Liquidity Contagion: a look at Emerging Markets

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Abstract

Emerging economies have passed an important stress test during the period 2008-09 and are now the key drivers for global growth of the world economy. Financial markets are today so interconnected that they are fragile to contagion. The issue of financial contagion was historically concerning Emerging Markets (EM). These latter attract foreign investors and massive investments funds in -and out- flows on very short horizons can be a source of contagion effects between markets. The analysis of the sovereign debt markets and particularly related CDS markets is of interest since it is at the very center of a new phenomenon: banks are not anymore the main source of systemic risk but sovereign economies are. As foreign investors represent the most of the volume traded, capital flows in these markets should also impact FX market. Their analysis is thus also central to this study. Indeed, the main risk for an asset manager is to get stuck with unwanted sovereign debt due to a dry up of market liquidity. The main contribution of this paper is the analysis of contagion looking at common markets liquidity problems to detect funding liquidity problems. We use the Credit Default Swap bond spread basis and the deviations from the Covered Interest Parity as liquidity measures respectively for sovereign debt and FX markets. Moreover, we distinguish interdependence and pure contagion using a state-space model with a time-varying volatility specification and we apply it to both returns and liquidity indicators.

JEL classification: G01, G15, C01, C32

Key words: Emerging Markets, Sovereign Debt Market, Spread Basis, Liquidity, Contagion Effects, Regime Switching models.

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1 Introduction

The term of *emerging markets* (EM hereafter) appears for the first time in 1981. Since then the World Bank classifies as EM any markets meeting at least one of the following criteria: (i) being located in a low or middle-income economy as defined by the World Bank, (ii) not exhibiting financial depth; the ratio of the countrys market capitalization to its GDP is low , (iii) existence of broad based discriminatory controls for non-domiciled investors, or (iv) being characterized by a lack of transparency, depth, market regulation, and operational efficiency. The creation of emerging markets is motivated by the need of developing countries to raise capital to finance their growth. Before the 2000s developing countries borrowed either from commercial banks or from foreign governments multilateral lenders (International Monetary Fund or World Bank). Capital flows to emerging markets increased dramatically. Commercial bank debt that was the dominant source of foreign capital is replaced by portfolio flows and foreign direct investment [Bekaert and Harvey (2003)].

EM are today considered as an asset class by many investors. Emerging economies have passed an important stress test during the period 2008-2009 and are now the key drivers for global growth of the world economy. As pointed out by the JP Morgan recent study, "*Potential growth rates for emerging economies of 5.8% now overshadow potential growth of only 1.6% for advanced economies*". This explains why these markets are associated with very interesting investment opportunities for any investor seeking both returns enhancement and diversification. Inflows into EM have reach a record of US\$70 billion in 2010 and will continue to grow as EM yields stay attractive in the context of current global bond markets. Also interesting to notice, the proportion of EM sovereign debt in local currency now account for around 80% of the total EM sovereign debt. As a consequence, any simple mean-variance portfolio optimization suggests a high allocation to EM debt. Different client surveys made by banks show an increase in EM debt allocation from around 20% in 2009 to around 25% one year later. However, EM investments must be carefully analyzed. They suffer from additional risk, such as liquidity risk and, in some cases, systemic risk, that are not taken into account in the basic mean-variance

World Bank define *low GDP* as less than 755 USD per capita.
fixed income and equity.

JP Morgan Securities, Emerging Markets Research, EM Moves into the Mainstream as an Asset Class, November 23, 2010

approach.

Investors must analyze EM investments opportunities with a particular focus on these liquidity and contagion dimensions. In this sense, the sovereign EM debt example is a good illustration. The volume of issuance stagnates in US dollars, while booming in local currencies, simply because investors favor emerging debt in local currency. The latter instruments have indeed two performance drivers: the local currency and the local bond yield, instead of only one (the credit spreads over US Treasuries) in the case of US dollars denominated debt. As a consequence, expected returns are higher, but new risks appear, with an additional exposure to the currency risk. Many examples clearly indicate some contagion channels that can appear between EM via FX markets. Moreover, this sensitivity to the FX liquidity can also create new contagion channels between EM debt and equity markets. Any investor who wants to reduce his risk exposure to one of the two markets will have an indirect impact on the other one via FX markets. Hence, the liquidity of Emerging FX markets is key to understand contagion effects and systemic risks in the EM context.

The aim of the present paper is to analyse contagion effects in emerging economies. In 2008-2009 a risk transfer from the financial to the public sector has occurred. Ejlsing and Lemke (2010) study the time varying dimension of this risk transfer. They show that, after the rescue packages, the sensitivity of bank CDS premia to further aggravations of the crisis declined while the sovereign sensitivity sharply increased. Acharya et al. (2011) provide evidence that financial sector bailouts and sovereign credit risk are intimately linked. Indeed, the government may have to issue sovereign bonds to finance a bank bailout. However, this issuance deteriorates the creditworthiness of the country. The reduction of its guarantees and existing sovereign bond values increases the sensitivity of the financial sector to future sovereign shocks. As a result, we show that banks are not anymore the source of the systemic risk as previously but the sovereigns are. We choose to focus on the sovereign Credit Default Swap (thereafter CDS) market that price the risk of loosing value for sovereign bond. Moreover, we analyze the dynamic of the CDS bond basis that is a liquidity indicator for this market. The contribution of this paper is twofold. First, we propose two new measures of liquidity for EM. Second, we model of contagion effects through the analysis of liquidity. Thus, we analyze in this paper, the contagion effects looking at common markets liquidity problems to detect funding liquidity problems.

During the past 20 years, financial markets became more and more interconnected and, as a consequence, more and more fragile to contagion. For example, massive investment funds' in- and out- flows on very short horizons can be a source of contagion effects. Brunnermeier and Pedersen (2009) distinguishes funding liquidity from market liquidity. The first characterizes the possibility for traders to find funds while the second characterizes the ease to trade an asset on the market. Traders provide market liquidity and their ability to do so depends on their capacity of funding. Funding liquidity is binding market liquidity as traders can only provide liquidity if they can access to fundings. In this paper, we analyze contagion on this funding liquidity perspective measuring the market liquidity of the FX market. In this paper, we study the liquidity in a funding perspective analyzing the re-correlation of market liquidity indicators. However, measuring the market liquidity can be made with several available measures. For example, Aitken and Winn (1997) report more than 68 measures for market liquidity. Many liquidity measures require the use of high-frequency transactions and quotes data, which may not be available for some markets, especially for emerging markets. Goyenko et al. (2009) focus on liquidity measures based on daily data and show that most measures are outperforming a liquidity benchmarks such as the effective or realized spread. Moreover, they expose two main difficulties. First, measuring liquidity depending on the availability of data. Second, computing liquidity measures only with price data. There exists few measures based of daily price data. Roll (1984) develops an implicit measure of the effective bid-ask spread based on the serial covariance of daily price changes. Hasbrouck (2004) uses a Bayesian estimation approach to estimate the Roll model and proposes a Gibbs measure of liquidity. Lesmond et al. (1999) use the proportion of zero return days as a proxy for liquidity. In this paper, our two liquidity indicators are rely on daily price data that are available on the main part of emerging countries. Using low frequency data allow the study of longer periods and the computation of estimation models for contagion.

Financial contagion is definitely a burning issue and a major concern in the academic literature, particularly since the end of 1990's. Since last summer, we observe some contagion phenomena that play a crucial role in exacerbating the sovereign debt problems in the euro area. But before this, the issue of financial contagion was mainly concerning EM with the Asian crisis 1997-1998, the Russian crisis 1998, the Brazilian crisis 1999, Turkish crisis in 2001 and

Argentinean crisis in 2002. This refers to the notion that financial markets move more closely together during turmoil (Bekaert and Harvey (2003)). Rigobon (2001) recall that if economists agree about which events have constituted instances of contagion, there is still no consensus on a definition of contagion. The World Bank provides three definitions of contagion: (i) *Broad definition*: contagion is the cross-country transmission of shocks or the general cross-country spillover effects., (ii) *Restrictive definition*: Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behavior, (iii) *Very restrictive definition*: Contagion occurs when cross-country correlations increase during crisis times relative to correlations during tranquil times. The latter is the more restrictive definition but is also the most widely used to measure it. Contagion occurs when cross-country correlations increase during troubled periods relative to correlations during tranquil times. In the main stream of literature, the analysis of contagion is mostly concentrated on testing the stability of econometric model parameters. However, Forbes and Rigobon (2002) show that the problem of heteroscedasticity has to be taken into account in order to measure pure contagion and not interdependence effects.

