & k\sigma_{\eta,t}^2 \end{bmatrix}$$

(5.28)

where $c \neq 0$ represents the shift from zero of the covariance between ε and η caused by investors behaviour shift. The assumed diagonality of $\Delta\Omega_\varepsilon^t$ (eq. 5.26) is necessarily violated. In this case the elements of $\Delta\Omega^t$ are unknown and so is its determinant. Indeed, dropping the $Cov(\varepsilon,\eta) = 0$ assumption expands the variance-covariance matrix of stock returns Ω^t to include all terms related to it. Unless one is willing to assume all these term to remain stable after a structural break, $\Delta\Omega^t$ includes also the changes in the covariance terms and therefore does not have the simple form of (5.27). Since there is no apparent reason why the covariance among factors should be stable while their variances increase, it is hard to see how that assumption could be justified. To this end it is worth recalling that if σ_η^2 increases while σ_ε^2 and the correlation coefficient between ε and η remain constant, $Cov(\varepsilon,\eta)$ increases. Therefore, in order to have a stable covariance after a structural break in η, the correlation coefficient must increase of the amount exactly offsetting the increase in σ_η^2. There is no reason why this should be the case. In presence of investor behaviour shifts (5.27) is therefore unknown. The *DCC* test is not able to identify the parameters' instability since $|\Delta\Omega_t|$ is unidentified even with stable parameters (i.e. it is not bound to zero by parameter stability)[8].

The *DCC* test rules out any role of investor behaviour shifts (i.e. of changes in the way investors assess the equilibrium stock prices starting from the fundamentals)

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[8] Alternatively, one could assume investor behaviour to be included in the common factor *w*. In this case, investor behaviour shifts caused by crises would violate the assumption $Cov(w,\eta)$ instead of that of $Cov(\varepsilon,\eta)$. (5.27) and thus $|\Delta\Omega_t|$ would be unknown for the same reason just explained. In general, any event affecting the variance of more than one factor causes the breakdown of Rigobon's identification strategy.

in the propagation of financial shocks across borders. This is at odds with the current consensus on financial contagion, which admits a relevant role played by investors' sentiments in recent episodes such as the East Asian crisis. As shown in the literature review in chapter 2, various theoretical models of investor-behaviour-driven contagion have been developed in recent years while empirical studies proved the existence of risk-appetite shifts or flight-to-quality phenomena as well as some evidence of jumps between multiple equilibria. The *DCC* assumptions appear then to be unjustifiable from a theoretical point of view and proved false by ample empirical evidence.

In fact, the *DCC* test has the same limit of the *FR* test: in order to achieve identification, it restricts a crisis to be a very specific structural break in the variance-covariance structure of the stock indexes. Namely, a crisis can only cause the increase of a subset of idiosyncratic elements' variance. This point is highlighted by Billio and Pelizzon (2003) as well. They argue that in the light of the quick spread of volatility across markets it is hard to believe that a crisis will cause heteroskedasticity in a subset of idiosyncratic elements only. In terms of our bivariate model, Billio and Pellizon argue that a crisis is likely to cause an increase in the variance of both ε and η. They show that in such a situation the *DCC* test is biased.

5.1.3   Extreme events-based tests

Other researchers try to deliver tests based on a less stringent set of assumptions. Favero and Giavazzi (2002) propose a two-step procedure to test for instability in foreign exchange expectations in the pre-euro *ERM* area. To do so, they estimate the interdependence of the interest rate differentials between 7 *ERM* countries and Germany, considered the centre of the *ERM* system, and then test whether such interdependence becomes stronger during turbulent times.

The two-step procedure is as follows: first a *VAR* including all *7* interest rate differentials in the sample is estimated and the residuals $u_{i,t}$ are obtained. The latter are intended to isolate the part of the differentials' variation caused by either idiosyncratic elements, simultaneous (*t* to *t*) interdependence or common shocks taking place in time *t* (the *VAR* is indeed controlling for shocks taking place in the past only). The residuals therefore represent the variation caused by the elements

included in our latent factor model (5.4). "Extreme" values of the residuals are then defined as those observations further than *3* estimated standard deviations from the mean. These extreme values are intended to identify extraordinary shocks. Then a set of *K* unique dummies $v_1...v_K$, each one identifying an extreme event, is defined as:

$$v_{i,t} = \begin{cases} 1 & |u_{i,t}| > 3\sigma_{u,i} \\ 0 & otherwise \end{cases} \tag{5.29}$$

where $u_{i,t}$ is the error from the *i*th equation of the *VAR* at time *t*.

The second stage of the test involves the estimation of the structural model of interest rate differential interdependence with $v_1...v_K$, the set of *K* unique dummies, each one identifying *K* extreme events as defined above. In a two-country setting, the model estimated in the second stage is:

$$x_{1t} = c_1 + \alpha_1 x_{1t-1} + \beta_1 x_{2t} + \gamma_1 v_1 + \gamma_2 v_2 + .. + \gamma_K v_K + e_{1t} \tag{5.30}$$

$$x_{2t} = c_2 + \alpha_2 x_{2t-1} + \beta_2 x_{1t} + \gamma_{K+1} v_1 + \gamma_{K+2} v_2 + .. + \gamma_{2K} v_K + e_{2t}$$

where x_{1t} and x_{2t} are the interest rate differentials for country *1* and *2* with respect to the German rate at time *t*. These are assumed to be a function of the interest rate differential in the other country, one-lagged own differential, and the extreme events dummies.

The presence of shift contagion is assessed by estimating (5.30) and testing the statistical significance of the extreme-event dummies (i.e. testing the *2K* hypotheses $\gamma_i = 0$, for *i=1,…,2K*). The idea is that if the propagation mechanism is stable during normal and "extreme" times, the set of dummies should not have any explanatory power as the β's should already explain all the interdependence between the markets. Indeed, the β's estimate the "normal" interdependence structure (i.e. the average interdependence in both tranquil and crisis times). If that is the interdependence structure in both tranquil and crisis times, the dummies are superfluous. A rejection of any of the null hypotheses $\gamma_i = 0$, for *i=1,…,2K* is therefore considered as a proof of unstable propagation mechanism or shift contagion.

Notice that if two markets register an "extreme" event simultaneously (i.e. if $\left|u_{1,t}\right| > 3\sigma_{u1}$ and $\left|u_{2,t}\right| > 3\sigma_{u2}$ in the two-country setting), the dummy assigned to that extreme event will represent a common shock rather than an idiosyncratic shock. Common shocks are then controlled for, although only "extreme" ones (i.e. those common shocks generating errors more than *3* standard deviations away from the mean).

The simultaneous interdependence of interest rate differentials (i.e. the fact that x_{1t} and x_{2t} appear as regressors in the other country's equation) raises the issue of endogeneity. This is dealt with by estimating the model with a Full Information Maximum Likelihood (*FIML*) estimator using three own lags and as instruments for the endogenous variables. The dummy variables are considered exogenous and therefore not instrumented but used as included instruments themselves. This feature of the test is contested by Pesaran and Pick (2004). They repeat the Favero and Giavazzi test instrumenting the dummies as well, to find very similar results anyhow.

Notice also that the simultaneous interdependence raises the issue of the identification of the system. Since each equation has one outcome variable with unrestricted parameter, one regressor must be excluded from each equation in order to achieve identification. To obtain this, Favero and Giavazzi restrict the lag structure in the system. The only lag assumed to influence the interest rate differentials is the one-period own lag. The restriction requires markets to react instantly, so that all the effect of foreign shocks must be internalised in the domestic outcome variable within the same period. The one-period lags of all others differentials are then excluded regressors that guarantee identification. In the two country setting, we have one unrestricted outcome variable and one excluded regressor (the other country's one-period own lag) per equation. The system is then just identified. The authors then move to an overidentified model by restricting to zero all the dummies coefficients that are found to be statistically insignificant.

FG test vs. DCC

The Favero and Giavazzi test (*FG* henceforth) is superior to the *DCC* in two aspects: first, with the use of dummies, it uses a full information estimation technique by estimating the interdependence equations on the full sample. The *DCC* implements

instead a limited information technique: it splits the data into two tranquil and crisis sub-samples and estimates the difference in the var-cov matrix of the two periods. As Favero and Giavazzi point out, the sample splitting can reduce greatly the unbiasedness and efficiency of the estimation, especially if one of the two samples has few observations. This is indeed the case of the *DCC* application in Rigobon (2002), where the crisis period is often comprising less than 15 observations. Favero and Giavazzi argue that their full information approach provides a test with higher power than the *DCC*.

The second aspect in which the *FG* test is superior is that it relies on less restrictive assumptions about the variance-covariance matrix of the errors. To see this, rewrite the *FG* second stage interdependence equations (5.30) as:

$$x_{1t} = c_1 + \alpha_1 x_{1t-1} + \beta_1 x_{2t} + \varepsilon_t \tag{5.31}$$
$$x_{2t} = c_2 + \alpha_2 x_{2t-1} + \beta_2 x_{1t} + \eta_t$$

with:

$$\varepsilon_t = \gamma_1 v_1 + \gamma_2 v_2 + .. + \gamma_K v_K + e_{1t} \tag{5.32}$$
$$\eta_t = \gamma_{K+1} v_1 + \gamma_{K+2} v_2 + .. + \gamma_{2K} v_K + e_{2t}$$

Notice the similarity of (5.31) with the non-reduced factor model (5.4). The former is identical to the latter with one lagged dependent variable added and with common shocks w restricted in the errors. ε and η represent the errors during both tranquil and crisis times, while e_1 and e_2 represent the error during tranquil times only (see 5.32).

As we have seen above, the *DCC* test is based on the structural model (5.4). Thus comparing ε and η in (5.31) with ε and η in (5.4) one can see the different assumptions regarding the variance-covariance matrix change during crises upon which the two tests hinge. The comparison can be made in the two-country setting without loss of generality and so we will do. First notice that to compare ε and η in (5.31) with ε and η in (5.4), one must take into account that the latter do not include common shocks while the former include extreme common shocks. Defining ε and

η in (5.31) and in (5.4) (and thus in the *FG* and *DCC* setting) respectively ε_{FG}, η_{FG} and ε_{DCC}, η_{DCC} we can thus write:

$$\varepsilon_{FG} = \varepsilon_{DCC} + \lambda_1 w^* \tag{5.33}$$

$$\eta_{FG} = \eta_{DCC} + \lambda_2 w^*$$

The idiosyncratic errors in the *FG* structural equations are equal to the idiosyncratic errors in the structural equations of the *DCC* plus the extreme common shocks w^*. The *DCC* test assumes $Cov(\varepsilon, w) = Cov(\eta, w) = Cov(\varepsilon, \eta) = 0$. Therefore, under the *DCC* assumptions, the variance-covariance matrix of $\varepsilon_{FG}, \eta_{FG}$ is:

$$\Omega^\varepsilon = \begin{bmatrix} \sigma^2_{\varepsilon_{DCC}} + \lambda_1^2 \sigma^2_w & \lambda_1 \lambda_2 \\ \bullet & \sigma^2_{\eta_{DCC}} + \lambda_2^2 \sigma^2_w \end{bmatrix} \tag{5.34}$$

In the *DCC* setting a crisis is an increase in one idiosyncratic element only, namely η. The matrix of changes in the variance-covariance matrix (5.34) brought by the crisis is then:

$$\Delta\Omega^\varepsilon = \begin{bmatrix} 0 & 0 \\ 0 & \Delta\sigma^2_{\eta_{DCC}} \end{bmatrix} \tag{5.35}$$

(5.34) tells us that under the *DCC* test's assumption the only correlation between ε_{FG} and η_{FG} is caused by the common factor and measured by the loadings $\lambda_1 \lambda_2$. (5.35) states that the correlation cannot be altered by a crisis. Furthermore, it states that a crisis can only increase the variance on one error, η_{FG}.

From this, one can see that the *FG* test imposes a less restrictive set of assumptions on the variance–covariance matrix of the errors ε_t, η_t. The only assumption made in the *FG* setting is that e_1 and e_2 are jointly normally-distributed and homoskedastic. In other words, the crisis dummies are assumed to filter any alteration to the normal and homoskedastic nature of the non-crisis errors e_1 and e_2. The dummies can however generate any heteroskedastic, autocorrelated and non-

normal structure, so that the variance-covariance matrix of ε and η is totally unrestricted (see 5.32). If then the var-cov matrix of ε and η must be equal to (5.34) under the *DCC* assumptions, it is instead totally unrestricted under the *FG* assumptions. Furthermore, the changes caused to the var-cov matrix by a crisis are also unrestricted in the *FG* while are restricted to (5.35) under the *DCC* assumptions.

