Sovereign Default and Liquidity Risks in the Bond and CDS Markets

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I hereby declare that this thesis entitled “Sovereign Default and Liquidity Risks in the Bond and CDS Markets” is the result of my own research except as cited in the references. This thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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Abstract

This thesis focuses on the different liquidity issues specific to the sovereign Credit Default Swap (CDS) market. As a first step, we present an empirical study of the pricing effect of liquidity and systematic liquidity risk in the sovereign CDS spreads. We do find a large evidence that the risk premium priced above the sovereign default risk is mainly driven by both bond and CDS liquidity risk, which implies that liquidity plays an important role in CDS spread movements. Secondly, we use a factor model in order to decompose sovereign CDS spreads into default risk, liquidity and correlation components. The main objective is to measure the weight of liquidity in the CDS spreads not by using liquidity proxies such as bid-ask spreads or volumes but by calibrating the model to the data. Our analysis reveals that sovereign CDS spreads are highly driven by liquidity (55.6% of default risk and 44.32% of liquidity) and that sovereign bond spreads are less subject to liquidity frictions and therefore could represent a better proxy for sovereign default risk (73% of default risk and 26.86% of liquidity). Our empirical results advance the idea that the increase in the CDS spreads observed during the crisis period was mainly due to a surge in liquidity rather than to an increase in the default intensity. Finally, we focus on the dynamic properties of the risk neutral liquidity risk premium embedded in the term structure of sovereign CDS spreads. We show that liquidity risk has a non-trivial role and participates directly to the variation over time of the term structure of sovereign CDS spreads. Our results show that CDS buyers earned a liquidity premium only during the pre-crisis period.
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Chapter 1

Introduction

Since early 80s, an extensive research has been done on stocks and bonds liquidity, here the literature is very large and we will only mention few papers particularly by Amihud and Mendelson (1986, 1991) who first state the relationship between liquidity and returns and show that stock expected returns are an increasing function of stocks illiquidity. In fact, liquidity is an elusive concept that is not observed directly and has a number of aspects that cannot be captured in a single measure. In line with that, Glosten and Milgrom (1985) provide evidence that inventory costs and adverse selection affect liquidity of securities through the order flow namely through the discounts or premiums that buyers or sellers are willing to pay. Easley, Hvidjkjaer and O’Hara (1999) introduced a new measure of liquidity risk based on the probability of informed trading. This measure reflects adverse selection coming from asymmetric information between traders and is computed using intraday quotes and trades.

Even though liquidity has been studied extensively in traditional markets, little research has been done in derivatives. We can mention some recent papers, for example in option markets we have Bollen and Whallen (2004), Cetin, Jarrow, Protter and Warachka (2006) and Garleau, Pedersen and Potoshman (2007) who study the effect on supply and demand on equity option prices. Deuskar, Gupta and Subrahmayam (2006) provide the empirical evidence that there is illiquidity discount in the interest rate option market meaning that illiquid interest rate options trade for higher prices
than liquid ones. Brenner, Eldor and Hauser (2001) find the same result for the non-tradable currency options. Also, Das and Hanouna (2009) show that lower equity market liquidity lead to higher CDS spreads.

Recent literature suggests that CDS spreads do not only account for credit risk and that liquidity may play a non-negligible role. Acharya and Johnson (2007) show the evidence of informed-based trading in credit derivatives market that causes adverse selection which in turn affects liquidity in CDS contracts. Berndt et al (2005) and Pan and Singleton (2008) show that corporate and sovereign CDS spreads are too high to account only for default risk, they suggested a liquidity factor as possible component to represent the non-default part. Following Berndt et al (2005), Tang and Yan (2007) studied empirically the effect of liquidity on corporate CDS spreads. Finally, Kucuk (2010) examine liquidity in the sovereign bond market and provide evidence that sovereign CDS spreads are more expensive than what is implied by the underlying sovereign bond yield because when news about a specific sovereign is bad, speculators without owning the reference entity speculate on worsening credit conditions by buying CDS contracts. The excess demand increases CDS spreads while bond prices do not change as much because speculation is not directly related to the reference entity.

With the recent debt crisis, the sovereign CDS market has attracted lot of interest and understanding its determinants has become capital not only for practitioners but also for policy makers. According to the BIS quarterly Review (December 2010) approximately 80% of the CDS market relates to corporate issuers and 20% to sovereign entities. However the sovereign CDS market has recorded the strongest growth showing 50% increase in gross positions (from 2009 to 2010).

The substantial increase in the trading activities in the sovereign CDS market implies that liquidity could be a potential driver of the spreads\textsuperscript{1}. Calice, Chen and Williams (2011) emphasize that the manipulation of market liquidity is often the primary mech-

\textsuperscript{1}Chordia and Subrahmanyam (2001) state that liquidity and trading activity are strongly linked as they are influenced by common factors.
anism through which speculative attacks are channeled. Therefore, if credit markets are subject to speculation, it is very relevant to thoroughly study the components of the sovereign CDS spreads and quantify how much of it account for default risk and liquidity. In a recent study, Tang and Yan (2010) examine the demand driven price pressure on corporate CDS spreads. By constructing a variable that measures the net trade imbalance called the net buying interest (NBI), the authors are able to show that there is a strong relation between changes in CDS spreads and NBI and that this latter contains information on the future CDS spread changes. In fact, this finding supports the idea that excessive trading in CDSs can have a significant impact on the spreads. For example, in the sovereign CDS case, default is very rare and in general when a country is in financial turmoil, other countries interfere to propose a bail-out package. If market participants know that default is highly unlikely, this might give them an incentive to speculate and sell CDS contracts in order to get the premium without fearing any default. If the sell-side is stronger than the buy-side then we have a trade imbalance that might affect CDS spreads even though the pure default risk hasn’t changed; this proves that liquidity has a strong influence on CDS pricing and it is therefore important to investigate it.

Therefore the contribution of this thesis is to present the first study that investigates empirically and theoretically different liquidity issues specific to the sovereign CDS market. In particular, we focus on the instrument-specific liquidity aspects of the CDS contract and on the systematic liquidity risk. We first start by analysing the liquidity of the 5 year sovereign CDS contract then we move to study the implied liquidity risk across the term structure of the sovereign CDS curve. Our results challenge the conventional idea that sovereign CDSs are a good measure of sovereign default risk and we provide empirical evidence that liquidity plays a substantial role in sovereign CDS spread movements.

The outline of this thesis is as follows. Chapter 2 describes the structure of the
credit default swap market and clarifies the link between CDS spreads and liquidity. Chapter 3 explores the relationship between the CDS spreads and the instrument-specific liquidity such as inventory costs, search frictions, and depth. Chapter 4 investigates the systematic liquidity risk effect on the sovereign CDS spreads by using the Liquidity-Adjusted CAPM framework of Acharya and Pedersen (2005). Chapter 5 extends the reduced-form model of Buhler and Trapp (2010) and presents its empirical results. Chapter 6 analyses the implied liquidity risk in term structure of the sovereign CDS spreads. Finally, Chapter 7 contains concluding remarks.
Chapter 2

Background Information on the CDS Market

2.1 Structure of the CDS market:

The structure of a standard CDS contract for sovereign issuers share many of its features with the corporates. The protection buyer pays a semi-annual premium, expressed in basis points per notional amount of the contract, to the protection seller. Settlement of a CDS contract is typically done by physical delivery of an admissible bond. The admissibility and the characteristics of the reference obligation are determined in the contract. Settlement of a CDS contract can also be done without owning any debt of the reference entity, these contracts are called naked credit default swaps allowing traders to speculate on debt issues and the creditworthiness of reference entities. Typically, only bonds issued in external markets and denominated in one of the standard specified currencies (euro, dollar, etc) are deliverable. In fact, bonds issued in domestic currency, issued domestically, or governed by domestic laws are not deliverable. For some sovereign issuers without extensive issuance of hard-currency denominated Eurobonds, loans may be included in the set of deliverable assets. The countries studied in this thesis (to be specified later on) have sizable amounts of outstanding sovereign bonds and their CDS contracts trade with “Bond” terms.

When a credit event occurs, we have two types of settlement: (1) either the protection
seller pays the buyer the par value of the bond in exchange for physical delivery of the reference entity ("physical settlement") or the protection seller directly pays the difference between the market value and the face value of the reference issue to the protection buyer ("cash settlement").

Typically, a sovereign CDS contract lists as credit events any of the following that affect the reference obligation: (1) obligation acceleration (2) failure to pay (3) restructuring or (4) repudiation/moratorium. Note that default is not included in this list, because there is no international bankruptcy court that applies to sovereign issuers.

2.2 The Credit Default Swap Market and Liquidity:

In this subsection, we aim to clarify why liquidity can represent an issue to dealers trading CDSs. CDS contracts are traded over the counter and typically in this market, two parties agree on the term of trade. Traders go through inter-dealer brokers and there might be delays in closing trades if the brokers do not find a counterparty that takes the opposite position. In fact, CDSs enable the transfer of credit risk from one party to another and for investors who want to be exposed for a limited period of time, the possibility to enter or exit a position with a relative ease and at a fair price is an important consideration, hence the importance of liquidity.

Fisher Black (1971), Kyle (1985) and Brunnermeir (2009) state that liquidity can be described as the degree to which an asset can be bought or sold in the market quickly without affecting the asset’s price and it has multiple facets that can be summarized in the following way. An asset is said to be liquid if (1) its bid-ask spread is small (tightness), (2) a large amount of the security can be traded without affecting the price (depth) (3) price recovers quickly after a demand or supply shock (resiliency).

The CDS market is not a continuous market because it requires that a dealer takes the opposite trade. The difficulty in matching a trade could create search frictions as
dealers may have to wait a certain amount of time before closing a position. Secondly, the problem of finding a counterparty could be associated with inventory costs as market participants may be facing funding constraints. Last but not the least, counterparty issues could also be linked to market depth; if an asset is not liquid (or deep) then it is difficult to trade. In summary, we have three main liquidity aspects that affect the CDS market: depth, inventory costs and search frictions.

2.3 The Credit Default Swap Market and Bond Liquidity:

Typically sovereigns tend to issue more bonds than corporates and the size of the bond market has an important influence on sovereign CDS spreads. In what follows, we discuss four main channels through which bond liquidity can impact the sovereign CDS market.

(1) Hedging: CDS contracts are often used to manage default risk which arises from the underlying entity. Therefore any bond yield movements (either caused by default risk or liquidity risk) could impact CDS spreads.

(2) Physical settlement and the “Cheapest-To-Deliver” (CTD) option: the majority of the CDS contract specifies physical delivery because the price determination of cash settlement is very involved. In fact the delivery option is more valuable when there are a wider variety of debt instruments eligible for delivery. In particular, some bond features (long maturity, a below-market coupon, and illiquidity) might make the CTD option particularly valuable. A recent paper by Ammer and Cai (2007) show that the CTD option introduces a source of uncertainty into the sovereign CDS market because CTD value changes with the liquidity and with the number of instruments eligible for delivery during the life of the CDS contract.

(3) Arbitrage: Duffie (1999) demonstrates that there is an arbitrage pricing relation among the following instruments: a risky floating rate bond trading at par, a risk-
free par floater of the same maturity, and a CDS contract of the same maturity that specifically references the risky bond. According to the author, the yield spread between risky and risk-free bonds must equal the CDS premium in order to avoid arbitrage, this is often called the CDS basis. However recent research showed that different factors might complicate this arbitrage relationship, for example liquidity is presented as one of these factors because liquidity premium in either bonds or CDSs may vary over time\(^1\). Moreover, the CTD option described above also complicates the arbitrage relationship.

(4) Arbitrage through synthetic positions: dealers could also create synthetic long and short positions in the CDS market in order to speculate on bond yields.

In the following chapters, we investigate the effect of both CDS and bond liquidity on sovereign CDS spreads.

\(^1\)Collin-Dufresne, Goldstein, and Martin (2001) conclude that liquidity premium explain much of the variation in investment-grade bond yield spreads.
Chapter 3

Sovereign Credit Default Swaps and Liquidity

3.1 Introduction

Liquidity is usually considered as a risk factor in traditional markets such as bonds, stocks and as we mentioned above many papers studied its effect on prices and returns. In fact, liquidity is even more important for opaque markets such as OTC markets where we typically have search frictions, transactions costs and asymmetric information. These factors inflate liquidity risk as documented by Amihud and Mendelson (1986, 1991, 2002). Therefore, the study of liquidity risk in the CDS market is particularly relevant.

The issue of liquidity risk in the sovereign CDS market has been briefly mentioned in Remonola et al (2008) and Pan and Singleton (2008) but to the best of our knowledge this chapter represents the first attempt to investigate the liquidity effect specific to the sovereign CDS contract. In particular, we focus on the liquidity aspects that typically affect OTC markets such as adverse selection, depth, search frictions and inventory costs. The closest study to ours are Acharya and Johnson (2007) and Tang and Yan (2007) who do similar type of work but focus only on the corporate CDS market.

Using DTCC data, we show that during crisis time search frictions and inventory costs do not represent a constraint to market participants and we provide a proxy
for the CDS liquidity premia of about 2.1%. Furthermore, our results reveal that the impact of bond liquidity on sovereign CDS spreads is higher during crisis time with a bond liquidity estimate of 4.8%. This indicates that the flight-to-liquidity episode in the sovereign bond market influences significantly the sovereign CDS market.

In the first part of this chapter, we introduce the regression model and define the dataset (Section 3.2). We then present the proxies utilised to test for the different facets of liquidity (Section 3.3). Section 3.4 discusses the implications of our results. Finally, in Section 3.5, we conclude the chapter.

3.2 Empirical Methodology:

3.2.1 Data Description:

In this subsection, we describe a part of the data used in the analysis, the rest will be presented in the relevant sections. The sovereign CDS dataset has been downloaded from Thomson Financial Datastream and spans from November 2005 to October 2010, it contains mid, bid and ask quotes in weekly frequency. Secondly, we obtain the gross notional, net notional and total number of CDS contracts in a weekly basis from DTCC clearing house through Reuters and the data spans from November 2008 to October 2010.

Regarding sovereign bond data, we downloaded bid-ask spreads, market value and prices from ISMA (International Securities Market Association) via Thomson Financial Datastream (from November 2005 to October 2010). Details about bond data will be presented in the relevant sections. Finally, the credit risk controls will be defined thoroughly in Section 3.3. The data was obtained for the following countries: Argentina, Chile, Mexico, Brazil, Turkey, Philippines, Korea, Malaysia and Indonesia. We focus on these countries in order to avoid any currency mismatch problem, as the sovereign CDS spreads are quoted in dollar and the main currency of the sovereign debt in emerging
markets is the dollar.

3.2.2 Regression with Clustering Method:

The objective of this paper is to examine the cross-sectional effect of liquidity in the sovereign CDS market. Our dataset is constituted of a pooled time series and cross-section unbalanced panel. When one deals with panel data, one has to be aware of two types of correlation that can distort the results: (1) observations from the same country cannot be treated as independent of each other, we thus have to control for the country effect (or the entity effect) (2) countries might be affected by the same macroeconomic conditions, we then need to control for the time effect. Peterson (2009) provides a detailed analysis on the different type of methodologies to use when one faces the issue of time and entity effects in a panel. When the country effect exists adjusting for entity clustering is the most efficient approach, however when time effect is present, adopting Fama-Macbeth approach is the preferred one. Finally, when both time and country effects exist in the data we have to address one parametrically (by using dummies) and then estimate standard errors by clustering on other dimension\(^1\).

Before starting the empirical analysis, it is important to determine the type of dependence present in the data. In fact, when the standard errors clustered by entity (or country) are much larger than the white standard errors (three to four times) then this is an indication of presence of a country effect and when the standard errors clustered by time are much larger than the white standard errors this is an indication of a time effect. We follow this methodology in order to determine the form of dependence in the data and find that both time and country effects exist even though the time effect is rather weak.

The regression model used in this study is presented in the following way:

\(^1\)Another possibility suggested is to address both time and country effects using dummies.
\[ CDS_{spreads_{it}} = a + b \times CreditRisk_{it} + c \times CDSLiquidity_{it} + \varepsilon_{it} \quad (3.1) \]

We regress CDS spread changes against credit risk controls and different liquidity proxies. We run the model by using dummies with the goal to retrieve robust standard errors. As a further step in our empirical analysis, we do a robustness check\(^2\).

### 3.3 Credit Risk Controls and Liquidity Measures:

As a first step of our empirical analysis we control for the default risk component, however before presenting the credit risk controls and the liquidity risk measures, it is important to put some theoretical framework to clarify exactly what we would like to test. The pricing framework of CDSs proposed by Duffie (1999), Dai and Singleton (2003), Pan and Singleton (2008) and others comprises three important elements: the risk neutral default rate \( \lambda \), the risk neutral loss given default \( L \) and the risk neutral liquidity premium \( l \) and is defined as follows: \( \lambda L + l \). Therefore, the theory suggests that the higher the liquidity risk, the higher should be the value of \( l \), implying higher CDS spreads because illiquid securities incur trading costs and investors would like to be compensated for that (Amihud, Mendelson and Pedersen (2005)).

#### 3.3.1 Credit Risk Controls:

As stated before, Duffie (1999) suggests two theoretical credit risk components in the pricing framework and we utilize his model as a guidance to control for the credit risk part of the CDS contract. In line with this, the sovereign literature proposes number

\(^2\)We do a robustness check using a fixed effect model. The fixed effect model is conditional upon the value of the intercepts, this approach makes sense if the entities in the sample are one of a kind (such as countries) and cannot be viewed as a random sample. Typically, the fixed effect is a good starting point when one deals with panel data set, the reason is that the correlation between individual intercepts and explanatory variables are ignored by random effect models and can only be handled by the fixed effect approach. To avoid any doubt we use the Hausman test to confirm that the fixed effect model is the model of choice. We do not present the results of the robustness check to save space.
of variables to control for sovereign credit risk:

3.3.1.1 Local Variables

The sovereign credit risk is largely impacted by the local state of the economy. Typically, local economic forces could impact the default-arrival process and the loss-given default. Thus in order to capture the state of local economy we use local stock market return (denominated in local currency), exchange rate of local currency against the dollar and sovereign’s holding of foreign reserves in US dollar (Longstaff et al (2010) and others).

We also use the term of trade in order to control for the effect of local economy. The terms of trade measures the price of a country’s export relative to its imports and changes in a country’s terms of trade affects its ability to generate dollar revenue from exports and therefore its ability to make payments on its external dollar denominated debt (Bulow and Rogoff (1989)). In fact, a country with more volatile terms of trade is more likely to experience a severe weakening of fundamentals which may force it into default (Mendoza (1995, 1997) and Hilscher and Nosbusch (2010)). Therefore, for each country included in the analysis, we download the terms of trade from Thomson Financial Datastream on a monthly basis and we use linear interpolation to obtain a weekly frequency.

3.3.1.2 International Variables

The countries included in the analysis typically have extensive economic relationships with other sovereigns. Therefore, the ability to repay the debt not only depends on the local economy but also on the global macroeconomic state. In order to capture the change in the state of the global economy, we use a number of measures mostly related to the US economy as recent literature proved that the prices of securities in US financial markets incorporate information about economic fundamentals that is relevant
to a broad cross-section of countries (Pan and Singleton (2008) and others). Thus in line with the literature we include equity- and fixed income-related variables to control for the global economy. On the equity side, we use the US VIX to capture the variation in US equity investments and on the fixed-income part, we include the five-year constant maturity treasury (CMT) because a change in this variable could signal variations in the US economic growth and in turn the global business cycle. We download US VIX in a weekly frequency from Datastream and 5 year CMT from H.15 Federal Reserve Statistical Release.

In total, we use six variables to control for the credit risk component of the sovereign CDS spreads (local stocks return, changes in the exchange rate, trade balance, total foreign reserves in dollar, US VIX and 5year CMT).

### 3.3.1.3 Sovereign Default Risk

We find that our credit risk controls produce only 28% R-squared. CDSs are generally considered to be a clean representation of the default risk, therefore the value of 0.28 may seem small. However it is important to note that sovereign defaults are rare and are not only determined by the ability or sometimes the willingness of the country to pay back its debt but are also subject to the lender capacity to force the repayment of the debt (Edwards (1984)). Secondly the R-squared value 0.28 is consistent with the view presented by Remonola et al (2008) and Longstaff (2010) who present evidence that sovereign CDS spreads are composed of default risk and risk premium components.

In the coming subsections, we test for the presence of bond and CDS liquidity.

### 3.3.2 Liquidity Proxies: Whole Sample Analysis

Standard sovereign CDS contracts that are quoted and traded do not apply to a specific debt instrument. In practice, any dollar denominated senior obligations are eligible for

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3In the study of Tang and Yan (2007), the control of default risk and liquidity level gives 60 % R-squared.
delivery⁴. In fact, if default happens then all eligible bonds could be delivered even if there are different from the instruments that investors were hedging initially. Therefore, in order to test for bond liquidity, we download for each country all the available US dollar denominated and internationally traded sovereign bonds in the market. We thus have 20 sovereign bonds for Argentina, 2 for Chile, 17 for Mexico, 25 for Brazil, 16 for Turkey, 11 for Philippines, 4 for Korea, 1 for Malaysia and 12 for Indonesia which gives a total of 108 sovereign bonds.

In what follows, we present different proxies to test for bond and CDS liquidity.

3.3.2.1 Sovereign Bond Depth

One important aspect of liquidity is depth, namely the price sensitivity to the amount of market activity; this is the measure used by Amihud (2002) to estimate stock liquidity. This measure can be interpreted as a daily response to one dollar of market activity, thus if the market is deep then large order is needed to change the price.

We estimate price sensitivity and market activity on a weekly basis by taking the price volatility and the total bond market value respectively of all the internationally traded US dollar denominated sovereign bonds. Therefore, by taking the ratio of price volatility over market activity, we should capture reasonably well the notion of market depth. Table 3.1 shows a negative coefficient that is significant at 10% level. The negative sign implies an inverse relationship between CDS spreads and bond depth. If bond depth is low or equivalently if bond liquidity is low, it increases CDS spreads, this is consistent with the idea that illiquid deliverable bonds can have an impact on CDS spreads.

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⁴For Asian sovereigns in the sample, all the bonds with maturity under 30 years are eligible for delivery. For all other countries, bonds of any maturity could be delivered.
3.3.2.2 Sovereign Bond Bid-Ask Spreads:

To capture bond liquidity spill-over on CDS spreads, we use bond bid-ask spread (BAS) as a measure of liquidity. As emphasized before, higher BAS is associated with higher illiquidity and if the bond market is illiquid we expect CDS spreads to be higher. We construct bond BAS for each country and take the weekly average for all the traded US dollar denominated sovereign bonds in the market (108 bonds for 9 countries).

Table 3.1 shows a negative and highly significant coefficient. The negative sign seems to be counter-intuitive because there is a positive relationship between sovereign bond bid-ask and CDS spreads. In a recent study, Kucuk (2010) discusses liquidity in the sovereign bond market and uses CDS spreads to estimate the default and the non-default component of emerging market sovereign bond yields. The author utilises the BAS as a direct measure of bond liquidity and divides the bond data into two groups: investment and speculative grades. He provides evidence that the BAS of investment grade bonds have positive impact on CDS-basis but speculative grade bonds show negative effect. Although the previous study is different from ours as it focuses on CDS basis and not on CDS spreads, it points to an important observation, speculative and investment grade liquidity measures (i.e. BAS) behave differently and this might be an explanation as to why the coefficient is negative instead of being positive.

3.3.2.3 Bond Price Volatility:

The empirical evidence for price volatility as liquidity proxy is mixed. For example, Houweling, Mentink and Vorst (2003) use yield volatility to measure illiquidity in corporate bonds. The authors state that in market microstructure models, dealers’ inventory costs are higher if information uncertainty is higher. One essential source of uncertainty in the bond market is related to the predictability of future yield movements. Therefore, the authors hypothesize that a higher yield volatility leads to larger bid-ask
spreads and thus to lower liquidity. Because of the inverse relationship between bond prices and yields, their finding implies that higher yields (or lower bond prices) lead to lower liquidity.

On the other hand, Shulman et al. (1993) use price volatility as a proxy for price uncertainty and find a significantly positive effect on bond spreads, meaning that the higher price volatility the lower the liquidity. Therefore bond spreads should increase to account for liquidity risk.

In our panel model, we regress CDS spread changes against credit risk controls and bond price volatility. In order to estimate bond volatility, we average at weekly basis bond price volatilities\(^5\). Table 3.1 shows a negative and significant coefficient at 5\% level. Our interpretation of the results is mixed. On one hand, if we follow the first stream of the literature, a negative coefficient implies that yield volatility leads to higher yield and thus to lower bond liquidity. As discussed before a reduced bond liquidity puts pressure on the CDS market, causing an increase in the spreads to account for liquidity risk. This finding is thus consistent with Houweling, Mentink and Vorst (2003). On the other hand, the second stream of the literature (i.e. Shulman et al. (1993)) suggests that the negative sign that we obtained in our regression is counter-intuitive, because higher price volatility is an indication of illiquid bond market which should increase CDS spreads instead of decreasing them.