The remainder of this paper is organized as follow. In section 2, we describe our two market liquidity indicators. Section 3 presents the data on CDS Bond Spread basis and FX market separately and proposes a preliminary data analysis. Section 4 is dedicated to the empirical results on liquidity and contagion. We introduce tests and methods which allow us to demonstrate the relation between our indicators and the emerging market liquidity. Finally, section 5 concludes the paper.

2 Methodology

This section is devoted to present the liquidity indicators and the model of contagion. We start by describing the CDS bond spread basis (basis hereafter) that evaluates the liquidity on the sovereign debt market and the Absolute deviations of the Covered Interest Parity (AbCD

(i) debt crises in 1982, (ii) the Mexican Tequila effect in 1994, (iii) the Asian crisis in 1997, (iv) the Russian and LTCM crisis in 1998, (v) Brazilian devaluation in 1999, (vi) the Internet Bubble in 2000, (vii) the Argentina default crisis in 2001 and recently (viii) the subprime crisis.

hereafter) that assesses the liquidity of the FX market.

2.1 Liquidity Indicators

Emerging markets exhibit some liquidity problems during the past ten years. We propose to evaluate the liquidity on sovereign debt market and on the FX market, using the basis and the AbCD.

2.1.1 For the sovereign debt market

There exists many determinants of liquidity on emerging sovereign debt markets. First of all, the size of the market is preponderant at the beginning of 2000s, when emerging markets are small. The increase of liquidity between 2005 and 2007 is partly due to the importance of inflows. However, the investor base has to stay as large as possible to guarantee market liquidity. This is the problem for Asia at the beginning of 2000's years. Nevertheless, the absence or inadequacy of hedging tools makes the market illiquid. Once again, this is the case in emerging markets early in 2000. Moreover, the valuation of the bond to its historical cost rather than its market value induces investors to keep their bonds to maturity. Thus, the secondary market is less liquid. These facts are common to all emerging markets that, at the start of their growth suffered from not being sufficiently developed relatively to the size of the inflows.

CDS were created in 1994 by J.P Morgan & CO. Since its creation the CDS market is rose until 2008 and has stagnated since. CDS became in a few years a standardized financial product used by most of the market major participants (banks, hedge funds, mutual funds...). Nowadays, it is one of the most popular tool for transferring credit risk. The CDS contract is defined as a bilateral contract that provides protection on the par value of a specified reference asset. The protection buyer pays a periodic fixed fee or a one-off premium to a protection seller. In return, the seller will make a payment on the occurrence of a specified credit event [Choudhry (2006), Mingle (2007)]. Then, CDS provides to buyer a protection against the risk of default by borrowers, named the entities. The default, also named *credit event* is contractually defined by the two parties and could be bankruptcy, failure to make a schedule payment, obligation default, debt moratorium, financial or debt restructuring and credit downgrade. This is important to

The main part of CDS are documented using the 2003 ISDA Credit Derivatives Definitions, as supplemented

precise that rating agencies have not influence in triggering CDS. Their actions may, but not need, taken into account. The protection buyer has to pay an amount of fees (also named CDS premium or CDS spread) to protection seller and receives a payoff if the underlying bond experiences a credit event. At the deal inception, the two parts define which kind of settlement they want. The CDS contract could be settled in one of two ways: cash or physical settlement. Most of the time, contracts are physically settled (about 75-85%). Although the CDS contract has a given maturity, it may terminate earlier if a credit event occurs. In this case, the protection seller has to pay an amount called the protection leg.

The basis is nothing else but correcting the CDS from the sovereign bond (CDS bond spread basis) is a way to cancel out the global macro effects when analyzing the commonality of sovereign risk. In other words, its a way to focus on long term liquidity. The basis is defined as the difference between the asset itself and its synthetic version. The no arbitrage theory of pricing CDS implies that the basis should be zero. However, in practice it is almost never the case. This is a result of a combination of factors. Indeed, the level of the basis could fluctuate for many reasons that could be split into two categories: technical and market factors. We mainly find in the technical factors the delivery option and counterparty risk. To characterize the first, we have to define what *deliverable options* means. CDS contracts usually allow buyer and seller to agree on a panel of alternative assets that the buyer can deliver in case of a credit event. However, this allows to the buyer to deliver the cheapest obligation that he possesses in his eligible basket of assets. However, this option does not add value systematically even in the case of sovereign debt market. The second is the counterparty risk. On the one hand, the protection seller can default and do not settle the protection buyer in case of a credit event. On the other hand, the buyer can also default and stop paying the CDS premium to the seller. However, some mechanisms like counterparty clearing system allow to reduce these risks (almost half of CDS are treated by clearing). Moreover, as we see on Levy (2009), if the default probability of the underlying bond and the default probability of the counterparty are not correlated, the two effects cancel each other out. Furthermore, counterparty risk is a joint event of two defaults. Thus, the excess premium associated is weighted by a product of two probabilities and should be really small, or negligible. Our aim being the analysis of the dynamic of the emerging market liquidity, we

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neglect the counterparty risk. Indeed, based on a demonstration proposed by Levy (2009), we focus on the liquidity premium induced by the movements of the basis on emerging markets.

CDS includes two legs corresponding to the premium payments and the default payment. The pricing of a CDS depends on the recovery amount (a recovery rate of par value and accrued interest). Following Duffie (1999) or Hull and White (2000) they expose two approaches for the CDS Spread pricing. The first that we call "no arbitrage" approach follows the idea that an investor can buy a CDS and the underlying bond to replicate the risk free rate. The second is based on a reduced-form model with random stopping time. We use the first one. Indeed, buying a risky bond and its CDS with the same maturity allow to the investor to eliminate the default risks associated with the bond. Assuming that there is no arbitrage opportunities, this portfolio should be equal to the value of the risk free bond with the same maturity. As in Zhu (2006), we price CDS premiums and Bonds separately. Then, we construct a portfolio that replicate the CDS contract and we obtain the CDS Spread Basis. In this context we assume a risk neutral world with three assets: a risk-free bond, a risky bond and a CDS contract.

Following Levy (2009), under the risk neutral valuation, we note the CDS premium, b satisfies:

$$\sum_{t=1}^T be^{-rt}F(t) = \int_0^T (100 - RV_t)e^{-rt}f(t)dt, \quad (1)$$

where T is the number of times till maturity or default, r is the risk-free rate, RV_t is the recovery value at time t , $f(t)$ is the probability of default at time t and $F(t)$ is the survival probability. The left hand side is called the Premium leg and the right hand side is called the Insurance leg.

The value of the risky bond is expressed as:

$$Y = \sum_{t=1}^T Ce^{-rt}F(t) + 100e^{-rT}F(T) + \int_0^T RV_te^{-rt}f(t)dt, \quad (2)$$

where C is the fixed coupon paid for each period.

And the value of a risk-free bond at risk-free rate r is expressed as:

$$F(t) = 1 - \int_0^t f(x)dx$$

$$100 = \sum_{t=1}^T r e^{-rt} + 100 e^{-rT}. \quad (3)$$

Then, we construct a portfolio that shorts the risky bond and buys the risk free bond subtracting (2) to (3), we obtain:

$$100 - Y = \sum_{t=1}^T r e^{-rt} + 100 e^{-rT} - \sum_{t=1}^T C e^{-rt} F(t) - 100 e^{-rT} F(T) - \int_0^T R V_t e^{-rt} f(t) dt. \quad (4)$$

But if we modify the risk-free bond equation to include default probability, we obtain:

$$100 = \sum_{t=1}^T r e^{-rt} F(t) + 100 e^{-rT} F(T) + \int_0^T 100 e^{-rt} f(t) dt \quad (5)$$

Then, the value of our portfolio is :

$$100 - Y = \sum_{t=1}^T (r - C) e^{-rt} F(t) + \int_0^T (100 - R V_t) e^{-rt} f(t) dt \quad (6)$$

However, rearranging with equation (4), we obtain:

$$100 - Y = \sum_{t=1}^T (b + r - C) e^{-rt} F(t) \quad (7)$$

Finally, the CDS Bond Spread Basis is expressed as:

$$b + (r - C) = \frac{100 - Y}{\sum_{t=1}^T e^{-rt} F(t)} \quad (8)$$

The CDS Spread Basis is then equal to zero since the risky bond is traded at par, ie $Y = 100$. Moreover, the fixed coupon of a par bond is equal to the bond's yield to maturity ($y = C$) and we have:

$$b - (y - r) = 0 \quad (9)$$

Moreover, assuming that there are two traders: (i) with high liquidity (h) and (ii) with low liquidity (l). Note b_i the CDS premium fair price for the trader i , $i = l, h, \tilde{S}$, the market price for

this CDS and p_i the probability to find in the first search a trader who are of type i . Then, we know that a trader who have liquidity problems, should pay an additional holding cost. Then, from equation (4) we obtain:

$$\sum_{t=1}^T b_h e^{-rt} F(t) = \int_0^T (100 - RV_t) e^{-rt} f(t) dt \quad \text{for high liquidity traders} \quad (10)$$

$$\sum_{t=1}^T b_l e^{-(r+d)t} F(t) = \int_0^T (100 - RV_t) e^{-(r+d)t} f(t) dt \quad \text{for low liquidity traders} \quad (11)$$

where d is the additional holding cost.