The *FG* test is then more robust than the *DCC*. In particular, we have seen that the *DCC* effectively rules out investor behaviour changes because it restricts a crisis to be a shock that does not alter the covariance between idiosyncratic shocks, while investor behaviour alters the covariance among idiosyncratic shocks. On the contrary, in the *FG* test a crisis can alter the covariance among idiosyncratic shocks. Therefore the *FG* test is robust to investor behaviour shifts and can detect breaks in the propagation mechanism under those circumstances as well.

The *FG* test results suggest the presence of shift contagion. Several dummies are found extremely significant, rejecting the hypothesis of a stable propagation mechanism even for advanced financial markets such as the *ERM* area ones. This is in contrast with the *DCC* results that found no breaks in the propagation mechanism of advanced markets such as the *EU* and the *US*. Furthermore, various dummies related to negative events have opposite signs in different equations, implying that the negative event had opposite effects on different exchange rates. Favero and Giavazzi give an interesting interpretation of such facts. They notice that the sign tends to be negative for the country with worse records in inflation targeting and commitment to euro parity and positive for the country with better records. It seems then that investors move towards the safer currencies when negative shocks of extraordinary size hit the *ERM* area. In other words, investors fly towards quality[9].

Variations on the *FG* test are provided by the Pesaran and Pick 2002 (*PP* henceforth) and the Bae, Karolyi and Stulz 2000 (*BKS* henceforth) tests. The *PP* test differs from the *FG* in two aspects only:

- instead of defining one dummy for each extreme event as *FG*, it defines a dummy for each currency market. This dummy will take value 1 every time an extreme event occurs anywhere. Therefore, all v dummies defined by *FG* are

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[9] Notice also that in this case the shift contagion generate a *decrease* in the cross-market correlation. Flight to quality phenomena can thus cause shifts of correlations in both directions.

condensed in one only dummy per market. In practice the *PP* test forces all extreme events to have the same effect (if any) on the exchange rate under investigation.

- The dummies are considered endogenous and therefore instrumented.

The results of the *PP* test are very similar to those of *FG*, several breaks to the propagation mechanism are found.

Bae, Karolyi and Stulz also identify extreme events as outliers in the errors of a *VAR*. Their first-stage is identical to the *FG*'s one. However, the outliers are then used to define the second stage's dependent variable. The latter is defined as the number of simultaneous extreme events occurring in the region. An example might help. The *BKS* test for Latin America is run as follows:

1) A *VAR* of all Latin American stock returns is estimated

2) Errors are extracted and extreme events ("exceedances" in *BKS* words) are defined as those observations standing more than three standard deviations away from the mean (just as in the *FG* setting)

3) The number of exceedances occurring in the same day in Latin America are defined "co-exceedances"

4) A multicothomous dummy is specified:

$$c = \begin{cases} 0 & no & co-exceedances \\ 1 & 1 & co-exceedance \\ 2 & 2 & co-exceedances \\ 3 & 3 & co-exceedances \\ 4 & 4+ & co-exceedances \end{cases} \tag{5.36}$$

so if $c = 1$ two Latin American countries showed an error more than three standard deviations from the mean in the same day.

5) Points 1) to 4) are repeated for other areas (East Asia, *EU*, *US*)

6) A probit model is estimated to investigate whether the probability of c being equal to 1,2,3 or 4 is increased by the occurrence of co-exceedances outside Latin America. In other words, the probit model estimates the effect of co-

exceedances outside Latin America on the conditional distribution of c, the number of co-exceedances in Latin America.

The test is applied to four regions: Latin America, East Asia, Europe and the *US*. The results are unambiguously against the stability of the propagation mechanism in Latin America and East Asia. Co-exceedances in other regions increase significantly the probability of co-exceedances in both regions. Europe and the *US* appear less sensitive to events in other regions, showing only marginal increases in the probability of domestic co-exceedances caused by extra-regional ones.

Filtering and the tests' power

A key feature of the *FG*, *PP* and *BKS* tests is the filtering of data: the residuals from the *VAR* are filtered in the sense that only extreme observations are given a dummy and then inserted in the second stage (or are considered "exceedances" in the *BKS* test). Therefore, only extreme events are assumed to cause breaks in the interdependence structure. If events smaller than those defined as extreme cause a break in the propagation mechanism, limiting the investigation of the existence of breaks to those caused by extreme events causes a loss of information contained in the data that could affect seriously the power of the test. The practical consequences of such filtering on the power of extreme-events based tests are investigated by Dungey et al. (2005) with a Monte Carlo experiment. They assume a three- countries model of shift contagion:

$$y_{1,t} = 4w_t + 2u_{1,t}$$
$$y_{2,t} = 2w_t + 10u_{2,t} + \delta 2u_{1,t} \quad\quad\quad (5.37)$$
$$y_{3,t} = 3w_t + 4u_{3,t} + 2\delta u_{1,t}$$

where w is a common factor affecting all three countries, and u_i is country i's idiosyncratic factor. They set $\delta = 0$ in tranquil times and $\delta \neq 0$ during crises. Country 2 and 3 are therefore affected by country's 1 idiosyncratic shocks only during crises, and it is precisely this propagation channel arising during crises that constitutes shift contagion. δ measures the strength of the contagion.

Notice that (5.37) is effectively a latent factor model just like (5.2) with no interdependence during tranquil times. Indeed, taking a three-country version of (5.2) and imposing $\gamma_i = 0$ for $i=1,2,3$ and $\gamma_i' = \delta$ for $i=2,3$. gives the system (5.37). As all the tests presented above were reducible to a test of the shift contagion hypothesis (5.11), they are reducible to a test of the hypothesis $\delta = 0$ in the system (5.37). The power of the tests presented above can thus be assessed by applying them to data generated by (5.41) and computing how often they detect shift contagion.

Dungey et al. generate 10000 replications of a dataset containing 100 "tranquil times" observations (where $\delta = 0$) and 50 "crises" observations (where $\delta \neq 0$) from the model (5.37). They assess the power of the five tests described above (*FR*, *DCC*, *FG*, *PP1*, *PP2, BKS*) by applying them on each replication and computing the percentage of times the tests detect shift contagion from country 1 to 2 and from 1 to 3. *PP1* and *PP2* represent two versions of the Pesaran and Pick test, with, respectively, instrumented and non-instrumented dummies.

Since shift contagion takes place in each replication of the experiment, the percentage of times the tests detect contagion should be as close as possible to 1. This is unlikely to occur, so that a less stringent request is that the power function of the test be monotonic in δ (i.e. that its power increases as δ does). Six different experiments are performed, to assess the power of the tests in different scenarios:

1) High autocorrelation of the common factor w
2) Medium autocorrelation of the common factor w
3) No autocorrelation of the common factor w
4) Increase in the variance of u_1 during crises
5) Increase in the variance of w during crises
6) Increase in the variance of w during crises with *ARCH* dynamics

Each experiment is repeated four times with, respectively, $\delta = 1,2,5,10$. In this way, the Monte Carlo exercise assesses each test's power function (i.e. the relationship between the strength of shift contagion and the percentage of times this is detected) as well.

In general, all tests exhibit very low power, especially when structural breaks are taking place (experiments 4 to 6). Even with the highest strength of contagion

$(\delta = 10)$ all tests exhibit power close to zero in at least one scenario. The performance of the three tests based on filtering (*FG*, *PP*, *BKS*) is particularly poor: in all six experiments they detect shift contagion in roughly 10% of times while in the some of the same scenarios the power of the *FR* and *DCC* tests is close to 1. Furthermore, all three tests have a very flat power function, meaning that their ability to detect shift contagion does not increase as its strength increases. In some cases the opposite is true, the probability of them detecting contagion falls as δ increases. Comparing the *DCC* and the non-instrumented *PP* test, one finds that the former has a significantly higher power in all experiments, sometimes four times bigger than the latter. Since both tests do not instrument to control for simultaneity bias, Dungey et al. argue that the reduction in power of the *PP* test represents "the information loss of using a filter that excludes important sample information". The fact that all tests based on filtering exhibit significantly lower powers than the others gives support to this statement.

So, while the *FG*, *PP* and *BKS* tests are preferable on the basis of their less stringent assumptions on the variance-covariance structure of the system and no sample splitting, their filtering process causes a severe loss in information. A trade-off between robustness and power of tests seems to be there. The *FR/DCC* approach has more power but can give wrong answers if the crisis does not take the specific form it assumes; the *FG/PP/BKS* approach deals with all forms of crises but detects shift contagion only when this is extremely strong (and not even then sometimes). In light of these considerations, a test that leaves the var-cov structure unrestricted, estimates the structural equation on the full sample and avoids the filtering process would retain the appealing features of both approaches: robustness and power. Providing such a test is the aim of the next section.

5.2 A Quantile Regression-based test for the instability of stock markets' interdependence

In this section I will provide a shift contagion test that, as the *FG*, *PP* and *BKS*, does not assume a particular form for $\Delta\Omega_{\varepsilon}^{t}$ and does not split the dataset into tranquil and crisis samples while retaining the desirable features of the *DCC* (i.e. it avoids the

filtering of data). This aim is pursued with the use of Quantile Regressions (*QR* henceforth). To illustrate the underlying idea, recall the latent factor model in eqs. (5.4):

$$x_{1t} = \alpha_1 w_t + \beta_1 x_{2t} + \varepsilon_t \qquad\qquad (5.38)$$
$$x_{2t} = \alpha_2 w_t + \beta_2 x_{1t} + \eta_t$$

The interdependence of stock markets x_{1t} and x_{2t} during tranquil times is measured by the βs. I call these "interdependence coefficients". Now assume that country *2*'s stock exchange is hit by a major negative shock such as a currency and/or banking crisis. If shift contagion takes place so that there is a break in the interdependence structure of the stock markets, the model becomes:

$$x_{1t} = \alpha_1 w_t + (\beta_1 + \delta_1) x_{2t} + \varepsilon_t \qquad\qquad (5.39)$$
$$x_{2t} = \alpha_2 w_t + (\beta_2 + \delta_2) x_{1t} + \eta_t$$

When x_{2t} is large and negative for idiosyncratic reasons (i.e. when η_t is large and negative), the effect of x_{1t} on x_{2t} increases by the amount δ_2 and the effect of x_{2t} on x_{1t} increases by δ_1. If the idiosyncratic elements are correlated via investor behaviour (or in general if returns are related in any way other than market interdependence or common factors), we will have that $Cov(\varepsilon, \eta) > 0$ and thus both η_t and ε_t will tend to be negative. Both stock markets will tend to show below-average returns for idiosyncratic reasons. In other words, both returns will be in the bottom tail of their distribution conditional on the regressors. It follows that, if the interdependence structure of the two markets is unstable, below-the-conditional-median observations of both x_{2t} and x_{1t} should be associated with different interdependence coefficients than those associated with median observations of x_{2t} and x_{1t}. If market interdependence increases during crises, the coefficients associated with below-the-conditional-median observations should be bigger than those associated with median observations. The presence of shift contagion can then be assessed by estimating the interdependence coefficients at the median and at the

bottom of x_{2t}'s and x_{1t}'s distributions and then testing their equality. This is the procedure implemented in the following.

In the above discussion I have assumed ε and η to be correlated so that when a crisis hits country *2* both ε and η will tend to be negative. In this setting, an increase in the interdependence coefficients at the bottom of x_{2t}'s and x_{1t}'s conditional distributions represents increased market interdependence *during crises*.

If instead ε and η are uncorrelated, bigger interdependence coefficients at the bottom of x_{2t}'s and x_{1t}'s conditional distributions represents increased sensitiveness to foreign shocks when the domestic market is underperforming for idiosyncratic reasons, whatever those reasons are.

ε and η are likely to contain both genuinely idiosyncratic elements (e.g. productivity growth) and elements generating correlation among the two (e.g. investor behaviour). In other words, η can be negative for low productivity growth or investors behaviour shifts caused by a crisis in country *1*. Aim of this test is however to detect the eventual instability of the shock propagation mechanism, for the reasons highlighted at the very beginning of the chapter. Therefore, distinguishing whether shift contagion takes place during crises or more generally when the domestic market is underperforming for idiosyncratic reasons is beyond the scope of this application.