3.3.2.4 Sovereign Bond Volume:

Recent empirical studies on liquidity dynamics have shown that higher volume does not necessarily lead to more liquid market. Jones (2002) finds no significant effect of changes in turnover on changes in bid-ask spreads. Evans and Lyons (2002) and Galati (2000) report no association between the liquidity and the level of activity on the foreign exchange market. In the U.S. Treasury market, Fleming (2003) finds that

\(^5\)We compute bond price volatility by taking the standard deviation of each bond price at 2 months rolling window.
neither trading volume nor trading frequency are consistently correlated with price impact or bid-ask spreads. Finally, a more recent paper by Johnson (2007) argue that the volume of trade is driven by the degree of rearrangement, or flux, of the trading population. While higher trading volume does not necessarily signal better liquidity (e.g. the 87' market crash), it is indicative of a higher population flux that leads to liquidity changes. Therefore, we can associate higher volume with higher liquidity risk. These results seem to challenge the basic intuition that states that a higher volume makes it easier to trade in a market; that was the original finding of Demsetz (1968), which is viewed as the starting point of the field of market microstructure. In this chapter, we follow the hypothesis of Johnson (2007) and associate a high volume with high liquidity risk.

To test for bond volume effect on the sovereign CDS market, we download the weekly market value of all the available US dollar denominated sovereign bonds. Datastream defines the market value as the current market value of the issue, that is, the current market price multiplied by the amount currently in issue. Then by computing the total market value of the sovereign bonds, we obtain a good proxy of the total traded volume.

The panel regression in Table 3.1 shows a positive coefficient. Although the level of significance is weak we do find evidence of a volume effect in the sovereign CDS market. The positive sign indicates that higher liquidity risk leads to higher CDS spreads.

3.3.2.5 CDS Bid-Ask Spreads:

The bid-ask spread reflects different facets of liquidity (adverse selection, handling costs,...) and is one of the most widely used liquidity measure in bond and stock markets; its importance has been proved since the first paper of Amihud and Mendelson (1986).

Because the CDS market is an OTC market, there are three important facets of
liquidity that are particularly relevant. We briefly mentioned two of them which are inventory costs and search frictions and we have another aspect which is the adverse selection. As shown by Acharya and Johnson (2007), adverse selection is particularly relevant to the corporate CDS market because lot of informed trading occurs which tend to intensify asymmetric information between market participants. Concerning our study, we are focusing on the sovereign CDS market and these instruments are less subject to adverse selection (Ammer and Cai (2007)). In fact, most of the relevant information that could impact sovereign CDS spreads such as national economy statistics or the state of government finances are publicly available so any new information tend to be quickly incorporated in the market. Following this, we assume that the adverse selection problem is non-existent and we only focus on two liquidity facets: search frictions and inventory costs\(^6\).

One anticipates bid-ask spreads to be higher if liquidity is low and high liquidity risk increases CDS spreads. We therefore expect to see a positive coefficient in the regression. The results show negative and insignificant coefficient (Table 3.1).

In Acharya and Johnson (2007), even though the authors presented the evidence of insider trading in the corporate CDS market they found that bid-ask spread had no explanatory power on CDS levels. In this study, even though our initial hypothesis is different from their paper as we assume that there is no insider trading in the sovereign market, we also find that bid-ask spreads do not impact CDS spreads. These results point to the difficult process of liquidity determination and our intuition suggests that the problem of assuming bid-ask spread or bid-ask percentage spread as being a good illiquidity proxy in the CDS market is not easy. On one hand, both measures are affected by the level of CDS premium and on the other hand there is a high correlation between CDS premium and CDS bid-ask. This, in fact, could account for the lack of

\(^6\)Even though we assume that there is no insider trading in the sovereign CDS market, we still have asymmetric information between dealers because credit derivatives are insurance contracts by definition. However, this asymmetric information is not high enough to encourage market participants to do insider trading.
level of significance and could also constitute a possible explanation of the negative coefficient in the regression.

3.3.3 Summary of the Results: Whole Sample Period

In summary, we tried different measures in order to test whether liquidity is priced in sovereign CDS spreads. In this analysis, we considered both CDS and bond related liquidity proxies. Even though the used measures are intuitive and reflect different facets of liquidity (e.g. search frictions, inventory costs, etc) they are not all significant and some show mixed results. However, we do find evidence of bond liquidity priced in sovereign CDS spreads. Our results show that, for the whole sample period, bond liquidity proxies have an impact on sovereign CDS spreads although the level of significance differs from one liquidity measure to another.

As a further step in this analysis, we follow Acharya and Pedersen (2005) methodology and attempt to quantify illiquidity premium by multiplying the coefficient estimates and the standard deviations of the corresponding liquidity proxies. We then take the significant liquidity proxies (bond depth, bond price volatility, bond volume and bond BAS) and multiply their standard deviations (3.39, 1.76, 14.14 and 0.75 respectively) by their corresponding coefficient estimates (-1.08, -2.55, 0.67 and -8.83). We find that the average bond liquidity premium associated with these four measures is 4.47 basis points. We did not include the effect of CDS liquidity in the quantitative evidence because CDS BAS is insignificant.

To the best of our knowledge this chapter is the first to provide a quantitative figure to the liquidity premium in the sovereign CDS market. In our sample we have 9 emerging countries and the average of CDS spreads is about 246.5 basis points, in terms of percentage the liquidity premium represents 1.8% of the sovereign CDS spreads. This

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7Bond liquidity has a stronger impact on CDS spreads than CDS liquidity.
8In case of negative signs, we take the absolute values because we are interested in the quantities.
figure is in line with the literature, for example Longstaff (2004) estimate the 5 year Treasury bond liquidity premium to 9.99 basis points and Longstaff, Mithal and Neis (2005) proxy the non-default component of the corporate bond spread to 8.6 basis points.

Our sample contains two periods that have different level of trading activities. Chordia et al (2001) emphasize that liquidity and trading activity are strongly linked as they are influenced by common factors. Garleanu, Pedersen and Poteshman (2007) mention that the imbalance of supply and demand in the CDS market can impact the character of liquidity effect and finally Tang and Yan (2007) state that cross-sectional variations in the liquidity effect on CDS spreads are very sensitive to the trading intensity. Thus, in order to better understand the liquidity features of the sovereign CDS market we split our sample in two: one period running from November 2005 to March 2008 and the other from April 2008 to October 2010.

3.4 Comparative Analysis: Pre-Crisis and Crisis Period:

The main aim of this section is to provide a comparative analysis between the pre- and crisis periods. The point is to observe how liquidity characteristics change with market conditions and see if liquidity risk is time-varying. In what follows, we mainly discuss the significance of the liquidity measures.

3.4.1 Pre-Crisis Period:

We restrict our empirical analysis to the pre-crisis period (from November 2005 to March 2008). Table 3.2 reveals that the results differ significantly from the whole sample period as none of the bond liquidity measures are significant (bond price volatility, bond depth, bond volume, bond BAS). This implies that the impact of bond market liquidity is weak during the pre-crisis period. Concerning the CDS-related liquidity measures, we find
that the CDS BAS is insignificant as well.

3.4.2 Crisis Period:

Due to the availability of Depository Trust and Clearing Corporation (DTCC) data for this sample period, we are able to test for different liquidity facets that characterize the CDS market such as depth, search frictions and inventory constraints.

3.4.2.1 Sovereign CDS Depth:

Using DTCC data, we test for market depth. We construct CDS depth measure by taking the ratio of spread sensitivity to CDS volume. To proxy CDS volume, we utilise the gross notional value provided by DTCC defined as the sum of the CDS contract bought (or equivalently sold) in a weekly basis and for the spread sensitivity we compute the standard deviation of the CDS spreads.

Table 3.4 reveals that CDS market depth has significant impact on CDS spreads. The coefficient is negative which indicates that low market depth (i.e. low liquidity) increases CDS spreads. This finding is in line with Tang and Yan (2007) who also find that low market depth increases corporate CDS spreads.

3.4.2.2 Search Frictions or Matching Intensity:

Search frictions are among the important facets of liquidity that are present in the OTC market. The CDS market is very opaque and the International Securities and Derivatives Association (ISDA) has revealed very few information about it. In a recent paper, Duffie, Garleanu and Pedersen (2005, 2006) show that search costs directly affect market liquidity and thus market prices. Moreover, Chacko, Jurek and Stafford (2007) show that market makers have a pricing power in search based markets.

In order to proxy for search frictions, we use the net notional value. DTCC defines
the net notional with respect to any single reference entity as the sum of the net protection bought by net buyers (or equivalently net protection sold by net sellers).

DTCC states that this measure is calculated by the counterparty family. We take as example a counterparty family A; on this particular family the total gross notional of CDS bought (sold) on reference entity X is 135,000,000 (-150,000,000) therefore the net position held by the counterparty family A on the reference entity X is -15,000,000. Thus, if we interpret this figure in terms of search frictions, the family A was only able to match a certain percent of her CDS position on reference entity X and therefore her net position is -15,000,000.

In fact, what DTCC reports is the aggregate net notional bought namely the position of a large number of families (i.e. family A,B,C, etc). Therefore, we consider the aggregate net notional as the best available proxy for search frictions or matching intensity in the sovereign CDS market.

High search friction (or lower matching intensity) are associated with high bid-ask spreads because it reflects the difficulty to find a counterparty willing to take the opposite trade. Therefore, higher search frictions should lead to higher CDS spreads, we thus expect a positive relationship.

Table 3.4 shows a negative and insignificant coefficient. This result suggests that for the crisis period search frictions are not priced in sovereign CDS spreads. This finding is consistent with the corporate CDS market where search frictions are not priced for the actively traded CDS contract (Tan and Yan (2007)).

3.4.2.3 Inventory Costs:

Brunnermeier and Pedersen (2009) mention that inventory costs are of a great importance for dealers facing funding constraints. Cao, Evans and Lyon (2006) provide evidence that inventory information can have significant impact on prices even though the risk related to fundamentals did not change. Concerning the CDS market, inven-
tory costs can constitute an obstacle to dealers entering a CDS trade (i.e. margin requirements and/or premium payment).

In order to proxy for this liquidity facet, we use the total number of contracts provided by DTCC. We take the difference between week \( t \) and week \( t-1 \) of the total number of contracts. For example, a negative difference would mean that less dealers were able to enter a CDS trade than the week before suggesting that funding costs are constraining, however, a positive difference would imply that more market participants entered into a CDS trade which in turn indicates that funding problems are trivial. In this study, we depart from this hypothesis in order to test for inventory costs. High inventory constraint leads to high bid-ask spreads, there is then a positive relationship between CDS spreads and inventory costs.

Table 3.4 indicates a positive and insignificant coefficient. The result implies that inventory costs are not priced in the sovereign CDS spreads. These findings differ from the corporate CDS market where inventory costs are priced.

3.4.2.4 CDS Volume and CDS BAS:

Table 3.4 shows that CDS volume ( proxied by CDS gross notional value) is insignificant and has negative sign which means that the volume effect is not priced in the sovereign CDS market. This result is not consistent with the corporate CDS market where a significant impact of CDS volume has been documented. Finally, Table 3.4 reveals that CDS BAS has a significant impact (i.e. at 10% level).

3.4.2.5 Bond Liquidity:

In what follows, we test for bond liquidity spill-over using the same bond liquidity proxies as for the whole sample analysis. Table 3.3 shows that bond price volatility and depth are insignificant. Moreover, sovereign bond BAS is significant at 1% level and
has a negative sign. Finally, the volume proxy is significant at 10% level. Overall, it seems that during the crisis period the impact of the bond liquidity is higher than the pre-crisis period.

### 3.4.3 Discussion:

In this subsection, we discuss the implications of our comparative analysis. The fact that CDS market depth is significant during the crisis period could explain why other liquidity measures such as inventory costs and search frictions are insignificant. Indeed, a deep market points to the ease of finding a trading partner for a given order and it may make search frictions and inventory costs less constraining. The interaction between different liquidity aspects (i.e. depth, inventory costs, search frictions) creates a “cross-sectional” variation in the liquidity effect that can account for the lack of level of significance for some facets of liquidity. This interaction effect was also reported in the corporate CDS market.

In order to provide a rough estimate of the liquidity premium priced in the sovereign CDS spreads during the crisis period, we multiply the coefficient values of the significant bond and CDS liquidity proxies (i.e. average bond BAS, bond volume, CDS BAS and CDS depth) by their respective standard deviations and we obtain an average of 12.89 bps (7.75 bps for CDS liquidity and 18.02 bps for bond liquidity). The average CDS premium of the sample during the crisis period is 372 bps therefore the average liquidity premium accounts for 3.5% of the sample (2.1% for CDS liquidity and 4.8% for bond liquidity).

The estimated sovereign CDS liquidity premium of 2.1% is lower than the one documented in the corporate CDS market (i.e. 11%). The difference between the two liquidity premium is quite high and one of the possible explanations could be related

\[ \text{DTCC does not provide any data for the period before 2008, therefore, we are not able to present a proxy for the liquidity premium embedded in the sovereign CDS spreads for the pre-crisis period.} \]
the intensity of asymmetric information embedded in each market. As documented by Acharya and Johnson (2007), there is adverse selection coming from informed traders in the corporate CDS market which may intensify search frictions and participate to the augmentation of liquidity risk. The magnitude of the asymmetric information between agents depends on informational advantages that banks typically have on borrowers credit quality, this supremacy of information encourage them to exploit opportunities by trading as insiders which in turn increase liquidity risk. However for the case of the sovereign CDS market, the banks are less likely to have informational power which may reduce the asymmetric information and deter any insider trading.

Furthermore the results show that for the pre-crisis period, all the bond-related liquidity measures are insignificant. However during the crisis two out of four bond-related liquidity measures (i.e. bond BAS and bond volume) are significant. This implies that a change in the trading activity of the sovereign bond market can influence sovereign CDS spreads. In fact, in times of recession investors rebalance their portfolio in order to buy less risky and more liquid assets and this is particularly relevant to the fixed income market. This phenomenon is known as flight-to-liquidity and flight-to-quality. In line with this, Beber et al (2009) study the effect of flight-to-liquidity and flight-to-quality in the sovereign bond market and provide evidence that, under recession, investors chase liquidity regardless of the credit quality because the short-term liquidity concerns become the priority. Our empirical results show that bond liquidity has more impact on sovereign CDS spreads during crisis time and this may be explained by the flight-to-liquidity phenomenon documented in the sovereign bond market.

Therefore, our findings suggest that in times of recession, it is not the search frictions nor the inventory costs that impact sovereign CDS spreads but rather bond liquidity seems to have the highest influence.
3.5 Conclusion:

In this chapter, we present an empirical analysis where we investigate the effect of liquidity on the sovereign CDS market. It is important to underline that the elusive nature of liquidity risk makes it hard to test especially for less transparent markets such as the OTC markets and that the results that we present are subject to the proxies used. However to the best of our knowledge, this study represents the first attempt to analyse the effect of search frictions, depth and inventory costs in the sovereign CDS market. Using DTCC data, we show that during crisis time search frictions and inventory costs do not represent a constraint to market participants and we provide a proxy of the CDS liquidity premia of about 2.1%. Furthermore, our results reveal that the impact of bond liquidity is higher during crisis time with a bond liquidity estimate of 4.8%. This indicates that the flight-to-liquidity episode in the sovereign bond market influences significantly sovereign CDS spreads.

Our study reveals that sovereign CDS liquidity is time-varying meaning that liquidity characteristics show dissimilar behavior in different states of the market. Pastor and Stambaugh (2003) emphasize that the time-variation of liquidity characteristics constitutes on itself a systematic liquidity risk that should be priced above liquidity levels. Therefore, in our next chapter, we investigate the effect of systematic liquidity risk on the sovereign CDS market.
Tables:

Table 3.1: **CDS and Bond Liquidity: Whole Sample Analysis**

We regress CDS spread changes against credit risk controls and liquidity proxies. In our panel model, we address country effect parametrically (i.e. by using dummies-not shown in the table) and cluster the standard errors by time. To control for default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT. Our liquidity proxies are: (1) CDS BAS (2) Bond Price Volatility (3) Bond Market Value (4) Bond BAS and (5) Bond Depth. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively.

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<th>Bond and CDS Liquidity Proxied by:</th>
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<th>(3)</th>
<th>(4)</th>
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<td>1.17</td>
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Table 3.2: CDS and Bond Liquidity: Pre-Crisis Period

We regress CDS spread changes against credit risk controls and liquidity proxies. In our panel model, we address country effect parametrically (i.e. by using dummies-not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT. Our liquidity proxies are: (1) CDS BAS (2) Bond Price volatility (3) Bond Market Value (4) Bond BAS and (5) Bond Depth. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively.

<table>
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Table 3.3: **Bond Liquidity: Crisis Period**

We regress CDS spread changes against credit risk controls and liquidity proxies. In our panel model, we address country effect parametrically (i.e. by using dummies-not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT. Our liquidity proxies are: (1) CDS BAS (2) Bond Price volatility (3) Bond Market Value (4) Bond BAS and (5) Bond Depth. ***, **** and ***** represent 1%, 5% and 10% significance level respectively.

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<td>-0.05</td>
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<td>0.13</td>
<td>-0.0014</td>
<td>0.06</td>
<td>-1.3e^-3</td>
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<tr>
<td>US VIX</td>
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<td>2.56</td>
<td>1.4</td>
<td>2.5</td>
<td>1.39</td>
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<tr>
<td>CMT 5 years</td>
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<td>-35.9</td>
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<tr>
<td>Liquidity</td>
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<td>-1.69***</td>
<td>-1.37</td>
<td>-0.74</td>
<td>1.73</td>
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<tr>
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<tr>
<td>R²</td>
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<td>0.28</td>
<td>0.282</td>
<td>0.284</td>
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Table 3.4: **CDS Liquidity: Crisis Period**

We regress CDS spread changes against credit risk controls and liquidity proxies. In our panel model, we address country effect parametrically (i.e. by using dummies-not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT. Our liquidity proxies are: (5) CDS BAS (6) Depth CDS (7) Search Frictions (8) CDS Volume and (9) Inventory Costs. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively.

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<th>(5)</th>
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<td>-0.52</td>
<td>-0.31</td>
<td>-0.53</td>
<td>-0.31</td>
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<td>-0.69</td>
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<tr>
<td>US VIX</td>
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<td>2.56</td>
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<td>2.32</td>
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<tr>
<td>CMT 5 years</td>
<td>-37.29</td>
<td>-1.49</td>
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<td>-49.31</td>
<td>-1.64</td>
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<td>-1.65</td>
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</tr>
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<td>Liquidity</td>
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<td>-1.69**</td>
<td>-15.12</td>
<td>-2.23**</td>
<td>-3.54</td>
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Chapter 4

Sovereign Credit Default Swaps and Systematic Liquidity Risk

4.1 Introduction

In this chapter, we focus on the correlation of fluctuations of liquidity measures across assets, these common fluctuations (also called systematic liquidity risk) are more likely to impact assets characterized by commonality. Our aim is to investigate whether systematic liquidity risk is a priced state variable and participates directly to sovereign CDS spread movements.

Recent literature provides evidence that commonality is an important source of risk in the sovereign CDS market. Longstaff et al (2010) document that the first principal component account for 64% of the variation in the sovereign CDS spreads across different markets, this percentage reaches 75% when the sample is restricted to the crisis period. Pan and Singleton (2008) investigate the default intensity and the recovery rate using the term structure of the sovereign CDS spreads and show that the first principal component captures 96% of the variation over-time of the CDS term structure. Finally, Augustin and Tedongap (2010) develop a consumption based model in order to link sovereign credit risk premia to consumption growth forecast, macroeconomic uncertainty and investors preferences. By using PCA, they find that three factors are sufficient to explain 95% of the commonality in spread movements.
All these papers document significant commonality in the sovereign CDS market\(^1\) which is an important source of risk because it may facilitate credit risk or liquidity contagion between different sovereign economies. We contribute to the literature by offering the first study that focuses entirely on sovereign entities by analyzing issues specific to the commonality in liquidity (or systematic liquidity risk). The closest study to ours is Meng and Gwilym (2008) where the authors investigate liquidity of CDSs (corporates and sovereigns) with a specific focus on how bid-ask spreads are affected by the characteristics of the contracts such as demand supply pressure, inventory risks and clientele effects. Although this latter study is very similar in spirit to that of Tang and Yan (2007) where the authors explain that liquidity participates to CDS spread changes, it differs by having a focus on the determinants of liquidity proxied by bid-ask spread. The other difference is related to the data used. Tang and Yan (2007) concentrate only on corporate entities while Meng and Gwilym (2008) pool together a large dataset where sovereign entities represent less than 20\% of the sample therefore the results are heavily biased towards the corporates. Finally, Meng and Gwilym (2008) find evidence of commonality in liquidity of all CDSs (corporates and sovereigns) consistent with the results of Tang and Yan (2007) for corporates.

Secondly, in contrast to Meng and Gwilym (2008), we do not attempt to analyze the determinants of the bid-ask spreads but, using a CAPM-type framework, we test whether systematic liquidity risk\(^2\) participates to CDS spread movements independently of any reassessment of the default risk. Furthermore, we also examine liquidity spiral effects which are described by Brunnermeier and Pedersen (2009) as the joint impact of market and funding liquidity risks\(^3\). To our knowledge, we are the first to empirically test for liquidity spiral effects in the CDS market.

\(^{1}\)Pastor and Stambaugh (2003) find that the systematic liquidity risk is priced in the expected stock return, they present as explanation the significant level of commonality present in the stock markets.

\(^{2}\)In our study, we use the terms market liquidity risk and systematic liquidity risk interchangeably.

\(^{3}\)Sovereign CDSs are subject to margin deposit and are therefore exposed to funding liquidity risk.
By applying the Liquidity-Adjusted CAPM of Acharya and Pedersen (2005), we find that, before the crisis, the risk premium priced above the default risk and liquidity level is mainly driven by CDS systematic liquidity risk. In times of low uncertainty, dealers use CDSs more for speculation than for hedging. Since speculation is not directly related to the reference entity or the underlying asset, it weakens the influence of the bond market. However in times of crisis, high default probability increases significantly global risk aversion which induce dealers to use CDSs to hedge their bond positions; hence the tightening of the relationship between CDS and bond markets. Thus, bond systematic liquidity risk becomes the main driver of the risk premium priced above the default risk and liquidity level. Furthermore, we provide evidence that the joint impact of market and funding liquidity risks (i.e. liquidity spiral) has no significant influence on CDS spreads. Finally, our results imply that speculation may participate to the widening of bid-ask spreads and that funding liquidity risk is more constraining during crisis time.

4.2 Related Literature

There is an increasing literature that focus on the market-wide liquidity triggered by common fluctuations across assets. Chordia et al (2000), Hasbrouk and Seppi (2001) and Huberman and Halka (1999) investigate systematic liquidity risk in the stock markets. Chordia et al (2002) find that the fluctuations in liquidity are correlated across stocks and bonds. Eisfeldt (2002) develops a model where liquidity fluctuations are correlated with real fundamentals such investment and productivity.

Indeed very few papers investigated the effects of systematic liquidity risk in the CDS market. Dunbar (2008) extends a reduced-form CDS pricing framework in order to include market liquidity and finds that this additional factor improves the explanatory power of the model. Tang and Yan (2007) provide evidence that systematic liquidity risk
is priced in corporate CDS spreads but its magnitude is very weak. Pu, Wang and Wu (2011) examine the potential effects of systematic liquidity and counterparty risks on corporate CDS spreads. After controlling for default risk part which represents 25% of the R-squared, they find that a significant portion of CDS spread changes is attributable to systematic counterparty and liquidity risks. Finally, Bongaerts, De Jong and Driessen (2011) also find that the effect of systematic liquidity risk in corporate CDS spreads is significant but economically small. In fact, these results are intuitive because market liquidity is mainly triggered by liquidity fluctuations across securities, these common shocks are less likely to affect corporate CDS spreads because these instruments are less exposed to global macroeconomic factors than their sovereign counterparts.

Other studies emphasize the importance of liquidity commonality across the bond and the CDS markets. Pu (2010) is one of the first paper that explores the properties of liquidity measures across corporate bond and CDS spreads. The author finds that there is a strong commonality across all the constructed liquidity measures and shows that a substantial amount of credit spreads could be explained by liquidity common factors. Calice, Vhen and Williams (2011) analyze the potential liquidity spill-over between sovereign bond and CDS markets during the European crisis in 2010. The authors report three important results. First, it is found that when the sovereign bond market liquidity dries up, CDS market liquidity increases significantly. Moreover, the paper shows a strong liquidity spill-over from the CDS to the bond market. Finally, the authors document that prior to the crisis, bond yields determined CDS spreads, however during the crisis the relationship inverted with CDS spreads taking the lead over bond yields.