Then, from these two equation we can extract the CDS premium for each type of traders as:

$$b_h = \frac{\int_0^T (100 - RV_t) e^{-rt} f(t) dt}{\sum_{t=1}^T e^{-rt} F(t)} \quad \text{for high liquidity traders} \quad (12)$$

$$b_l = \frac{\int_0^T (100 - RV_t) e^{-(r+d)t} f(t) dt}{\sum_{t=1}^T e^{-(r+d)t} F(t)} \quad \text{for low liquidity traders} \quad (13)$$

Obviously, trade occurs only if $b_h < \tilde{b} < b_l$. Moreover, introduce the value of search process V . The trader have to be indifferent between searching alone of buying at a market maker. Then:

$$V = p_h b_h + p_l (V + C) = \frac{p_h b_h + C p_l}{1 - p_l} \quad (14)$$

where C is the search cost.

Then, we obtain the market price $\tilde{b}$ that is equal to:

$$\tilde{b} = V = b_h + \frac{C p_l}{1 - p_l} \quad (15)$$

with $\frac{C p_l}{1 - p_l}$ is the additional spread for the asset (CDS and bond that we note respectively S_{CDS} and S_{bond}).

We note $\tilde{b}$ is the market price for the CDS, equal to $\tilde{b} = b + S_{CDS}$ and $\tilde{y}$ is the market price for the bond, equal to $\tilde{y} = y + S_{bond}$. Then, taking into account liquidity, equation (16) is

expressed as:

$$\tilde{b} = \tilde{y} - r - (S_{bond} - S_{CDS}) \quad (16)$$

As we see in Ammer and Cai (2007), the CTD option could be valuable for the emerging sovereign debt market. However, our model is based on the fact that there exists some frictions interfering with exact arbitrage between CDS and bonds particularly the liquidity of the sovereign debt market. In this context, it becomes really difficult to model and evaluate the CTD option. Indeed, Ammer and Cai (2007) propose to measure the spread part that could be attributed to CTD option. Their model requires two strong assumptions allowing to measure the CTD option: the recovery rate is independent of time-to-default and the CTD option is the only friction. However, this is empirically proved that market liquidity is one of the main friction interfering in the arbitrage relation between the CDS premium and the bond yield spread over the risk free rate. Moreover, the recovery rate is time dependent given that it corresponds to the recovery rate of the underlying bond. Then, as the CTD option, although valuable, is sometimes null we neglect it in our model to focus on the market liquidity. To conclude, the parity between CDS and risky bond should hold only for the pure risk component that is priced into the two assets. Then, we can expect a non zero basis when liquidity differences exist.

2.1.2 For the FX market

Sovereign debt markets in local currency is today actively traded. Moreover, their returns are driven by local currency as well as by bond yield and as a consequence, they suffer from the behavior of the FX market. Emerging markets experience a reduced market depth and despite the fact that the FX market is the largest market in the world, it experiences liquidity problems. One common knowledge is that Covered Interest Parity (thereafter CIP) cannot be verified in crisis periods. Indeed, the CIP theorem states that the interest differential between two assets, identical in every respect except currency of denomination, should be zero once allowance is made for cover in the forward exchange market [Taylor (1989)]. In other words, the absence of arbitrage opportunities state that two instruments with the same future cash-flows should be traded at the same price. Fong et al. (2008), Baba and Packer (2009), Fong et al. (2010) and

Griffoli and Ranaldo (2010) bring out the relation between CIP deviations and liquidity.

As a result, in theory, there is no interest rate arbitrage opportunities between those two currencies. Many studies confirm this result. However, the theory does not take into account market frictions. Among them, we find the market liquidity that creates a difference between theory and practice. Indeed, in practice, although these deviations are not always profitable, they are the result of market frictions. Moreover, the theory is in contradiction with the profit that practitioners make out of these strategies. We claim (as in Roll et al. (2007)) that CIP and particularly these deviations could be interpreted as a liquidity indicator on FX market. The CIP is expressed as:

$$\frac{(1 + i_d^k)}{(1 + i_f^k)} = \frac{F^k}{S} \quad (17)$$

where i_d^k and i_f^k are respectively domestic and foreign interest rates of maturity k , F^k is the forward rate with maturity k and S is the spot rate.

We assume that any deviation from equation [17] represents a pure risk-free arbitrage opportunity in a frictionless world. Thus, the liquidity indicator for the FX market is the Absolute CIP Deviations (or $AbCD$). We note, with the same notations:

$$AbCD^k = \left| \left[\frac{(1 + i_d^k)}{(1 + i_f^k)} \right]^{\frac{D}{365}} - \frac{F^k}{S} \right| \quad (18)$$

where D is the number of days to maturity of forward and deposit contracts (only if interest rates are quoted in percent per annum).

$AbCD$ are time varying due to market liquidity frictions. Deviations of CIP in other words $AbCD$ significantly different from zero, could be one necessary, though insufficient condition, of economically profitable arbitrage opportunities. Fong et al. (2008) demonstrate that shocks to either liquidity are short-lived and both variables revert to their average level in a relative short period. However, $AbCD$ should never be equal (or almost equal) to zero. In this paper, we use the relation between $AbCD$ and market liquidity as Fong et al. (2008) that show that liquidity has a significant impact on subsequent $AbCD$ and the longer the maturity the larger $AbCD$ (as

we see on figure 1).

Figure 1 – Absolute Covered Interest Rate Parity Deviation, the longer maturity the larger $AbCD$. (1month, 3months and 6months from darkest to lightest). Database is ranging from 01/01/2002 to 25/02/2011.

2.2 Enhanced Carry Trade

The asset management approach that we analyze in this paper leads to change the computation of our liquidity indicator, the basis. Indeed, this latter, as we exposed above, is only true while the investor have dollar denominated assets. However, an asset manager who has a sovereign debt portfolio invests in several different instruments that are denominated in several different currencies, especially in the local sovereign debt. Thus, the CDS Bond Spread basis that compares CDS premium denominated in dollar and the local currency denominated sovereign debt is biased. To tackle this problem, we compute and correct the P&L or profit and loss, of a investment strategy corresponding to the basis. The computation of the P&L is the way that traders refer to the daily change of the value of their trading positions. The P&L is generally defined as the difference between the value at time $t + 1$ and the value at time t . Thus, we expose how to compute the P&L of a standard carry trade strategy, before introduce it in the

computation of an enhanced carry trade P&L based on a sovereign investment strategy.

2.2.1 Standard Carry trade

When a foreign interest rate is significantly greater than the domestic interest rate, asset managers can easily make a profit, lending in the foreign country an amount previously borrowed in their domestic country. Thus, a standard carry trade strategy implies to borrow low-interest-rate currencies and lend high-interest-rate currencies regardless the exchange rate risk. We distinguish two cases, the empirical and the theoretical. Note into a dynamic dimension, X_t the spot rate at time t such as 1 unit of local currency is equal to X_t dollars. Thus, we can expose the standard carry trade strategy as:

$$(1 + r_{t,1M}^{\$}) = \frac{X_{t+1}}{X_t}(1 + r_{t,1M}^{loc}) \quad (19)$$

where $r_{t,1M}^{\$}$ is the domestic interest rate and $r_{t,1M}^{loc}$ is the foreign interest rate both with a one month maturity.

The left part is the cost of the short position corresponding to borrow 1 dollar while the right part is the investment made in the foreign country. In a theoretical framework, X_{t+1} will be replaced by F_t the forward rate and coming back to a covered arbitrage relation explained above with the *AbCD*. However, the valuation of the forward rate requiring the application of a model, its application is considered as theoretical. Then, we use the first strategy exposed to enhance the sovereign carry trade that is an uncovered strategy from the exchange rate risk.

We see in that case that we benefit from the difference between domestic and foreign interest rates. However, this benefits are made at a short term horizon. We analyze in this paper the availability to benefit from the spread between long term local rates. Thus, we add into the standard carry trade strategy, the investment in long term assets both for domestic and foreign countries.