This test is again nested in the latent factor model presented at the beginning of the chapter. Take (5.2) as the model describing the interdependence structure at the median and (5.8) as the model describing the interdependence at the, say, 1% quantile of the dependent variable's conditional distribution (i.e. the extremely negative conditional stock returns). Testing the equivalence of the interdependence coefficients at the median and 1% quantile is identical to test the hypothesis (5.11), the standard shift contagion test nested in the latent factor model approach.

However, the *QR* approach implies some differences with respect to the shift contagion tests presented above. By estimating the market interdependence at different quantiles of the dependent variable's conditional distribution, the *QR* test investigates whether foreign shocks have different repercussions on the domestic market *depending on the latter's idiosyncratic performance*. On the other side,

traditional shift contagion tests investigate whether foreign shocks have different repercussions on the domestic market depending on the size of those shocks or the degree of volatility in the global markets (i.e. *depending on foreign markets' performance*). This implies a difference between what shift contagion means in standard tests and in the *QR* test. In standard ones, shift contagion means that "big" negative foreign shocks (or extraordinary volatility) have stronger domestic repercussions than "small" ones, *whatever the domestic market's idiosyncratic performance*. The break in the propagation mechanism is then caused by an extraordinary negative event abroad. Differently, in the *QR* test shift contagion means that negative foreign shocks have stronger domestic repercussions when the idiosyncratic performance is poor, *whatever the size of the foreign shock*. Here the break in the propagation mechanism is caused by an extraordinary negative idiosyncratic performance. However, both types of instability generate shifts in markets' interdependence. Investigating them sheds light on the key aspects discussed at the very beginning of this chapter.

Another difference is the definition of a crisis. In all correlation-based tests such as the *FR* and the *DCC* the test is made operational by splitting the sample into a high and a low volatility sub-samples. There is a great deal of arbitrariety in this procedure. To give an example, consider the *DCC* test applied on the East Asian crisis. Here Rigobon defines the tranquil sample as the one running from 2-Jan-1997 to 2-Jun-1997 (the day the Thai central bank abandoned the dollar peg and let the Baht float). Three alternative crisis periods are then defined, starting respectively from: 10-Jun-1997, 27-Oct-1997, 1-Dec-1997. These dates correspond to respectively: the immediate aftermath of the Thai devaluation, the explosion of Hong-Kong short-term interest rates (widely considered as the moment in which the crisis went international) and the devaluation of the Korean Wong. Using the first crisis sub-sample, the *DCC* test detects shift contagion in Latin America, using the other two windows it does not. What result should be trusted? The problem is that one cannot compare the results since they are based on different datasets: the different results could be due to sampling variance only. It follows that one cannot say that, since the window containing the Thai devaluation is the only rejecting parameters stability, the Thai devaluation was the only event causing shift contagion. Billio and Pellizzon (2003) show that this problem is systematically affecting the *DCC* test. Performing the *DCC* test on rolling windows, they find that even a 3-days shift in the

latter changes the test result from clear-cut rejection to acceptance of the null of no shift contagion. This is in fact what happens in Rigobon's application as well. In the Latin American and East Asian zones one finds rejections and acceptances of the null hypothesis by shifting the border between crisis and tranquil times by a week.

A similar problem plagues extreme-event-based tests such as the *FG*. Recall that the latter defines an "extreme event" as a *VAR* residual lying 3 or more estimated standard deviations from the mean. This definition is clearly arbitrary (why not 4 nor 2 standard deviations?) and it makes the size of a shock defined as "extreme" positively related to the volatility in the sample. The higher the volatility in the sample, the bigger the absolute size of an observation lying more than 3 standard deviations from the mean. Also, changing the definition of a crisis (shifting the number of standard deviations necessary to be categorized as an extreme event) alters the structural model estimated. Indeed, the higher the standard deviations determining the threshold, the lower the number of dummies included in the model. Therefore, as in the *DCC* setting, one cannot compare the results from tests based on different crisis definitions. Different results can be generated by different covariances among estimated parameters.

In this aspect the *QR* test is preferable because it allows the comparison of results arising from different definitions of crisis. In the *QR* setting a "crisis" is a quantile on which the structural model is estimated and the interdependence parameter compared with the median one. Clearly, the definition of crisis as the 1% rather than the 2% quantile is arbitrary as the other tests' definitions were. Potentially, one could limit the arbitrariness by estimating the interdependence parameter at all quantiles and then compare it with the median one. Therefore, a complete mapping of the interdependence across the whole conditional distribution of the domestic stock returns could be carried out, in search for breaks. The instability of the propagation mechanism could then be tested without relying on an arbitrary definition of crisis. In practice, estimating a model with 100 simultaneous equations is unfeasible. First, one would need a huge dataset to guarantee enough degrees of freedom and, second, a standard computer would probably be unable to carry the burden of calculations involved. Since the model's variance-covariance matrix is bootstrapped, even a much more parsimonious model such as the one estimated in the present chapter proved challenging for a standard computer. Therefore, one is likely to have to choose a limited number of quantiles on which to base the test. The definition of a crisis is then

arbitrary in the *QR* setting as well. The latter is however still preferable because, contrary to the other tests, it allows comparisons among tests based on different definitions of crises. Let us say, for example, that one tests for the difference between the interdependence coefficient at the median and at the 1% and 5% quantiles. If the second test does not reject parameters equality but the first does, this is due only to the different weight assigned to the observations in the sample in the two different quantile regressions. The structural model and the data on which the latter is estimated are identical in the two tests, and therefore the eventual difference in the results cannot be generated by sampling variance or different correlation among different regressors. It must arise from the different interdependence at different quantiles of the dependent variable's conditional distribution only. Therefore, the *QR* tests allows for a direct comparison of results arising from different definitions of crisis. This is indeed done in the robustness analysis below, where the *QR* test is applied on different extreme quantiles.

The *QR* setting avoids filtering the data, therefore extracting more information that extreme-event-based tests from the same dataset. We have seen above that the filtering causes important informational losses, so that avoiding filtering should make the *QR* a more powerful test than the extreme-event-based ones. Also, the *QR* estimates the structural model on the full sample while the *DCC* estimates the model on two sub-samples in order to compare the results from the two. As seen, this causes a relevant loss of information, reason for which the *QR* should be a more powerful test than the *DCC* as well.

Finally, the *QR* test leaves the variance-covariance matrix of the idiosyncratic factors and its change during crisis unrestricted. This makes it a more robust test than the *DCC* and, in particular, a test robust to investor behaviour shifts. Since these have been widely recognized as at least an important source of contagion, this seems a relevant advantage. In order to treat this issue in some detail, a formal discussion of the test methodology is needed. For this reason, this discussion is postponed to the methodology section below.

5.3 Methodology and Econometric Issues

5.3.1 The estimated model

The estimated model is a multivariate equivalent of (5.38) with two common shocks proxies *NY* and *CPS*:

$$y_{it} = \alpha + \beta C_{it} + \gamma_0 NY_t + \gamma_1 CPS_t + u_t \qquad (5.40)$$

where:

y_{it} is the percentage change in country *i*'s stock market index in month *t*

C_{it} is the contagion index for country *i* in month *t*. This is defined as:

$$C_{it} = \sum_{j \neq i} \left(M_{ijt} * y_{jt} \right) \qquad (5.41)$$

it is the sum of the returns of all stock markets but *i*, weighted by the relative importance of market *j* for market *i*. The weights are normalized so that they add up to one. This allows for a clear interpretation of the coefficient associated with contagion index. The relative importance is measured by the degree of bilateral trade over country's *i*'s *GDP*:

$$M_{ijt} = \frac{EX_{ijt}}{GDP_{it}} \qquad (5.42)$$

The definition of the contagion index and the weighting scheme follow the same line of thought exposed in the fourth chapter. For a justification of the index and a detailed description see equation 4.3 and related discussion.

NY_t is the percentage change of the New York Stock Exchange Composite index in month *t*. This variable is intended as a proxy for common shocks affecting financial markets such as shocks on oil prices or the *US* monetary policy for example.

CPS_i is the monthly change in the average *US* spread between 90-Day AA and A2/P2 Non-financial Commercial Paper. This is intended as a measure of investors' risk perception and tolerance. As one can see in Figure 5.3, the spread's hikes coincide with all major crises in the sample: the Russian-LTCM crisis, the dotcom crash, the Argentinean devaluation and finally the current global credit crunch are spotted at first sight. The huge spike at the end of the 2008 summer is particularly interesting. It is on September the 15th , the day Lehmann Brothers filed for bankruptcy.

Figure 5.3
AA – A2 commercial paper spread
US market
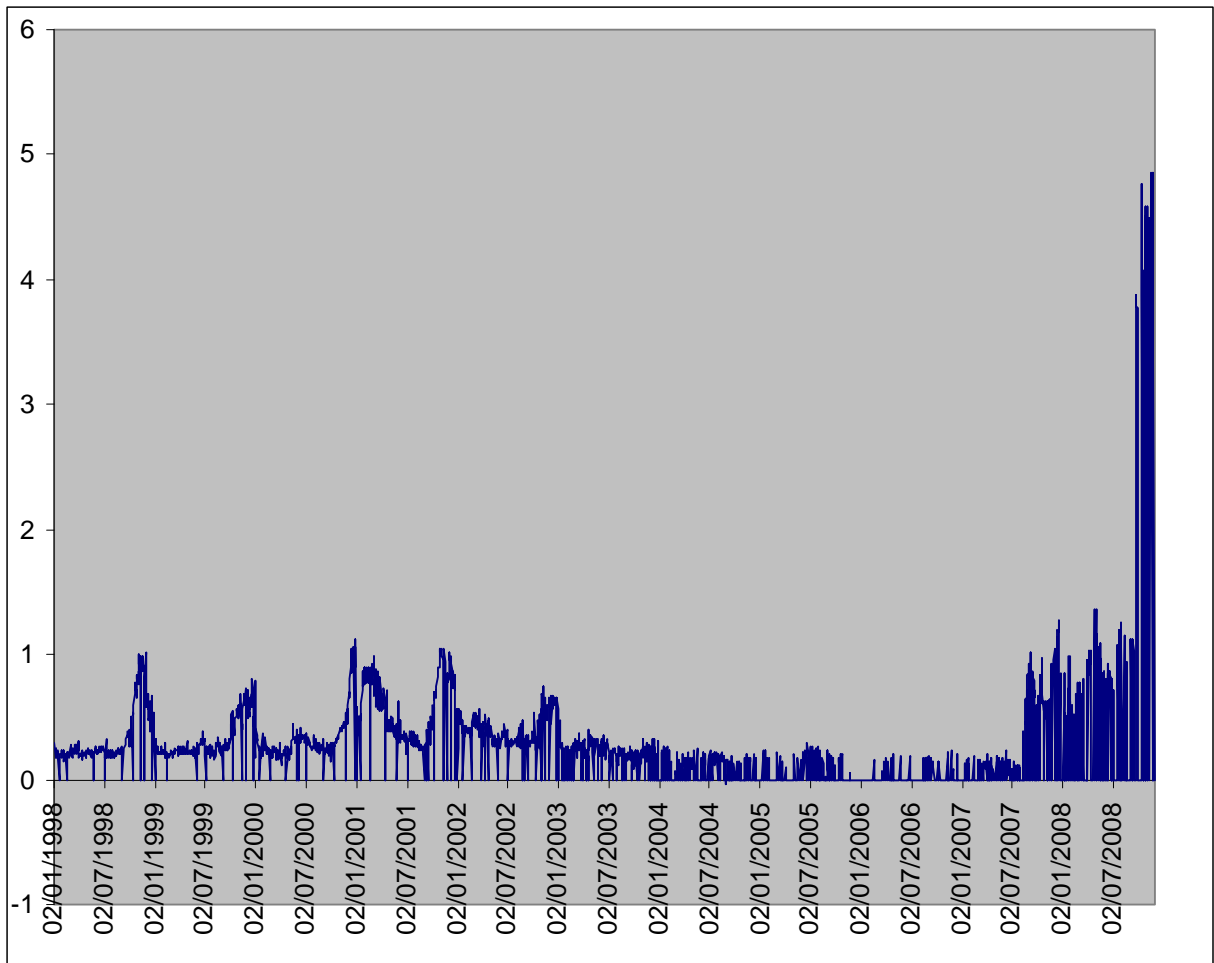
The figure shows how the commercial paper spread follows closely the events on global markets, and how the premium required by investors to buy riskier commercial

paper increases markedly every time a negative shock hits the markets. The spread provides therefore a good measure of the shifts in investors' risk assessment and/or tolerance. During tranquil times, low risk is perceived (and tolerance is relatively high), and as a consequence investors require a small premium to buy riskier paper. When a crisis shakes the markets investors re-assess the risk of default upwards and therefore increase that premium. Also, investors might become more risk-averse after a major negative giving rise to fight-to-quality phenomena. As discussed earlier in this thesis, there is broad consensus that shifts in investors' behaviour played a role in the transmission of turbulence across financial markets in the '90s. By affecting more market simultaneously, investors' behaviour shift would bias the interdependence coefficients upwards just as another common shock. *CPS* is then included in the estimated model in order to avoid this possibility.