The research spirit of this study is more in line with Longstaff et al (2011) and Remolona et al (2008) where the authors decompose sovereign CDS spreads into expected loss and default risk premium components. Longstaff et al (2011) view the risk premium as a compensation to unpredictable changes in the default arrival rate; this is what they
call the “distress” risk. The authors quantify this risk premium by taking the difference between theoretical values of CDS spreads under both the risk neutral and physical measures and find that on average the risk premium represents a third of the sovereign CDS spreads. Remonola et al (2008) also disentangle sovereign CDS spreads by using rating information. In fact, the studies of Longstaff et al (2011) and Remonola et al (2008) are similar in spirit, the difference lies in the risk that the papers study, while the former focuses on “distress” risk, the latter discusses the “jump-at-default” risk. In this chapter, we contribute to the literature by mainly focusing on the systematic liquidity risk effect on sovereign CDS spreads. It is important to note that because of the strong ties between sovereign CDS and bond markets, systematic liquidity risk could not only be triggered by the sovereign CDS market itself but also by the sovereign bond market (Pu (2010) and Calice, Vhen and Williams (2011)). Therefore, in this study we focus on both effects.

As a first step in our analysis we start by controlling for the default risk\textsuperscript{4} and the liquidity level, then we construct different liquidity risk factors and test whether these are priced in addition to the control variables. Similarly to the previous chapter, we focus on nine emerging markets (i.e. Argentina, Brazil, Mexico, Korea, Philippines, Malaysia, Turkey, Chile and Indonesia). By examining systematic liquidity risk, we aim to clarify further the source of commonality that characterizes the sovereign CDS market and shed some light on the drivers of sovereign CDS spreads.

In Section 4.3, we introduce the model used to test for systematic liquidity and funding liquidity risk. In Section 4.4, we define the data and the methodology used and in Section 4.5 we discuss the implications of our results. Finally, in Section 4.6, we conclude.

\textsuperscript{4}We control for default risk using the same variables as for Section 3.3 of Chapter 3.
4.3 Liquidity-Adjusted CAPM

As specified in Chapter 2 and 3, liquidity could be an obstacle to CDS dealers for many reasons (depth, timing, prices etc...). However since there is a high correlation\(^5\) between different liquidity measures, it is highly likely that systematic liquidity risk influences instrument-specific liquidity\(^6\) which may create more frictions to CDS dealers who want to exit or enter a position for a limited amount of time.

In their CAPM framework, Acharya and Pedersen (2005) propose that systematic liquidity risk be represented by three components: (1) the sensitivity of the liquidity of individual securities to market-wide liquidity shocks (\(\beta^2\)); (2) the sensitivity of the return of individual securities to market-wide liquidity shocks (\(\beta^3\)); and (3) the sensitivity of the liquidity of individual securities to market return (\(\beta^4\)). The unconditional Liquidity-Adjusted CAPM relates the expected excess return of a security at time \(t\), \(E(r_t - r^f_t)\), to the expected level of liquidity, \(E(c_t)\), the market beta (\(\beta^1\)) and the three liquidity sensitivities mentioned above in the following form:

\[
E(r_t - r^f_t) = E(c_t) + \lambda \beta^1 + \lambda \beta^2 - \lambda \beta^3 - \lambda \beta^4
\]  

(4.1)

where \(\lambda = E(\lambda_t) = E(r^M_t - c^M_t - r^f_t)\) is the market risk premium, with \(r^M_t\) and \(c^M_t\) being the market return and liquidity measure at time \(t\) respectively. One of the benefits of Acharya and Pedersen’s framework (AP-thereafter) is that it presents a simple theoretical model that helps explain how asset prices are affected by liquidity risk and commonality in liquidity.

In this study we are working with CDS spreads and since by nature CDS contracts do not have initial costs at the inception, the concept of percentage returns is not well defined\(^7\). Therefore, we use CDS spread changes as a proxy for CDS returns. In what follows we present the constructed variables that aim to capture three types of

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\(^5\)Subsection 4.4.3 discusses the correlation between the different liquidity factors.

\(^6\)We use the term instrument-specific liquidity and liquidity level interchangeably.

\(^7\)This point is discussed in details in the Appendix of this chapter.
systematic liquidity risk that could impact sovereign CDS spreads. We first start with CDS and bond systematic liquidity risk then we discuss liquidity spiral effects.

4.3.1 CDS Systematic Liquidity Risk Betas:

To accommodate the CDS market, the equation (4.1) could be rewritten in the following way:

$$E(CDS_t) - DefaultRisk = E(c_{t}^{CDS}) + \lambda \beta^{2i} - \lambda \beta^{3i} - \lambda \beta^{4i} \tag{4.2}$$

Where the beta risk factors corresponding to the CDS systematic liquidity risk of each country\(^8\) \(i\) are defined as follows:

$$\beta^{2i} = \frac{Cov(c_{t}^{CDS} - E_{t-1}(c_{t}^{CDS}), c_{M}^{CDS} - E_{t-1}(c_{M}^{CDS}))}{var(r_{M}^{CDS} - E_{t-1}(r_{M}^{CDS}) - c_{M}^{CDS} - E_{t-1}(c_{M}^{CDS}))} \tag{4.3}$$

$$\beta^{3i} = \frac{Cov(r_{t}^{CDS}, c_{M}^{CDS} - E_{t-1}(c_{M}^{CDS}))}{var(r_{M}^{CDS} - E_{t-1}(r_{M}^{CDS}) - c_{M}^{CDS} - E_{t-1}(c_{M}^{CDS}))} \tag{4.4}$$

$$\beta^{4i} = \frac{Cov(c_{t}^{CDS} - E_{t-1}(c_{t}^{CDS}), r_{M}^{CDS} - E_{t-1}(r_{M}^{CDS}))}{var(r_{M}^{CDS} - E_{t-1}(r_{M}^{CDS}) - c_{M}^{CDS} - E_{t-1}(c_{M}^{CDS}))} \tag{4.5}$$

where \(\beta^{2}\) is the sensitivity of the liquidity of individual CDS to market-wide liquidity shocks; \(\beta^{3}\) the sensitivity of the return of individual CDS to market-wide liquidity

\(^8\)We focus on nine emerging countries (i.e. Argentina, Brazil, Mexico, Korea, Philippines, Malaysia, Turkey, Chile and Indonesia).
shocks; and $\beta^4$ the sensitivity of the liquidity of individual CDS to the CDS market return. $c^{CDS}_t$ is the CDS bid-ask spread. $r^{CDS}_M$ and $c^{CDS}_M$ correspond to CDS market return and CDS market liquidity proxied respectively by a weekly average of CDS changes and a weekly average of CDS bid-ask spread of the countries included in the market portfolio which are Argentina, Turkey, Brazil, Mexico, Philippines, Korea, Chile, Malaysia, Indonesia, Russia, Columbia, Venezuela, Peru, Hungary, Panama, South Africa, Ukraine, Bulgaria, Israel, China, Croatia, Poland, Romania, Qatar, Thailand, Japan, Kazakhstan, Australia, Lithuania, Latvia and Czech Republic. The constructed market portfolio will enable us to capture the effect of systematic liquidity risk.

In order to estimate the liquidity betas defined above, we first need to construct liquidity shocks. Since we are using weekly data, for each week and for each CDS we filter out the persistence of liquidity by using an AR(2) process.

$$c^{CDS}_t = a + \gamma_1 c^{CDS}_{t-1} + \gamma_2 c^{CDS}_{t-2} + \varepsilon_t$$  (4.6)

where $c^{CDS}_t$ represents the bid-ask spreads and $\varepsilon_t$ the liquidity shocks or innovations. Throughout the analysis, the construction of the innovations will be conducted in the same way.

As specified above, the AP model puts lot of emphasis on market liquidity, it thus represents a suitable modeling framework for sovereign CDS spreads as they are mostly linked to global macro factors. Our main aim is to test whether the risk premium related to these betas is priced above the default risk and liquidity level. The estimation of the CDS liquidity betas is conducted over the entire sample resulting in one set of betas for each country (Table 4.1).

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9The same countries have been used in the study of Longstaff et al [2010].

10Typically the construction of the hypothetical market portfolio is an issue in the CAPM framework (Roll [1977]).

11In some cases we use AR(3) to make the autocorrelation between lag 1 and 2 less than 5%.

12Since we control for default risk in the same manner as in Section 3.3 of Chapter 3, in equation (4.2) we ignore $\beta^{1i}$ because it represents the systematic default risk.
4.3.2 Bond Systematic Liquidity Risk Betas:

There is also a large evidence that the sovereign bond market has a significant impact on CDS spreads. For instance, Calice, Vhen and Williams (2011) find strong liquidity spill-over between sovereign bond and CDS markets. Thus, similarly to the previous section, we accommodate equation (4.1) in order to take into consideration the bond liquidity spill-over. The main assumption is that there are market-wide liquidity shocks that are transmitted to the sovereign CDS market. In fact, in case of default, CDS sellers of country $i$ can deliver all country-specific eligible bonds even if they may be different from the instruments that investors were initially hedging which imply that country-specific bond liquidity could influence CDS spreads in addition to the market-wide bond liquidity. Therefore, in this subsection, we analyse liquidity spill-over from (1) the country-specific bond portfolio and (2) the market-wide bond portfolio.

In what follows, we extend the Liquidity-Adjusted CAPM framework defined above and explore all the potential channels through which bond liquidity could influence CDS spread changes. In other terms, after controlling for default risk and bond liquidity level, we examine the liquidity effect of the country-specific bond portfolio (through $\beta^{5i}$) and of the market-wide bond portfolio (through $\beta^{6i}$, $\beta^{7i}$ and $\beta^{8i}$). The model is defined as follows:

$$E(CDS_t) - DefaultRisk = E(c_t^{Bond}) + \lambda \beta^{5i} + \lambda \beta^{6i} + \lambda \beta^{7i} + \lambda \beta^{8i}$$

(4.7)

where $\beta^{5i}$ represents the sensitivity of CDS liquidity to country-specific sovereign bonds.

$$\beta^{5i} = \frac{Cov(c_t^{CDS} - E_{t-1}(c_t^{CDS}), c_t^{Bonds} - E_{t-1}(c_t^{Bonds}))}{\text{var}(r_t^{Bonds} - E_{t-1}(r_t^{Bonds}) - c_t^{Bonds} - E_{t-1}(c_t^{Bonds}))}$$

(4.8)
$r^Bonds_L$ represents the average bond bid-ask spread of the country-specific bond portfolio. $r^Bonds_L$ is the average total return of the country-specific bond portfolio including the interest payments, as well as the appreciation or depreciation in bond prices. $r^Bonds_L$ is computed in the following way:

$$r^Bonds_L_t = r^Bonds_L_{t-1} \times \frac{P_t + A_t + NC_t + CP_t}{P_{t-1} + A_{t-1} + NC_{t-1}}$$

(4.9)

where $P_t$ is the clean bond price, $A_t$ is the accrued interest, $NC_t$ is the next coupon and $CP_t$ is the value of any coupon received on time $t$ or since time $t-1$.

The aim of the risk factor $\beta^{5i}_i$ of country $i$ is to capture the impact of the Cheapest-To-Deliver (CTD) option on sovereign CDS liquidity as suggested by the literature\textsuperscript{13}. If liquidity dries up in the country-specific bond market, it may cause frictions to CDS sellers who, in case of default, have to find a cheap and liquid bond to deliver. As we stressed above the CTD is more valuable when the number of deliverable bonds is high, this value should be incorporated in the CDS contract, however if the cheapest bond is illiquid then CDS spreads should reflect that change. For example for the case of Argentina and Chile we have 20 and 3 deliverable bonds respectively, this difference have a direct implication on the value of CTD and thus CDS spreads. To estimate the CTD effect, we construct a portfolio of all active and available dollar denominated country-specific sovereign bonds and take the average of the bid-ask spreads to proxy for liquidity.

Moreover, the second goal of $\beta^{5i}_i$ is also to capture the potential liquidity spill-over

\textsuperscript{13}Ammer and Cai (2007) suggest that CTD option could be an obstacle to CDS liquidity.
coming from the bond market through hedging. In fact, if traders use mainly CDSs for hedging purposes then any movement of bond yields either caused by default or liquidity risk can impact CDS spreads\textsuperscript{14}.

\( \beta_{6i} \), \( \beta_{7i} \) and \( \beta_{8i} \) introduced in equation (4.7) aim to measure the commonality in liquidity between sovereign CDS and bond markets and are defined as follows:

\[
\beta_{6i} = \frac{\text{Cov}(c_{t}^{\text{CDS}} - E_{t-1}(c_{t}^{\text{CDS}}), c_{M}^{\text{Bonds}} - E_{t-1}(c_{M}^{\text{Bonds}}))}{\text{var}(r_{M}^{\text{Bonds}} - E_{t-1}(r_{M}^{\text{Bonds}}) - c_{M}^{\text{Bonds}} - E_{t-1}(c_{M}^{\text{Bonds}}))}
\]

(4.10)

\[
\beta_{7i} = \frac{\text{Cov}(r_{t}^{\text{CDS}}, c_{M}^{\text{Bonds}} - E_{t-1}(c_{M}^{\text{Bonds}}))}{\text{var}(r_{M}^{\text{Bonds}} - E_{t-1}(r_{M}^{\text{Bonds}}) - c_{M}^{\text{Bonds}} - E_{t-1}(c_{M}^{\text{Bonds}}))}
\]

(4.11)

\[
\beta_{8i} = \frac{\text{Cov}(c_{t}^{\text{CDS}} - E_{t-1}(c_{t}^{\text{CDS}}), r_{M}^{\text{Bonds}} - E_{t-1}(r_{M}^{\text{Bonds}}))}{\text{var}(r_{M}^{\text{Bonds}} - E_{t-1}(r_{M}^{\text{Bonds}}) - c_{M}^{\text{Bonds}} - E_{t-1}(c_{M}^{\text{Bonds}}))}
\]

(4.12)

The betas represent the sensitivity of CDS liquidity risk to sovereign bond market liquidity \( (\beta_{6i}) \), the sensitivity of CDS spreads to sovereign bond market liquidity \( (\beta_{7i}) \) and the sensitivity of CDS liquidity risk to sovereign bond market return \( (\beta_{8i}) \). \( r_{M}^{\text{Bonds}} \) corresponds to the return of the overall bond portfolio. In order to estimate \( r_{M}^{\text{Bonds}} \), we utilize the JP Morgan Emerging Market Bond Index (EMBI) which is the most comprehensive US dollar denominated emerging market debt benchmark. Included in the index are the US dollar-denominated Brady bonds, Eurobonds and traded loans issued by sovereign and quasi sovereign entities. The countries of the EMBI index are: Ar-

\textsuperscript{14}It is important to note that although the aim of this beta risk factor is to capture systematic liquidity risk coming from the “local” bond market, the results could be weakened by the small number of available bonds that some of countries have (i.e. Chile and Malaysia have only two and one traded sovereign bonds respectively).
gentina, Brazil, Mexico, South Korea, Russia, Venezuela, Philippines, Poland, Malaysia, Panama, Bulgaria, Nigeria, China, Ecuador, Peru, Colombia, Morocco, Greece, Turkey, Hungary, Croatia, Lebanon, South Africa, Algeria, Thailand, Chile, Cote D’ivoire. To proxy for liquidity in the overall bond market $c_{M}^{Bonds}$, we download for each country mentioned above the bid-ask spreads of all active sovereign bonds traded in the international market which make a total of 274 bonds and take the weekly average to measure the overall bond liquidity. The beta estimations are conducted over the entire sample resulting in one set of risk factors for each country (Table 4.2).

Brunnermeier and Pedersen (2009) emphasize that market liquidity is closely linked to the level of funding available. They argue that in crisis time market illiquidity could be reinforced by funding liquidity creating what they call a “liquidity spiral”. In what follows, we discuss the issues related to the joint effect of market and funding liquidity risks and relate it to the sovereign CDS market.

4.3.3 Liquidity Spiral: The Joint Effect of Market and Funding Liquidity Risks:

In this subsection we create an “unified” measure that captures the joint impact of market liquidity and funding liquidity $\beta^t(i.e. liquidity spiral)$ and test whether it has an influence on the sovereign CDS spreads.

The sovereign CDS market is an ideal laboratory to test for liquidity spiral effect because it fulfills all the conditions mentioned by Brunnermeier and Pedersen (2009): (1) there is a high level of commonality which could intensify market liquidity shocks (2) CDS contracts are subject to funding liquidity because trading involves collateral agreement and thus access to funding and (3) there is large amount of speculative trading in the CDS market.

\textsuperscript{15}The number of countries included in the JPMorgan EMBI index is higher than that of the global CDS portfolio constructed in subsection 4.3.1. As mentioned above, the construction of the hypothetical market portfolio in any CAPM framework is typically an issue in asset pricing (Roll [1977]); therefore as long as the market portfolio is global enough, the number of countries included in each case should not constitute a problem to our analysis.
Brunnermeier and Pedersen (2009) mention that liquidity spirals could occur in crisis time when both market and funding liquidity are low (margin spiral and loss spiral\(^{16}\)). Because of mutual reinforcement, the joint impact of market and funding liquidity is larger than the sum of their separate effects. Therefore, testing for each effect separately may not give us an accurate measure of the joint impact as there may be an incremental liquidity shock not embedded neither in market liquidity nor in funding liquidity risk.

In the previous sections we extensively explained the potential effects of market liquidity coming from both sovereign CDS and bond markets. At this stage, we aim to clarify and motivate why funding liquidity is a risk to CDS traders and establish a link to liquidity spirals. In fact, the different uses of CDSs will help us understand why funding liquidity can impact CDS spreads. As we specified before, CDSs can be used for hedging default risk, speculation and/or exploiting trading opportunities through arbitrage. First, we start by relating the funding liquidity to arbitrage and then we explain the link between speculation and funding needs.

Although in theory, arbitrage does not involve any risk and requires no capital, in reality arbitrage is risky. As Bhanot and Guo (2010) and many other authors discussed, arbitrage entails the purchase of the bond, the CDS and borrowing an amount corresponding to the price of the bond. In fact, the arbitrageur cannot borrow the entire bond price against the collateral (the bond) and typically, the lender requires a haircut or a margin to protect himself against any sudden movement of the collateral. The amount of haircut/margin required changes as it depends on the ability of the lenders to sell the collateral in case the borrower defaults. On top of these margin requirements, the availability of funds is also an issue to arbitrageurs because the financing of the trade (through the repo) is a short term financing. Therefore, the agents are obliged to roll-over their position in order to match the maturity of the CDS and the bond which

\(^{16}\)Brunnermeier and Pedersen (2009) explain that margin spirals occur if margins are increasing in a situation where the markets are illiquid. However, loss spirals emerge when funding shocks worsen market liquidity leading to big losses on speculators initial positions.
creates a roll-over risk as it is not guaranteed that the initial repo rate stays constant.

Furthermore speculation, which constitutes an important part of CDS trading activity, is also closely related to funding liquidity. Typically even though CDS contract are swaps with zero-value at inception there are margin requirements that are imposed on every CDS dealer. The value of this margin changes during the life of the contract and could be very constraining if one has a large CDS position because the total margin of all positions cannot exceed a trader’s capital at any time. In their paper, Brunnermeir and Pedersen (2009) mention that traders finance their trades through borrowings from agents who set the margins to control their Value-at-Risk. Since agents can readjust their margins in each period, traders or speculators bear the funding liquidity risk coming from higher margins which could destabilize them and force them to delever their positions. The authors show that in time of crisis this phenomenon can intensify as most of traders are forced to reduce their positions which ultimately negatively impact market liquidity.

Having emphasized the importance of funding liquidity in the CDS market, we proxy for it using both libor spreads (difference between 3-months libor rates and 3 months T-bills) and the general collateral repo rate (the rate at which an arbitrageur can borrow to fund his position). Moreover, we construct a new measure $\beta^o_t$ in order to capture a possible co-variation of funding and market liquidity (i.e. liquidity spiral). The main goal behind the construction of this variable is to pick up any incremental liquidity effect that could not be captured by doing a separate analysis on market and funding liquidity risk. Equation (4.13) illustrates how we test for the significance of the risk premium $\lambda$ specific to the (liquidity) spiral risk effect.

$$E(CDS_t) - DefaultRisk = E(c_i^{CDS}) + \lambda \beta^o_t$$

(4.13)

where
\[
\beta_t^\var = \frac{\text{Cov}(\text{Libor}_t^i - E_t-1(\text{Libor}_t^i), c_M^{\text{CDS}} - E_t-1(c_M^{\text{CDS}}))}{\text{var}(r_M^{\text{CDS}} - E_t-1(r_M^{\text{CDS}}) - c_M^{\text{CDS}} - E_t-1(c_M^{\text{CDS}}))}
\]

(4.14)

or

\[
\beta_t^\var = \frac{\text{Cov}(\text{repo}_t - E_t-1(\text{repo}_t), c_M^{\text{CDS}} - E_t-1(c_M^{\text{CDS}}))}{\text{var}(r_M^{\text{CDS}} - E_t-1(r_M^{\text{CDS}}) - c_M^{\text{CDS}} - E_t-1(c_M^{\text{CDS}}))}
\]

(4.15)

where \(\text{Libor}_t^i\) and \(\text{repo}_t\) correspond to the proxies used to estimate funding liquidity risk. Similarly to the other liquidity betas, \(r_M^{\text{CDS}}\) and \(c_M^{\text{CDS}}\) represent CDS market return and CDS market liquidity respectively. Since the estimation of \(\beta_t^\var\) is common to all sovereign countries resulting in one beta factor, we use a 3 month rolling window to construct a time-varying liquidity beta.

### 4.4 Regression Analysis and Results:

#### 4.4.1 Data

The 5 year sovereign CDS dataset has been downloaded from Thomson Financial Datastream. It spans from November 2005 to October 2010 and contains mid, bid and ask quotes in weekly frequency. Regarding the sovereign bond data, we take bid-ask spreads and bond returns from Thomson Financial Datastream. The bond data was obtained for the following countries: Argentina, Brazil, Mexico, South Korea, Russia, Venezuela, Philippines, Poland, Malaysia, Panama, Bulgaria, Nigeria, China, Ecuador, Peru, Colombia, Morocco, Greece, Turkey, Hungary, Croatia, Lebanon, South Africa, Algeria, Thailand, Chile, Cote D’ivoire. In order to avoid any currency mismatch, we focus on nine emerging markets (i.e. Argentina, Brazil, Mexico, Korea, Philippines,
Malaysia, Turkey, Chile and Indonesia), as their sovereign CDSs are quoted in dollar and the main currency of the sovereign debt in emerging markets is the dollar. We downloaded the JPMorgan EMBI from Bloomberg in weekly frequency. Concerning the funding liquidity proxies, we downloaded the collateral repo rate and the 3 months Libor rate from Datastream in weekly frequency. Finally, the 3 months T bills is taken from H.15 Federal Reserve Statistical Release.

4.4.2 Empirical Methodology

As a first step of our empirical analysis, we control for default risk and liquidity level in our panel dataset. Peterson (2009) provides a detailed analysis on the different type of methodologies to use when one faces the issue of time and entity effects in a panel. The author shows that when both time and country effects exist in the data then it is preferable to address one parametrically (i.e. country dummies) and then estimate standard errors by clustering on the other dimension (i.e. time clustering). Therefore, we run a fixed effect regression by introducing dummies to control for the country effect and cluster the standard errors by time in order to obtain robust estimations. Moreover, to control for the liquidity level we follow the approach of Tang and Yan (2007) and use the bid-ask spreads for CDSs and bonds. In the second step, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk beta factors by doing a cross-sectional regression i.e. by taking the average for each reference entity. Since the beta risk factors are constant “within” each entity but change “between” entities there is no time series correlation however we still have to correct for the cross-sectional correlation. We then use the “between” effect which is the equivalent of running a regression by taking the means across time of each variable in the model.

The estimation of the time-varying liquidity spiral $\beta_t^9$ is slightly different because we only have to control for the time-series correlation. The reason is because $\beta_t^9$ is similar across the studied countries (i.e. Argentina, Brazil, Mexico, Korea, Philippines,
Malaysia, Turkey, Chile and Indonesia). In this situation, we also run a two-stage regression. In the first part, we input variables that have both cross-sectional and time-series correlation\textsuperscript{17}, then we extract the residuals and run the second stage regression which only comprises the variables that have time-series correlation\textsuperscript{18}.

It is important to note that we have 9 cross sectional units and different liquidity risk beta factors to estimate. Therefore in order to avoid consuming degrees of freedom at the second stage regression, we test for the beta risk factors individually and then evaluate the overall liquidity effect by computing $\beta_{net}^{i} = \beta^{2i} - \beta^{3i} - \beta^{4i}$. The significance of the coefficients would imply that systematic liquidity risk is priced above the default risk and the liquidity level.

4.4.3 Descriptive Statistics:

In this subsection, we intend to present a descriptive statistics of the data and discuss the correlation between the different liquidity risk betas.