2.2.2 Credit Carry Trade toward an Enhanced Carry Trade

Following the same idea, we consider a credit carry trade strategy as a standard carry trade strategy investing in sovereign debt and therefore with a longer maturity. Indeed, the arbitrage

is on long term assets as a CDS premium and the sovereign generic bond yield with a 5 years maturity. As we see above, this strategy is expressed in two parts. The first part corresponds to borrow 1\$ in our domestic country with 5 years maturity while the second part is the return of investing in the foreign sovereign debt with 5 years maturity. Under the absence of arbitrage opportunity assumption, the short and the long strategy should be equal as:

$$(1 + r_{t,5Y}^{\$}) = \frac{X_{t+1}}{X_t}(1 + r_{t,5Y}^{loc}) - S_{t,5Y}^{loc} \quad (20)$$

where $r_{t,5Y}^{\$}$ and $r_{t,5Y}^{loc}$ are the domestic and foreign rates with 5 years maturity, $S_{t,5Y}^{loc}$ is the CDS premium covering against the default of the foreign country.

This relation is adjusted from the exchange rate and the foreign investment is covered against the default risk of the country. Thus, this relation is nothing else but the basis in a case of an international portfolio that can be described as:

$$S_{t,5Y}^{loc} = (1 + r_{t,5Y}^{loc}) - \frac{X_t}{X_{t+1}}(1 + r_{t,5Y}^{\$}) \quad (21)$$

However, in our case, the P&L at time t of the enhanced carry trade strategy that corresponds to the P&L of the basis, B_t is:

$$B_t = S_{t,5Y}^{\$} - \left[\frac{X_t}{X_{t+1}}(1 + r_{t,5Y}^{loc}) - (1 + r_{t,5Y}^{\$}) \right] \quad (22)$$

In this case, we assimilate the risk-free rate to the cost of borrowing money in our domestic country. This basis computation method allows to compare countries and their markets which are denominated in different currencies that is the case of a portfolio approach. Moreover, studying contagion effects in terms of liquidity problems requires a multivariate analysis. Thus, each basis time series has to be comparable with an other one. In other words, they have to be denominated in the same currency with the same maturity.

2.3 Contagion models

To our knowledge, the first empirical study of financial market contagion has been made by King and Wadhwani (1990) who show that an increase in price volatility in the United States leads

to a rise in the correlation of returns across markets. However, although financial contagion is a major concern in literature, it is still not clear how measure it. Indeed, there is no consensus about its definition. The broad one describes contagion as a general process of shock transmission across countries. However, this definition does not allow to measure contagion effects considering data availability. Thus, we find in literature some papers that use the restrictive definition. This latter characterizes the financial contagion as the propagation between countries of shocks in excess of what should be expected by fundamentals and considering the co-movements triggered by the common shocks. However, although more restrictive, this definition implies another measurement problem. Indeed, as Bekaert and Harvey (2003) emphasize, there may have disagreement considering the definition of fundamentals. As a result and following Forbes and Rigobon (2001), the main part of the literature uses the very restrictive definition explaining a contagion phenomena as the change in the transmission mechanisms that take place during a turmoil period.

This third definition has the advantage of easily allowing to measure contagion effects as in Bertero and Mayer (1989), King and Wadhwani (1990) or Calvo and Reinhart (1996) that are interested in correlation shifts during turmoil times. Thus, measuring contagion effects resumes to estimating jumps in the correlation between financial time series, or, in other words, if the parameters of the econometric model shift when turmoils occur. In this way, Rigobon (2001) proposes a good survey of parameter stability tests, which are mainly based on Ordinary Least Square estimates, Principal Components, Probit models and correlation coefficient analysis. Rigobon (2000), Forbes and Rigobon (2001), Rigobon (2003a), Rigobon (2003b) propose to study difference in change of the covariance. However, many studies point out a number of methodological problems and particularly the problem of heteroscedasticity. Rigobon (2001) and Forbes and Rigobon (2002) who generalize the approach of Boyer et al. (1999) show that correlation coefficients are biased. These latter are conditional on market volatility. During turmoil periods, market volatility increases and estimates of cross market correlations are biased upward. Indeed, this can lead to accept the contagion hypothesis while false. The authors develop an adjusted correlation coefficient that correct the bias caused by heteroscedasticity. They distinguish pure contagion from interdependence and show that there is no contagion but

after bias correction of heteroscedasticity

interdependence during the Mexican or the Asian crisis contrary to previous findings. Indeed, interdependence and pure contagion do not have the same effects on asset allocation strategies. The first is characterized by an increase of the correlations between countries. However, this fact is only due to the rise of volatility for all of concerned countries. Moreover, pure contagion is defined as a rise in correlation that is not the result of economic fundamentals and an increase of volatility. Pure contagion has a biggest implication in principle of diversification, then it appears crucial to correct the volatility to avoid spurious results.

Thus, many studies, using different econometric methods tried to avoid the problem of heteroscedasticity. Among them, ARCH and GARCH (for Generalized AutoRegressive Conditional Heteroskedasticity) models are largely used in contagion analysis. Hamao et al. (1990) estimate conditional variance with GARCH model and test the correlation between three different markets. Edwards and Susmel (2001) include regime switching in a ARCH modeling to take into account systematic changes. Their model points out large correlations during times of high market volatility, that confirms the existence of contagion effects. However, multivariate GARCH models provide more efficient tools for analyzing comovements and volatility spillover between financial assets. Wang and Nguyen Thi (2007), Chiang et al. (2007) or Naoui et al. (2010) also estimate contagion with Dynamic Conditional Correlation that allow for tracking the evolution of the correlation between two or more assets. Kenourgios et al. (2010) use an Asymmetric Generalized Dynamic Conditional Correlation model and study the correlations between the four BRIC countries (i.e: Brazil, Russia, India and China), the US and UK markets. The use of an asymmetric model allows to see that bad news increase dramatically the equity conditional correlations among the BRIC and developed markets.

In addition to the problem of heteroscedasticity, Boyer et al. (1999) point out that the methods previously described have an exogenous definition of the crisis periods that may lead to spurious conclusions. Using a state-space model with a time-varying volatility specification is the solution to tackle this problem. Billio and Caporin (2005) propose a multivariate Markov Switching Dynamic Conditional Correlation GARCH model to estimate contagion effects. This class of models allows for discontinuity in the propagation mechanism to assume that international propagation mechanisms are discontinuous. A markov chain is introduced to describe this discontinuity and allows the endogenous definition of the crisis periods. Moreover, dynamic

correlation permits to analyze the dynamics of contagion. Many other authors explore Markov switching models like Ramchand and Susmel (1998), Chesnay and Jondeau (2001) or Ang and Bekaert (2002). Billio et al. (2005) show the Markov switching model abilities to estimate contagion. This approach define contagion as a break that produces non-linearities in the linkages among financial markets. They emphasize that when using Markov switching models: (i) the heteroscedasticity problem is solved, (ii) the definition of the crisis periods is made endogenous, (iii) the estimations are more efficient because of the full-information approach and (iv) the distinction between long and short run breaks in the factor loadings of the long and short run factors risk is allowed.

Our approach is in the line of Pelletier (2006) that has been used in the context of portfolio allocation [Giamouridis and Vrontos (2007)]. It allows in particular to decrease the number of variance parameters to consider. Thus, our model is a combination of a mixture model for the correlation matrix and a Threshold GARCH model [or TGARCH, Zakoian (1994)] to take into account asymmetric volatility dynamics. However, our estimation method imposes to assume that the heteroscedasticity is asset specific and not common across assets.

Note the K asset returns are defined by:

$$r_t = H_t^{1/2} U_t, \quad (23)$$

where $U_t | \Phi_{t-1} \sim iid(0, I_K)$, U_t is the $T \times K$ innovation vector, and Φ_t is the information available up to time t .

The conditional covariance matrix H_t is decomposed into [Bollerslev (1990) or Engle (2002)]:

$$H_t \equiv S_t \Gamma_t S_t, \quad (24)$$

where S_t is a diagonal matrix composed of the standard deviation $\sigma_{k,t}$, $k = 1, \dots, K$ and Γ_t is the $(K \times K)$ correlation matrix. Both matrices are time varying.

The conditional variance follows a TGARCH(1,1) such that:

$$\sigma_{i,t} = \omega_i + \alpha_i^- \min(\epsilon_{i,t-1}, 0) + \alpha_i^+ \max(\epsilon_{i,t-1}, 0) + \beta_i \sigma_{i,t-1}, \quad (25)$$

where ω_i , α_i^- , α_i^+ and β_i are real numbers.

Under assumptions of: $\omega_i > 0$, $\alpha_i^- \geq 0$, $\alpha_i^+ \geq 0$ and $\beta_i \geq 0$, σ_i, t is positive and could be interpreted as the conditional standard deviation of $r_{i,t}$. However, it is not necessary to impose the positivity of the parameters and the conditional standard deviation is the absolute value of $\sigma_{i,t}$. To take into account asymmetries estimating pure contagion effects in order to improve the filtering of co-movements.