Equation (5.40) is estimated at the median and *6* different quantiles (*.01 .05 .1 .9 .95 .99*). The shift contagion tests are a test of the null hypothesis:

$$\beta_q = \beta_M \qquad q=0.01, 0.05, 0.1, 0.9, 0.95, 0.99 \tag{5.43}$$

where β_M is the interdependence coefficient in the median equation while β_q is the one in the quantile q equation. A rejection of the null is interpreted as the detection of shift contagion.

System estimation

In order to perform the test (5.43) it is necessary to estimate a system of *7* equations (one per quantile) and obtain the systemic variance-covariance matrix. This procedure is implemented by the Stata command *sqreg*. Following the method suggested by Koenker and Bassett (1982), the *sqreg* command estimates all the equations in the system simultaneously and then obtains the inter-quantile var-cov matrix of the estimators by bootstrapping. The estimated system is then formed of *7* equations identical to (5.40), each one fitted on one of the *7* quantiles listed above:

$$y_{it} = \alpha^{99} + \beta^{99} C_{it} + \gamma_0^{99} NY_t + \gamma_1^{99} CPS_t + u^{99}{}_t$$

…

$$y_{it} = \alpha^M + \beta^M C_{it}^M + \gamma_0^M NY_t + \gamma_1^M CPS_t + u^M{}_t \qquad (5.44)$$

…

$$y_{it} = \alpha^1 + \beta^1 C_{it} + \gamma_0^1 NY_t + \gamma_1^1 CPS_t + u^1{}_t$$

Pooling

One could estimate the system (5.44) for each of the *N* countries in the sample. This procedure would however require the estimation of *N* systems of *Q* equations (one per quantile) with *K* parameters each. We want to estimate the difference among the median and *6* quantiles coefficients, with *4* regressors per equation on a sample of *57* countries. The procedure would then require the estimation of *7*4*57=1596* parameters. Furthermore, since we want to test the difference between coefficients in different quantile equations, the systemic var-cov matrix has to be estimated. Therefore, we would have to estimate *57* var-cov matrices, one for each country. Although we have a relatively big sample consisting of almost *7000* observations, the need for instrumentation (discussed further down) imposes to keep the number of estimated parameter at the lowest possible level. Pooling the data reduces the number of parameters to be estimated to *4*7=28* plus one systemic var-cov matrix. This is therefore the procedure pursued. One only system is estimated on the pooled sample:

$$y = \alpha^{99} + \beta^{99} C + \gamma_0^{99} NY + \gamma_1^{99} CPS + u^{99}$$

…

$$y = \alpha^M + \beta^M C^M + \gamma_0^M NY + \gamma_1^M CPS + u^M \qquad (5.45)$$

…

$$y = \alpha^1 + \beta^1 C + \gamma_0^1 NY + \gamma_1^1 CPS + u^1$$

where *y* is an *NTx1* vector with *T* observations for each of the *N* countries in the sample, *C* is the *NTx1* vector containing the contagion index *C* while both *NY* and *CPS* are *Tx1* vectors stacked *N* times.

By pooling data, (5.45) estimates the *cross-country average effect* of foreign stock returns on the conditional distribution of domestic stock returns at quantile *q*. The *QR*

setting tests the stability of the *cross-country average interdependence*. Clearly, it would be more informative to estimate (5.44) country by country and then testing the stability of the interdependence differences across quantiles. This is however unfeasible because of the above considerations.

Another potential problem is that, by pooling data from all countries, these are unified in one only dependent variable *y* with probability distribution *f(y)*. If stock returns are more volatile in *EMEs* than in financial centres (*FCs* henceforth), the tails of *f(y)* will include more observations from *EMEs* than from *FCs*. Since quantile regressions fitted at the extreme quantiles assign more weight on extreme observations, the estimated coefficient from those extreme quantile regressions will represent the coefficient of *EMEs* more than that of financial centres. The difference between the extreme and median coefficient could then be generated by different interdependence of different countries, rather than a change in the interdependence structure brought by the negative idiosyncratic performance. By looking at the country composition of observations at the median and at the tails of the dependent variable distribution, one can indeed notice a very different country composition. Table (5.1) provides the percentage of observations from *FCs* (Euro-area, *US*, Canada, Australia, New Zealand, Norway, Sweden and Switzerland) and *EMEs* in the two quantiles range centred on the quantile of interest. For example, the first row gives the percentage of *FCs* and *EMEs* observations in the 0-2 quantiles range of the stock returns' distribution. The second row gives the same percentages for the 4-6 quantiles range and so on. *FCs* account for 31.6% of the overall observations in the sample (see MEAN row). However, they are disproportionally represented in the in the median range, where they account for 44.1% of the observations. In the bottom quantile they represent only 19.9% of the observations and even less (6.6%) in the top quantile. There are notable differences in country composition across different quantiles of *y*'s distribution. *EMEs* are far more present in the extreme quantiles, proving the higher volatility of their stock markets. Even if Table 5.1 disaggregates data of *y*'s *unconditional* distribution while the relevant distribution for the *QR* test is *conditional* on the regressors, these results call for prudence in interpreting eventual differences in the interdependence coefficients. The relevance of this issue for the test results is investigated with robustness tests below.

Earlier I have affirmed that the *QR* test is more robust than the *DCC* because, contrary to the latter, it leaves the variance-covariance matrix of the idiosyncratic errors unrestricted. Now we can see this formally. For simplicity, assume for now that the *QR* test is performed on one quantile only, say *0.01*, against the median with a sample of two countries. The estimated system is then:

$$y_{it} = \alpha^M + \beta^M C_{it}^M + \gamma_0^M NY_t + \gamma_1^M CPS_t + u^M{}_t \tag{5.46}$$

$$y_{it} = \alpha^1 + \beta^1 C_{it}^1 + \gamma_0^1 NY_t + \gamma_1^1 CPS_t + u^1{}_t$$

and the variance-covariance matrix of the system errors u^1 and u^M is:

$$\Omega^S = \begin{bmatrix} \sigma_{u^M}^2 & Cov(u^M, u^1) \\ \bullet & \sigma_{u^1}^2 \end{bmatrix}$$

Since the data is pooled, we have that the errors in (5.46) are:

$$u^M = \begin{bmatrix} \varepsilon_1^M \\ ... \\ \varepsilon_T^M \\ \eta_1^M \\ ... \\ \eta_T^M \end{bmatrix} \tag{5.47}$$

and:

$$u^1 = \begin{bmatrix} \varepsilon_1^1 \\ ... \\ \varepsilon_T^1 \\ \eta_1^1 \\ ... \\ \eta_T^1 \end{bmatrix} \tag{5.48}$$

where $\varepsilon_1^M, \varepsilon_T^M, \eta_1^M$ and η_T^M are respectively country 1's error in time 1 and T and country 2's error in time 1 and T in the median equation. $\varepsilon_1^1, \varepsilon_T^1, \eta_1^1$ and η_T^1 are the equivalent errors in the first quantile equation. In other words, the errors in (5.46) are the stacked country error vectors. It follows that $\sigma_{u^M}^2$ is the *cross-country average* variance of the error in the median equation. In other words:

$$\sigma_{u^M}^2 = \frac{\sigma_{\varepsilon^M}^2 + \sigma_{\eta^M}^2}{2} \qquad (5.49)$$

where $\sigma_{\varepsilon^M}^2$ and $\sigma_{\eta^M}^2$ are the sample variance of ε^M and η^M. Since the cross-country average $\sigma_{u^M}^2$ is unrestricted, so are the two elements that make up the average, the single country error's variances. More importantly, ε^M and η^M can be correlated so that $Cov(\varepsilon^M, \eta^M)$ is also unrestricted. Summing up, the var-cov matrix of the country idiosyncratic errors in the median equation ε^M and η^M is totally unrestricted.

Furthermore, since $\sigma_{u^1}^2$, the average error variance in the 1% quantile equation, is unrestricted, the *difference* $\sigma_{u^M}^2 - \sigma_{u^1}^2$ is also unrestricted. Being the difference among averages unrestricted, so is the difference among its elements: $\Delta\sigma_\varepsilon^2 \equiv \sigma_{\varepsilon^M}^2 - \sigma_{\varepsilon^1}^2$, $\Delta\sigma_\eta^2 \equiv \sigma_{\eta^M}^2 - \sigma_{\eta^1}^2$ and $\Delta Cov \equiv Cov(\varepsilon^M, \eta^M) - Cov(\varepsilon^1, \eta^1)$.

We therefore have that the variance and covariance of the country idiosyncratic shocks ε and η can take any value and can change in any way from the median to the 1% quantile. In other words, the *cross-quantile* changes in the Variance-Covariance matrix of the country idiosyncratic shocks ε and η:

$$\Delta\Omega_t^\varepsilon = \begin{bmatrix} \Delta\sigma_\varepsilon^2 & \Delta Cov \\ \bullet & \Delta\sigma_\eta^2 \end{bmatrix} \qquad (5.50)$$

is totally unrestricted. The *QR* test is then robust to any form of variance shock caused by a crisis. Comparing this with the changes in the Variance-Covariance matrix of the country idiosyncratic shocks assumed by the bivariate *DCC*:

$$\Delta\Omega_t^\varepsilon = \begin{bmatrix} 0 & 0 \\ 0 & \Delta\sigma_\eta^2 \end{bmatrix} \tag{5.51}$$

one can see why the *QR* is more robust. Furthermore, we have seen how this implies that the *QR* test is robust to shift contagion driven by investors behaviour shifts while the *DCC* is not.

5.3.2 Simultaneity bias and instrumentation

If stocks returns are interdependent (i.e. if the true β's are positive), *C* determines *y* as well as the reverse. Movements in *u* affect other countries' fluctuations and therefore *C*. It follows that the error term is not independent from the latter. If the true β's are positive, simple *QR* regressions will then give biased and inconsistent estimators, and the bias will be directly proportional to the interdependence of stock returns. The econometric procedure needs to take into consideration the likely endogeneity present in the model. As usual, the tool used to overcome these problems is instrumentation. This poses another question: what instruments are likely to be relevant and valid? Relevance (i.e. the partial correlation of excluded instruments with the instrumented variables) can be achieved in this model exploiting the mild autocorrelation exhibited by stock markets indexes at a monthly level. This is the reason why the analysis is carried out on monthly data. Daily and weekly data on stock markets fluctuations resemble random walks, making own lags irrelevant instruments. This point is made by both Walti (2003) and Pick (2007). Monthly data exhibits instead a certain degree of autocorrelation, high enough to make the lags relevant instruments. The relevance of the lags as instruments in this setting is tested via Bound's partial-Rsquared, which will be provided and discussed in the results section below. Of course one could look for other variables to use as instruments. However, stock markets movements are notoriously hard to predict. Own lags are then the variable most likely to provide relevant instruments.

Since the choice of how many and how old lags to use as instruments is somewhat arbitrary, I performed the first stage with a series of lags combinations. I have tried instrumenting *C* using its own lags from the first up to the twelfth, in several different combinations. The lag structure that provided the highest correlation

is the one including the second lag only. This is therefore the lag structure used to instrument C in the *QR* test.