Table 4.1 shows that the CDS liquidity risk factors of the country (Chile) with the highest CDS bid-ask spreads has the highest sensitivity to the CDS market-wide liquidity ($\beta^{2i}$) and the highest sensitivity to the CDS market return ($\beta^{4i}$). This suggests that illiquid assets are the most sensitive to market liquidity.

The bond liquidity risk factors (Table 4.2) show that the country with the highest bid-ask spread (Argentina) has the lowest sensitivity to local bond market ($\beta^{5i}$), the highest sensitivity to bond market return ($\beta^{8i}$) and the highest sensitivity to bond market liquidity ($\beta^{7i}$). The implications of $\beta^{7i}$ and $\beta^{8i}$ are the same as above as it seems that assets that are relatively illiquid are more sensitive to the market. The result of $\beta^{5i}$ suggests different interpretations. In fact, Argentina has 22 international sovereign bonds and the low value of $\beta^{5i}$ indicates that the potential impact of the CTD option on CDS liquidity is very weak which could be explained by the high number of

\textsuperscript{17}The variables are local stocks, exchange rate, trade balance, reserve in dollar and CDS BAS.
\textsuperscript{18}The variables are VIX, 5 years CMT and $\beta^{9i}_{libor/Repo}$.
sovereign bonds available for delivery\footnote{The result on $\beta_{5i}$ is mixed for the others countries that benefit from a high number of sovereign bonds such as Brazil, Mexico and Turkey.}.

Furthermore, from Table 4.1 and 4.2, we can observe that the estimations of liquidity risk betas produce very small values, this is because we are doing our analysis with liquidity innovations rather than liquidity levels. Finally, Table 4.3 shows that there is high correlation between liquidity risk factors and bid-ask spreads (BAS), this reflects what the literature designates as commonality in liquidity. We are particularly interested in the correlation coefficients of CDS BAS with $\beta_{2i}$, $\beta_{3i}$ and $\beta_{4i}$ and bond BAS with $\beta_{5i}$, $\beta_{6i}$, $\beta_{7i}$ and $\beta_{8i}$. For example the correlation between CDS BAS and $\beta_{2i}$ is -0.72 and the correlation between bond BAS and $\beta_{7i}$ is 0.68. Although the high level of correlation is interesting in itself, it creates collinearity that could complicate the task of statistically distinguishing systematic liquidity risk and liquidity level.

4.4.4 Description of the Results: Whole Sample Period

After controlling for default risk and CDS liquidity level, our results show that CDS liquidity factors $\beta_{2i}$, $\beta_{3i}$ and $\beta_{4i}$ are insignificant (Table 4.4). The results suggest that for the period covering the whole sample, CDS systematic liquidity risk is not priced in the CDS spreads.

The findings on bond systematic liquidity risk suggest different interpretations. In fact, even though $\beta_{5i}$ and $\beta_{6i}$ are insignificant, $\beta_{7i}$ and $\beta_{8i}$ are highly significant increasing the R-squared of the second stage regression to 0.9 (Table 4.5). This suggests that liquidity risk of the sovereign bond market has an important influence on sovereign CDS spreads. The coefficients of $\beta_{7i}$ and $\beta_{8i}$ show positive signs indicating that (1) the higher the sensitivity of CDS spreads to sovereign bond market liquidity the higher the spreads and (2) the higher the sensitivity of CDS liquidity to sovereign bond returns the higher the spreads. The interpretations of results for $\beta_{7i}$ are intuitive because the lower
the liquidity (i.e. the higher the liquidity risk) in the bond market, the higher should be the CDS spreads\textsuperscript{20} to account for higher frictions costs that dealers bear when they implement arbitrage strategies between both markets. The positive sign of $\beta_{8i}$ indicates that when returns are low, bonds are less attractive which could increase liquidity risk.

In the second part of the analysis, we test whether there are any CDS systematic liquidity risk factors priced above bond liquidity level. The findings show that the only CDS liquidity risk factor priced above bond liquidity is $\beta_{3i}$ increasing the R-squared to 0.89, this underlines the importance of systematic liquidity risk in the sovereign CDS market.

4.4.5 Description of the Results: Comparative Analysis

In the coming subsection we split our sample in order to study the behavior of liquidity in the pre and crisis periods. For each sample, we re-estimate the systematic liquidity risk factors resulting in a new set of betas.

4.4.5.1 Before Crisis

We do the same analysis but we restrict our dataset to the period before 2008. We observe that controlling for the default risk on its own produce an R-squared of 0.40 which is higher than the whole sample analysis 0.28 (Table 4.6).

Concerning CDS systematic liquidity risk, our findings suggest that only $\beta_{3i}$ is significant increasing the R-squared to 0.59 (Table 4.6). The overall effect of systematic liquidity risk $\beta_{net}^{i}$ is highly significant at 1% level suggesting 0.7183 R-squared\textsuperscript{21}.

\textsuperscript{20}High liquidity risk causes an increase in bond yields which in turn augment CDS spreads because of the one-to-one relationship between bond yields and CDS spreads.

\textsuperscript{21}Following Acharya and Pedersen (2005), $\beta_{net}^{i}$ represents the overall net effect of CDS liquidity risk and is defined $\beta_{net}^{i} = \beta_{2i} - \beta_{3i} - \beta_{4i}$.
shows a negative sign which seems counter-intuitive since an increase in market liquidity risk should drive CDS spreads up and not decrease them as the negative sign infers. However the overall liquidity effect $\beta_{net}^i$ displays a positive sign in line with our intuition. Furthermore, our empirical result reveals that the none of the bond liquidity risk beta factors are priced in the CDS spreads (Table 4.7).

In summary, we can conclude that the effect of CDS systematic liquidity risk is more important that previously shown (i.e. Table 4.4), however the impact of bond liquidity risk is considerably reduced during the pre-crisis period. This suggests that during normal conditions, CDS spreads are mostly impacted by default risk and CDS systematic liquidity risk.

4.4.5.2 During Crisis

The control of default risk shows an R-squared of 0.29. Among the CDS liquidity risk factors, only $\beta_{3i}$ is significant and the overall effect of systematic liquidity risk ($\beta_{net}^i$) is also significant suggesting an R-squared of 0.34 which is smaller than the R-squared 0.7183 of the pre-crisis period (Table 4.8). The signs of $\beta_{3i}^i$ and $\beta_{net}^i$ are positive and negative respectively.

The bond liquidity risk factors show interesting results (Table 4.9). For the first time, $\beta_{5i}$ and $\beta_{6i}$ are significant at 10% and 5% level respectively. These results demonstrate that, during the crisis period, bond systematic liquidity risk has a higher impact than the CDS systematic liquidity risk. The signs of $\beta_{5i}^i$ and $\beta_{6i}^i$ will be discussed thoroughly in the coming section.

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22 In the pre-crisis period, the control of default risk produces an R-squared of 0.4 while the R-squared of the crisis period is only 0.29. This seems counter-intuitive because default risk and thus the R-squared should be higher during crisis time. However, these results are in line with what we found in Chapter 5 as we provided evidence that during the crisis there is a surge in liquidity and a decrease in pure default risk.

23 We observe in Tables 4.5 and 4.6 that the R-squared of bond liquidity risk are higher than that of CDS liquidity risk. The R-squared of $\beta_{net}^i$ is 0.34.
4.5 Discussion

4.5.1 CDS and Bond Systematic Liquidity Risk:

Our results show that for the pre-crisis period the effect of bond systematic liquidity risk is weak. However, CDS systematic liquidity risk has a significant impact on CDS spreads. However, during the crisis period, the effect of bond systematic liquidity risk is high and tend to dominate the effect of CDS systematic liquidity risk.

The interesting part of this analysis is to observe that $\beta_{5i}^i$ is significant at 10% level. The $\beta_{5i}^i$ risk factor was constructed using only country-specific sovereign bonds in order to capture liquidity coming from the “local” bond market. The significance of this risk factor reveals very important implications. Indeed, if $\beta_{5i}^i$ represents liquidity risk coming from the CTD then the impact of this risk factor is compatible with the idea that illiquidity of deliverable bonds has a direct impact on CDS spreads because CDS dealers bear more costs or frictions to find cheap and liquid bonds.

Intuitively, one might expect the CTD option to have greater influence on CDS spreads when there is a higher probability that protection buyers will exercise it and this is what we observe in our results as we show that during crisis period CTD has more influence on CDS spreads. This reveals that the CTD option is an increasing function of the probability of default because CDS sellers would not worry about which bonds they might have to deliver unless there is a high probability of default. Furthermore, the results for $\beta_{5i}^i$ are consistent with Ammer and Cai (2007) who present a variety of evidence showing that CTD option affects CDS spreads and that its value is increasing with the probability of a default event$^{24}$.

On the other hand, the impact of $\beta_{5i}^i$ on CDS spreads can also be interpreted in a different way. Typically in crisis time, higher probability of default may create a panic in financial markets which pushes CDS dealers to trade CDS contracts more for hedging than for speculation or arbitrage purposes. If the majority of users are hedgers then

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$^{24}$We believe that the weak level of significance of $\beta_{5i}^i$ due to the low number of deliverable bonds. In fact, the impact of the CTD option might be more important for countries that benefit from a high number of deliverable bonds but less obvious to detect for sovereigns that issued few bonds.
CDS spreads should follow closely bond yields spreads whether the yields are driven by default or liquidity risk and this might also explain the significance of $\beta^{5i}$.

Furthermore, $\beta^{5i}$ has a positive coefficient, in other words the higher the sensitivity of CDS liquidity to the country-specific bond market the higher the CDS spreads. This result is intuitive because CTD option introduces an additional source of uncertainty that negatively affects the CDS contract and thus increases the spreads\(^{25}\).

### 4.5.2 Liquidity Spiral Effect:

The results in Table 4.10 show that CDS spreads are not affected by $\beta^{9t}$ for the pre and crisis periods. These findings suggest that even though in theory traders face a liquidity spiral effect, it does not carry any risk premium. In fact this could be intuitive during the pre-crisis period because liquidity issues may be more relevant during crisis time. However, for the period including the crisis, the results are counter-intuitive and this requires some clarification.

Brunnermeier and Pedersen (2009) mention two types of liquidity spirals: margin and loss spiral. A margin spiral occurs if margins are increasing when markets are illiquid. If margins increase in liquid markets, it is relatively easy for speculators to refund themselves; however in a situation where liquidity is low, an increase in margins harms speculators ability to finance their positions which in turn lowers market liquidity. This scenario is likely to happen in the CDS market. However, the influence of the loss spiral on CDS spreads is less obvious. A loss spiral occurs if an increase in market liquidity triggers losses in speculators existing positions which worsen their funding problems forcing them to sell-off their assets. The selling-off decreases asset prices and creates even more losses to speculators. Even though this scenario is possible for assets such as equity or bonds, it may be not be similar for CDSs. Indeed, if a loss spiral happens

\(^{25}\)Dealers face additional uncertainty because they do not know which of the sovereign bonds will be liquid enough for delivery, especially in crisis time when the sovereign bond market experiences a flight-to-liquidity episode. In line with this, $\beta^{6i}$ which specifically characterizes this phenomenon of flight-to-liquidity as it captures the impact of the overall bond liquidity on CDS spreads, has a positive and significant impact on CDS spreads.
during crisis time and dealers sell CDSs to get their premium in order to increase their
funding capability then the selling-off would not necessary drop CDS spreads because
market participants would still want to hedge their default risk by buying protections.
Thus the demand and supply in the CDS market would be more stable (Figure 4.2).
This might present an explanation as to why the liquidity spiral has no significant effect
on CDS spreads.

4.5.3 Summary:

Our main finding is that, during the pre-crisis period, the risk premium priced above
the default risk and liquidity level is mainly driven by CDS systematic liquidity risk
(Table 4.6). The reason we present is in times of low uncertainty, dealers use CDSs
more for speculation than for hedging and since speculation is not directly related to
the reference entity or the underlying asset, it weakens the influence of the bond market
(Table 4.7). However in times of crisis, high default probability increases significantly
global risk aversion which induces sovereign investors to hedge their bond positions
hence the tightening of the relationship between CDS and bond markets. Therefore,
bond systematic liquidity risk becomes the main driver of the risk premium priced above
the default risk and liquidity level (Table 4.9).

In order to support our results we create a measure to assess speculators ability
to trade before and during the crisis period. As previously mentioned, CDS trading
requires a collateral agreement from both sides of the trade and therefore dealers need
access to funding. Therefore, there is one-to-one relationship between speculation and
access to funds because the incentive to trade as a speculator is largely dependent on
capital availability. In what follows, we attempt to construct a measure that should
capture speculators ability to access funding.

Speculation is largely dependent on the available funds which in turn depend on past
returns (Boyson, Stahel and Stulz (2008)). Therefore, in order to test for speculation
effect, we construct a hedge fund return index\(^{26}\) (HFRI). The index is an average of the following indices: Equity Market Neutral, Fixed Income-Corporate Index, Relative value Index, Fixed-Income Asset Backed Index and Fixed-Income Convertible Arbitrage Index\(^{27}\). All the indices are downloaded from Hedge Fund Research\(^{28}\) website in monthly basis and we use linear interpolation to lower the frequency and match the weekly data. The HFRI will be used as a measure to test for capital access and indirectly as a proxy for speculation effect.

As a first step, we control for default risk and liquidity levels and regress CDS changes on the HFRI. The results prior and during the crisis are reported in Table 4.11.

It seems that, prior to the crisis, access to capital does not seem to impact CDS changes, namely in quiet times market volatility would not harm speculators capital. However, the crisis period reveals that HFRI is highly significant and shows a negative sign. The negative sign indicates that negative hedge fund return or lower access to capital increases CDS spreads. If, as our results suggest, hedge funds have lower access to capital during crisis time, they are then less inclined to buy CDS protections\(^{29}\) which lowers liquidity for protection buyers until a new equilibrium is reached and this is what we observe in Figure 4.2 as we see a narrowing of bid-ask spreads during the crisis\(^{30}\).

In the pre-crisis period, HFRI is insignificant this indicates that, in less volatile market conditions, access to capital is relatively easy. Therefore margin calls\(^{31}\) are not

\(^{26}\) According to Bank of America estimate reported by Duffie (2008), banks and hedge funds are the largest market participants with 33%, 31% (39%, 28%) of the buy (sell) side of CDS trading activities. Recent papers study the use of CDSs by banks. Minton, Stulz and Williamson (2009) use data from the Federal Reserve Bank of Chicago Bank Holding Company database (BHC) in order to analyze CDS positions. The authors find that CDS trading is concentrated among large banks and that CDSs were mostly used for trading than for hedging purposes. Van Ooijen et al (2010) analyze the relation between the probability of default of E.U banks and the use of credit derivatives and find that these instruments tend to inflate default risk which may not be consistent with hedging motives. On the other hand, Hirle (2009) provide evidence that commercial banks are net buyers of credit protection suggesting that banks may be hedging. Since there is no clear consensus in the literature on the main goals behind the use of CDSs by banks, we assume that the majority of trades that banks do are on behalf of their clients (i.e to hedge client positions) and that hedge funds are the main speculators as they face little regulation. Therefore, we utilise the hedge fund return index to proxy for the hedge fund access to capital.

\(^{27}\) The definition of the indices are provided in Hedge Fund Research website: http://www.hedgefundresearch.com/.

\(^{28}\) By using the definitions in the Hedge Fund Research website, we focus on indices that are likely to capture speculation and arbitrage in the fixed income and equity markets. This leaves us with Equity Market Neutral, Fixed Income-Corporate Index, Relative value Index, Fixed-Income Asset Backed Index and Fixed-Income Convertible Arbitrage Index.

\(^{29}\) Bank of America study (2007) reports that hedge funds are net CDS protection buyers.

\(^{30}\) This is also suggest that wide bid-ask spread may be due to an excess of CDS buyers in the market.

\(^{31}\) According to Brunnermeier and Pedersen (2009), there is one-to-one relationship between volatility and margin requirements. A surge in market volatility increases margin calls harming speculators' ability to trade.
constraining which may encourage speculators to buy protections which in turn lead to an excess of supply of CDS protection buyers. The surplus of protection buyers widens the bid-ask spreads as we can observe in Figure 4.2.

In summary, our results lead to two conclusions (1) speculation may impede sovereign CDS liquidity since the excess of protection buyers disturbs the balance of supply and demand and therefore widens the bid-ask spreads (2) funding liquidity risk (i.e. capital availability) has an effect on CDS spreads but seems to be more predominant in crisis time.

4.6 Conclusion

We present an empirical analysis where we investigate the effect of systematic liquidity risk on sovereign credit default swap spreads. We focus on the aspect of liquidity that is caused by the correlation of fluctuations of liquidity measures across assets. These common fluctuations are more likely to impact assets characterized by commonality. Therefore, the main aim of this chapter is to investigate whether systematic liquidity risk affects CDS spread movements.

By applying the Liquidity-Adjusted CAPM framework of Acharya and Pedersen (2005), we find that, before the crisis, the risk premium priced above the default risk and liquidity level is mainly driven by CDS systematic liquidity risk. The reason we present is in times of low uncertainty, dealers use CDSs more for speculation than for hedging and since speculation is not directly related to the reference entity or the underlying asset, it weakens the influence of the bond market. However in times of crisis, high default probability increases significantly global risk aversion which induces sovereign investors to hedge their bond positions; hence the tightening of the relationship between CDS and bond markets. Therefore, bond systematic liquidity risk becomes the main driver of the risk premium priced above the default risk and liquidity level.
Furthermore, we provide evidence that the joint impact of market and funding liquidity risks (i.e. liquidity spiral) have no significant influence on CDS spreads. Finally, our results imply that speculation may participate to the widening of bid-ask spreads and that funding liquidity risk is more constraining during crisis time.

In summary, our study provides empirical evidence that market or systematic liquidity risk is a priced state variable. Thus, further research would be warranted to understand the pricing implications of the systematic liquidity risk in a CDS pricing model. In the next chapter, we extend the reduced-form model of Buhler and Trapp (2010) and investigate its tractability.
4.7 Appendix CDS Returns:

The CAPM framework involves a direct use of the excess return as the main dependent variable. CDS contracts do not have initial costs at the inception, therefore the concept of percentage returns is not well defined. In our study we chose to proxy returns with CDS changes.

To the best of our knowledge, there is no consensus in the literature on how to define CDS returns. In one of the few papers that tackle this issue, Berndt and Obreja (2009) extract CDS returns using a CDS pricing model. In what follows, we first replicate their methodology and then explain the reasons why we chose to not adopt their approach to estimate CDS returns.

Berndt and Obreja (2009) advance the idea that over a short term interval the change in value of a CDS contract is equal to minus the CDS changes multiplied by the value of T-year annuity $A(T)$.

$$\Delta V_{CDS} = -\Delta CDS \ast A(T) \quad (4.16)$$

where $\Delta V_{CDS}$ represents the change in value of the CDS contract and $A(T)$ is the annuity defined as:

$$A(T) = \frac{1}{2} \sum_{j=1}^{2T} r(j/2).q(j/2) \quad (4.17)$$

$r(j/2)$ and $q(j/2)$ represent the risk-free discount factor and the risk-neutral survival probability respectively. Both variables are divided by two in order to account for the semi-annual payment. In order to proxy for the risk-free discount rate, we use a cubic spline algorithm to bootstrap, from the Treasury Constant Maturity Curve, the values of the zero-coupon bonds. To estimate $q(j/2)$, we assume a constant risk neutral default
intensity $\lambda$ which lead to a survival probability equal to:

$$q(j/2) = e^{-\lambda/2}$$  \hspace{1cm} (4.18)

In line with Berndt and Obreja (2009), we compute the default intensity $\lambda$ directly from CDS spreads by using a discrete-time approximation of the CDS pricing formula defined as follows:

$$CDS * A(T) = L * \frac{1}{2} \sum_{j=1}^{2T} r(j/2)[q(j-1/2) - q(j/2)]$$  \hspace{1cm} (4.19)

$L = 1 - Recovery$ and is the risk neutral loss rate in the event of default. The left hand side of the equation represents the value of the protection-buyer leg and the right hand side the value of the protection seller at the initiation of the contract. Rearranging equation (4.19) we can infer the default intensity $CDS/2 = L(e^{\lambda/2} - 1)$ which leads to:

$$\lambda = 2 \times log(1 + \frac{CDS}{2 \times L})$$  \hspace{1cm} (4.20)

Plugging back equation (4.20) into (4.18) and assuming a value for the recovery rate, we can estimate CDS returns. For corporate CDSs, the standard approach is to assume 40% recovery, however for the case of sovereigns there is no consensus on the recovery rate. A recent research by Credit Suisse (2010)\textsuperscript{32} reports the recovery values\textsuperscript{33} in some recent defaults. The report shows that recovery values of sovereign defaults can be extremely variable (from 5 to 95%). The average of these recoveries is 39%, however the standard deviation is quite high reaching 26%; this in fact implies that each sovereign default requires to be considered on its own. In any case, we follow Pan and Singleton (2008) and set $L = 75\%$ which gives a recovery value of 25%.

\textsuperscript{32}Credit Suisse (2010): Sovereign CDS Primer

\textsuperscript{33}The recovery value is the market price as a % of nominal of the bonds just after default has occurred.
In Figure 4.1, we plot our estimation of CDS returns (i.e. equation 4.16) and compare it to CDS changes (i.e. CDS(t)-CDS(t-1)). We can see that the behavior of CDS returns is very different from CDS changes especially for the period coming after September/October 2008. The magnitude of the Y-axis on both graphs is also dissimilar. In fact, these results raise many questions about the validity of CDS returns extracted from a pricing model as return values can be heavily influenced by the assumption made on the recovery rate. Moreover, in order to compare CDS changes and returns under the same Y axis, we take the CDS log changes (i.e. log(CDS(t)/CDS(t-1))) and compare them to CDS returns. Figure 4.1 shows that the discrepancy is still present between both measures.

We mentioned above the issue of recovery rate, however there is also another difficulty that could arise during the estimation of default intensity $\lambda$. When following the approach of Berndt and Obreja (2009), we assumed a constant risk neutral default intensity, this assumption goes against the findings of Pan and Singleton (2008) that show the one-factor log-normal stochastic process captures quite well the behavior of the default intensity of sovereign CDS spreads. Therefore, by assuming constant intensity $\lambda$, we take the risk of not capturing default risk dynamics.

In summary, the uncertainty around the inputs of a CDS pricing model can heavily influence the estimation of CDS returns. Therefore in order to avoid any complication, we use CDS changes as a proxy for CDS returns.
Figures:

Figure 4.1: Time Series Plot of CDS Changes (Top), CDS Returns (Middle) and CDS Log Changes (Bottom)
Figure 4.2: Time Series Plot of Bid-Ask Spreads (in bps)
Tables

Table 4.1: CDS Liquidity Risk Values

The table shows the values of CDS liquidity betas. The estimation of liquidity risk is conducted over the entire sample resulting in one set of betas for each country $i$. The table shows small values, this is because we are doing the analysis with liquidity innovations rather than liquidity levels. BAS is the average bid-ask spreads. $\beta^{2i}$ is the sensitivity of the liquidity of individual CDS to market-wide liquidity shocks, $\beta^{3i}$ the sensitivity of the return of individual CDS to market-wide liquidity shocks and $\beta^{4i}$ the sensitivity of the liquidity of individual CDS to the market return.

<table>
<thead>
<tr>
<th>Country</th>
<th>BAS</th>
<th>$\beta^{2i}$ $(10^{-6})$</th>
<th>$\beta^{3i}$ $(10^{-4})$</th>
<th>$\beta^{4i}$ $(10^{-5})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chile</td>
<td>-0.22</td>
<td>1.09</td>
<td>2.25</td>
<td>13</td>
</tr>
<tr>
<td>Malaysia</td>
<td>-0.09</td>
<td>0.27</td>
<td>2.18</td>
<td>-7.9</td>
</tr>
<tr>
<td>Korea</td>
<td>-0.08</td>
<td>0.42</td>
<td>3.59</td>
<td>1.43</td>
</tr>
<tr>
<td>Mexico</td>
<td>-0.04</td>
<td>-0.09</td>
<td>2.61</td>
<td>0.725</td>
</tr>
<tr>
<td>Indonesia</td>
<td>-0.04</td>
<td>0.17</td>
<td>3.43</td>
<td>0.7</td>
</tr>
<tr>
<td>Philippines</td>
<td>-0.03</td>
<td>0.1</td>
<td>0.87</td>
<td>-5.5</td>
</tr>
<tr>
<td>Argentina</td>
<td>-0.029</td>
<td>-0.0054</td>
<td>29</td>
<td>10.3</td>
</tr>
<tr>
<td>Brazil</td>
<td>-0.026</td>
<td>0.02</td>
<td>0.72</td>
<td>-0.93</td>
</tr>
<tr>
<td>Turkey</td>
<td>-0.029</td>
<td>0.1</td>
<td>2.47</td>
<td>-7.33</td>
</tr>
</tbody>
</table>
Table 4.2: Bond Liquidity Risk Values

The table shows the values of bond liquidity betas. The estimation of liquidity risk is conducted over the entire sample resulting in one set of betas for each country $i$. The table shows small values, this is because we are doing the analysis with liquidity innovations rather than liquidity levels. BAS represents the average bid ask spreads of the dollar denominated sovereign bonds available for each country and $*$ is the total number of sovereign bonds per country. $\beta^5_i$ represents the sensitivity of the liquidity of sovereign CDS to country-specific sovereign bonds. $\beta^6_i$ is the sensitivity of CDS liquidity risk to sovereign bond market liquidity, $\beta^7_i$ the sensitivity of CDS spreads to sovereign bond market liquidity and $\beta^8_i$ the sensitivity of CDS liquidity risk to sovereign bond market return.