The correlation matrix is defined as:

$$\Gamma_t = \sum_{n=1}^N \mathbb{1}_{(\Delta_t=n)} \Gamma_n, \quad (26)$$

where $\mathbb{1}$ is the indicator function, Δ_t is an unobserved Markov chain process independent from U_t which can take N possible values ($\Delta_t = 1 \dots, N$) and Γ_n are correlation matrices. Regime switches are assumed to be governed by a transition probability matrix $\Pi = (\pi_{i,j})$, where

$$Pr(\Delta_t = j | \Delta_{t-1} = i) = \pi_{i,j}, \quad i, j = 1, \dots, N.$$

This approach allows to discriminate between on the one hand the volatility dynamics through S_t and on the other one the correlation dynamics through the state variable Δ_t .

Finally, coming back to liquidity, we know that the contagion between markets drives their in and outflows, and liquidity moves consequently. In the line of the above approach, we can link contagion and liquidity moves by comparing the commonalities between the liquidity indicators introduced in the previous sections and the volatility and correlation series. If the commonality is between liquidity and volatility, there is no contagion effect. On the contrary, if the liquidity shock has an impact on the correlation matrix, liquidity can be considered as a contagion channel.

3 Data description

In this paper, we use data on sovereign bond yield spreads, sovereign CDS, interest rates and foreign exchange rates. We have 18 emerging markets: Argentina, Brazil, Chile, China, Czech, Egypt, Hungary, India, Indonesia, Mexico, Peru, Philippines, Poland, Russia, Slovakia, South Africa, Taiwan, Thailand, Turkey. However, for data availability reasons, we restrict our analysis to 9 of them that are present both in sovereign debt and FX markets from 01/01/2007 to 25/02/2011.

All data are downloaded for emerging market countries of Lehman Brothers MSCI Emerging Market Index before filtering. The time series covers many of the recent crisis and allows us to explore emerging markets behavior during economic disturbances. We obtain sovereign CDS premium daily data from Bloomberg and all other data from Thomson DataStream. These CDS Premiums are based on 5-year U.S. dollar contracts, for senior claims, and they assume a recovery rate of 25%. We use as risk-free rate the US Swap rate 30/360 paid semi annually.

Finally, we limit our FX market sample to countries that match the CDS Bonds Spread basis database. CIP deviations are computed on daily data of Thomson DataStream provided by WM Reuters: (i) daily spot exchange rates, (ii) daily deposit rates, (iii) daily forward exchange rates. We take 1-week, 1-month and 1-year forward rates and 1-month and 3-months deposit rates. All data are available except for deposit rate of Peru which only exists for 6-months or 1-year maturities and Malaysian forward for 1-week maturity. Table 6 gives the data availability for each of the sovereign borrowers. We take the smallest common time period across countries.

	Mean	Std	Minimum	Median	Maximum	Relative Std
Brazil	151.45	86.17	61.50	121.84	586.41	56.90%
Chile	84.36	64.77	12.50	72.53	322.96	76.78%
Hungary	217.13	150.55	17.34	215.00	629.76	69.34%
Mexico	143.40	100.28	28.17	118.63	601.21	69.93%
Poland	109.52	84.65	7.67	117.00	415.00	77.30%
Russia	214.34	201.95	36.88	146.75	1113.38	94.22%
South Africa	165.50	114.50	24.57	145.28	654.96	69.18%
Thailand	114.41	69.42	31.84	103.23	489.56	60.67%
Turkey	231.86	101.96	118.61	193.06	824.61	43.97%

Table 1 – Summary statistics for CDS premiums from 1-1-2007 to 2-25-2011. Results are expressed in basis points and percentage.

Brazil, Chile, Hungary, Mexico, Poland, Russia, South Africa, Thailand and Turkey.

Table (1) provides descriptive statistics for the sovereign CDS premiums, in other words, for the sovereign default risk. The wide range of averages highlights the high degree of heterogeneity among countries with a maximum average of 231.86 for Turkey and a minimum of 84.36 for Chile. Moreover, the relative standard deviation ranges from 44% for Turkey to 94% for Russia. For example, the cost of credit protection for Russia ranges from 36.88 to 1,113.38 basis points when it ranges for Chile only from 12.50 to 322.96.

4 Empirical Results

Keeping in mind that the main fear of an asset manager is to get stuck with unwanted position, we present some results that show a re-correlation phenomena during the last crisis. This concern is especially true when the re-correlation effects come from a liquidity problem. Thus, we focus on the smoothed probabilities to be in the state of high correlations and the difference between the correlations of being in one or an other state. We analyze both the sovereign debt and the FX markets. We show that the behavior of our liquidity indicators is similar for most countries of our sample. Moreover, we highlight that pure contagion effects occurs on both markets even if the results are more easily interpretable for the sovereign debt market.

4.1 Liquidity Description

Even knowing that the basis is theoretical not only driven by the market liquidity, this is important to summarize the empirical commonality studying its correlation with a well known liquidity indicator, the Bid-Ask spread. On the one hand, we start this study by analyzing the Pearson's correlation coefficient. The first line of the table 2 analyzes the link between our sovereign debt market liquidity indicator and Bid-Ask spread of the sovereign CDS market. The correlations are all greater than 0.53 in absolute value that confirms the good behavior of the basis as a liquidity indicator or rather than an illiquidity indicator as we highlight the negative correlation with the Bid-Ask spread. On the other hand, although the re-correlation problem has an inter countries dimension, we outline the correlation between our liquidity indicators both for sovereign debt market and for the FX market over the whole sample for each country. Thus, on the second line of the table, we show that Hungary, Poland and Turkey liquidity indicators

are strongly related. In other words, the liquidity problems appear almost at the same time on both markets. However, we focus on the commonalities between countries and this inter markets correlations is studied in this paper comparing the timing of re-correlation phenomena in our multivariate analysis.

	Brazil	Chile	Hungary	Indonesia	Mexico	Peru	Poland	Russia	South Africa	Thailand	Turkey
Basis/Bid-Ask Spread	-0,58	0,67	-0,18	0,87	-0,62	-0,87	-0,18	-0,94	-0,58	-0,53	-0,91
Basis/AbCD	0,68	-0,59	0,89	-0,09	0,57	0,01	0,84	0,36	0,56	0,53	0,74

Table 2 – Correlations between AbCD and Bid Ask Spread or AbCD and Basis. The coefficients displayed here are computed by Pearson methodology. Low correlations (less than 0.5) are in bold type.

Our empirical study of the market liquidity indicators confirms some stylized facts and the collapse of Lehman Brothers just as the 2007-2008 financial crisis are strongly highlighted. The figure 2 presents, for each of the 9 emerging countries, the CDS Bond Spread basis expressed in P&L. The first conclusion is that an arbitrage strategy started in 2007 could be profitable. Indeed, we show that all basis became clearly negative between 2007 and 2011. Every basis except Russia have positive values of P&L at the begin of 2007. Moreover, all basis time series have practically the same behavior. They were stable from the start of 2007 until the middle of 2007, when they started to decrease. Note that the basis highlights problems of liquidity from the summer 2007, i.e the start of the financial crisis while many indicators just show the Lehman Brothers collapse.

After a first decrease in the middle of 2007, the basis P&L fall down at the end of 2008. Moreover, the indicators became extremely volatile until 2009. Except Hungary for which the basis stays highly volatile between 2009 and 2001, all other countries see their basis come back to a stable state. However, the liquidity level, although stable, are lower that before the summer 2007. Furthermore, we show that the levels of liquidity are between 0.1848 for Brazil and -2,3384 for Hungary. The level of basis is however homogeneous among our sample. This first graphical analysis allows us to see the high correlations that it could have between liquidity indicators. However, we have to study the commonalities with a non linear multivariate model that tackles the heteroscedasticity problem to estimate pure contagion effects after controlling the volatility.