5.3.3 *Quantile regression and instrumentation*

Amemiya (1982) proposed a class of two-stage estimators for *QR* models with endogenous variables and called it "two-stage least absolute deviation" estimators (*2SLAD*). This is the equivalent of a *2SLS* procedure where the second stage is a quantile regression. In fact, Amemyia showed how *2SLAD* contains *2SLS* as a special case. Powell (1986) derived the large-sample properties of such estimators, which have since become well established in the literature. The underlying idea is indeed simple enough. The regressors suspected to be endogenous are regressed on the whole set of exogenous variables. The fitted values of these first-stage regressions are then introduced in the second-stage (quantile) regression. The variance-covariance matrix of the coefficients is then obtained via bootstrapping. There is a long literature on bootstrap methods for quantile regression estimators, so that a bootstrap with a valid resampling scheme is a well established way of obtaining a consistent estimator for the variance of the estimator (see Buchinsky (1995) and Koenker (2005) and references therein). The valid resampling scheme is implemented by bootstrapping both stages of the procedure. In other words, each bootstrap replication generates a subset of observations on which the first and second stage equations are estimated. The estimate for the coefficient is the one estimated on the full sample, while the var-cov matrix of coefficients is obtained by calculating the variance of each second-stage coefficient around the coefficient estimated on the full sample. We thus have the following procedure:

<u>First Stage</u>: estimation of

$$C_{it} = \delta_0 + \delta_1 C_{it-2} \tag{5.52}$$

<u>Second Stage</u>: estimation of the system

$$y = \alpha^{99} + \beta^{99}\hat{C} + \gamma_0^{99} NY + \gamma_1^{99} CPS + u^{99}$$

$$\dots$$

$$y = \alpha^{M} + \beta^{M}\hat{C} + \gamma_0^{M} NY + \gamma_1^{M} CPS + u^{M} \tag{5.53}$$

$$\dots$$

$$y = \alpha^{1} + \beta^{1}\hat{C} + \gamma_0^{1} NY + \gamma_1^{1} CPS + u^{1}$$

where the coefficients' superscripts denote the quantile the regression is fitted upon. $\hat{C}$ is the vector of fitted values from equation (5.52). The system contains *7* equations, one for each of the *6* extreme quantiles (*0.99 0.95 0.9 0.1 0.05 0.01*) and the median. Both stages are bootstrapped and the β's, their standard errors, t-statistics and *95%* confidence interval saved.

The joint estimation of the *7* equations allows the bootstrapping of the systemic variance-covariance matrix containing the variance of all coefficients of all equations and their intra- and cross-equation covariances. In this way, one can obtain estimates for the six differences $\beta^{99} - \beta^{M}$, ... , $\beta^{1} - \beta^{M}$ and their standard errors, t-statistics and 95% confidence intervals. These constitute the core of the shift contagion test. The rejection of their *t*-tests' null is interpreted as evidence of shift contagion. I have written a Stata program (ado file) that performs the two-stage *QR* procedure just described. A copy of the ado file is provided in Appendix 1.

The *2SLAD* estimator has been recently criticized by Hansen and Chernozhukov (2006). The authors affirm that, even if *2SLAD* have an established history, the estimator is not very general. As a consequence, they not only recommend a more general method, but in their footnote 1 on page 493 they clarify that the older two-stage method will produce inconsistent estimates when the effects of the endogenous variables vary across quantiles. This could pose a problem for our test, since in presence of shift contagion the effect of the endogenous variable (the contagion index itself) would indeed vary, potentially giving biased estimates. However, no assessment of the size of the bias is carried out by the authors. The empirical relevance of the theoretical result in Hansen and Chernozhukov (2006) is thus unclear still. Given its established position in econometrics, I will apply the *2SLAD* estimator.

5.3.4   Heterogeneity and Autocorrelation

The system (5.53) is estimated on the pooled sample. However, we are dealing with a panel dataset constituted by countries. In presence of a country-specific idiosyncratic unobservable, a pooled estimation might generate serial correlation in the error. The existence of country-effect is likely: some countries' stock exchanges may have maintained higher growth rates than others for idiosyncratic reasons, independent of markets' interdependence or common shocks. Since the contagion index C is instrumented using own lags, the presence of autocorrelation could render the instruments themselves endogenous, as discussed at length in the previous chapter (see section *4.3.2*). This does not however seem to be an issue here since a standard autocorrelation test such as the one suggested by Wooldridge (2002, p.177) cannot reject the null of no autocorrelation of the residuals of the structural equations.

5.3.5   Stationarity

The dataset includes *121* observations per country. From the time-series nature of the dataset arises the issue of stationarity. Since we are estimating the mutual effect of stock indexes' growth on each other, we need to ensure the stationarity of the series. Otherwise, spurious relationship could be found and mistaken for interdependence. However, since all variables enter the model as percentage changes, this should not be a problem. It is unlikely that, for example, stock indexes grow or fall at an ever faster *rate*. This is indeed confirmed by Augmented Dickey-Fuller tests, which reject the unit-root null for each stock market without any doubt.

5.3.6   Identification

The systemic nature of the estimated model raises the issue of identification. This is however easily solved. Recalling the estimated system (5.53) one can see the equations do not contain any outcome variable with unrestricted parameter (i.e. any dependent variable form other equations). The equations are therefore not simultaneous and the identification of the system depends on the identification of each equation singularly. This in turn is guaranteed by the standard assumption of instruments exogeneity.

5.3.7   *Data*

The test exploits data from four sources: the International Financial Statistics (*IFS*) and the Directorate of Trade Statistics (*DOTS*) complied by the *IMF* , the *WDI* database compiled by the World Bank and the *FRED* dataset compiled by the Federal Reserve Board.

The *IFS* database has been introduced and described in the previous chapter. It provides monthly, quarterly and yearly data on stock market indexes. Given the speed at which stock markets fluctuations are transmitted across borders, monthly data are preferred as quarterly and yearly data would probably lose most of the dynamics by averaging out higher frequency oscillations. In fact, monthly data themselves are likely to lose a good deal of the stock markets dynamics. However, for the sake of instrumentation higher frequency data are not a viable option. Walti (2003) and Pick (2007) both showed how shift contagion tests in which the simultaneity bias is dealt with via the use of the financial variable's lags as instruments is likely to give results as biased as a standard *OLS* if the autocorrelation of the financial variable is sufficiently weak. They notice how this is often the case in contagion tests performed on high-frequency (daily) financial data that are typically resembling a random walk. For this reason, I have applied the test to monthly data that instead showed some autocorrelation, at least of first and second order. In such a setting, problems associated with a weak instrumentation should be less pressing. The estimation of a standard *2SLS* interdependence equation supports this view. The model gives good results: relevant and exogenous instruments, correct signs and extremely significant second-stage coefficients (see below). This clearly does not need to hold for quantile regressions but, as we will see shortly, it does.

All data used in the analysis apart from those on exports and commercial paper spreads are taken by the *IFS* database. Data on exports disaggregated for country of destination is taken from the *DOTS* database, while data on exports' share of *GDP* is provided by the *WDI* database. The latter are provided at yearly frequency and they are therefore transformed in monthly data by assigning the same value to all months of the same year. Data on commercial paper spreads are taken from the *FRED* dataset. All data apart from the latter have been downloaded using the *ESDS* access system based at the University of Manchester.

The sample covers 57 countries from January 1998 to December 2007, giving 121 monthly observations for each country, for a total of 6897 observations. Also, exports data from the 1996-98 period are used in calculating the weightings. The countries included in the sample are: Argentina, Australia, Austria, Bangladesh, Brazil, Canada, Chile, Hong Kong, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Korea, Kuwait, Latvia, Lebanon, Malaysia, Mauritius, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Qatar, Russian Federation, Saudi Arabia, Singapore, Slovak Republic, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Trinidad and Tobago, Turkey, Ukraine, Venezuela and the United States.

Summary statistics are given in table 5.2 while table 5.3 provides selected quantiles of the dependent variable's unconditional distribution.

5.4 Results and interpretation

5.4.1 Preliminary estimations

Before delving into the *QR* test results, a standard *2SLS* estimation of (5.40) with *C* instrumented with its own 2nd lag is carried out. This gives an idea of the overall relationship existing between domestic stock markets fluctuations and the regressors at the basis of the *QR* test. It seems informative to look at the average relationship between domestic and foreign stock markets fluctuations before analysing it at different quantiles. The results are presented in Table 5.4. The column (1) gives the results for the standard *2SLS* mean regression. All coefficients are correctly signed and extremely significant. A 1% increase in the contagion index causes a 0.41% increase in the domestic stock index value. Therefore, a 1% increase in all foreign other stock markets raises the domestic market by 0.41% on average and ceteris paribus. Looking at the common shock proxies, the model estimates that a 1% increase in the spread between *AA* and *A2 US* commercial paper is associated with an average 0.0034% decrease in domestic stock markets. This number is surprisingly small. To give an idea, between July and December 2008 the spread rose from 0.11 to 1.08, representing an 818% increase in 5-months, by far the biggest since the Federal

Reserve started keeping this statistics. According to the estimated coefficient this huge rise in risk perception/aversion should have caused a mere 0.00291% decrease on average stock market returns. The coefficient is however correctly signed and significant, which is enough for a control variable. Finally, a 1% increase in the *NYSE* index causes an average 0.36% increase in world markets.

The *2SLS* exercise gives information about the instrumentation that will be used in the *QR* test as well. It represents indeed the first stage of the test. Although the *2SLS* procedure is here applied on the full sample while the *QR* test performs it on the random subsets generated by the bootstrap procedure, it gives an idea of the quality of the instrumentation. The second lag of *C* appears to be a relevant instrument: its partial R-squared is quite low (0.0477), but the F-stat is 1168.18, associated with a P-value of zero. More importantly, as we will see below the coefficients associated with *C* are very significant in the second stage, a fact that hardly happen if *C*'s instrumentation is weak.

Regarding the orthogonality of the instrument, this cannot be directly tested in the *QR* framework. Moreover, as the model is just identified, there are no overidentifying restrictions to be tested so that the orthogonality cannot be tested in the *2SLS* regression either. However, re-running the first stage with one more instrument allows testing the exogeneity of the 2nd and the other lag used. I have gone along this way using the instrumentation including the 2nd lag and the other lag with highest partial correlation with *C*. Since the latter is the sum of foreign stock markets fluctuations, the instruments with the highest correlation with *C* are the ones most likely to be also correlated with the domestic market's fluctuations (i.e. the dependent variable). They are the most likely to be endogenous. If then the combination with the highest correlation with *C* is exogenous, we can have some confidence in the 2nd lag's exogeneity. The most highly correlated combination is the one with the 2nd and the 6th lag. Applying the Hansen-Sargan test for overidentifying restrictions on the latter gives a statistic of 0.008 associated with a P-value of 93.08. The null of instruments exogeneity cannot be rejected, and the high P-value allows to trust the exogeneity of these instruments. Clearly, the likely exogeneity of the two lags as instrument in the *2SLS* regression does not need to hold for the 2nd lag only and also cannot be generalized to the quantile regressions. The above result must then be interpreted as a hint of the instrument exogeneity. However, the fact that no error autocorrelation is detected in the structural equations makes it hard to conceive why a lagged variable

should be endogenous (see Sections *5.3.4* and *4.3.2* for a detailed discussion of the issue).

If foreign markets' fluctuations have stronger repercussions on the domestic market when the latter is faring badly for idiosyncratic reasons, the coefficients of the mean regression just presented may average out very different coefficients associated with extreme negative quantiles and thus be scarcely informative. In this light, it is interesting to compare the results just discussed with those of the same model estimated at the median. The latter is less sensitive than the mean to outliers and should therefore give a fairer idea of the model's relationship during "normal" times. These are presented in column (2) of Table 5.4. This is a special case of the model described in (5.52)-(5.53) with the median equation only and 200 bootstrap replications.

We can see that there are relevant differences between the median and mean coefficients indeed. The coefficient associated with the contagion index is 0.239 in the median regression. Compared with the 0.414 mean estimate, it represents a 42% drop in the estimated interdependence. The commercial paper spread coefficient also becomes smaller in the median regression (-24%), while the median *NY* coefficient is 21% bigger than its mean counterpart. Given the differences between median and mean coefficients, investigating the relationship among stock markets returns at the extremes of their distribution seems an informative exercise. To this we now turn.