<table>
<thead>
<tr>
<th>Country</th>
<th>$*$</th>
<th>BAS</th>
<th>$\beta^5_i (10^{-5})$</th>
<th>$\beta^6_i (10^{-6})$</th>
<th>$\beta^7_i (10^{-2})$</th>
<th>$\beta^8_i (10^{-5})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malaysia</td>
<td>1</td>
<td>0.43</td>
<td>3.7</td>
<td>-4.2</td>
<td>0.026</td>
<td>13</td>
</tr>
<tr>
<td>Chile</td>
<td>3</td>
<td>0.55</td>
<td>72</td>
<td>7.5</td>
<td>0.03</td>
<td>21</td>
</tr>
<tr>
<td>Korea</td>
<td>5</td>
<td>0.60</td>
<td>13</td>
<td>-4.9</td>
<td>0.037</td>
<td>5.01</td>
</tr>
<tr>
<td>Philippines</td>
<td>20</td>
<td>0.65</td>
<td>-7.0</td>
<td>-3.7</td>
<td>0.019</td>
<td>-9.2</td>
</tr>
<tr>
<td>Mexico</td>
<td>18</td>
<td>0.65</td>
<td>5.2</td>
<td>-0.12</td>
<td>0.045</td>
<td>8.4</td>
</tr>
<tr>
<td>Indonesia</td>
<td>11</td>
<td>0.78</td>
<td>-73</td>
<td>-13</td>
<td>0.033</td>
<td>14</td>
</tr>
<tr>
<td>Turkey</td>
<td>18</td>
<td>0.80</td>
<td>-11</td>
<td>-3.1</td>
<td>0.012</td>
<td>-5.4</td>
</tr>
<tr>
<td>Brazil</td>
<td>24</td>
<td>0.88</td>
<td>-1.9</td>
<td>-0.48</td>
<td>0.03</td>
<td>1.18</td>
</tr>
<tr>
<td>Argentina</td>
<td>22</td>
<td>2.31</td>
<td>1.8e^-3</td>
<td>-6.04</td>
<td>0.71</td>
<td>46</td>
</tr>
</tbody>
</table>
Table 4.3: Correlation of Liquidity Risk Factors

The table shows the average correlation coefficients between CDS bid-ask spread, bond bid-ask spread, CDS liquidity risk and bond liquidity risk for Argentina, Brazil, Chile, Mexico, Philippines, Malaysia, Korea, Indonesia and Turkey. The correlation coefficients demonstrate the high level of commonality in liquidity. BAS is the average bid-ask spreads. $\beta^2_i$ is the sensitivity of the liquidity of individual CDS to market-wide liquidity shocks, $\beta^3_i$ the sensitivity of the return of individual CDS to market-wide liquidity shocks and $\beta^4_i$ the sensitivity of the liquidity of individual CDS to the market return. $\beta^5_i$ represents the sensitivity of the liquidity of sovereign CDS to country-specific sovereign bonds. $\beta^6_i$ is the sensitivity of CDS liquidity risk to sovereign bond market liquidity, $\beta^7_i$ the sensitivity of CDS spreads to sovereign bond market liquidity and $\beta^8_i$ the sensitivity of CDS liquidity risk to sovereign bond market return.

<table>
<thead>
<tr>
<th></th>
<th>CDS BAS</th>
<th>$\beta^2_i$</th>
<th>$\beta^3_i$</th>
<th>$\beta^4_i$</th>
<th>Bond BAS</th>
<th>$\beta^5_i$</th>
<th>$\beta^6_i$</th>
<th>$\beta^7_i$</th>
<th>$\beta^8_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS BAS</td>
<td>1</td>
<td>-0.72</td>
<td>0.15</td>
<td>-0.40</td>
<td>0.18</td>
<td>-0.56</td>
<td>-0.48</td>
<td>0.15</td>
<td>-0.17</td>
</tr>
<tr>
<td>$\beta^2_i$</td>
<td>-0.72</td>
<td>1</td>
<td>-0.22</td>
<td>0.49</td>
<td>-0.24</td>
<td>0.66</td>
<td>0.53</td>
<td>-0.25</td>
<td>0.14</td>
</tr>
<tr>
<td>$\beta^3_i$</td>
<td>0.14</td>
<td>-0.22</td>
<td>1</td>
<td>0.52</td>
<td>0.67</td>
<td>-0.02</td>
<td>-0.22</td>
<td>0.99</td>
<td>0.84</td>
</tr>
<tr>
<td>$\beta^4_i$</td>
<td>-0.40</td>
<td>0.49</td>
<td>0.52</td>
<td>1</td>
<td>0.32</td>
<td>0.46</td>
<td>0.33</td>
<td>0.52</td>
<td>0.74</td>
</tr>
<tr>
<td>Bond BAS</td>
<td>0.18</td>
<td>-0.24</td>
<td>0.67</td>
<td>0.33</td>
<td>1</td>
<td>-0.08</td>
<td>-0.17</td>
<td>0.68</td>
<td>0.51</td>
</tr>
<tr>
<td>$\beta^5_i$</td>
<td>-0.56</td>
<td>0.66</td>
<td>-0.02</td>
<td>0.46</td>
<td>-0.08</td>
<td>1</td>
<td>0.91</td>
<td>0.001</td>
<td>0.15</td>
</tr>
<tr>
<td>$\beta^6_i$</td>
<td>-0.48</td>
<td>0.53</td>
<td>-0.22</td>
<td>0.33</td>
<td>-0.17</td>
<td>0.91</td>
<td>1</td>
<td>-0.18</td>
<td>-0.05</td>
</tr>
<tr>
<td>$\beta^7_i$</td>
<td>0.15</td>
<td>-0.25</td>
<td>0.99</td>
<td>0.52</td>
<td>0.68</td>
<td>1</td>
<td>0.001</td>
<td>-0.18</td>
<td>1</td>
</tr>
<tr>
<td>$\beta^8_i$</td>
<td>-0.17</td>
<td>0.14</td>
<td>0.84</td>
<td>0.74</td>
<td>0.51</td>
<td>0.15</td>
<td>-0.05</td>
<td>0.82</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 4.4: CDS Liquidity Risk Proxied by Betas Factors: Whole Sample Period

We regress CDS spread changes against default risk, liquidity level controls and liquidity risk proxies. In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the CDS BAS. In the second stage regression, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk factors by doing a cross-sectional regression i.e by taking the average for each reference entity. $R^2$ and $R^2\cdot$ represent the R-squared of the first and the second stage regressions respectively. $β_2^i$ is the sensitivity of the liquidity of individual CDS to market-wide liquidity shocks, $β_3^i$ the sensitivity of the return of individual CDS to market-wide liquidity shocks and $β_4^i$ the sensitivity of the liquidity of individual CDS to the market return. $β_{net}^i$ is defined as $β_2^i-β_3^i-β_4^i$. *, ** and *** represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th>CDS Liquidity risk Proxied by:</th>
<th>$β_2^i$</th>
<th>$β_3^i$</th>
<th>$β_4^i$</th>
<th>$β_{net}^i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>t</td>
<td>Coef</td>
<td>t</td>
</tr>
<tr>
<td>Const</td>
<td>1.44</td>
<td>0.17</td>
<td>1.44</td>
<td>0.17</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-2.21</td>
<td>-1.19</td>
<td>-2.21</td>
<td>-1.19</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.172</td>
<td>0.4</td>
<td>0.172</td>
<td>0.4</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>-5e^-3</td>
<td>-0.24</td>
<td>-5e^-3</td>
<td>-0.24</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>-7e^-4</td>
<td>-0.11</td>
<td>-7e^-4</td>
<td>-0.11</td>
</tr>
<tr>
<td>US VIX</td>
<td>1.18</td>
<td>1.80</td>
<td>1.18</td>
<td>1.80</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>-27.6</td>
<td>-0.98</td>
<td>-27.6</td>
<td>-0.98</td>
</tr>
<tr>
<td>CDS Liquidity level</td>
<td>-21.86</td>
<td>-0.9</td>
<td>-21.86</td>
<td>-0.9</td>
</tr>
<tr>
<td>CDS Liquidity Risk</td>
<td>0.029</td>
<td>0.61</td>
<td>9.59e^-6</td>
<td>0.49</td>
</tr>
<tr>
<td>N</td>
<td>2278</td>
<td>2278</td>
<td>2278</td>
<td>2278</td>
</tr>
<tr>
<td>Clusters</td>
<td>256</td>
<td>256</td>
<td>256</td>
<td>256</td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>R$^2\cdot$</td>
<td>0.05</td>
<td>0.03</td>
<td>0.16</td>
<td>0.04</td>
</tr>
</tbody>
</table>
We regress CDS spread changes against default risk, liquidity level controls and liquidity risk proxies. In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the bond BAS. In the second stage regression, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk factors by doing a cross-sectional regression i.e by taking the average for each reference entity. $R^2$ and $R^{2*}$ represent the R-squared of the first and the second stage regressions respectively. $\beta_{5i}$ represents the sensitivity of the liquidity of sovereign CDS to country-specific sovereign bonds. $\beta_{6i}$ is the sensitivity of CDS liquidity risk to sovereign bond market liquidity, $\beta_{7i}$ the sensitivity of CDS spreads to sovereign bond market liquidity and $\beta_{8i}$ the sensitivity of CDS liquidity risk to sovereign bond market return. "*, ** and *** represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th>Bond Liquidity risk Proxied by:</th>
<th>$\beta_{5i}$</th>
<th>$\beta_{6i}$</th>
<th>$\beta_{7i}$</th>
<th>$\beta_{8i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef t</td>
<td>Coef t</td>
<td>Coef t</td>
<td>Coef t</td>
<td>Coef t</td>
</tr>
<tr>
<td>Const</td>
<td>22.45</td>
<td>1.16</td>
<td>22.45</td>
<td>1.16</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-2.26</td>
<td>-1.22</td>
<td>-2.26</td>
<td>-1.22</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.12</td>
<td>0.3</td>
<td>0.12</td>
<td>0.3</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>-1.8e^-3</td>
<td>-0.10</td>
<td>-1.8e^-3</td>
<td>-0.10</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>-6.9e^-4</td>
<td>-0.10</td>
<td>-6.9e^-4</td>
<td>-0.10</td>
</tr>
<tr>
<td>US VIX</td>
<td>1.17</td>
<td>1.75</td>
<td>1.17</td>
<td>1.75</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>-28.64</td>
<td>-1.03</td>
<td>-28.64</td>
<td>-1.03</td>
</tr>
<tr>
<td>Bond Liquidity level</td>
<td>-8.83</td>
<td>-1.18</td>
<td>-8.83</td>
<td>-1.18</td>
</tr>
<tr>
<td>Bond Liquidity Risk</td>
<td>3.15e^-5</td>
<td>0.806</td>
<td>-2.3e^-3</td>
<td>-0.32</td>
</tr>
<tr>
<td>N</td>
<td>2278</td>
<td>2278</td>
<td>2278</td>
<td>2278</td>
</tr>
<tr>
<td>Clusters</td>
<td>256</td>
<td>256</td>
<td>256</td>
<td>256</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
<td>0.28</td>
</tr>
<tr>
<td>$R^{2*}$</td>
<td>0.00</td>
<td>0.01</td>
<td>0.901</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Table 4.5: Bond Liquidity Risk Proxied by Betas Factors: Whole sample
Table 4.6: CDS Liquidity Risk Proxied by Betas Factors: Before Crisis

In this table, we restrict our analysis to the pre-crisis period from November 2005 to Mars 2008. We regress CDS spread changes against default risk, liquidity level controls and liquidity risk proxies. In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the CDS BAS. In the second stage regression, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk factors by doing a cross-sectional regression i.e by taking the average for each reference entity. $R_1^2$ and $R_2^2$ represent the R-squared of the first and the second stage regressions respectively. $\beta_{2i}$ is the sensitivity of the liquidity of individual CDS to market-wide liquidity shocks, $\beta_{3i}$ the sensitivity of the return of individual CDS to market-wide liquidity shocks and $\beta_{4i}$ the sensitivity of the liquidity of individual CDS to the market return. $\beta_{\text{net}}^i$ is defined as $\beta_{2i} - \beta_{3i} - \beta_{4i}$. ’,*,’**’ and ’***’ represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th>CDS Liquidity risk Proxied by:</th>
<th>$\beta_{2i}$</th>
<th>$\beta_{3i}$</th>
<th>$\beta_{4i}$</th>
<th>$\beta_{\text{net}}^i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>0.64</td>
<td>0.26</td>
<td>0.64</td>
<td>0.26</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-0.72</td>
<td>-1.39</td>
<td>-0.72</td>
<td>-1.39</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>-0.32</td>
<td>-2.88</td>
<td>-0.32</td>
<td>-2.88</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>0.017</td>
<td>0.80</td>
<td>0.017</td>
<td>0.80</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>-0.006</td>
<td>-0.82</td>
<td>-0.006</td>
<td>-0.82</td>
</tr>
<tr>
<td>US VIX</td>
<td>-0.26</td>
<td>-1.42</td>
<td>-0.26</td>
<td>-1.42</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>6.30</td>
<td>0.88</td>
<td>6.30</td>
<td>0.88</td>
</tr>
<tr>
<td>CDS Liquidity level</td>
<td>-2.89</td>
<td>-0.43</td>
<td>-2.89</td>
<td>-0.43</td>
</tr>
<tr>
<td>CDS Liquidity Risk</td>
<td>$9.26e^{-6}$</td>
<td>0.01</td>
<td>$-1.61e^{-5}$</td>
<td>$-3.22^{**}$</td>
</tr>
</tbody>
</table>

| | | | | |
|---|---|---|---|
| N | 1053 | 1053 | 1053 | 1053 |
| Clusters | 117 | 117 | 117 | 117 |
| $R^2$ | 0.40 | 0.40 | 0.40 | 0.40 |
| $R^{2*}$ | 0.0 | 0.596 | 0.07 | 0.7183 |

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Table 4.7: Bond Liquidity Risk Proxied by Betas Factors: Before Crisis

In this table, we restrict our analysis to the pre-crisis period from November 2005 to Mars 2008. We regress CDS spread changes against default risk, liquidity level controls and liquidity risk proxies. In our panel model, we address country effect parametrically (i.e. by using dummies-not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the bond BAS. In the second stage regression, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk factors by doing a cross-sectional regression i.e by taking the average for each reference entity. \( R^2 \) and \( R^2* \) represent the R-squared of the first and the second stage regressions respectively. \( \beta_{5i} \) represents the sensitivity of the liquidity of sovereign CDS to country-specific sovereign bonds. \( \beta_{6i} \) is the sensitivity of CDS liquidity risk to sovereign bond market liquidity, \( \beta_{7i} \) the sensitivity of CDS spreads to sovereign bond market liquidity and \( \beta_{8i} \) the sensitivity of CDS liquidity risk to sovereign bond market return. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th>Bond Liquidity risk Proxied by:</th>
<th>( \beta_{5i} )</th>
<th>( \beta_{6i} )</th>
<th>( \beta_{7i} )</th>
<th>( \beta_{8i} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>3.04</td>
<td>0.35</td>
<td>3.04</td>
<td>0.35</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-0.72</td>
<td>-1.4</td>
<td>-0.72</td>
<td>-1.4</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>-0.32</td>
<td>-2.88</td>
<td>-0.32</td>
<td>-2.88</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>0.018</td>
<td>0.85</td>
<td>0.018</td>
<td>0.85</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>-6.8e^-3</td>
<td>-0.81</td>
<td>-6.8e^-3</td>
<td>-0.81</td>
</tr>
<tr>
<td>US VIX</td>
<td>-0.26</td>
<td>-1.41</td>
<td>-0.26</td>
<td>-1.41</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>6.22</td>
<td>0.86</td>
<td>6.22</td>
<td>0.86</td>
</tr>
<tr>
<td>Bond Liquidity level</td>
<td>-1.10</td>
<td>-0.31</td>
<td>-1.10</td>
<td>-0.31</td>
</tr>
<tr>
<td>Bond Liquidity Risk</td>
<td>-9.07e^-7</td>
<td>-0.08</td>
<td>-3.8e^-4</td>
<td>-1.36</td>
</tr>
</tbody>
</table>

N 1053 1053 1053 1053
Clusters 117 117 117 117
\( R^2 \) 0.4 0.4 0.4 0.4
\( R^2* \) 0.00 0.21 0.23 0.053
Table 4.8: CDS Liquidity Risk Proxied by Betas Factors: During Crisis

In this table, we restrict our analysis to the crisis period from April 2008 to October 2010. We regress CDS spread changes against default risk, liquidity level controls and liquidity risk proxies. In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the CDS BAS. In the second stage regression, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk factors by doing a cross-sectional regression i.e by taking the average for each reference entity. $R^2$ and $R^2*$ represent the R-squared of the first and the second stage regressions respectively. $\beta^2_i$ is the sensitivity of the liquidity of individual CDS to market-wide liquidity shocks, $\beta^3_i$ the sensitivity of the return of individual CDS to market-wide liquidity shocks and $\beta^4_i$ the sensitivity of the liquidity of individual CDS to the market return. $\beta^i_{\text{net}}$ is defined as $\beta^2_i - \beta^3_i - \beta^4_i$. ’*, ’** and ’***’ represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th>CDS Liquidity risk Proxied by:</th>
<th>$\beta^2_i$</th>
<th>$\beta^3_i$</th>
<th>$\beta^4_i$</th>
<th>$\beta^i_{\text{net}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef t</td>
<td>Coef t</td>
<td>Coef t</td>
<td>Coef t</td>
<td>Coef t</td>
</tr>
<tr>
<td>Const</td>
<td>1.18 0.08</td>
<td>1.18 0.08</td>
<td>1.18 0.08</td>
<td>1.18 0.08</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-3.38 -1</td>
<td>-3.38 -1</td>
<td>-3.38 -1</td>
<td>-3.38 -1</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.39 0.62</td>
<td>0.39 0.62</td>
<td>0.39 0.62</td>
<td>0.39 0.62</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>-0.045 -0.48</td>
<td>-0.045 -0.48</td>
<td>-0.045 -0.48</td>
<td>-0.045 -0.48</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>0.002 0.28</td>
<td>0.002 0.28</td>
<td>0.002 0.28</td>
<td>0.002 0.28</td>
</tr>
<tr>
<td>US VIX</td>
<td>1.48 1.88</td>
<td>1.48 1.88</td>
<td>1.48 1.88</td>
<td>1.48 1.88</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>-36.9 -1.2</td>
<td>-36.9 -1.2</td>
<td>-36.9 -1.2</td>
<td>-36.9 -1.2</td>
</tr>
<tr>
<td>CDS Liquidity level</td>
<td>-115.9 -1.33</td>
<td>-115.9 -1.33</td>
<td>-115.9 -1.33</td>
<td>-115.9 -1.33</td>
</tr>
<tr>
<td>CDS Liquidity Risk</td>
<td>-1.75 -1.06</td>
<td>-1.3e -3</td>
<td>-4.78*</td>
<td>8.2e -4 1.17</td>
</tr>
<tr>
<td>N</td>
<td>1229</td>
<td>1229</td>
<td>1229</td>
<td>1229</td>
</tr>
<tr>
<td>Clusters</td>
<td>139</td>
<td>139</td>
<td>139</td>
<td>139</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
<td>0.29</td>
</tr>
<tr>
<td>$R^2*$</td>
<td>0.13</td>
<td>0.76</td>
<td>0.16</td>
<td>0.34</td>
</tr>
</tbody>
</table>

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Table 4.9: Bond Liquidity Risk Proxied by Betas Factors: During Crisis

In this table, we restrict our analysis to the pre-crisis period from April 2008 to October 2010. We regress CDS spread changes against default risk, liquidity level controls and liquidity risk proxies. In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the bond BAS. In the second stage regression, we maintain the control on the default risk and liquidity level and regress the residuals against the liquidity risk factors by doing a cross-sectional regression i.e by taking the average for each reference entity. $R^2$ and $R^2\cdot$ represent the R-squared of the first and the second stage regressions respectively. $\beta^{5i}$ represents the sensitivity of the liquidity of sovereign CDS to country-specific sovereign bonds. $\beta^{6i}$ is the sensitivity of CDS liquidity risk to sovereign bond market liquidity, $\beta^{7i}$ the sensitivity of CDS spreads to sovereign bond market liquidity and $\beta^{8i}$ the sensitivity of CDS liquidity risk to sovereign bond market return. 

$\cdot$, $\cdot\cdot$ and $\cdot\cdot\cdot$ represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th>Bond Liquidity risk Proxied by:</th>
<th>$\beta^{5i}$</th>
<th>$\beta^{6i}$</th>
<th>$\beta^{7i}$</th>
<th>$\beta^{8i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>t</td>
<td>Coef</td>
<td>t</td>
</tr>
<tr>
<td>Const</td>
<td>30.27</td>
<td>1.1</td>
<td>30.27</td>
<td>1.1</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-3.5</td>
<td>-1.05</td>
<td>-3.5</td>
<td>-1.05</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.31</td>
<td>0.53</td>
<td>0.31</td>
<td>0.53</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>-0.069</td>
<td>-0.66</td>
<td>-0.069</td>
<td>-0.66</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>1.5e^-3</td>
<td>0.17</td>
<td>1.5e^-3</td>
<td>0.17</td>
</tr>
<tr>
<td>US VIX</td>
<td>1.45</td>
<td>1.79</td>
<td>1.45</td>
<td>1.79</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>-31.71</td>
<td>-1.05</td>
<td>-31.71</td>
<td>-1.05</td>
</tr>
<tr>
<td>Bond Liquidity level</td>
<td>-9.73</td>
<td>-1.18</td>
<td>-9.73</td>
<td>-1.18</td>
</tr>
<tr>
<td>Bond Liquidity Risk</td>
<td>1.5e^-4</td>
<td>1.99**</td>
<td>8.9e^-3</td>
<td>2.58**</td>
</tr>
</tbody>
</table>

| N                               | 1229 | 1229 | 1229 | 1229 |
| Clusters                        | 139  | 139  | 139  | 139  |
| $R^2$                           | 0.28 | 0.28 | 0.28 | 0.28 |
| $R^2\cdot$                      | 0.36 | 0.49 | 0.10 | 0.00 |
We regress CDS spread changes against default risk, liquidity level controls and liquidity spiral proxies. In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. Since our liquidity spiral proxy is fixed across countries by changes within each country, we only have to control for the time-series correlation. In this situation, we also run a two-stage regression. In the first part, we regress CDS spread changes against variables that have both cross-sectional and time-series correlations (local stocks, exchange rate, trade balance, reserves in dollar and CDS BAS), then we extract the residuals and run the second stage regression which only comprises the variables that have time-series correlation (VIX, 5 years CMT and \( \beta_{Libor}^9 \) or \( \beta_{Repo}^9 \)). \( \beta_{Libor}^9 \) (or \( \beta_{Repo}^9 \)) represents the proxy for the liquidity spiral effect for the pre-crisis period and \( \beta_{Libor}^{9+} \) (or \( \beta_{Repo}^{9+} \)) for the crisis period. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively. \( R^2^∗ \) represents the R-squared of the second stage regression.