The second part of this first graphical liquidity description focus on the FX market liquidity. Keeping in mind that AbCD measures deviations from the CIP, we know that a liquidity problem

Figure 2 – Basis P&L for each of the 9 emerging countries. The results are presented on the whole sample from the 01/01/2007 to the 02/25/2011.

will be represented by a large value of AbCD and this value is constrained to be positive. The graphical analysis is less obvious than in the case of sovereign debt market. The heterogeneity of the liquidity behavior is greater than with the Basis. Indeed, although we see an increase of volatility around September 2008 for almost all countries, we observe different behaviors during the remaining periods of the sample. The Brazil has the FX liquidity indicator that is the more volatile, even during "calm" periods. However, its dynamic is almost the same as Russia, Turkey and Mexico that exhibit a progressive increase of illiquidity between the start of 2007 until the end of 2008, when the Lehman Brothers collapse occurs. At this time, the AbCD of these countries is at its maximum around 0.7-0.8 for Brazil and Mexico and equal to 0.3398 for Russia. After the end of 2008, we show an improvement of the FX market liquidity for each of those countries. The Chile's AbCD is relatively lower, but except the peak exhibited in September 2008, its behavior has no commonalities with other countries. Next, Hungary's AbCD

is very low until a sharp increase from the middle of 2007 until 2009, excepting in September 2008 when there was a strong short increase of the liquidity. Then, this latter decreases and stays lower until 2011. This stable behavior behavior is also highlighted for Poland, that has good liquidity on its FX market, even almost perfect at the end of 2007 before a large increase at the begin of 2008. Then, the illiquidity is very volatile but stays at a high level. In the case of South Africa, the Lehman Brothers collapse is not obviously detectable. We distinguish two periods with an increase until the end of 2008 before the liquidity improves until the end of our sample. To finish, the Thailand's AbCD is very volatile at the begin of 2007 and the end of 2008 when it goes to its maximum of 0.0421.

Figure 3 – AbCD for each of the 9 emerging countries. The results are presented on the whole sample from the 01/01/2007 to the 02/25/2011.

Studying the graphical representation of our FX market liquidity indicator, we show that the commonalities will be less obvious than for the sovereign debt market. However, this indicator is also more volatile and taking into account the heteroscedasticity may lead to detect contagion

effects.

4.2 Pure contagion rather than interdependence

The major part of the contagion measurement literature is devoted to test the parameter stability of an econometric model. Indeed, a shift of these parameters is interpreted as a change in terms of correlation, i.e. a contagion phenomena. However, following Pelletier (2006), we study the probability to be in a state of "low correlations" versus "high correlations". Our first results show that the first one is assimilated to "normal" times while the second one is assimilated to "crisis" times. Thus, we start our study by analyzing the re-correlation phenomena in terms of prices before to focus on liquidity problems. Our aim is to reveal the existence of contagion effects in emerging markets during the last crisis, particularly in terms of financial flows. Although both of these two subjects are actively debated on the recent literature, there are only few papers that study both contagion effects and liquidity, especially together. Moreover, we study emerging countries because since the recent crisis, we saw that the risk is no longer supported by the banks but by the states. Thus, sovereign CDS market has also a key role to play in the detection of crisis. It could be considered as a leading indicator of emerging economy turmoils.

We first present results for price data, on sovereign debt and FX markets. We focus on 9 emerging countries that is already too many to make the estimation of our model with a one-step likelihood maximization method. Thus, we firstly estimate univariate TGARCH for each of countries in our dataset. We report the results of the estimation of TGARCH for CDS data in table 3 and for FX data in table 4. We only present the detailed results for the model with TGARCH since the results for the correlation models do not depend on the univariate model for the standard deviations used in the first step. The correlation model are robust to the specification of the standard deviations. Thus, we choose TGARCH model to take into account the asymmetry in the variance. We not only consider a shift in terms of correlations with the Markov switching focusing on the correlation matrix but we control the correlation analysis from asymmetric variance problems. The results of TGARCH estimation present a brief statement of the market price behavior. We see for the CDS market that a decrease of the CDS premium have a smaller impact on the return volatility than an increase. Indeed, the CDS premium is a hedge against the country risk of default. Thus, an increase of their value means that the risk

of default of the country increases, that is a bad news as a negative returns for an equity. We make the same observation for the FX market.

	Brazil	Chile	Hungary	Mexico	Poland	Russia	South Africa	Thailand	Turkey
omega	8.56E-06	1.40E-06	5.21E-07	1.06E-06	6.26E-07	1.31E-06	1.04E-06	1.52E-06	1.67E-05
	<i>4.26E-06</i>	<i>2.69E-06</i>	<i>3.51E-07</i>	<i>1.01E-06</i>	<i>3.53E-07</i>	<i>1.41E-06</i>	<i>9.03E-07</i>	<i>1.89E-06</i>	<i>1.00E-05</i>
alpha-	0.0244	0.0640	0.0907	0.0000	0.0687	0.0565	0.0518	0.0819	0.0209
	<i>0.0152</i>	<i>0.0303</i>	<i>0.0548</i>	<i>0.0149</i>	<i>0.0303</i>	<i>0.0234</i>	<i>0.0326</i>	<i>0.0311</i>	<i>0.0365</i>
alpha+	0.1993	0.2111	0.0549	0.2007	0.1513	0.1201	0.0991	0.0956	0.1582
	<i>0.0678</i>	<i>0.0975</i>	<i>0.0317</i>	<i>0.0464</i>	<i>0.0380</i>	<i>0.0310</i>	<i>0.0256</i>	<i>0.0364</i>	<i>0.0529</i>
beta	0.8757	0.8303	0.8816	0.8994	0.8554	0.8833	0.8984	0.8701	0.8874
	<i>0.0214</i>	<i>0.0642</i>	<i>0.0479</i>	<i>0.0209</i>	<i>0.0340</i>	<i>0.0265</i>	<i>0.0346</i>	<i>0.0367</i>	<i>0.0502</i>

Table 3 – TGARCH Parameters for CDS data. Standard deviations are in italic.

	Brazil	Chile	Hungary	Mexico	Poland	Russia	South Africa	Thailand	Turkey
omega	2.16E-06	3.62E-06	5.71E-07	5.25E-07	6.83E-07	1.10E-07	3.08E-06	4.83E-07	3.81E-06
	<i>1.01E-06</i>	<i>2.43E-06</i>	<i>2.47E-07</i>	<i>2.09E-07</i>	<i>3.36E-07</i>	<i>2.00E-08</i>	<i>1.13E-06</i>	<i>2.09E-07</i>	<i>1.47E-06</i>
alpha-	0.1729	0.1496	0.0671	0.1884	0.0829	0.1006	0.1306	0.2673	0.1672
	<i>0.0470</i>	<i>0.0502</i>	<i>0.0233</i>	<i>0.0526</i>	<i>0.0270</i>	<i>0.0323</i>	<i>0.0364</i>	<i>0.0831</i>	<i>0.0506</i>
alpha+	-0.1238	-0.0334	-0.0671	-0.1312	-0.0659	-0.0796	-0.1187	0.1001	-0.1505
	<i>0.0531</i>	<i>0.0536</i>	<i>0.0161</i>	<i>0.0535</i>	<i>0.0217</i>	<i>0.0271</i>	<i>0.0419</i>	<i>0.1131</i>	<i>0.0587</i>
beta	0.8648	0.8091	0.9615	0.8716	0.9441	0.9390	0.9020	0.6824	0.8565
	<i>0.0300</i>	<i>0.0518</i>	<i>0.0222</i>	<i>0.0249</i>	<i>0.0209</i>	<i>0.0178</i>	<i>0.0222</i>	<i>0.0579</i>	<i>0.0381</i>

Table 4 – TGARCH Parameters for FX data. Standard deviations are in italic.

Looking at Figure 4 where we plot the smoothed probabilities of being in regime two at each point of time for CDS market and Basis. We see that the correlations appear to be dynamic. This figure shows that we frequently move between regimes. For each date, there is little uncertainty about the regime of correlations. In our case, the regime two corresponds to the high correlation state. The process is spending more time in regime one on our range of data and spells in regime one are shorter on average than in regime two. This is explained by the estimate of the transition probability matrix, which is very similar across the various models with two regimes. The probability of being in regime two at time t conditional on being in regime two at time t , $p_{2,2}$ is around 0.99. That means a very high level of persistence in the Markov chain. Indeed, we are almost in the case of an absorbing state. In comparison, for regime one this probability is around 0.9. Despite the fact that these probabilities are close in value, as Pelletier (2006) shows, there exists a large difference between these values. Indeed, after 5 periods, these probabilities are respectively almost equals to 0.95 and 0.55. We show that the magnitudes of almost all the

Indeed, $0.99^5 = 0.95$ and $0.90^5 = 0.55$

correlations in regime one are smaller than in regime two. Indeed, the correlations is greater for each pair of countries except for Mexico-Russia and Mexico-Turkey on the CDS market. Moreover, the log-likelihood of the RSDC estimation is greater than those of CCC estimation by more than 200 points.

Figure 4 – Smoothed Probabilities to be in the state of high correlations. Smoothed probabilities are computed following Hamilton, chapter 22. The results are both for the CDS market between 01/01/2007 and 25/02/2011.