5.4.2   The QR test

Table 5.5 provides the results for the full *7*-equations model estimation. Only the parameters of interest and the related statistics are presented. For each parameter the table provides the estimated coefficient, its bootstrapped standard error, *t* statistic with associate *P*-value and 95% confidence interval. The first seven rows give the statistics for the contagion index *C* for the seven quantiles, starting from 1% up to 99%. The following six rows provide the statistics for the estimated differences between the extreme and the median coefficients.

Focusing on the contagion coefficients *b1* to *b99*, we can see that they show substantial instability and that this takes the form expected. The coefficients at the bottom tail of the distribution (*b1* to *b10*) are notably bigger than at the median, while

b90-b95 are roughly the same size or smaller than the median coefficient. These results suggest a clear pattern: when the domestic market is performing worse than its median (conditional on the regressors' value) it becomes more sensitive to foreign shocks, when it performs better, its behaviour is more idiosyncratic. An exception is when the market is doing extremely well (*b99*). In this case, the domestic market seems very sensitive to foreign shocks, somewhat challenging the previous statement. The 99th quantile coefficient and, as we will see shortly, its difference from the median are however not statistically significant.

The size of the coefficients' difference is notable: the coefficients on the 5% and 10% quantiles *b5* and *b10* are respectively 0.72 and 0.78, roughly three times bigger than the median coefficient (0.24), while the 1% quantile coefficient is 1.47, six times bigger than the median one. To interpret these numbers, consider that the unconditional median market performance is 1.3% while its 5% and 10% quantiles are respectively -6.4% and -10% (see table 5.3). This means that when the domestic stock market is growing at 1.3% and all regressors are zero, a 1% fall in all foreign markets will push it down by 0.24%, while when the domestic market is falling by 6.4% to 10% the same fall in foreign markets will push the domestic market down by roughly 0.7%. When the domestic market is falling by 18% (1% quantile of the dependent variable), a 1% fall will push it down by 1.47%. The results suggest that the mechanism of shocks propagation across stock markets is extremely unstable. When the domestic market is underperforming for idiosyncratic reasons it seems much more sensitive to foreign shocks than when it is performing averagely (or better medianly). Moreover, the worse the domestic market's idiosyncratic performance, the stronger the domestic effects of foreign shocks.

The top tail of the distribution paints a very different picture: the effects of foreign shocks are either the same or smaller than at the median. The contagion coefficient at the 90% quantile is 0.07, compared to 0.24 at the median. Thus, the same change in foreign stock indexes is estimated to be more than three times more contagious *at the median*. Considering that *y*'s unconditional 90% quantile is 0.09, this means that when the domestic market is growing by 1.3% and all regressors are zero, foreign shocks have roughly three times as big effects than when the domestic market is growing by 9%. When the domestic market is growing by 12.9% (the 95% quantile) the coefficient is 0.27, roughly the same as the median one. Therefore, when the market is doing very well for idiosyncratic reasons foreign shocks are affecting it as

or less than when it is at its median performance. When the domestic market is doing exceptionally well (+24%, the 99% quantile) the coefficient is however estimated around 1.2, notably bigger than the median estimate. It seems therefore that there is a break here as well and that foreign shocks are felt more strongly also when the domestic market idiosyncratic performance is exceptionally good, not only exceptionally bad.

The higher coefficients at both extremes of the distribution are somewhat surprising, and may question the validity of the analysis. It could be that, rather than a break in the propagation mechanism, it is common shocks not controlled for by the common shocks proxies that cause stock markets to appear highly correlated in periods of high volatility (if the latter is caused by those uncontrolled common shocks). This is however at odds with two strong findings of the analysis: firstly, only the 99th quantile coefficient is markedly bigger than the median, while if white common shocks are the driving forces behind those differences, we should have all top tail coefficients bigger than the median, just as for the bottom tail ones. Secondly, all top tail coefficients are not statistically significant while all negative ones are. Again, if common shocks are the driving forces behind the results, these should be more symmetric, we should have significant coefficients at both extremes of the distribution. Instead the analysis identifies a statistically significant increasing effect of foreign shocks on the domestic market at the bottom tail of the distribution only. This is a key finding: bottom tail estimated coefficients are consistently bigger than the median and significant, while top tail ones follow unclear patterns and are non significant.

This is reflected in the estimated differences among extreme and median coefficients, which is the key point of this study. So far, we have indeed described how different the estimated coefficients are across quantiles. However, to substantiate the apparent instability of the propagation mechanism we need to assess the statistical significance of the highlighted differences. This is done by estimating the difference between the coefficients at the extreme quantiles and at the median and then applying a standard t test. A rejection of the t tests is interpreted as a proof of propagation mechanism instability, a proof of shift contagion.

The estimated differences, their bootstrapped standard errors and all other relevant statistics are provided in the bottom six rows of table 5.5. The difference

between *b10*, *b5*, *b1* and *b50* is significant at the 0.5%, 5% and 12% significance level, respectively. There is unequivocal evidence of breaks in the propagation mechanism: when the domestic stock market is underperforming (conditional on the independent variables) it is more sensitive to foreign shocks than when it is doing normally (the evidence is however weaker when the market is doing exceptionally bad). Moreover, the more below the median the domestic performance, the stronger the estimated foreign shocks effect becomes. On the other side, there is no evidence of breaks in the top tail of the distribution. The differences between the three top coefficients and the median one are all insignificant at any reasonable level. Stock markets do not appear to be more sensitive to foreign shocks when they are performing above the median (again, conditional on the independent variables).

As noticed earlier, *EMEs* are more represented at the extreme of the dependent variable unconditional distribution while *FC*s are more represented at the median. If that is true for *y*'s conditional distribution as well, it could be that the cross-quantile differences in the estimated coefficient are simply due to the fact that *EMEs* are more sensitive than *FC*s to external shocks. In this case, the difference in the estimated coefficients would not be proof of shift contagion. Rather, it would be proof of higher sensitivity of *EMEs* than *FC*s to foreign shocks. However, if this would be the case we should find that the interdependence coefficients are bigger than the median at both extremes of *y*'s distribution. If anything, the top quantiles should show the biggest and most significant coefficients since *EMEs* are even more dominant there than at the bottom quantiles (see Table 5.1). What we find is instead that the estimated coefficients at the top half of the distribution are smaller than their bottom tail equivalent and not statistically different from the median one, while the bottom ones are. Therefore, the country composition does not seem to be the force behind the results. To substantiate this claim we will however split the dataset in two samples, one including *EMEs* only and another including *FCs* only, and re-run the *QR* test on the two country-homogenous samples. If the sceptic is right and the differences in coefficients are only caused by the higher sensitivity of *EMEs* we should see no cross-quantile differences in the coefficients of the country-homogenous samples. This and other robustness tests are presented in the next section.

5.5   *Sensitivity analysis*

In this section I examine whether the evidence of shift contagion provided by the baseline model is robust to the following alterations:

a)   Homogenous country composition sample. As just discussed, the higher presence of *EMEs* observations at the extremes of the dependent variable's distribution could be behind the higher coefficients found in the extreme quantiles equations. In this case the test would not give evidence of contagion, rather of the higher sensitivity of *EMEs* to foreign shocks. To test this hypothesis, the sample is split between *EMEs* and *FCs*. The results of the *QR* test on the two samples are given by models *S1* and *S2* respectively.

b)   Different extreme quantiles. The choice of what quantiles are considered extreme and thus compared with the median is arbitrary. To limit the arbitrariness of such choice, the analysis is re-run on different quantiles. In model *S3*, the extreme quantiles are (*0.02 0.07 0.15 0.85 0.93 0.98*) while in model *S4* they are (*0.03 0.09 0.20 0.80 0.91 0.97*). By shifting the investigated quantiles one is effectively changing the definition of "exceptional" times (i.e. the definition of "crisis" in the bottom quantiles case). Notice that, with respect to the baseline model, *S3*'s and *S4*'s extreme quantiles are closer to the median, so that the test for contagion becomes more stringent under these specifications. In order to find significant differences among the extreme quantiles coefficients and the median one in *S3* and *S4*, we must have that the break happens in less exceptional cases than the ones identified in the baseline model.

c)   Different time span. Six observations are excluded from the beginning and the end of the sample in models *S5* and *S6* respectively. *S5's* sample excludes most of the aftermaths of the East Asian crises since it starts in July 1998, while *S5's* excludes the current global credit crunch since its ends in June 2007. These two events are arguably the biggest global shocks to financial markets occurred in the baseline sample period 1998-2007, both in terms of the macroeconomic volatility they generated and the real global *GDP* drop they caused. It is then sensible to test whether such

extraordinary events caused the break found in the baseline model or whether the instability is independent from them.

d)   Unweighted contagion index. Stock markets of countries with no relevant trade or financial linkages are often moving together, especially during turbulent times. It was this phenomenon during the crises in the '90s that gave rise to the concept of unexplained-by-fundamentals contagion. By weighting the contagion index *C* for trade intensity, the baseline analysis focuses on the propagation of stock market fluctuations among trade partners. If however other channels of propagation uncorrelated to trade connect stock markets, the analysis would give excessive weight to trade partners as source of shocks. For this reason model *S7* re-estimates the baseline model with an unweighted contagion index.

e)   *NY* substituted by *iUS*. *NY* proxies common shocks affecting all stock markets simultaneously. Wall Street could however be affected by events in other markets, in which case *NY* could be endogenous. A variable commonly used as a proxy for common shocks is the Fed discount rate. The latter is less likely to be influenced by the performance of foreign stock market than the *NYSE*. For this reason, I substitute *NY* with the monthly change in the Fed discount rate (*iUS*) as a proxy for common shocks. In this way, common shocks should still be controlled for, and by a variable less likely to be endogenous. The results of this exercise are presented in the model *S8*.

Tables 5.6 to 5.13 provide the results for the eight variations of the baseline model just described.

The disaggregation of the sample into *EMEs* and *FCs* gives many interesting insights. It proves that country composition cannot be the driving force behind the results. Were this the case, we should see the coefficients in the two country-homogeneous samples more or less constant across quantiles. Instead there are marked differences in their coefficients (see Tables 5.6-5.7). The *EMEs*-only regressions produce a pattern very similar to that of the baseline model: higher coefficients in the bottom tail, stable coefficients in the top tail except for the 99th quantile. *FCs* show the same pattern in the bottom tail of the distribution (higher coefficients at the extremes) but a very different pattern in the top tail. Somewhat

surprisingly, the contagion coefficients turn negative: when *FCs* are overperforming, foreign shocks have opposite-sign effects on the domestic market. To our analysis, the key finding is however that both types of countries show breaks in the bottom tail coefficients. Furthermore, these are bigger and more significant in the *FCs* sample than in the *EMEs* one. If the higher presence of *EMEs* at the extremes is what causes the bigger bottom tail coefficients found in the baseline model, the contrary should be seen: *EMEs* should be more sensitive than *FCs* to foreign shocks and should therefore show bigger and more significant coefficients. Therefore, the results seem driven more by *FCs* than by *EMEs*, since the former show bigger bottom tail coefficients than the latter and more statistically significant differences.

The contagion identified in the baseline model is therefore hardly explainable by the different country composition. However, the pooling of *EMEs* and *FCs* increases markedly the precision of the estimation: the baseline estimates show smaller standard errors than both *S1* and *S2* at all quantiles. The difference between *EMEs* and *FCs* stock markets' performances seems to help to providing the variance necessary to identify the estimated parameters.

Finally, the very different pattern of top tail coefficients between the two types of countries is noteworthy. It could explain the scarce significance of those coefficients in the baseline model. In fact, the latter pools together countries showing opposite reactions to foreign shocks when overperforming. As a consequence, the estimated pooled contagion coefficient may be biased towards zero. Comparing the top tail coefficients *b90*, *b95* and *b99* in the baseline, *EMEs* and *FCs* only regressions gives support to this conjecture: the *EMEs* coefficients are always the biggest, the *FCs* the smallest and the baseline ones lay in between, as if they average out the two extremes. In the bottom tail of the distribution, *EMEs* and *FCs* coefficients are much closer and the baseline coefficients are also close to the latter and significant.