### Table 4.10: Liquidity Spiral Effect

<table>
<thead>
<tr>
<th>Liquidity Spiral Effect Proxyed by:</th>
<th>( \beta_{Libor}^9 )</th>
<th>( \beta_{Repo}^9 )</th>
<th>( \beta_{Libor}^{9+} )</th>
<th>( \beta_{Repo}^{9+} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>Coef</td>
<td>t</td>
<td>Coef</td>
<td>t</td>
</tr>
<tr>
<td>Const</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-0.75</td>
<td>-1.43</td>
<td>-0.75</td>
<td>-1.43</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>-0.32</td>
<td>-2.92</td>
<td>-0.32</td>
<td>-2.92</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>(-2.2e^{-3}) (0.21)</td>
<td>(-2.2e^{-3}) (0.21)</td>
<td>(5e^{-3}) (0.27)</td>
<td>(5e^{-3}) (0.27)</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>(-1.4e^{-3}) (-0.28)</td>
<td>(-1.4e^{-3}) (-0.28)</td>
<td>(3e^{-3}) (0.27)</td>
<td>(3e^{-3}) (0.27)</td>
</tr>
<tr>
<td>US VIX</td>
<td>-0.18</td>
<td>-1.15</td>
<td>-0.18</td>
<td>-1.15</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>2.52</td>
<td>0.59</td>
<td>2.53</td>
<td>0.59</td>
</tr>
<tr>
<td>CDS Liquidity level</td>
<td>(-2.43) (-0.67)</td>
<td>(-2.43) (-0.67)</td>
<td>(-39.4) (-1.18)</td>
<td>(-39.4) (-1.18)</td>
</tr>
<tr>
<td>Funding Liquidity Risk</td>
<td>(-1.7e^{-3}) (-0.13)</td>
<td>(-7e^{-4}) (-0.07)</td>
<td>(-0.029) (-0.09)</td>
<td>(-0.34) (-0.19)</td>
</tr>
<tr>
<td>N</td>
<td>1053</td>
<td>1053</td>
<td>1229</td>
<td>1229</td>
</tr>
<tr>
<td>Clusters</td>
<td>117</td>
<td>117</td>
<td>139</td>
<td>139</td>
</tr>
<tr>
<td>( R^2^∗ )</td>
<td>0.39</td>
<td>0.39</td>
<td>0.28</td>
<td>0.28</td>
</tr>
</tbody>
</table>
Table 4.11: Speculation Effect

We regress CDS spread changes against default risk, liquidity level controls and the Hedge Fund Return Index (HFRI). In our panel model, we address country effect parametrically (i.e. by using dummies—not shown in the table) and cluster the standard errors by time. To control for the default risk we use 6 variables: local stocks, exchange rate, reserves in dollar, trade balance, VIX and the 5 years CMT, for the liquidity level we utilise the CDS bid-ask spreads (BAS). $HFRI^+$ represents a proxy for the speculation effect for the pre-crisis period and $HFRI^{++}$ for the crisis period. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively. $R^2$ represents the R-squared of the second stage regression.

<table>
<thead>
<tr>
<th>Speculation Proxied by:</th>
<th>$HFRI^+$</th>
<th></th>
<th>$HFRI^{++}$</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>t</td>
<td>Coef</td>
<td>t</td>
</tr>
<tr>
<td>Const</td>
<td>0.38</td>
<td>0.32</td>
<td>-0.77</td>
<td>-0.15</td>
</tr>
<tr>
<td>Local Stocks</td>
<td>-0.60</td>
<td>-1.69</td>
<td>-3.95</td>
<td>-2.39</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>-0.65</td>
<td>-6.52</td>
<td>-1.47</td>
<td>-4.24</td>
</tr>
<tr>
<td>Reserve in Dollar</td>
<td>$6.5e^{-3}$</td>
<td>0.51</td>
<td>$5.3e^{-3}$</td>
<td>0.14</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>$-2.8e^{-3}$</td>
<td>-0.92</td>
<td>$4.5e^{-3}$</td>
<td>0.36</td>
</tr>
<tr>
<td>US VIX</td>
<td>-0.57</td>
<td>-2.94</td>
<td>2.01</td>
<td>4.63</td>
</tr>
<tr>
<td>CMT 5 years</td>
<td>-25.36</td>
<td>-4.79</td>
<td>-35.4</td>
<td>-2.10</td>
</tr>
<tr>
<td>CDS Liquidity level</td>
<td>-0.97</td>
<td>-0.20</td>
<td>-27.58</td>
<td>-0.5</td>
</tr>
<tr>
<td>HFRI</td>
<td>-1.18</td>
<td>-1.49</td>
<td>-3.70</td>
<td>-3.33∗</td>
</tr>
</tbody>
</table>

| N                       | 1033     | 1029 |
| Clusters                | 117      | 139 |
| $R^2$                   | 0.39     | 0.31 |
Chapter 5

Do Sovereign Credit Default Swaps Represent a Clean Measure of Sovereign Default Risk? A Factor Model Approach

5.1 Introduction:

The objective of this chapter is to quantify the size of the liquidity component in the sovereign CDS spreads by utilising a CDS pricing model and to provide a detailed decomposition of the spreads by using information from both CDS and bond markets.

In fact, few papers tried to decompose sovereign CDS spreads in order to isolate the default risk from the risk premium. Longstaff et al (2011) found that a third of the sovereign CDS spreads is attributable to the distress risk premium. Remonola et al (2008) show that jump-at-default risk is priced in the sovereign CDS spreads without quantifying its magnitude. In the bond literature there are papers that study credit and liquidity effects on sovereign bond yields such as Codogno, Favero and Missale (2003), Geyer, Kossmeier and Pichler (2004), Beber, Brandt and Kavajecz (2009), Favero, Pagano and Thadden (2010), Schwarz (2010) and Monfort and Renne (2011). All these papers agree that liquidity is present in sovereign bond yields. We differ from the previous studies by using information from both CDS and bond markets to do our decomposition because both assets are driven by the same default risk and their liquidity
are highly correlated (Pu (2010) and Calice, Vhen and Williams (2011)). In fact, by \textit{jointly} calibrating the model to both CDS and bond data we are able to use a large amount of information on sovereign default risk and thus present a better decomposition and estimate the components more precisely.

In order to carry out this analysis, we extend the factor model of Buhler and Trapp (2010)-BT thereafter. BT framework is a reduced-form credit risk model that contains credit risk and liquidity effects of both CDS and bond spreads. It allows us to jointly estimate default risk using information from both bond and CDS markets and measure the correlation components between default risk and liquidity. Favero, Pagano and Thadden (2010) argue that an estimation that ignores the interaction effect between the aggregate default risk and liquidity may underestimate the impact of liquidity on prices. The fact that our model enables us to estimate the correlation parameters between default risk and other risk premium is one of the key differences between our study and that of Longstaff et al (2011) and Remonola et al (2008).

Our results reveal that default risk represents on average 73\% of the bond spreads, liquidity 26.86\% and correlation risk 0.0014 \%. On the CDS side we find that, on average, default risk account for 55.6\% of the spreads, liquidity for 44.32\% and correlation risk for 0.043\%. Our findings reveal that sovereign CDS spreads are highly driven by liquidity and that sovereign bond spreads are less subject to liquidity frictions and therefore could represent a better proxy for sovereign default risk. Secondly, we show empirically that flight-to-liquidity and systematic liquidity play a non-negligible role and contributes to both sovereign bond and CDS spread movements. Finally, our decomposition exercise puts forward the idea that the increase in the CDS spreads observed during the crisis period was mainly due to a surge in liquidity rather than to an increase in the default intensity.

Our paper has important implications for practitioners and policy makers and enhances our understanding of the main drivers of sovereign bonds and most importantly
sovereign CDS spreads because if high CDS spreads imply high liquidity instead of high default risk then central banks could take appropriate measures to monitor the liquidity embedded in the spreads.

To the best of our knowledge this chapter provides several contributions to the literature. Firstly, we provide the first study that attempts to quantify the size of the liquidity component in the sovereign CDS market. Secondly our model extension enables us to study the joint effect of systematic liquidity and flight-to-liquidity in both sovereign bond and CDS markets, an analysis that hasn’t been accomplished yet. Finally, by studying the correlation risk premium between default risk and liquidity we are able to provide a better decomposition than the one documented in Remonola et al (2008) and Longstaff et al (2011).1

In the following subsections, we discuss the related literature and the motivation behind our model extension. In Section 5.2, 5.3 and 5.4, we present in more details the model extension, introduce our data and describe the calibration procedure respectively. In Section 5.5, we discuss the results for each rating. Finally in Section 5.6 we conclude.

5.1.1 Related Literature:

A large amount of literature have tried to explain the components of corporate bond yields2. A consensus from these studies is that corporate bond yields are heavily influenced by other factors than credit risk, such as liquidity risk, tax and macroeconomic variables. Longstaff et al (2005) present the first study that uses CDS spreads to decompose bond yields and find that the non-default component is time-varying and heavily influenced by bond liquidity factors. In the same spirit, Han and Zhou (2007) study the corporate bond yields using the term structure of CDS spreads and find that

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1In the next subsection, we will discuss in some details how our study improves the sovereign CDS spread decomposition presented in Remonola et al (2008) and Longstaff et al (2011).

the non-default component fluctuates with macroeconomic variables and stock market liquidity.

The bond literature also tried to measure the non-default component of the sovereign bond yields. Codogno, Favero and Missale (2003) study the determinants of the euro-area differentials with both monthly and daily data and found that international factors rather than domestic ones have strong explanatory power while liquidity plays a role for few countries. Geyer, Kossmeier and Pichler (2004), using a CIR model, find that bond yields for EMU countries are mainly explained by a global risk factor and that liquidity does not have any impact. Beber, Brandt and Kavajecz (2009) study the components of sovereign bond yields and use the CDS data for European sovereigns to measure the effect of flight-to-quality and flight-to-liquidity. They shown that credit and liquidity risks are positively correlated and that credit risk represents the majority of the sovereign bond yields. Favero, Pagano and Thadden (2010) also explore the determinants of the sovereign bond yields by taking into account the interaction effect between aggregate default and liquidity risks, they show that default risk explains the majority of the sovereign bond yields and that liquidity plays a minor role. Schwarz (2010) investigate the effect of liquidity risk on sovereign bond yields and find that market liquidity explains 68% of the widening of sovereign bond spreads, this value is surprisingly high and is in sharp contrast with what has been documented in the literature. Panyanukul (2010) examines the effects of liquidity on sovereign bond returns and show that the combined effect of liquidity level and liquidity risks can explain roughly 1% of extra yield spreads for the countries that have higher sensitivity to market liquidity shocks. Finally, Monfort and Renne (2011) provide and estimate an affine term structure model that directly measures liquidity and credit risks in the term structure of euro bonds. They find that the liquidity part of the spreads is less important than the credit related one even though liquidity effect is non trivial.

In fact, the studies of Longstaff et al (2005) and Han and Zhou (2007) mentioned
above consider that CDS spreads are not subject to liquidity risk, however there is a growing literature that acknowledges the importance of liquidity in the CDS market. Qui and Yu (2011) provide the first study that explores the determinants of endogenous liquidity provision in the corporate CDS market. The authors treat liquidity as being endogenously determined by information heterogeneity and frequency of uninformed trading. One of their main findings suggests that endogenous liquidity provision in the CDS spreads is an increasing function of the level of information heterogeneity present in the market. They empirically prove that the information flow is increasing with the number of CDS quote providers and this is particularly relevant under unfavorable credit conditions. Finally, they report a mixed result by arguing that the degree of information heterogeneity plays a capital role on how liquidity affects CDS spreads.

All these papers show that liquidity plays an important role in CDS spreads which lead other studies to extend the model of Longstaff, Mithal and Neis (2005) (LMN—thereafter) to account for CDS liquidity in order to measure the non-default component of corporate bond yields. Lin et al (2009) extend the LMN model to incorporate CDS liquidity effect and quantify the size of liquidity component in both corporate CDS and bond spreads. They are able to show that liquidity represents on average 13% of the CDS spreads. Secondly, they provide evidence that on average corporate bond yield are composed of 47% of default risk, 30% of taxes and 23% of liquidity factor. Buhler and Trapp (2010) also extend the LMN model but differ from Lin et al (2009) by taking into account the correlation effect between credit and liquidity risks and between bond and CDS liquidity risks. Therefore by calibrating their model to both CDS and bond data they are able to capture important dynamics at cross-sectional and time-series level. Overall, they show that 60% of bond spreads are to due to default risk, 35 % to liquidity risk and 5 % to correlation between credit and liquidity risks. For the CDS spreads, credit risk represents 95%, liquidity 4% and correlation 1%.

On the sovereign CDS side, few papers tried to isolate default risk from the risk
premium. Longstaff et al (2011) and Remonola et al (2008) decompose the sovereign CDS spreads into default risk and risk premium components, while the former focuses on “distress” risk, the latter discusses the “jump-at-default” risk. Our paper differs from the previous literature by not only focusing on the effect of instrument-specific liquidity and systematic liquidity risk but also by using information from both bonds and CDSs to carry out the analysis.

Decomposing sovereign CDS spreads using information from both bonds and CDSs is essential in many aspects. Typically both markets are highly integrated because they share the same default risk. Secondly there is large literature showing that bond and CDS liquidity risks are highly correlated. Amadei et al (2011) study the issues related to the European sovereign CDS market and its relation with the bond market. They find that, during the recent crisis, bond-CDS arbitrage relation didn’t hold. However when the sovereign bond market is less liquid, CDSs have the leading role in terms of price discovery. Furthermore, the authors find no clear evidence that speculation has a direct effect on sovereign bond prices, therefore any regulatory measure taken against speculation must be assessed with caution because this might hamper the functioning of the sovereign bond market. Ismailescu and Philips (2011) investigate the impact of CDS trading initiation on sovereign bonds from the perspective of market completeness, price discovery and borrowing costs. The authors report that CDSs are not redundant assets and contribute to an incremental increase of pricing information of about 67%. However, the authors show that this result differs at a cross sectional level. Countries with high openness do not benefit as much from price informativeness gains. Finally, according to the paper, CDS introduction appears to provide a liquidity service to investment grade sovereigns resulting in lower borrowing costs. Foley-Fisher (2010) examines the relationship between government bond and CDS spreads during the recent financial crisis and shows that there is a violation of arbitrage conditions between both markets occurring at different times and in different countries. Fontana and Scheicher (2010)
document that the recent repricing of the sovereign credit risk in Europe is mainly driven by common factors. Furthermore, the authors show that the flight-to-liquidity episode observed in the European bond market increased the CDS spreads more than the corresponding bond yields. Finally, Arce et al (2011) analyze the relationship between sovereign bond and CDS spreads from three angles. Firstly, the authors find that there is a persistent deviation from the parity relationship between CDS and bond spreads and that this deviation accelerated during the subprime crisis. Secondly, they find that counterparty risk indicators, funding costs and liquidity have significant impact on the CDS-bond basis. Moreover, the authors analyze what market leads the pricing discovery by using the approach of Gonzalo and Granger (1995) and conclude that global risk aversion, funding costs, market liquidity and debt volume are all playing an important role in determining which market leads the discovery.

All these papers emphasize that bonds and CDSs share common features hence the importance of doing a joint calibration in order to present a better decomposition of the spread components. In the following subsection, we discuss the BT model extension.

5.1.2 Systematic Liquidity and Flight-To-Liquidity Risks:
As we previously emphasized, the sovereign CDS market is subject to a high level of commonality across countries. In Chapter 4, we empirically showed that systematic liquidity participates to the sovereign CDS spread movements. To this end, we extend the CDS pricing model of Buhler and Trapp (2010) however we differentiate ourselves from the authors by not only focusing on the sovereign CDS market but also by including an extra factor to test for the influence of the systematic liquidity.

Moreover, we also investigate the flight-to-liquidity effect. As highlighted by Beber, Brandt and Kavajecz (2009), during some subperiods large flows in the sovereign bond market are almost exclusively determined by liquidity and not credit quality be-

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Buhler and Trapp (2010) focus mainly on the instrument specific liquidity of the corporate CDS spreads.
cause investors rebalance their portfolios and chase the most liquid bonds regardless of their default risk, this is what the authors name as flight-to-liquidity risk. Since bond liquidity has an importance influence on the defaultable leg of the CDS contract, it is plausible that the flight-to-liquidity risk affects the liquidity of the deliverable sovereign bonds. While Buhler and Trapp (2010) mention only bond liquidity, in this chapter, we depart from the assumption that flight to liquidity risk adds more weight to the CDS defaultable leg and may decrease sovereign CDS spreads. We thus add an extra liquidity adjustment to take into account the potential influence of the flight-to-liquidity.\footnote{In Chapter 4, we showed that bond systematic liquidity or flight-to-liquidity risk is more pressurizing during the crisis time.}

In summary, we have two sources of risk that have a substantial influence on sovereign CDS spreads. Therefore, by extending the original model of Buhler and Trapp (2010) we aim to provide a comprehensive framework that contains the major sources of risk that affect both CDS and bond spreads. To the best of our knowledge, we provide the first study that analyses the impact of both systematic and flight-to-liquidity risk in the sovereign CDS market. In the following section, we present our model in some details.

5.2 Model Definition: The Sovereign Market Case

In our model, we choose the default-free zero coupon bond as "liquidity numeraire" and depart from the assumption that the risk-free rate is independent from the default and the liquidity intensities (Longstaff et al (2005), Pan and Singleton (2008)). Therefore, the risk structure of our model is composed of:

$$D(t, \tau) = \exp(-\int_{t}^{\tau} r_s ds)$$  \hspace{1cm} (5.1)
where $D(t, \tau)$ is the risk-free discount factor,

$$P(t, \tau) = \exp(-\int_t^\tau \lambda_s ds)$$

(5.2)

where $P(t, \tau)$ is the risk neutral survival probability and

$$L(t, \tau) = \exp(-\int_t^\tau \gamma^l_s ds)$$

(5.3)

where $L(t, \tau)$ is the risk neutral liquidity intensity. The superscript $l$ in the liquidity intensity $L(t, \tau)$ refers to either CDS or bond liquidity.

CDS spreads can be impacted by default risk, instrument-specific liquidity and possibly by liquidity changes in CDS and bond markets. Typically, high liquidity risk is accompanied by high bid-ask spreads and thus high CDS spreads. On one hand, liquidity risk increases the price of buying CDS protection because the ask quote has to compensate the CDS seller (i.e. dealer) for the credit and liquidity risk. On the other hand, liquidity risk also reduces the price of selling CDS protection, the intuition is that CDS buyers (i.e. dealer) will only agree to buy the protection at a cheap price (i.e. low bid). Therefore, the bid-ask spread constitutes a hidden cost to market participants when they trade assets and we measure its effect with the following liquidity intensities $\gamma^{\text{ask}}(t)$ and $\gamma^{\text{bid}}(t)$.

In our setting, we make the assumption that systematic liquidity risk may inflate or

\footnote{$\gamma^{\text{ask}}(t)$ and $\gamma^{\text{bid}}(t)$ measure only the effect of the instrument specific liquidity.}
deflate CDS bid-ask spreads. Therefore one of the goals of our model is to measure how much extra effect can systematic liquidity risk have on the bid-ask spreads in addition to the effect that is due only to the instrument-specific liquidity described above. We thus add another liquidity intensity \( \gamma^{sys}(t) \) in order to measure the extra effect specific to the systematic liquidity risk.

Concerning the bonds, we also try to capture the impact of bond liquidity \( \gamma^b(t) \) and the risk of flight-to-liquidity \( \gamma^{gb}(t) \) in the sovereign bond market. The intuition is that the flight-to-liquidity risk creates liquidity shocks that may not be captured by the standard bond liquidity discount factor \( \gamma^b(t) \).

We thus have six risk factors: the default intensity \( \lambda(t) \), CDS liquidity \( \gamma^{ask}(t), \gamma^{bid}(t) \), systematic liquidity intensity \( \gamma^{sys}(t) \), bond liquidity intensity \( \gamma^b(t) \) and the flight-to-liquidity intensity \( \gamma^{gb}(t) \). The structure of the factor model can be summarized as follows:

\[
\begin{align*}
\begin{pmatrix}
    d\lambda(t) \\
    d\gamma^b(t) \\
    d\gamma^{ask}(t) \\
    d\gamma^{bid}(t) \\
    d\gamma^{gb}(t) \\
    d\gamma^{sys}(t)
\end{pmatrix} &=
\begin{pmatrix}
    1 & g_b & g_{ask} & g_{bid} & g_{gb} & g_{sys} \\
    f_b & 1 & w_{b,ask} & w_{b,bid} & w_{b,gb} & w_{b,sys} \\
    f_{ask} & w_{ask,b} & 1 & w_{ask,bid} & w_{ask,gb} & w_{ask,sys} \\
    f_{bid} & w_{bid,bid} & w_{bid,ask} & 1 & w_{bid,gb} & w_{bid,sys} \\
    f_{gb} & w_{gb,b} & w_{gb,ask} & w_{gb,bid} & 1 & w_{gb,sys} \\
    f_{sys} & w_{sys,b} & w_{sys,ask} & w_{sys,bid} & w_{sys,gb} & 1
\end{pmatrix}
\begin{pmatrix}
    dx(t) \\
    dy^b(t) \\
    dy^{ask}(t) \\
    dy^{bid}(t) \\
    dy^{gb}(t) \\
    dy^{sys}(t)
\end{pmatrix} \\
\end{align*}
\]

(5.4)

The left hand-side of the equation (5.4) represents the correlated intensities and
the right-hand side the factor matrix multiplied by the pure intensities. One of the assumptions of our model is that the pure intensities \( x(t) \) and \( y(t) \), which represent pure default risk and liquidity, are not correlated neither at time-series nor at cross-sectional level. On the other hand, the factor sensitivity matrix reflects the interactions between default risk, instrument-specific liquidity and market liquidity. For instance, the default intensity \( \lambda(t) \) can be written in the following form:

\[
\lambda(t) = x(t) + g_b * y^b(t) + g_{ask} * y^{ask}(t) + g_{bid} * y^{bid}(t) + g_{gb} * y^{gb}(t) + g_{sys} * y^{sys}(t)
\]

(5.5)

The matrix approach will enable us to isolate the pure intensities from their correlated components and therefore present accurate decomposition of the CDS spreads.

The parameter \( f \) in the factor matrix represents the impact of pure default risk \( x \) on the liquidity intensity \( \gamma(t) \), \( g \) corresponds to the impact of pure liquidity \( y(t) \) on the credit risk premium \( \lambda \). A negative sign of \( f \) is likely if high sovereign default risk decreases bond liquidity. In line with this, Favero, Pagano and Thadden (2010) find that there is a negative relationship between aggregate default risk and liquidity. The parameter \( w \) captures the interactions between CDS and bond liquidity.

Bonds and CDSs can be a substitute to each other, in fact if there is high liquidity risk in the bond market investors will use CDSs as an alternative to take long (short) credit risk positions which might reduce CDS liquidity risk. On the other hand, if market participants use CDSs mainly to hedge their bond positions then high CDS liquidity risk may increase bond liquidity risk. This two way relationship causes liquidity spill-
over\(^6\) from one market to another. For example, in the factor sensitivity matrix, we introduced \(w_{gb, ask}\) which represents the interaction between the flight-to-liquidity\(^7\)(\(gb\)) and the CDS ask quote (\(ask\)). If the flight-to-liquidity risk influences the liquidity of the deliverable bonds, CDS buyers may require a discount which translates into a lower ask quote.

In this setting, we assume a CIR process for the pure default intensity in order to ensure that the default arrival rate is always non-negative:

\[
dx_t = (\alpha - \beta \cdot x(t)) \cdot dt + \sigma \sqrt{x(t)} \cdot dW^\lambda(t)
\]

Concerning the pure liquidity intensity \(y_t\), we follow the approach of Longstaff et al (2005) and assume a Gaussian process in order to allow liquidity to take both positive and negative values:

\[
dy^l_t = \eta \cdot dW^l(t)
\]

\(^{5.6}\)

\(^{5.7}\)

\(W^l\) and \(W^\lambda\) are independent Brownian motions specific to the liquidity and the default intensities respectively. \(\alpha, \beta, \eta > 0, \sigma > 0\) represent the parameters specific to each intensity.

### 5.2.1 Bond Market:

The price of a defaultable bond denoted as \(CB(t)\) is the sum of expected semi-annual coupon bond weighted by the default probability and the bond liquidity discount factor.

\(^{\text{Commonality risk may also intensify the liquidity spill-over effect which could in turn inflate the influence of the systematic liquidity (\(gb\)) on the credit risk premium \(\lambda\).}}\)

\(^{\text{In this study we use bond market liquidity and flight-to-liquidity interchangeably.}}\)
We assume that the recovery $R$ is equal to 25% of the face value $F$. We also adopt the discrete time setting in order to match the coupon semi-annual payment date $t_i$ ($t_1, t_2, ..., t_{10}$).

$$CB(t) = c \sum_{i=1}^{n} D(t, t_i) \star E_t[P(t, t_i) \star L^b(t, t_i) \star L^{gb}(t, t_i)] +$$

$$F \star D(t, t_n) \star E_t[P(t, t_n) \star L^b(t, t_n) \star L^{gb}(t, t_n)] +$$

$$R \star F \star \sum_{j=1}^{n} D(t, t_j) \star E_t[\triangle P(t, t_j) \star L^b(t, t_j) \star L^{gb}(t, t_j)]$$

(5.8)

In this framework we assume that default can only happen at the payment date $t_j$ ($t_i = t_j$) and that recovery occurs the following day. The last term of $CB(t)$ corresponds to the recovery after default has occurred. $D(t, t_i)$ denotes the zero coupon bond, $L^b(t, t_i)$ the bond liquidity discount factor, $L^{gb}(t, t_i)$ the flight-to-liquidity discount factor, $P(t, t_n)$ the survival probability until time $t_n$ and $\triangle P(t, t_j) = P(t, t_{j-1}) - P(t, t_j)$ the probability of surviving from time $t$ to time $t_{j-1}$ and defaulting between $t_{j-1}$ and $t_j$. All the expectations are taken under the risk neutral measure. The intuition behind the inclusion of $L^b(t, t_i)$ and $L^{gb}(t, t_i)$ is that sovereign bonds could be influenced by their own liquidity and by the flight-to-liquidity risk.