These results allow us to split the whole sample into two periods. Before the end of 2008, the probability to be in regime two (i.e. high correlations) stays at a low level and relatively less volatile. We can see some peaks but as the probability $p_{1,1}$ is equal to 0.89 we observe from time to time, some peaks during the "calm period". However, after the collapse of Lehman Brothers, we see that this probability is very high, and almost always equal to one. This fact is confirmed by the behavior, almost absorbing, of the state two. Indeed, the probability to be in state two both at time t and $t - 1$ ($p_{2,2}$) is equal to 0.99. Then, we show that, on the sovereign debt market, the behavior of the risk supported by the countries is more correlated during the

last crisis than during the period before. Whether we consider the definition of the contagion given by Forbes and Rigobon (2001), and the distinction made between interdependence and pure contagion, the recent crisis exhibits strong pure contagion effects.

The case of the FX market is almost similar as we see on the figure(5). However, the results on the liquidity re-correlation analysis are more difficult to be interpreted. Our study focus on the same set of countries. The transition probabilities are very close to those obtained for the sovereign debt market. Thus, we see at the end of 2008, the probability to be in the state two strongly increases and stays at a level, close to one. As for the sovereign CDS market, the FX market is more correlated during crisis period than during calm period. The currencies suffer from the same problem and know strong pure contagion effects. That proves that the emerging FX markets are under stress when a crisis episode occurs. This result may be interpreted as a confirmation that the main part of investors in emerging markets are foreigners.

Figure 5 – Smoothed Probabilities to be in the state of high correlations. Smoothed probabilities are computed following Hamilton, chapter 22. The results are both for the FX market between 01/01/2007 and 25/02/2011.

To confirm our results, we have to define if the two correlation matrices are significantly separate. In other terms, we test the number of regimes. However, the Markov switching approach in our model does not allow to apply standard methods. Indeed, under the null hypothesis, a nuisance parameter is not identified. Garcia (1998) shows that asymptotic theory works for Markov switching only assuming the validity of the score distribution. However, the asymptotic distribution is not so far from the standard Chi-square distribution while our likelihood ratio statistic is much greater than critical value of this distribution. Then, we conclude that a model is better with two regimes and confirm the significance of the difference between the two correlation matrices. To compute this statistic, we have to compare the likelihood of our model, RSDC with two regimes and the CCC model which is assimilated to a RSDC with only one regime.

Whether contagion effects on prices are strong as we see below, another key point in the crisis impact is the liquidity. We focus on the liquidity contagion effects of sovereign debt market. Indeed, it is crucial for an asset manager to know if the re-correlation problem that we show above is due to a liquidity problem. If this case occurs, the asset manager could get stuck with an unwanted sovereign debt. Thus, we apply the same model as below on our liquidity indicator: the CDS-bond basis.

As we see on the figure 6, the probabilities to be in the state two of the CDS market and the basis are highly correlated. Especially for the regime switching in October 2008 which occurs exactly at the same time on both of two. This result means that the re-correlation phenomenon on the CDS market is due to a liquidity problem on the sovereign debt market.

	Brazil	Chile	Hungary	Mexico	Poland	Russia	South Africa	Thailand	Turkey
Brazil		0.363	0.303	0.146	0.366	0.048	0.172	0.295	0.045
Chile	0.240		0.181	0.279	0.253	0.314	0.193	0.181	0.224
Hungary	0.218	0.177		0.276	0.232	0.316	0.205	0.281	0.342
Mexico	0.090	0.177	0.202		0.353	0.018	0.158	0.242	0.091
Poland	0.298	0.189	0.281	0.287		0.381	0.355	0.277	0.438
Russia	0.016	0.199	0.329	-0.011	0.386		0.114	0.230	0.069
South Africa	0.154	0.180	0.245	0.117	0.396	0.159		0.245	0.249
Thailand	0.097	0.055	0.144	0.050	0.139	0.113	0.173		0.270
Turkey	0.001	0.171	0.287	-0.010	0.413	0.041	0.178	0.120	

Table 5 – Differences between the two regimes correlations matrices (high minus low). The blue part of the matrix corresponds to the CDS market and the black part corresponds to the Basis.

Figure (7) shows that the conclusion is really different and less obvious for the FX market and its liquidity indicator. Indeed, the AbCD, especially its contagion behavior does not react

Figure 6 – Smoothed Probabilities to be in the state of high correlations. CDS market is represented by dark line and Basis by the blue dotted line. Smoothed probabilities are computed following Hamilton, chapter 22. The results are both for the CDS market and the basis between 01/01/2007 and 25/02/2011.

as the FX market (and the CDS market). We see that the probability to be in the state of high correlations strongly decreases after the Lehman Brothers collapse in October 2008 and stays around zero until today except for the start of 2010 when this probability shows a relatively short peak. This result confirms that the liquidity problem on the sovereign debt market is the main cause of the re-correlation phenomenon on the CDS market. Indeed, this contagion effect can not be associated with a liquidity problem on the FX market as the figure (7) proves.

Figure 7 – Smoothed Probabilities to be in the state of high correlations. FX market is represented by dark line and AbCD by the blue dotted line. Smoothed probabilities are computed following Hamilton, chapter 22. The results are obtained for the FX market and its liquidity indicator the AbCD between 01/01/2007 and 25/02/2011.

5 Conclusion

EM have experienced many financial crisis with contagion problems. However, they are today the key drivers for global growth of the world economy. They propose very attractive investment opportunities for asset managers who consider them as an asset class. Nevertheless, the main risk for an asset manager is to lose diversification benefits in his/her portfolio. In this paper, we analyze a new data set of emerging markets, only recently studied. We propose a liquidity measure for a long term analysis under constraint of data using the deviations from the Covered Interest Parity and the CDS bond spread basis as liquidity indicators respectively for FX and sovereign debt markets. We implement a statistical model to detect and analyze contagion capable to differentiate pure contagion and interdependence. Indeed, the re-correlation phenomena empirically showed prohibits to use Markowitz approach. This analyze needs a non-linear model to capture heteroscedasticity and shifts in correlations. Our approach is in the line with Pelletier

(2006). However, we use a Threshold GARCH model to tackle the heteroscedasticity problem and focus on pure contagion effects. Then, the possible shifts of correlations are estimated by a regime switching model in the second step of our estimation procedure. Thus, we show that the basis measures emerging market liquidity and there exists a re-correlation effects after October 2008. The difference between correlations during quiet period and turmoil period is significant proving that pure contagion effects occur during the 2007-2008 crisis. This study is particularly relevant because re-correlation phenomena and pure contagion hamper the diversification benefits of an asset allocation and it is crucial for an international portfolio manager to take into account both of these effects.

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A Estimation of RSDC

The estimation of this model is made in two part: (i) the univariate estimation of standardized residuals with TGARCH model and maximum likelihood and, (ii) the estimation of correlation matrices and probabilities to be in state n ($n = 1, \dots, N$) with an EM algorithm (Dempster et al. (1977)). Making the estimation in two parts is preferable when the number of observed series is more than a few. Indeed, the number of parameters could become very large.

We should introduce θ the complete parameter space, that we split in two parts by: θ_1 that corresponds to the parameter space of the univariate volatility model and θ_2 that corresponds to the parameter space of the correlation model. Then, in a first time we compute the log-likelihood taking a correlation matrix equal to the identity matrix. In other words, we estimate univariate TGARCH model for each asset.

A.1 First Step

To model the full covariance matrix we model the standard deviations and the correlations separately. This first step focus on the estimation of standard deviations.

The parameters of univariate TGARCH model are estimated with maximum likelihood. Take the case of a TGARCH(1,1) as presented in section 1. We have to specify the distribution of U_t to estimate with maximum likelihood. In our case, U_t are *iid* and normally distributed [$U_t \sim \mathcal{N}(0, 1)$] to consider gaussian likelihood. However, we don't make the assumption that is the true law of U_t .