Shifting the definition of exceptional times (i.e. of the extreme quantiles) does not alter the results substantially: bottom tail coefficients are still positively signed, notably bigger than the median one, increasing as one moves towards the extreme and significant, while top tail coefficients are also bigger than the median but less so and always non-significant (see Tables 5.8-5.9). Similarly the differences with the median are positive and significant in the bottom tail while close to zero and non-significant in the top tail. It is further reassuring that the differences becomes smaller and loose

significance as one moves the extreme quantiles closer to the median: as the exceptional times becomes less exceptional, their difference with respect to normal times is less pronounced.

The East Asian and the current financial crisis did not have a fundamental effect on the results either: the pattern found in models *S5* and *S6* tracks closely the one found in the baseline estimation (see Tables 5.10-5.11). The same is true when the contagion index is left unweighted (see Table 5.12). Using the Fed discount rate instead of the *NYSE* performance as a proxy for common shocks has instead notable effects on the estimates. Focusing on the bottom tail coefficients, the contagion pattern is even stronger here than in the baseline model: the *b10*, *b5* and *b1* coefficients increase markedly in size and significance while the opposite is true for the median coefficient, which falls to 0.12 (from 0.23 in the baseline model) and looses significance. As a consequence, the differences between extreme and median coefficients are even bigger and more significant (see Table 5.13). One could think this to be generated by the inability of *iUS* to proxy for common shocks. If *iUS* does not identify common shocks, these move stock markets together therefore generating a positive bias in the estimated contagion coefficients. However, the positive bias should push all coefficients up, since it should increase cross-markets correlations at all quantiles. The median and the top tail coefficients are instead smaller in *S8* than in the baseline model and non-significant, with *b95* and *b99* turning even negative. Common shocks cannot be behind the increased contagion found in *S8*.

The same pattern emerged in the baseline estimation is then found in all variations: the coefficients at the bottom quantiles are positively signed, notably bigger than the median one, increasing as one moves towards the extreme and significant, while those at the top quantiles are similar to the median coefficient (or even negative) and non-significant. Furthermore, the differences between the coefficients at negative extreme quantiles and at the median are positive and significant while at the top tail of the distribution no significant difference is found. We can thus say that different country composition, definitions of crises, time spans, trade weights and control variables used do not alter the key finding of the analysis: the higher sensitivity of stock markets to foreign shocks when the former are underperforming for idiosyncratic reasons.

5.6   Conclusions

Correlation-based contagion tests such as the Forbes and Rigobon (2000) and the *DDC* test introduced by Rigobon (2003) are not very general. They are able to detected contagion only if a crisis generates a very specific structural break. I have argued that this is at odds with the presence of investors' behaviour shifts. These have been widely documented in the recent literature on contagion, and various theoretical models of contagion driven by sentiment shifts have been developed. Correlation-based tests seem then both unappealing theoretically and based on assumptions proven wrong in the major crises that took place in the 1990s.

Extreme-value-based tests such as the Favero and Giavazzi (2002), the Pesaran and Pick (2004) and the Bae et al. (2000) provide more robust alternatives. Contrary to the two tests above, these leave the changes in the idiosyncratic factors' var-cov matrix caused by a crisis unrestricted. However, by limiting the investigation of the existence of breaks in the propagation mechanism only to those caused by "extreme" events, they do not use all the information available in the dataset. As shown by Dungey et al (2005), this reduces seriously the power of those tests in detecting contagion.

The aim of this chapter was to provide a contagion test that retained the appealing unrestricted heteroskedasticity form assumed by the second class of tests while use the full information contained in the dataset as the first class of tests. In this way, the test would provide robustness and power together. This was pursued with an application on stock markets' returns of the two-stage quantile regression technique first suggested by Amemyia (1982). The test was based on the idea that if the propagation mechanism is stable (i.e. if there is no shift contagion), then the effect of shocks coming from foreign stock markets on the domestic one should be similar across the whole distribution of the dependent variable. Thus, a structural equation estimating the interdependence of stock markets should give similar coefficients at the extremes of the dependent variable's conditional distribution as well as at the median. This was tested by estimating a system of seven equations, a median one and three extreme quantiles per part (*0.01 0.05 0.1 0.9 0.95 0.99*), and then testing the null of no difference between the interdependence coefficient across all quantiles and the median. The working hypothesis was that contagion would cause the interdependence coefficients to be bigger at the bottom of the dependent variable's distribution (i.e.

that markets' interdependence would increase during crises or exceptionally bad idiosyncratic performances).

Applying this procedure on a sample of 57 stock market indexes in the 1998-2007 period sizable differences between coefficients at the extreme quantiles and the median were found. These differences are in line with the working hypothesis: at the bottom quantiles the coefficients are bigger than at the median, while they are smaller or similar at the top quantiles. Therefore, while the interdependence coefficient is more or less stable when the domestic market is performing at or above its conditional median, it becomes bigger and bigger as its performance worsens. The differences in the bottom quantiles coefficients are both statistically significant and economically relevant. According to the estimates, with all regressors equal to zero, while a roughly stable market (i.e. a market rising by 1.3%, its unconditional median performance) will react to a percentage point drop in all foreign markets with a 0.24% fall, a plummeting market (falling by 18%, the 1% quantile) will be six times more reactive to foreign shocks, dropping by 1.5% after the same foreign shock. The analysis gives then clear evidence of increased stock markets' interdependence during crises or in general when the latter are underperforming for idiosyncratic reasons.

As pointed out in the opening of this paper, the issue of instability has been studied because it sheds light on three important aspects of financial and international economics: the effectiveness of international portfolio diversification in reducing risk, the effectiveness of microprudential bank regulation and the empirical relevance of crisis-contingent versus non-crisis-contingent contagion models. Regarding the latter, this chapter's findings are consistent with crisis-contingent models such as multiple equilibria models and in general models based on a shift in investor behaviour during crises. In this light it is interesting that tests able to detect contagion in presence of investors behaviour shifts (*FG*, *PP*, *BKS* and *QR*) do detect it in the late '90s period, while the others (*FR/DCC*) do not. The empirical findings of the four models give support to the interpretation of those contagion episodes as a negative shift in investors' behaviour triggered by a crisis onto other countries. Regarding the other aspects, the substantial shift in the propagation of shocks identified by this analysis calls into question the effectiveness of international portfolio diversification based on historical asset returns correlation in reducing risk as well as the effectiveness of the Basel II accord. Being based on Value-at-Risk measures, the latter's capital adequacy requirements are likely to be lower than needed as stock markets correlation increases

in turbulent times. Calls for different measures of assets risk to be included in the Basel III accord under development are indeed common.

It is worth highlighting that the instability identified by the *QR* test is caused by the domestic situation rather than the size of the foreign shocks hitting the domestic market. This analysis shows indeed that foreign negative shocks have stronger effects on the domestic market when this is performing below its conditional median, irrespective of the size of the foreign shock. Extreme-event based tests showed instead that extraordinary negative foreign shocks have stronger proportional effects than normal negative ones, irrespective of the domestic market's performance. Thus, this analysis highlights a new type of contagion, one that depends on the domestic performance of the market rather than on the size of the foreign shock. The general policy implication of this research is thus that, by acting on domestic factors affecting the performance of stock markets, not only would policymakers boost their stock market performance, but they would also render the stock market more resilient to foreign, uncontrollable shocks.

Table 5.1
Country composition
of stock returns at
different quantiles

Quantile	FCs	EMEs
1%	0.199	0.801
5%	0.252	0.748
10%	0.267	0.733
50%	0.441	0.559
90%	0.212	0.788
95%	0.142	0.858
99%	0.066	0.934
MEAN	0.316	0.684

Table 5.2
Summary Statistics

Variable		Mean	Std. Dev.	Min	Max
Domestic stock market return	overall	0.014	0.086	-0.625	2.129
	between		0.008	0.003	0.05
	within		0.085	-0.625	2.094
Contagion index	overall	0.015	0.053	-0.316	0.428
	between		0.005	0.008	0.0289
	within		0.053	-0.33	0.413
NYSE composite index return	overall	0.005	0.036	-0.123	0.103
	between		0	0.0052	0.005
	within		0.036	-0.123	0.103
Commercial paper spread	overall	0.085	0.549	-0.622	4.973
	between		0	0.0849	0.085
	within		0.549	-0.622	4.973

Observations: 6783; Countries: 57; Periods
(months) 121.
All variables in monthly percentage changes

Table 5.3
Stock market returns
quantiles

Quantile	Value	Difference
1%	-0.18054	-0.19366
5%	-0.10078	-0.11389
10%	-0.06481	-0.07793
25%	-0.02321	-0.03633
50%	0.013117	
75%	0.047707	0.034589
90%	0.090962	0.077844
95%	0.128781	0.115664
99%	0.242296	0.229179

Table 5.4
Mean (2SLS) versus median (2SLAD)
estimation of the contagion model

	(1)	(2)
	mean	median
C	0.414***	0.239***
	(0.109)	(0.0746)
dcps	-0.00344*	-0.00259*
	(0.00190)	(0.00142)
NY	0.366***	0.444***
	(0.106)	(0.0622)
Constant	0.00655***	0.00584***
	(0.00149)	(0.00113)
R-squared	0.128	0.066
Observations	6669	
Countries	57	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.5
QR test results
Baseline model

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	1.472	0.799	1.84	0.065	-0.093	3.038
b5	0.788	0.290	2.72	0.007	0.220	1.356
b10	0.726	0.177	4.10	0.000	0.379	1.073
b50	0.239	0.109	2.19	0.029	0.025	0.453
b90	0.068	0.265	0.26	0.798	-0.452	0.588
b95	0.274	0.393	0.70	0.486	-0.496	1.043
b99	1.199	1.228	0.98	0.329	-1.209	3.606
b1 - b50	1.233	0.795	1.55	0.121	-0.325	2.791
b5 - b50	0.549	0.278	1.97	0.049	0.003	1.094
b10 - b50	0.487	0.173	2.82	0.005	0.148	0.825
b90 - b50	-0.171	0.246	-0.70	0.485	-0.653	0.310
b95 - b50	0.035	0.382	0.09	0.928	-0.714	0.783
b99 - b50	0.960	1.218	0.79	0.431	-1.429	3.348
Observations	6669					
Countries	57					
Replications	200					

Table 5.6
QR test results
Model *S1*: *EME*s sample

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	1.387	1.039	1.34	0.182	-0.648	3.423
b5	0.561	0.420	1.34	0.182	-0.262	1.385
b10	0.595	0.311	1.91	0.056	-0.015	1.204
b50	0.243	0.166	1.47	0.142	-0.082	0.568
b90	0.238	0.394	0.60	0.546	-0.534	1.010
b95	0.343	0.470	0.73	0.466	-0.578	1.264
b99	1.397	1.552	0.90	0.368	-1.645	4.439
diff01	1.144	1.048	1.09	0.275	-0.910	3.198
diff05	0.318	0.417	0.76	0.445	-0.499	1.135
diff10	0.352	0.294	1.20	0.231	-0.224	0.928
diff90	-0.005	0.363	-0.01	0.989	-0.716	0.706
diff95	0.100	0.463	0.22	0.829	-0.807	1.007
diff99	1.154	1.569	0.74	0.462	-1.921	4.230
Observations	4563					
Countries	39					
Replications	200					

Table 5.7
QR test results
Model *S2*: *FC*s sample

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	1.062	0.970	1.09	0.274	-0.839	2.963
b5	1.200	0.484	2.48	0.013	0.252	2.148
b10	0.921	0.423	2.18	0.029	0.093	1.749
b50	0.279	0.193	1.44	0.149	-0.100	0.658
b90	-0.066	0.403	-0.16	0.869	-0.857	0.724
b95	-0.322	0.503	-0.64	0.522	-1.308	0.664
b99	-0.351	1.528	-0.23	0.818	-3.346	2.643
diff01	0.783	0.937	0.83	0.404	-1.055	2.620
diff05	0.921	0.444	2.08	0.038	0.051	1.790
diff10	0.642	0.354	1.81	0.070	-0.052	1.335
diff90	-0.346	0.401	-0.86	0.389	-1.131	0.440
diff95	-0.601	0.513	-1.17	0.241	-1.607	0.404
diff99	-0.631	1.515	-0.42	0.677	-3.600	2.338
Observations	2106					
Countries	18					
Replications	200					