---

8In this study, we follow market convention and assume a recovery of 25% across all ratings. Pan and Singleton (2008) study the recovery implicit in the term structure of sovereign CDS spreads and find that the estimate of the recovery rate are in the region of 25% for Turkey and Korea. However Mexico displays a recovery rate of about 50%. In order to ensure that our results are robust, we repeat our analysis using the recovery rate of 20%, 40% and 50% for the rating A, BBB and BB and we find no significant changes in our decomposition results (section 5.5.2).

9Our model could be easily extended to allow for stochastic settlement times in case of a credit even. However since our framework is multi-dimensional we make this assumption in order to gain computational speed.
5.2.2 CDS Market:

The CDS contract has two legs: the fixed leg where CDS buyers pay a semi-annual premium and the floating leg where CDS sellers receive the premium until default occurs. In the same way as for the bonds, we assume that default only happens at the payment dates, therefore we do not have any accrual payments. The fixed leg is defined as follows:

\[
CDS_{\text{fix}}^{\text{ask/bid}}(t) = s^{\text{ask/bid}} \cdot (\sum_{i=1}^{n} D(t, t_i) \cdot E_t[P(t, t_i) \cdot L^{\text{ask/bid}}(t, t_i) \cdot L^{\text{sys}}(t, t_i)])
\]

(5.9)

For the CDS ask/bid premium, we assume that spreads are not only influenced by the default arrival rate \( P(t, t_i) \) but also by liquidity. Therefore, \( L^{\text{ask/bid}}(t, t_i) \) and \( L^{\text{sys}}(t, t_i) \) reflect the part of the CDS spreads that is attributed to the instrument-specific\(^{10}\) and the systematic liquidity respectively. For instance, if the CDS market as a whole is illiquid, this may exacerbate asset illiquidity therefore the dealer is likely to increase (decrease) the ask (bid) quote to compensate for the additional risk that systematic liquidity represents.

On the other hand, the value of the floating or defaultable leg is described as follows:

\[
CDS_{\text{float}}^{\text{ask/bid}}(t) = F \cdot \sum_{j=1}^{n} D(t, T_j) \cdot E_t[\Delta P(t, t_j)]
\]

\[
- R \cdot D(t, t_j) \cdot E_t[\Delta P(t, t_j) \cdot L^b(t, t_j) \cdot L^{gb}(t, t_j)]
\]

\(^{10}\)The instrument-specific liquidity reflects the aspects of liquidity that are specific to the asset for instance transaction costs, depth, etc.
The equation implies that CDS sellers get the bond principal minus the recovery value which, as we mentioned in the previous subsection, could be impacted by bond liquidity and flight-to-liquidity risk. This double effect is valid whether the settlement is physical or cash because if the sovereign bond market is illiquid then the value of the cheapest-to-deliver bond could be affected.

Overall, the theoretical CDS and bond values for sovereigns should incorporate all these aspects in order to have a comprehensive picture of the different risks that could influence the spreads. In Appendix 5.7.1, we present the analytical solutions for equations (5.8), (5.9), and (5.10) using the exponential affine framework.

5.3 Data and Descriptive Statistics:

We focus on emerging market countries to run our analysis. Similarly to the previous chapters, our data spans from November 2005 to September 2010. For the term structure of the default free interest rate, we follow the approach of Longstaff et al (2005) and Pan and Singleton (2008) and use the Treasury Curve commonly known as CMT. We collect the data on a daily basis from the Federal Reserve H.15 statistical release for the constant maturity six-month, one, two, three, five, seven, ten, twenty and thirty year rates. We then use the cubic spline algorithm to infer the discount factors at semi-annual intervals.

We download bid, ask and mid of the 5-year CDS spreads on a daily basis from Datastream Reuters for the following countries: Chile, Korea, Mexico, Colombia, Peru, Brazil, Philippines, Indonesia and Turkey. We pick a country only if it has at least two bond issues\textsuperscript{11}. The dataset contains more than 35,000 observations. For the purpose of our study, we also collect the current and the historical S&P credit rating from

\textsuperscript{11}The S&P historical ratings are not given at regular intervals but only when upgrades or downgrades occur.
Datastream. We assign a rating to a country by giving a number to each rating category and taking the average of our sample period (we round up if necessary). The ratings that we obtain are as follows:

<table>
<thead>
<tr>
<th></th>
<th>Bra</th>
<th>Chile</th>
<th>Indo</th>
<th>Philip</th>
<th>Tur</th>
<th>Peru</th>
<th>Colo</th>
<th>Mex</th>
<th>Kor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratings</td>
<td>BBB</td>
<td>A</td>
<td>BB</td>
<td>BB</td>
<td>BB</td>
<td>BBB</td>
<td>BBB</td>
<td>BBB</td>
<td>A</td>
</tr>
</tbody>
</table>

This results in four rating categories A, BBB and BB. For each category we take the averages of the CDS mid quotes and the bond prices.

We obtain the bond data on a daily basis from Datastream. We collect the bid, ask and mid prices for each dollar denominated bond issued by the relevant country and focus only on fixed coupon bonds with no option embedded. The bid/ask are ICMA data, these are quotes provided by 30 investment banks. At the end of each working day, their closing bid and ask quotes are sent to Xtrakter where they are validated and processed to provide an average bid and ask for each security\(^{12}\).

In our implementation we are interested in the bid, ask and mid yields. Since they are not directly downloadable, we need to compute them in order to compare the 5-year bond spreads with the 5-year sovereign CDS spreads.

Sovereign bonds are semi-annual coupon bonds which means that for a bond price \( P_t(C, N, \tau) \), the annual yield-to-maturity can be computed in the following way:

\[
P_t(C, N, \tau) = \sum_{i=1}^{N} \frac{C}{2} (1 + \frac{y_t}{2})^{-(\tau+0.5(i-1))} + F * (1 + \frac{y_t}{2})^{-(\tau+0.5(N-1))}
\]

\[\text{(5.11)}\]

where \( C \) is the annual coupon rate\(^{13}\), \( F \) the face value, \( N \) the number of remaining coupon payments and \( \tau = \frac{T-t}{T} \) the ratio of the number of days until the next coupon payment.

\(^{12}\)Besides for Chile which has two bond issues, each country has large number of bonds. In fact, the diversity in the maturity dates will be useful in providing a good estimate for the 5 year bond spread.

\(^{13}\)We assume that the first coupon payment occurs in the first settlement date of our time series.
payment to the number of days in the coupon period.

In order to estimate sovereign bond spreads using equation (5.11), we first need to extract the risk-free rate. Therefore, for each bond we solve for the synthetic default-free bond with identical coupon and maturity as the defaultable bond. This is done in two steps, first we use the default free term structure of interest rate (i.e Treasury curve) to compute the price of default-free coupon bonds as the sum of discounted zero coupon rates multiplied by $C/2$, then we solve for the default-free yield. Finally, we compute the bond spread by taking the difference between defaultable bond yields and synthetic default-free coupon bonds.

The last phase consists of computing the five year bond spreads. In fact, it would be ideal if we had a five year bond available at each time step in order to compare it with CDS spreads, however this is rarely the case. To address this problem we use the interpolation method implemented by Houweling and Vorst (2005).

Our dataset runs from 2005 to 2010, therefore the CDS maturity dates associated with our sample are from 2010 to 2015, hence we need bond with maturities from 2010 to 2015 to estimate the 5 year bond spreads. The countries that we picked do not always have a set of 6 bonds that mature exactly in 2010/2011/2012/2013/2014/2015, therefore when a bond maturity is missing we use as proxy a bond that has the closest maturity to the missing one. This methodology enables us to interpolate bond spreads to match CDS maturity.

Figure 5.1 shows the results for each rating class. The figures show that credit and CDS spreads for rating A, BBB and BB track each other very closely although it seems that on average bond credit spreads are slightly higher than CDS spreads.
5.4 Measuring Credit Risk, Liquidity, Systematic Liquidity and Correlation Premium:

5.4.1 Description of the Time Series Properties:

Using the grid search technique\(^\text{14}\), we estimate the parameters of the factor sensitivity matrix and the 6 intensity processes defined in equation (5.4) for each rating (i.e. A, BBB and BB). We fit the model to the data with a very small error. We obtain a mean error of 0.305, 0.35 and 0.369 bps for both bond and CDS spreads for rating A, BBB and BB respectively. In Figure 5.2, we plot the model-implied bond and CDS spreads with the actual data. We can see that the model tracks very well the data even when there are spikes, this is due to a daily cross-sectional fitting.

Table 5.2 presents the descriptive statistics of the estimated parameters. It shows that default intensities are positive across all the ratings however liquidity intensities have both negative and positive values. The signs are consistent with the assumptions made on the processes driving the intensities. The table also reveals that the magnitude of the pure default risk \(x\) increases as the rating deteriorates this is consistent with the idea that default risk has higher importance when the rating is low.

On the other hand, Table 5.2 reveals that the weight of bond liquidity \(y^b\) for rating BB is lower than for the other ratings (i.e. ratings A and BBB). However, similarly to the default risk, it appears that the weight of the flight-to-liquidity \(y^{gb}\) is higher as we decrease in the rating quality. In fact, our results show an interesting pattern; as default risk increases, the weight of the instrument specific (or bond) liquidity decreases but that of the flight-to-liquidity increases substantially which indicate that bond market liquidity is more pressurizing for lower quality ratings which is in turn imply that bond market flows head towards low rated countries. These results are consistent with those of Beber et al (2009) who find that during some sub-periods large flows in the bond market are determined almost exclusively by liquidity consideration than by credit risk

\(^{14}\)Appendix 5.7.2 defines in details the steps of the calibration procedure.
Finally, Table 5.1 reports the latent factors of the CIR and Gaussian processes defined in Section 5.2. As we can see, ratings BBB and BB have parameters that are in the same range. However, rating A has higher liquidity volatilities than the other ratings which may suggest that, due to the low weight of default risk (Table 5.2), the volatility that rating A experienced during our sample period (Figure 5.1) was mostly captured by liquidity. As we will explain in Section 5.5.1, this phenomenon may be partly explained by the flight-to-quality effect where investors prefer to buy and hold safer securities, this means that the increase in demand and supply in rating A substantially augments its liquidity volatility.15

5.4.2 Estimation Procedure:

In this subsection, we plug back the calibrated intensities into the CDS and the bond pricing formula (equation (5.8), (5.9) and (5.10)) and decompose the spreads in order to retrieve the default and the non-default components of each asset. We decompose the credit spreads into a pure credit risk component $bd$, a pure liquidity component $bl$, a pure global bond liquidity component $blg$ and a correlation component $bc$. In the same spirit as BT, $bd$, $bl$ and $blg$ correspond to the bond spread if only credit risk, liquidity and bond market liquidity are priced, in that case the factor sensitivities are equal to 0 ($f = g = w = 0$) and pure and correlated intensities coincide. $bc$ corresponds to the part of the bond spreads resulting from the correlation effect between credit and liquidity risk ($f \neq g \neq w \neq 0$). The sum of the four components mentioned above corresponds to the full bond spreads with maturity and payment dates equal to those of the CDSs.

Likewise, we disentangle the CDS spreads into four components: a pure credit risk

15This finding also seems to be consistent with Beber et al (2009) who find that liquidity plays a non-trivial role for low credit risk countries.
component \(sdg\), a pure liquidity component \(sl\), a pure systematic liquidity component \(slg\) and a correlation component \(sc\). \(sdg\) corresponds to the theoretical mid spread without a CDS liquidity effect\(^{16}\). In the second step, we consider CDS liquidity \(sl\) and systematic liquidity \(slg\) without taking into account the correlation components \((f = g = w = 0)\). In the last step, we consider the correlation \((sc)\) between credit risk and CDS liquidity. The sum of the four components indicates the full theoretical value of the CDS spreads\(^{17}\).

5.5 Credit Risk, Liquidity, Systematic Liquidity Risk and Correlation Premium: Cross-Sectional Results:

5.5.1 Factor Sensitivities:

In this subsection we present the results related to the factor sensitivity matrix and discuss the interactions between credit, liquidity and systematic liquidity risks. In order to interpret the results, we use the signs of the mean of the pure liquidity intensities (Table 5.2) combined with the signs of the sensitivity factors (Table 5.3) in order to infer whether the impact on the correlated intensities is positive or negative (equation \((5.4)\)).

5.5.1.1 Rating BB:

Table 5.3, shows that pure default risk \(x\) has a positive impact on bond liquidity \((f_b)\). The positive sign suggests that high default risk increases bond liquidity which might put forward the idea that agents show strong interest in trading bonds with low rating. Secondly, it seems that pure default risk \(x\) influences negatively CDS ask liquidity \((f_{ask})\) implying that high default risk leads to low CDS ask liquidity (i.e. high liquidity risk) which in turn means that dealers sell protection at a higher ask quote, the result is

\(^{16}\)sdg is measured by the default free rate, default probability, bond liquidity and bond market liquidity.

\(^{17}\)A more detailed definition on how to measure credit and liquidity risks is available in Appendix B of Buhler and Trapp (2010).
intuitive as high credit risk increases the cost of the CDS protection. On the other
hand, we observe that pure default risk \( x \) impact positively CDS bid liquidity \( (f_{\text{bid}}) \)
indicating that high default risk leads to high CDS bid liquidity and therefore higher
bid quote. The results of \( f_{\text{ask}} \) and \( f_{\text{bid}} \) advance that an increase in the pure default
risk doesn’t influence in a similar manner the bid and the ask quotes. This might be
explained by the fact that for the case of rating BB an increase in the pure default
risk augments the ask and the bid quotes in the same time because dealers are willing
to buy protections from investors in order to sell them back at a higher ask. In fact,
dealers may find it profitable to buy protections at high bid because they know that
they could sell them at an attractive price. Moreover, the negative sign of \( f_{\text{sys}} \) indicates
that an increase in the pure default risk decreases systematic liquidity resulting in a
higher ask, this result is also in line with \( f_{\text{ask}} \).

On the other hand, the table reveals that \( g_{\text{ask}} \) and \( g_{\text{bid}} \), the parameters representing
the impact of CDS ask and bid liquidity on credit risk premium \( \lambda \), carry negative signs,
this result suggests that high liquidity decreases the credit risk premium, this is in line
with our intuition as in case of high liquidity, the impact of CDS liquidity risk decreases
which makes the credit risk premium \( \lambda \) closer to the pure default risk \( x \). On the other
hand, the impact of the systematic liquidity on the credit risk premium \( \lambda \) (i.e. \( f_{\text{sys}} \)) is
also negative\(^{18}\) which is in line with \( g_{\text{ask}} \) and \( g_{\text{bid}} \) implying that the lower the effect of
liquidity the lower the distance from the pure default risk \( x \).

Bond liquidity \( g_b \) and bond market liquidity \( g_{gb} \) display negative signs which indicates
that high bond liquidity decrease the credit risk premium \( \lambda \). In fact, high bond liquidity
makes the influence of the delivery option on the defaultable leg of the CDS contract
insignificant\(^{19}\). This leads to a decrease of the credit risk premium narrowing the gap

\(^{18}\)\( f_{\text{sys}} \) is positive, however the pure liquidity intensity \( y^{\text{sys}} \) has negative sign which implies negative impact on the
credit risk premium \( \lambda \).

\(^{19}\)When the bond market is illiquid and the number of liquid bonds are limited, the Cheapest-To-Deliver (CTD) option
becomes valuable. If the value of the CTD changes, dealers may require additional compensation which in turn could
lead to an increase in the CDS spreads. On the other hand, when the bond market is liquid, the impact of the CTD is
insignificant because dealers will easily find a bond to deliver in case of default.
between $\lambda$ and the pure default risk $x$.

The parameters $(w_{b,\text{ask}}$ and $w_{b,\text{bid}}$) reflecting the liquidity spill-over between bonds and CDSs show negative and positive sign respectively. This implies that high bond liquidity increases CDS bid liquidity and slightly decreases CDS ask liquidity. This means that for rating BB an increase in bond liquidity tend to be accompanied with a bid-initiated transaction in the CDS market. This finding is consistent with the substitution effect as investors could take a long credit risk position in the CDS market and sell it back in the bond market\textsuperscript{20}.

The positive sign of the bond liquidity spill-over $w_{gb,g}$ reveals that high bond market liquidity leads to high bond liquidity implying a positive correlation between bond market and bond liquidity.

Finally, the parameters $w_{\text{sys,ask}}$ and $w_{\text{bid,sys}}$ showing the interaction between the systematic liquidity and CDS liquidity display a negative and a positive sign respectively\textsuperscript{21}. This indicates that high systematic liquidity increases CDS ask liquidity (i.e. lower ask) and decreases CDS bid liquidity (i.e. lower bid). This finding reveals that when the CDS market as a whole is liquid (or illiquid) this tend to decrease (increase) the cost of the CDS protection and decrease (increase) the sale price. In other words, systematic liquidity risk can deflate liquidity risk from the ask (i.e. lower ask) and inflate it from the bid side (i.e. lower bid) of the CDS quotes. Therefore, the impact of systematic liquidity risk can be different from both the bid and the ask side of the CDS contract. This finding supports our model and implies that systematic liquidity risk carries an extra premium because if the CDS market is illiquid then the liquidity of individual CDSs change.

\textsuperscript{20}This result is also consistent with the negative sign of $w_{gb,\text{ask}}$ and the positive sign of $w_{gb,\text{bid}}$ which indicate that high bond market liquidity leads to high CDS bid liquidity and low CDS ask liquidity.

\textsuperscript{21}We recall that the pure intensity $y^{\text{sys}}$ has negative sign combined with the negative sign of $w_{\text{sys,ask}}$, this leads to a positive impact of the liquidity intensity $\gamma^{\text{ask}}$. 

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5.5.1.2 Rating BBB:

The results of rating BBB are not very dissimilar from rating BB and we will only highlight the differences. Table 5.3, shows that the pure default risk $x$ affects positively both CDS ask ($f_{ask}$) and CDS bid liquidity ($f_{bid}$) meaning that high default risk improves CDS liquidity by decreasing the ask and increasing the bid quotes respectively. However, high default risk seems to increase systematic liquidity ($f_{sys}$), which infers that when rating BBB observes an increase in default risk investors trade less frequently in the CDS market which in turn inflates liquidity risk. This result is in contrast with rating BB.

Similarly to rating BB, $g_{ask}$, $g_{bid}$ and $g_{gb}$ are negative suggesting that high liquidity decreases the credit risk premium $\lambda$. In case of high liquidity, the effect of liquidity risk weakens and the credit risk premium $\lambda$ converges to the pure default risk $x$. However $g_{b}$ has no influence on the credit risk premium $\lambda$.

The parameters $w_{b,ask}$ and $w_{b,bid}$ show positive signs. This implies that high bond liquidity leads to high CDS liquidity decreasing the CDS ask and increasing the CDS bid quote. This finding is interesting because it shows that when there is high bond liquidity investors hedge their positions with CDSs increasing the liquidity of the CDS market.

5.5.1.3 Rating A:

Pure default risk $x$ has a negative impact on bond liquidity ($f_{b}$) which suggests that high default risk decreases bond liquidity. This result is in contrast with rating BBB and BB but is intuitive because high credit risk makes investors more risk averse and therefore bond liquidity decreases. Secondly, the pure default risk $x$ affects positively both CDS ask ($f_{ask}$) and CDS bid liquidity ($f_{bid}$) meaning that for the case of rating A, high default risk improves CDS liquidity from both the bid and ask quotes. Overall,
it seems that the impact of $f_{ask}$ and $f_{bid}$ is relatively small comparing to the rating BB and BBB. Similarly to rating BB, high default risk decreases systematic liquidity ($f_{sys}$), however the magnitude of the impact is low.

On the other hand, the table shows that $g_{ask}$ and $g_{bid}$, the parameters characterizing the impact of CDS liquidity on the credit risk premium $\lambda$, have negative and positive signs respectively which indicate that high CDS liquidity increases CDS ask and decrease CDS bid liquidity. This is equivalent to say that the ask side is closer to the pure default risk $x$ than the bid side. This scenario is likely to happen in a market where investors prefer to buy and hold safer securities instead of selling them, hence the increase in liquidity on the ask side. This phenomenon is similar to the flight-to-quality effect.

In contrast with rating BBB and BB, bond liquidity $g_{b}$ and bond market liquidity $g_{gb}$ carry positive signs implying that high bond liquidity increases the credit risk premium $\lambda$, this result seems to be counter intuitive as an increase in liquidity should reduce the liquidity risk effect and bring the credit risk premium closer to the pure default risk. Finally, the effect of bond liquidity spill-over ($w_{b,gb}$) and systematic liquidity risk ($w_{sys,ask}$ and $w_{sys,bid}$) both display similar effects to the previous ratings.

5.5.1.4 Summary:

Overall, the results of the factor sensitivity matrix indicate that the interaction between credit risk and liquidity is dependent on the quality of the rating. However there are common features across all the ratings that are worth highlighting. First of all, our findings show that CDS liquidity and systematic liquidity (or CDS market liquidity) are positively correlated\textsuperscript{22}. If CDS market liquidity is low it negatively influences the instrument-specific liquidity and vice versa. This finding supports the idea that systematic liquidity risk carries a premium and participates directly to the

\textsuperscript{22}This result is implied from the signs of $w_{sys,ask}$ and $w_{sys,bid}$.

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CDS spread movements. Moreover, Table 5.3 also shows that bond liquidity and bond market liquidity are positively related\footnote{This relationship is deduced from the sign of parameter $w_{b,gb}$.}. This result backs the initial assumption that flight-to-liquidity risk can exacerbate the (il)liquidity of deliverable bonds and put more weight on the defaultable leg of the CDS contract.

In their original paper, Buhler and Trapp (2010) find that, in the corporate CDS market, the pure liquidity intensities $y^l$ (with $l=\text{ask, bid or b}$) do not affect the credit risk premium $\lambda$ however the pure default risk $x$ has an impact on the liquidity intensities $\gamma^l$. For the case of the sovereign CDS market, we find that there is a two-way interaction between credit risk and liquidity\footnote{With one exception for the bond market liquidity where the pure default risk $x$ does not influence $y^{gb}$, however the liquidity intensity $\gamma^{gb}$ impacts the credit risk premium $\lambda$.}. Furthermore, we find that high bond liquidity tends to be accompanied with high CDS liquidity\footnote{This result is implied from the positive signs of $w_{b, ask}$ and $w_{b, bid}$ and the pure liquidity intensities $y^{bid}$ and $y^{ask}$ for rating A, BBB and BB. There is one exception for rating BB where $w_{b, ask}$ has a negative sign but its effect is very weak as it is equal to -0.0019.}, this is consistent with the hedging effect\footnote{This result is in line with the original paper of Buhler and Trapp (2010) who also report a hedging effect between the corporate bond and the CDS market.}. If investors mainly hedge their bond position with CDSs, then an increase in the trading activities in the bond market will lead to an increase in CDS liquidity.

5.5.2 Premia Components:

In this subsection, we present the results of the decomposition exercise that we briefly discussed in section 5.4.3 and we do a comparative analysis across the different ratings. Table 5.4, presents the model implied premium components of each rating for bonds and CDSs\footnote{As discussed in Duffie (1999) and Duffie and Liu (2001) the yield spreads on fixed-coupon bonds cannot be directly compared to CDS spreads. The comparison is only valid if the maturity of both bonds and CDSs are identical and if the bonds are priced at par.}. Panel A shows that the difference in value of the bond pure credit risk premium $bd$ across ratings is relatively small. However, the bond pure liquidity premium $bl$ increases in percent term as the rating quality increases. This result indicates that investors give more importance in trading assets with lower rating which explains their high liquidity level (i.e. low liquidity risk). On the other hand, the bond pure global
liquidity premium \( blg \) (i.e. flight-to-liquidity) increases as the rating decreases, this shows that rating BB is the most sensitive to changes in bond market liquidity. The overall magnitude of the correlation premium \( bc \), representing the interaction between credit risk and liquidity, is quite small\(^{28}\), this is consistent with the idea that the risk effect coming from the correlation risk is very weak.

Panel B shows the results of the CDS decomposition. The table reveals that CDS pure credit risk premium \( sdg \) is increasing in percentage as the rating quality deteriorates. This indicates that the weight of default risk is increasing in importance when the rating is low. This is consistent with the bond decomposition results in Panel A as rating BB has the highest percentage of the default risk. Secondly, the CDS pure liquidity premium \( sl \) has the highest weight in rating A, although it seems that the difference across the rating A, BBB and BB is not as significant as it is for the bond market. Furthermore, the findings of the CDS pure global liquidity premium \( slg \) (i.e. systematic liquidity) are similar to those of the bonds as the lowest ratings (i.e. BBB and BB) have the highest weights. The fact that \( slg \) is (nearly) equally important across the ratings highlights the importance of the systematic liquidity in the sovereign CDS market. Overall, Panel B of Table 5.4 demonstrates that CDS liquidity is not highly dependent on the rating quality (or equivalently the default intensity)\(^{29}\) and its effect is relatively stable across the ratings.