Note $\theta_1 = (\omega, \alpha^-, \alpha^+, \beta)$. Then, the gaussian likelihood is:

$$L(\theta_1) = L(\theta_1; r_0, \dots, r_T) = \prod_{t=1}^T \frac{1}{\sqrt{2\pi\tilde{\sigma}_t^2}} \exp\left(-\frac{r_t^2}{2\tilde{\sigma}_t^2}\right) \quad (27)$$

with $\tilde{\sigma}_t$ are obtained recursively ($\forall t \geq 1$) as:

$$\tilde{\sigma}_{i,t} = \omega_i + \alpha_i^- \min(\epsilon_{i,t-1}, 0) + \alpha_i^+ \max(\epsilon_{i,t-1}, 0) + \beta_i \tilde{\sigma}_{i,t-1}$$

Taking the logarithm, maximize the likelihood is like minimize the log-likelihood $\tilde{l}_t(\theta_1)$ that

is defined by:

$$\tilde{l}_t = \tilde{l}_t(\theta_1) = \frac{r_t^2}{\tilde{\sigma}_t^2} + \log(\tilde{\sigma}_t^2)$$

Then, $\hat{\theta}_1$ is the solution of:

$$\hat{\theta}_1 = \arg \min_{\theta_1} \frac{1}{T} \sum_{t=1}^T \tilde{l}_t(\theta_1) \quad (28)$$

After the estimation of parameters, we get the standardized residuals, noted $\tilde{U}_t$ as:

$$\tilde{U}_t = \frac{r_t}{\tilde{\sigma}_t}$$

In the next step, we use it to estimate the correlation matrices. We introduce a regime switching to add dynamic and to measure pure contagion by the probability to be in the state n (in our case $n = 1, 2$).

A.2 Second Step

In this second part of estimation of our model, we use the Expectation Maximization algorithm (EM thereafter). The main advantage is the possibility to taking into account high number of parameters coming from each Γ_n .

A.2.1 EM Algorithm

This algorithm is presented in Hamilton (1994, chapter 22). We have to estimate the vector of parameters θ_2 calculating the result of:

$$\tilde{\theta}_2 = \arg \min_{\theta_2} \left[\frac{1}{2} \sum_{t=1}^T K \log(2\pi) + \log(|\Gamma_t|) + \tilde{U}_t' \Gamma_T^{-1} \tilde{U}_t \right] \quad (29)$$

Unlike the first step, we have to use Hamilton filter because in this part of the estimation, Δ_t is unobserved. Moreover, the number of parameters increases at a quadratic rate with the number of asset returns. Then, to realize these estimation, we use EM algorithm that have not restrictions on the number of parameters.

Then, results of Hamilton (1994, chapter 22) expose that Maximum Likelihood estimates of the transition probabilities (i) and the correlation matrices (ii) satisfy:

$$(i) \quad \tilde{\pi}_{i,j} = \frac{\sum_{t=2}^T P \left[\Delta_t = j, \Delta_{t-1} = i | \underline{\tilde{U}}_T; \tilde{\theta}_2 \right]}{\sum_{t=2}^T P \left[\Delta_{t-1} = i | \underline{\tilde{U}}_T; \tilde{\theta}_2 \right]} \quad (30)$$

$$(ii) \quad \tilde{\Gamma}_n = \frac{\sum_{t=1}^T (\tilde{U}_t \tilde{U}_t') P \left[\Delta_t = n | \underline{\tilde{U}}_T; \tilde{\theta}_2 \right]}{\sum_{t=1}^T P \left[\Delta_{t-1} = n | \underline{\tilde{U}}_T; \tilde{\theta}_2 \right]} \quad \text{for } n = 1, 2 \quad (31)$$

Estimates of transition probabilities are based on the smoothed probabilities. We could see that $\tilde{\Gamma}_n$ is not directly a correlation matrix. It must be rescaled because their diagonal elements are not imposed to be equal to one. Off-diagonal elements are between -1 and 1 . This step is need because the product of standardized residuals is not constrained to have elements between -1 and 1 . Then we rescale Γ_t at each iteration as:

$$\Gamma_t = D_t^{-1} \tilde{\Gamma}_t D_t^{-1} \quad (32)$$

where D_t is a diagonal matrix with $\sqrt{\tilde{\Gamma}_{n,n,t}}$ on row n and column n .

The algorithm starts with initial values $\tilde{\theta}_2^{(0)}$ for the vector θ_2 . With $\tilde{\theta}_2^{(0)}$ we can compute a new vector $\tilde{\theta}_2^{(1)}$ based on equations (30) and (31). The algorithm works until the difference between $\tilde{\theta}_2^{(m)}$ and $\tilde{\theta}_2^{(m+1)}$ is less than a defined threshold.

A.2.2 Computation

We develop in this subsection the method to compute the EM algorithm. The elements of the transition probabilities matrix, $\tilde{\pi}_{i,j}$ are defined as the ratio of consecutive probabilities ($P[\Delta_t = j, \Delta_{t-1} = i | \underline{\tilde{U}}_t, \theta_2]$) and the probabilities to be in state j at time t . They are obtained iteratively from $t = 1$ to T .

Note that, conditional probability is defined by [see Hamilton, (22.3.7)]:

$$P[\Delta_t = j | \underline{\tilde{U}}_t, \theta_2] = \frac{\pi_j \times f(\underline{\tilde{U}}_t | \Delta_t = j, \theta_2)}{f(\underline{\tilde{U}}_t | \theta_2)} \quad (33)$$

where $f(\tilde{U}|\Delta_t = j, \theta_2)$ is the probability density of the multivariate normal distribution with zero mean and Γ_j as covariance matrix, evaluated for $\tilde{U}_t$.

With equation (33), we compute probabilities at time $t = 1$. Then, we compute consecutive probabilities recursively:

$$P[\Delta_t = j, \Delta_{t-1} = i | \tilde{U}, \theta_2] = P[\Delta_{t-1} = i | \tilde{U}, \theta_2] \times P[\Delta_t = j | \tilde{U}, \theta_2] \times \pi_{i,j} \quad (34)$$

where $P[\Delta_t = j | \tilde{U}, \theta_2] = f(\tilde{U} | \Delta_t = j, \theta_2)$.

Then, conditional probabilities to be in state j at time t are then obtained by the ratio of the sum of the two consecutive probabilities of being in state j at time t and the sum of all consecutive probabilities.

Introduce the notation $\xi_{t|\tau}$, the $(N \times 1)$ vector whose j^{th} element is $P[\Delta_t = j | \tilde{U}_\tau, \theta_2]$. This notation allows to present two cases of $\xi_{t|\tau}$: (i) for $t > \tau$ it represents a forecast about the regime and (ii), for $t < \tau$ it represents the smoothed inference (about the regime in date t based on data obtained through some later date τ). Then, we focus on smoothed probabilities that is defined by:

$$\tilde{\xi}_{t|\tau} = \tilde{\xi}_{t|t} \odot \{\Pi' \cdot [\tilde{\xi}_{t+1|T}(\div) \tilde{\xi}_{t+1|t}]\} \quad (35)$$

Smoothed probabilities are obtained by iterating on backward for $t = T, T-1, T-2, \dots, 1$. We come back from equation (34) to compute consecutive probabilities with smoothed probabilities. Then, we compute $\theta_2^{(m)}$ with equation (30) and (31) rescaling at each iteration the correlation matrix with equation (32).

The breaking rule of the algorithm is defined by the fact that the correlation matrix computed by the last iteration is almost equal to the previous correlation matrix. We have to define a threshold under which, we consider that matrices are equal.

A.2.3 Initialisation of the Algorithm

To start the algorithm, we have to choose the space of initial parameters, $\theta_2^{(0)}$. In this space, we input correlation matrices for each state of our model (in our case, two). The algorithm starts with one matrix of correlations of the state (1) equal to identity matrix. For the second state, we use the Gramian matrix method (Holmes (1991)) to generate random correlation matrix. Note that a correlation matrix have to be definite semi positive with diagonal elements are equal to one and off-diagonal elements are between -1 and 1 .

For a K -variate process, we generate K independent pseudo-random vectors normally distributed, τ_i . We use the Gramian matrix $T'T$ where $T := (t_1, \dots, t_K)$ and t_i is the i^{th} column. Then, we normalize the matrix as: $t_i = \tau_i / \|\tau_i\|$.

B List of Countries

Table 6 – List of countries in database and available dates. In blue, countries for which the data are available for all markets from the 01/01/2007 to the 25/02/2011.

	Start	End
Argentina	01/06/2007	25/02/2011
Brazil	03/08/2005	25/02/2011
Chile	01/09/2010	25/02/2011
China	01/12/2003	25/02/2011
Colombia	29/03/2004	25/02/2011
Czech Republic	01/01/2002	25/02/2011
Egypt	02/09/2009	25/02/2011
Hungary	01/01/2002	25/02/2011
India	01/01/2002	25/02/2011
Indonesia	14/05/2003	25/02/2011
Malaysia	01/01/2002	25/02/2011
Mexico	01/01/2002	25/02/2011
Peru	29/09/2006	25/02/2011
Philippines	01/10/2010	25/02/2011
Poland	11/02/2002	25/02/2011
Russia	03/01/2005	25/02/2011
Slovakia	06/10/2004	31/12/2008
South Africa	01/01/2002	25/02/2011
Thailand	04/01/2005	25/02/2011
Turkey	24/08/2005	25/02/2011