Table 5.8
QR test results
Model *S3*: different quantiles

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b2	0.794	0.483	1.64	0.100	-0.152	1.741
b7	0.777	0.249	3.12	0.002	0.289	1.265
b15	0.522	0.163	3.20	0.001	0.202	0.841
b50	0.239	0.109	2.19	0.029	0.025	0.453
b85	0.109	0.213	0.51	0.607	-0.307	0.526
b93	0.218	0.332	0.66	0.511	-0.432	0.868
b98	0.851	0.601	1.42	0.157	-0.328	2.030
b2 - b50	0.555	0.481	1.15	0.248	-0.387	1.498
b7 - b50	0.537	0.234	2.30	0.021	0.080	0.995
b15 - b50	0.282	0.157	1.79	0.073	-0.026	0.591
b85 - b50	-0.130	0.192	-0.68	0.499	-0.506	0.247
b93 - b50	-0.021	0.316	-0.07	0.947	-0.640	0.598
b98 - b50	0.612	0.601	1.02	0.309	-0.566	1.790
Observations	6669					
Countries	57					
Replications	200					

Table 5.9
QR test results
Model *S4*: different quantiles

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b3	0.743	0.381	1.95	0.051	-0.004	1.491
b9	0.755	0.197	3.84	0.000	0.369	1.141
b20	0.426	0.124	3.45	0.001	0.184	0.669
b50	0.239	0.109	2.19	0.029	0.025	0.453
b80	0.089	0.158	0.56	0.574	-0.221	0.399
b91	0.201	0.285	0.70	0.481	-0.358	0.759
b97	0.437	0.462	0.95	0.343	-0.467	1.342
b3 - b50	0.504	0.375	1.34	0.179	-0.231	1.240
b9 - b50	0.516	0.189	2.74	0.006	0.147	0.886
b20 - b50	0.187	0.123	1.52	0.128	-0.054	0.429
b80 - b50	-0.150	0.148	-1.01	0.311	-0.441	0.140
b91 - b50	-0.038	0.266	-0.14	0.886	-0.560	0.483
b97 - b50	0.198	0.458	0.43	0.665	-0.699	1.095
Observations	6669					
Countries	57					
Replications	200					

Table 5.10
QR test results
Model *S5*: different time span

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	1.225	0.863	1.42	0.156	-0.467	2.916
b5	0.837	0.318	2.63	0.009	0.213	1.461
b10	0.707	0.204	3.47	0.001	0.308	1.107
b50	0.244	0.132	1.85	0.064	-0.014	0.501
b90	0.080	0.320	0.25	0.803	-0.547	0.707
b95	0.264	0.503	0.53	0.599	-0.721	1.249
b99	1.088	1.383	0.79	0.431	-1.623	3.800
b1 - b50	0.981	0.872	1.13	0.260	-0.727	2.689
b5 - b50	0.593	0.321	1.85	0.064	-0.035	1.222
b10 - b50	0.464	0.197	2.36	0.018	0.078	0.849
b90 - b50	-0.164	0.290	-0.56	0.573	-0.732	0.405
b95 - b50	0.021	0.467	0.04	0.965	-0.894	0.935
b99 - b50	0.845	1.375	0.61	0.539	-1.851	3.540
Observations	6669					
Countries	57					
Replications	200					

Table 5.11
QR test results
Model *S6*: different time span

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	1.406	0.734	1.91	0.055	-0.033	2.845
b5	0.735	0.311	2.36	0.018	0.125	1.344
b10	0.688	0.201	3.42	0.001	0.293	1.082
b50	0.304	0.116	2.61	0.009	0.076	0.532
b90	0.200	0.278	0.72	0.472	-0.345	0.744
b95	0.267	0.412	0.65	0.517	-0.540	1.074
b99	1.099	1.130	0.97	0.331	-1.116	3.314
b1 - b50	1.102	0.727	1.52	0.130	-0.323	2.527
b5 - b50	0.431	0.312	1.38	0.167	-0.181	1.042
b10 - b50	0.384	0.195	1.97	0.049	0.002	0.766
b90 - b50	-0.104	0.258	-0.40	0.686	-0.610	0.401
b95 - b50	-0.037	0.406	-0.09	0.927	-0.832	0.758
b99 - b50	0.795	1.111	0.72	0.474	-1.382	2.972
Observations	6669					
Countries	57					
Replications	200					

Table 5.12
QR test results
Model *S7*: unweighted contagion index

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	2.622	1.651	1.59	0.112	-0.614	5.859
b5	1.997	0.683	2.93	0.003	0.659	3.335
b10	2.104	0.342	6.15	0.000	1.434	2.775
b50	0.589	0.183	3.22	0.001	0.230	0.947
b90	0.022	0.465	0.05	0.962	-0.889	0.934
b95	0.449	0.626	0.72	0.473	-0.778	1.676
b99	2.359	2.013	1.17	0.241	-1.587	6.305
b1 - b50	2.034	1.644	1.24	0.216	-1.188	5.255
b5 - b50	1.408	0.667	2.11	0.035	0.100	2.716
b10 - b50	1.516	0.338	4.48	0.000	0.853	2.179
b90 - b50	-0.567	0.449	-1.26	0.207	-1.446	0.313
b95 - b50	-0.140	0.634	-0.22	0.825	-1.382	1.103
b99 - b50	1.770	2.022	0.88	0.381	-2.193	5.733
Observations	6669					
Countries	57					
Replications	200					

Table 5.13
QR test results
Model *S8*: *iUS* substituting *NY*

	Observed Coefficient	Bootstrap Std. Err.	z	P>|z|	Normal [95% Conf.	Based Interval]
b1	2.396	1.052	2.28	0.023	0.334	4.459
b5	1.728	0.640	2.70	0.007	0.474	2.983
b10	0.948	0.443	2.14	0.032	0.079	1.818
b50	0.121	0.163	0.74	0.457	-0.198	0.441
b90	-0.565	0.370	-1.53	0.126	-1.290	0.159
b95	-0.688	0.573	-1.20	0.230	-1.811	0.435
b99	-1.963	1.762	-1.11	0.265	-5.415	1.490
b1 - b50	2.275	1.071	2.13	0.034	0.177	4.374
b5 - b50	1.607	0.645	2.49	0.013	0.342	2.872
b10 - b50	0.827	0.431	1.92	0.055	-0.018	1.673
b90 - b50	-0.687	0.343	-2.00	0.045	-1.358	-0.015
b95 - b50	-0.810	0.552	-1.47	0.143	-1.892	0.273
b99 - b50	-2.084	1.740	-1.20	0.231	-5.493	1.326
Observations	6669					
Countries	57					
Replications	200					

Appendix 1: STATA ado file performing the QRtest

```
use C:\…\Dset.dta
log using  C:\…\QRtest4.log, replace

drop v1-NYSE
drop w1-dw57
drop cps Cnw
drop if y==.
rename dNYSE NY

program QRtest, rclass
      sort country time
      quietly {
            tempvar xb
            reg C L2.C L6.C dcps NY
            predict `xb'
            }

      sqreg y `xb' dcps NY, quantile (1 5 10 50 90 95 99) reps(2)
            return scalar b1 = [q1]`xb'
            return scalar b5 = [q5]`xb'
            return scalar b10 = [q10]`xb'
            return scalar b50 = [q50]`xb'
            return scalar b90 = [q90]`xb'
            return scalar b95 = [q95]`xb'
            return scalar b99 = [q99]`xb'
            return scalar diff01 = [q1]`xb'- [q50]`xb'
            return scalar diff05 = [q5]`xb'- [q50]`xb'
            return scalar diff10 = [q10]`xb'- [q50]`xb'
            return scalar diff90 = [q90]`xb'- [q50]`xb'
            return scalar diff95 = [q95]`xb'- [q50]`xb'
            return scalar diff99 = [q99]`xb'- [q50]`xb'
            end

bootstrap b1 = r(b1) b5 = r(b5) b10 = r(b10) b50 = r(b50) b90 =
r(b90) b95 = r(b95) b99 = r(b99) diff01 = r(diff01) diff05 =
r(diff05) diff10 = r(diff10) diff90 = r(diff90) diff95 = r(diff95)
diff99 = r(diff99) , reps (1000) seed(1): QRtest
```

CHAPTER 6 - FINAL CONCLUSIONS

The study of financial contagion has developed into the study of which channels render financial markets of different countries interdependent, and how stable the interdependency is across time. This thesis investigated both aspects, integrating the currency mismatches phenomenon in the picture.

The theoretical model presented in chapter 3 showed how currency mismatches render exchange rate volatility detrimental to the aggregate supply via its effect on firms' costs of funding. External disturbances such as trade shocks or flight to quality phenomena can translate into higher exchange rate volatility and thus affect the domestic supply. This channel does not need direct trade or financial linkages to work, so that volatility can theoretically be transmitted to any country with substantial liability dollarization. This is a situation in which several EMEs have found themselves. Notably, some of the worst affected countries in the '90s crises fell in this category: Argentina affected by the Mexican crisis in 1995, Indonesia and Korea affected by the Thai crisis in 1997, Brazil affected by Russia in 1998. Also, the same countries shared at most weak trade or financial linkages with the crisis countries. It is indeed this fact that led researchers to blame investor behaviour for the spread and virulence of the contagion. Notably, the shift in investor behaviour documented in those episodes was considered mostly irrational, detached from fundamentals. The model presented in Chapter 3 provides a different interpretation of contagion. The latter is still viewed as potentially caused by a shift in investor behaviour, but this is a consequence of the objective deterioration of the economy's fundamentals (i.e. of the increased perceived volatility of the exchange rate and therefore the risk associated with loans to the country). Contagion is thus related to fundamentals, although to a previously neglected one: exchange rate volatility in a dollarized financial system.

Where trade links between countries are present, theoretical models suggested that currency mismatches might magnify the effects of trade level shocks (i.e. shocks to the level of net exports). This is an important issue in the theory of contagion as trade has been identified as the major source of output co-movements across countries from both the literature on optimal currency area and financial contagion. Currency mismatches' magnifying effect of trade shocks' real effects could then explain at least partly the higher observed output volatility in EMEs. To assess the empirical

relevance of this argument, chapter 4 tested three related hypotheses: a) that currency mismatches magnify the real effects of negative trade shocks, b) that currency mismatches magnify trade-related output volatility (i.e. that they magnify the real effects of trade shocks of either sign) and c) that currency mismatches generate asymmetric trade shocks propagation (i.e. that negative trade shocks propagate more strongly than positive in presence of currency mismatches).

The results give strong support for all first three hypotheses: currency mismatches magnify the real effects of trade shocks, both positive and negative. They also generate asymmetry in the propagation mechanism, with negative trade shocks being felt more strongly than positive ones.

These findings show that foreign disturbances such as output fluctuations can propagate in very different strength, depending on various factors such as the sign of the shock and the presence of currency mismatches. In other words, the propagation mechanism of output fluctuations seems unstable. If this is true for output fluctuations, what about financial variables fluctuations? This issue has been given much attention in the literature, for the reasons explained in the opening of chapter 5.

This thesis contributed to the debate proposing a new instability test, based on Quantile Regressions. This was applied to monthly stock market data, giving strong support to the instability hypothesis. When stock markets are doing badly for idiosyncratic reasons (i.e. when their aggregate index is dragged down by domestic factors), swings in foreign stock indexes are felt more strongly than when the domestic market is rallying for idiosyncratic reasons. The estimated differences in the effects of foreign disturbances are both statistically significant and economically relevant: while a roughly stable market (i.e. a market rising by 1.3%, its unconditional median performance) will react to a percentage point drop in all foreign markets with a 0.24% fall, a plummeting market (falling by 18%, the 1% quantile) will be six times more reactive, dropping by 1.5% after the same foreign shock. The analysis gives then clear evidence of increased stock markets' interdependence when the latter are underperforming for idiosyncratic reasons.

The thesis' main findings can be summarized in three points:

      a)   currency mismatches are a key factor determining the direction and strength of the transmission of disturbances across financial markets

b)	among these disturbances increases in macroeconomic volatility can be theoretically as damaging as deterioration in the levels of macroeconomic fundamentals, so that increases in uncertainty about the macroeconomic environment is as damaging as its certain deterioration in presence of currency mismatches. The empirical relevance of this point has to be however tested.

c)	the propagation of shocks across stock markets is unstable, with cross-market correlations increasing markedly during turbulent times.

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