Regarding the bond decomposition, for rating A, we find that on average the pure credit risk premium \( bd \), represents 73.8% of the sovereign bond spreads, bond pure liquidity premium \( bl \), 19.49%, bond market liquidity premium \( blg \), 6.6% and the correlation premium \( bc \), 0.00079%. For rating BBB, \( bd \), represents 71.2% of the sovereign bond spreads, \( bl \), 13.9%, \( blg \), 14.6% and \( bc \), 0.003%. Finally for rating BB, \( bd \), cor-

\(^{28}\)The fact that the correlation risk premium is very small (or close to zero) does not imply that the credit and liquidity risk are independent but it means that the risk coming from the correlation between the credit and liquidity risk is small to insignificant. Table 5.3 shows that signs of the interactions are both positive and negative, the opposite signs might reduce effect of the correlation risk between the intensities and might also explain the weak weight of the correlation component.

\(^{29}\)The quality of the rating and the magnitude of the default risk are inversely related. The lower the rating the highest the default intensity.
responds to 74% of the sovereign bond spreads, $bl$, to 5%, $blg$, to 20.9% and $bc$, to 0.00053%.

These findings indicate that the pure default risk represents the majority of the bond spreads and that liquidity plays a minor role. This result is largely supported by the sovereign literature. Geyer et al (2004) and Codogno et al (2003) find that the yield differentials under the EMU are mainly explained by a common default risk factor measured by the difference between corporate and government bond yields and that liquidity effects have a trivial role. Using a sample period from 2003 to 2004, Beber et al (2009) study the default versus liquidity decomposition in the sovereign bond market and find that credit represents 89% of sovereign bond spreads while liquidity account for 11%. Favero et al (2010) show that the aggregate risk proxied by the difference between US corporate and government bonds is the most important explanatory variable for Euro-area differentials and that a liquidity effect is present for only few countries. Finally, Monfort and Renne (2011) show that the liquidity part of the spreads is less important than the credit part even though liquidity plays a non-trivial role\textsuperscript{30}.

On the other hand, the results of the CDS decomposition show that, for rating A, the CDS pure credit risk premium $sdg$ represents on average 54.5% of the CDS spreads, CDS pure liquidity premium $sl$, 24.1%, CDS pure global liquidity premium $slg$, 21.5% and the CDS correlation premium $sc$, 0.0035%. For rating BBB, $sdg$, corresponds to 55.7% of the CDS spreads, $sl$, to 16.1%, $slg$, to 28.1% and $sc$, to 0.038%. Finally, for rating BB $sdg$, corresponds to 56.6% of the CDS spreads, $sl$, to 16.4%, $slg$, to 26.8% and $sc$, to 0.09%.

The weight of the pure credit risk in the sovereign CDS spreads seems to be smaller than the one of the corporate CDSs\textsuperscript{31}. In fact, few papers decompose sovereign CDSs.

\textsuperscript{30}Although our results on bond spreads are in line with the majority of sovereign literature they are not consistent with Schwarz (2010). In her approach, the author regresses the bond yield differentials against credit risk and liquidity risk proxies and explains that market liquidity account for 68% of sovereign bond spreads, this is surprisingly high. In fact, using sovereign CDS differentials as a credit risk proxy in the regression is a questionable method because it might reduce the credit risk explanatory power and this may explain why liquidity represents significant portion of the bond yields.

\textsuperscript{31}BT(2010) and Lin et al (2009) find that credit risk represent 95% and 87% of corporate CDS spreads respectively.
spreads. Remonala et al (2008) provide the first study in this direction and show that the jump-at-default risk is priced in the sovereign CDS spreads. Longstaff et al (2010) extend the model of Pan and Singleton (2008) in order to decompose sovereign CDS spreads and calculate the risk premium related to distress risk. By applying the model to a large set of countries, they find that on average 34% of the spreads are due to distress risk premium. If we take the average risk premium of the countries that both this study and Longstaff et al (2010) have in common, we obtain a value of 41% in the latter. The magnitude of the liquidity premium that we find across all the ratings is 44.33%. Finally, our results show that, on one hand, flight-to-liquidity risk has an impact both on the credit risk premium $\lambda$ and on the CDS bid-ask spreads. On the other hand, systematic liquidity risk also influences CDS bid-ask spreads.

As a further step in our analysis, we split our sample period into a pre-crisis and a crisis period and we do the same decomposition exercise as before. Surprisingly, Table 5.4 indicates that the magnitude of the pure default risk is higher during the pre-crisis than the crisis period. In fact, the difference is even more striking for the CDS market. In contrast with the default risk, we observe that the liquidity component increase in magnitude during the crisis time and the difference is more discernable for the instrument specific liquidity ($bl$) of the CDS market. This suggests that default risk and CDS liquidity move in opposite direction, when default risk is high liquidity decreases (or liquidity risk increases) and vice versa. This negative (positive) relationship between the aggregate sovereign default risk and liquidity (liquidity risk) has also been documented in recent papers by Beber et al (2009) and Favero et al (2010). Therefore,

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32 The countries that Longstaff et al (2011) and this paper have in common are Brazil, Chile, Colombia, Korea, Mexico, Philippines, South Africa and Turkey, thus Longstaff et al (2011) cover 80% of our sample.
33 The parameter $g_{gb}$, representing the influence of bond market liquidity or flight-to-liquidity on the credit risk premium $\lambda$, shows a significant impact.
34 The parameters $w_{gb,bid}$ and $w_{gb,ask}$ reflecting the interaction between bond market liquidity and CDS liquidity risks also have an impact.
35 The parameters $w_{ask,sys}$ and $w_{bid,sys}$ representing the impact of systematic liquidity on the CDS bid-ask spreads are all significant.
36 The pre-crisis period runs from November 2005 to January 2008 and the crisis period spans from January 2008 to September 2010.
37 The negative relationship between default risk and liquidity is not totally consistent with the signs of the parameters of the factor sensitivity matrix. The reason is because the factor sensitivity matrix has been retrieved by calibrating the
this decomposition puts forward the idea that the increase in the CDS spreads observed during the crisis period was mainly due to a surge in liquidity rather than to an increase in the default intensity.

In summary, our analysis reveals that sovereign CDS spreads are highly influenced by liquidity and that sovereign bond spreads are less subject to liquidity frictions which implies that bond spreads could represent a better proxy for sovereign default risk. Secondly, as Table 5.4 shows, bonds and CDSs are exposed to the flight-to-liquidity and systematic liquidity risks respectively which stress the importance of these risks in sovereign CDS spread movements. Finally, the weight of the correlation premium is negligible relatively to the other risk factors.

5.6 Conclusion:

In this chapter, we provide the first study that quantifies the size of the default risk, liquidity and correlation components in sovereign CDS spreads. In order to carry out this analysis, we extend the factor model of Buhler and Trapp (2010) and jointly calibrate it to both sovereign CDS and bond data. By doing so, we are able to use a large amount of information on sovereign default risk and thus present a better decomposition of sovereign bond and CDS spreads. Our results reveal that default risk represents on average 73% of the bond spreads, liquidity 26.86% and correlation risk 0.0014%. On the CDS side we find that, on average, default risk account for 55.6% of the spreads, liquidity for 44.32% and correlation risk for 0.043%.

Overall, our results reveal that sovereign CDS spreads are highly driven by liquidity and that sovereign bond spreads are less subject to liquidity frictions and therefore could represent a better proxy for sovereign default risk. Secondly, we show empirically that flight-to-liquidity and systematic liquidity play a non-negligible role and contributes to model to the whole sample period (i.e. pre-crisis and crisis period at the same time).
both sovereign bond and CDS spread movements. Finally, our decomposition exercise puts forward the idea that the increase in the CDS spreads observed during the crisis period was mainly due to a surge in liquidity rather than to an increase in the default intensity.

Our results find large support in the literature. Codogno, Favero and Missale (2003), Geyer, Kössmeier and Pichler (2004), Beber, Brandt and Kavajecz (2009), Favero, Pagano and Thadden (2010) and Monfort and Renne (2011) provide evidence that default risk represents the majority of bond spreads and that liquidity plays a minor role. On the other hand, Longstaff et al (2011) document that 41% of sovereign CDS spreads are due to distress risk premium, we report that liquidity represents 44.33% of the CDS spreads.

In summary, this chapter indicates that liquidity plays an important role in the 5 year sovereign CDS spread movements. Further research should be done to better understand the effects of liquidity at term structure level. In the next chapter, we study the liquidity risk implied in the term structure of the sovereign CDS curve.
5.7 Appendices:

5.7.1 Appendix 1: Analytical Solutions for the Discount Factors:

In this appendix, we present in some details the derivations of the discount factors of equation (5.8), (5.9) and (5.10). The derivations of the discount factors are similar across the CDS bid, CDS ask and bonds. Therefore, we present only the solutions for the bonds.

A. Solving the Expectations in the CDS and Bond using the PDE approach (simultaneous discount factor): \( D(t, T_i) \times E_t[P(t, t_i) \times L^b(t, t_i) \times L^g_b(t, t_i)] \)

Let’s denote \( x(t) = \lambda^i(t) \), \( \lambda^i \) corresponds to the pure default intensity.

\[
E_t[P(t, t_i) \times L^b(t, t_i) \times L^g_b(t, t_i)] = E_t[exp(-\int_0^\tau (\lambda_s + \gamma_b^b + \gamma_{gb}^b) ds)]
\]
\[
= E_t[exp(-\int_0^\tau (1 + f_b + f_{gb}) \times \lambda^i ds)] \times E_t[exp(-\int_0^\tau (1 + g_b + w_{gb,b}) \times y^b ds)]
\]
\[
E_t[exp(-\int_0^\tau (g_{ask} + w_{b,ask} + w_{gb,ask}) \times y^{ask} ds)] \times E_t[exp(-\int_0^\tau (g_{bid} + w_{b,bid} + w_{gb,bid}) \times y^{bid} ds)]
\]
\[
E_t[exp(-\int_0^\tau (w_{b,gb} + g_{gb} + 1) \times y^{gb} ds)] \times E_t[exp(-\int_0^\tau (w_{b,sys} + g_{sys} + w_{gb,sys}) \times y^{sys} ds)]
\]

\( (5.12) \)

This decomposition allows us to retrieve the independent intensities which in turn enables us to solve each expectation separately. We first solve for \( P(\lambda, T) = E_t[exp(-\int_0^\tau (1 + f_b + f_{gb}) \times \lambda^i)] \) and apply Ito Lemma to get the PDE:
\[-(1 + f_b + f_{gb}) \cdot \lambda_i \cdot P(\lambda, t) - P_T + P(\lambda - \beta \cdot \lambda^i) + \frac{1}{2} \cdot P \cdot \sigma^2 \cdot \lambda^i = 0\]

(5.13)

We guess a solution for the $P(\lambda, T)$

\[P(\lambda, T) = a_1(T) \cdot e^{\text{exp}}(-a_2(T) \cdot \lambda^i \cdot (1 + f_b + f_{gb}))\]

(5.14)

We solve for $a_1(T)$ and $a_2(T)$ by solving the following system of ODEs:

\[
\begin{align*}
-1 - a_2' - \beta \cdot a_2 + \frac{\sigma^2}{2} \cdot (1 + f_b + f_{gb}) \cdot a_2^2 &= 0 \\
-a_1' + \alpha \cdot a_1 \cdot (1 + f_b + f_{gb}) \cdot a_2 &= 0
\end{align*}
\]

(5.15)

We retrieve the following solutions:

\[a_1(T) = \left(\frac{1 - \kappa}{1 - \kappa \cdot e^{\text{exp}}(\phi(\tau - t))}\right)^{\frac{2}{\sigma^2}} \cdot e^{\text{exp}}\left(\frac{\alpha \cdot (\beta + \phi)}{\sigma^2} \cdot (\tau - t)\right)\]

(5.16)

\[a_2(T) = \frac{\phi - \beta}{\sigma^2 \cdot (1 + f_b + f_{gb})} + \frac{2 \cdot \phi}{\sigma^2 \cdot (1 + f_b + f_{gb}) \cdot (\kappa \cdot e^{\text{exp}}(\phi(\tau - t)) - 1)}\]

(5.17)
where

\[ \phi = \sqrt{2 \sigma^2 \left(1 + f_b + f_{gb}\right)} + \beta^2 \]

(5.18)

and

\[ \kappa = \frac{\beta + \phi}{\beta - \phi} \]

(5.19)

We solve liquidity discount factors in the same manner, we have in total 5 liquidity intensities:

\[ F(\gamma, T) = E_t[\exp(-\int_0^\tau K \cdot yds)] \]

(5.20)

where "K" changes with the liquidity intensity:
\[ K = (1 + g_b + w_{gb,b}) \]

\[ K = (g_{ask} + w_{b,ask} + w_{gb,ask}) \]

or

\[ K = (g_{bid} + w_{b,bid} + w_{gb,bid}) \]

\[ K = (w_{b,gb} + g_{gb} + 1) \]

\[ K = (w_{b,sys} + g_{sys} + w_{gb,sys}) \]  

(5.21)

We then derive the PDE and guess a solution for \( F(\gamma, T) \)

\[-\gamma_t * K * F(\gamma, T) - F_T + \frac{1}{2} * F_{\gamma\gamma} * \eta_t^2 = 0 \]

(5.22)

\[ F(\gamma, T) = a_3(T) * \exp(-a_4(T) * K * \gamma) \]

(5.23)

Solving a system of ODEs:

\[
\begin{align*}
    a_4'(T) &= -1 \\
    -a_3'(T) + \frac{1}{2} * \eta^2 * T^2 * K^2 * a_3(T) &= 0
\end{align*}
\]

(5.24)
We retrieve:

\[ a_4(\tau - t) = \tau - t \]  \hspace{2cm} (5.25)

\[ a_3(\tau - t) = \exp\left(\frac{K^2 \cdot \eta^2 \cdot (\tau - t)^3}{6}\right) \]  \hspace{2cm} (5.26)

B. Solving the Expectation in the CDS and Bond using the Moment Generating Function (MGF) (non-simultaneous discount factor):

\[ E_t[\triangle P(t, t_i) \ast L^b(t, t_i) \ast L^{gb}(t, t_i)] = E_t[(P(t, t_{j-1}) - P(t, t_j)) \ast L^b(t, t_i) \ast L^{gb}(t, t_i)] \]  \hspace{2cm} (5.27)

Assume \( t = 0 \), \( t_{j-1} = t_1 \) and \( t_j = t_2 \) where \( t < t_j < t_{j-1} \)

\[ E_t[P(t, t_1) \ast L^b(t, t_2) \ast L^{gb}(t, t_2)] = E_t[\exp\left(-\int_t^{t_1} \lambda_s \, ds\right) \ast \exp\left(-\int_t^{t_2} \gamma^b_s \, ds\right) \ast \exp\left(-\int_t^{t_2} \gamma^{gb}_s \, ds\right)] \]

\[ = E_t[\exp\left(-\int_t^{t_1} \lambda_s \, ds\right) \ast \exp\left(-\int_t^{t_1} \gamma^b_s \, ds\right) \ast \exp\left(-\int_t^{t_2} \gamma_s \, ds\right)] \ast \exp\left(-\int_t^{t_1} \gamma^{gb}_s \, ds\right) \ast \exp\left(-\int_t^{t_2} \gamma^{gb}_s \, ds\right)] \]
Using the previous solutions of \( P(\lambda,T) \), we transform the correlated intensities to non-correlated ones:

\[
E_t[P(t, t_1) * L^b(t_1, t_2) * L^{gb}(t_1, t_2)] = \\
E_t[exp(- \int_t^{t_1} (1 + f_b + f_{gb}) * \lambda^t ds) * exp(- \int_t^{t_2} (f_b + f_{gb}) * \lambda^t ds)] * \\
E_t[exp(- \int_t^{t_1} (1 + g_b + w_{gb,b}) * y^b ds) * exp(- \int_t^{t_2} (1 + w_{gb,b}) * y^b ds)] * \\
E_t[exp(- \int_t^{t_1} (g_{ask} + w_{b,ask} + w_{gb,ask}) * y^{ask} ds) * exp(- \int_t^{t_2} (w_{b,ask} + w_{gb,ask}) * y^{ask} ds)]* \\
E_t[exp(- \int_t^{t_1} (g_{bid} + w_{b,bid} + w_{gb,bid}) * y^{bid} ds) * exp(- \int_t^{t_2} (w_{b,bid} + w_{gb,bid}) * y^{bid} ds)] * \\
E_t[exp(- \int_t^{t_1} (w_{gb,sys} + w_{b,sys} + g_{sys}) * y^{sys} ds) * exp(- \int_t^{t_2} (w_{b,sys} + w_{gb,sys}) * y^{sys} ds)]* \\

(5.29)

\[K_{1i} = (w_{gb,sys} + w_{b,sys} + g_{sys}) \text{ and } K_{2i} = (w_{b,sys} + w_{gb,sys}) \text{ where } i = 1,2, \ldots 6. \]

\( K_1 \) and \( K_2 \) change with the liquidity intensity.

Using the law of iterated expectation we can solve the “second” exponential in each line by using \( P(\lambda,T) \) and \( F(\gamma,T) \) and transforming the equations into MGFs.
The final result for the default intensity is:

\[
E_t[exp(- \int_t^{t_1} (1 + f_b + f_gb) \lambda^i ds) * exp(- \int_t^{t_2} (f_b + f_gb) \lambda^i ds)] = \\
E_t[exp(- \int_t^{t_1} (1 + f_b + f_gb) \lambda^i ds) * E_t[exp(- \int_t^{t_2} (f_b + f_gb) \lambda^i ds)]
\]

\[
= -a_1(t_1, t_2) * E_t[exp(- \int_t^{t_1} (1 + f_b + f_gb) \lambda^i ds) * exp(-a_2(t_1, t_2) * (f_b + f_gb) \lambda^i(t_1))] = (5.30)
\]

where \(a_1(t_1, t_2)\) and \(a_2(t_1, t_2)\) are defined in Appendix 5.7.1.A.

The final result for the liquidity process is:

\[
E_t[exp(- \int_t^{t_1} K_{1i} yds) * exp(- \int_t^{t_2} K_{2i} yds)] = E_t[exp(- \int_t^{t_1} K_{1i} yds) * E_t[exp(- \int_t^{t_2} K_{2i} yds)]
\]

\[
= a_3(t_1, t_2) * E_t[exp(- \int_t^{t_1} K_{1i} * y(t)ds) * exp(-a_4(t_1, t_2) * K_{2i} * y(t_1)ds)] = (5.31)
\]

where \(a_3(t_1, t_2)\) and \(a_4(t_1, t_2)\) are defined in Appendix A.

Equation (5.28) and (5.29) are MGFs that will be solved in order to retrieve the closed form solution of the expectations\(^{38}\).

\(^{38}\)The MGF will be solved using the Proposition 6.2.4 of Lamberton and Lapoyre (page 162), this proposition is used to characterize the joint law of \((X_t, \int_0^t X_s ds)\) (in our case \(X_t\) is either equal to \(\lambda^i\) or \(y^i\)) and is the key to any pricing within the CIR model. To solve the MGF of the liquidity intensities, we use the same law by assuming that a Gaussian process is a special case of a CIR process.
Solving the MGF of the default intensity gives:

\[
P(t, (1+f_b+f_gb), (f_b+f_gb)) = -a_1(t_1, t_2) \ast E_t[\exp(- \int_t^{t_1} (1+f_b+f_gb) \lambda_s ds) \ast \exp(-a_2(t_1, t_2) \ast (f_b+f_gb) \lambda_s(t_1))]
\]

The guessed solution is:

\[
P(t, (1 + f_b + f_gb), (f_b + f_gb)) = a_1(t_1, t_2) \ast b_1(t_1, t_2) \ast \exp(-b_2(t_1, t_2) \ast \lambda^t) \quad (5.32)
\]

where:

\[
b_1(t_1, t_2) = \frac{2 \ast \phi \ast \exp\left(\frac{\tau_1 - t}{2} \ast (\phi + \beta)\right)}{\sigma^2 \ast a_2(t_1, t_2) \ast (f_b + f_gb) \ast (\exp(\phi(\tau_1 - t) - 1) + \phi - \beta + \exp(\phi(\tau_1 - t))(\phi + \beta))^{\frac{\tau_1 - t}{2}}}
\]

(5.33)

\[
b_2(t_1, t_2) = \frac{a_2(t_1, t_2) \ast (f_b + f_gb) \ast (\phi + \beta + \exp(\phi(\tau_1 - t))(\phi - \beta) + 2 \ast (1 + f_b + f_gb) \ast ((\exp(\phi(\tau_1 - t) - 1) + \phi - \beta + \exp(\phi(\tau_1 - t))(\phi + \beta)))}{\sigma^2 \ast a_2(t_1, t_2) \ast (f_b + f_gb) \ast (\exp(\phi(\tau_1 - t) - 1) + \phi - \beta + \exp(\phi(\tau_1 - t))(\phi + \beta))}
\]

(5.34)

Solving the MGF of the liquidity intensities leads to:

\[
L(t, K_1, K_2) = a_3(t_1, t_2) \ast E_t[\exp(- \int_t^{t_1} K_1 \ast yds) \ast \exp(-a_4(t_1, t_2) \ast K_2 \ast y(t_1)ds)]
\]

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We guess a solution

\[ L(t, K_1, K_2) = a_3(t_1, t_2) * b_3(t_1, t_2) * \exp(-b_4(t_1, t_2) * y) \]

\[(5.35)\]

\[ b_3(t_1, t_2) = \exp \left[ \frac{\eta^2 * K_2^2}{6} * (\tau_1 - 1)^3 + \frac{\eta^2 * K_2^2}{2} * a_4(t_1, t_2) * (\tau_1 - 1)^2 + \left( \frac{\eta^2 * K_2 * a_4(t_1, t_2)}{2} \right) * a_4(t_1, t_2) * K_2 * (\tau_1 - 1) \right] \]

\[(5.36)\]

and

\[ b_4(t_1, t_2) = a_4(t_1, t_2) * K_2 + K_1 * (\tau_1 - 1) \]

\[(5.37)\]
5.7.2 Appendix 2: Calibration Procedure: Grid Search Method

We calibrate the model to bond and CDS data for the following ratings: A, BBB and BB. Our calibration procedure is similar in spirit to Buhler and Trapp (2010), however since our model involves many parameters it is worth discussing in details the calibration and the different robustness checks carried throughout the analysis. As mentioned before, we assume a CIR process (equation (5.6)) for default intensity and a Gaussian process (equation (5.7)) for liquidity intensities, this gives us a total of 8 parameters (\( \mu, \beta, \sigma, \eta^b, \eta^{ask}, \eta^{bid}, \eta^{gb}, \eta^{sys} \)).

- We initialize a 8-dimensional grid for the drift and the diffusion parameters listed above. \( j \) represents the grid number and \( i \) the grid point in the grid \( j \).

  (a) The initialized vector \( (\mu_{ij}, \beta_{ij}, \sigma_{ij}, \eta^b_{ij}, \eta^{ask}_{ij}, \eta^{bid}_{ij}, \eta^{gb}_{ij}, \eta^{sys}_{ij}) \) defines the parameters in each grid point \( i \) in grid \( j \).

  (b) In each grid point \( i \), we initialize the factor matrix \( H_{ijk} \) where \( k \) counts the number of iterations. \( k \) will be different across the ratings.

  (c) The calibration is done at cross-sectional level. Assuming that the initialized parameters in step (a) are true, for each time \( t \) (where \( t = 1, 2, ..., T \) ) we numerically specify the parameters \( (\lambda_{ij}, \gamma^b_{ij}, \gamma^{ask}_{ij}, \gamma^{bid}_{ij}, \gamma^{gb}_{ij}, \gamma^{sys}_{ij})(t) \) that minimize the sum of squared differences between the theoretical values and the observed prices (i.e. CDS and bond yield spreads both in basis points). Step (c) is performed by assuming \( H_{ijk} \) to be an identity matrix, this leads to a one-to-one relationship between the correlated and the independent intensities.

\[
(\hat{\lambda}_{ij}, \hat{\gamma}^b_{ij}, \hat{\gamma}^{ask}_{ij}, \hat{\gamma}^{bid}_{ij}, \hat{\gamma}^{gb}_{ij}, \hat{\gamma}^{sys}_{ij})(t) = \arg\min \Sigma_{n=1}^{N}(P_{n}^{mod} - P_{n}^{obs})^2
\]
where $P_{n}^{\text{mod}}$ represents the model price, $P_{n}^{\text{obs}}$ the observed values and $n$ the number of cross-sectional units.

(d) In order to determine the true factor matrix $H_{ijk}$, we need to minimize the “element-wise-sum” of the squared differences between the assumed latent factors in step (a) and the empirical variance, covariance and autocovariance. We denote this sum as $M_{ijk}(H_{ijk})$.

(e) To minimize $M_{ijk}(H_{ijk})$ we need to numerically change the parameters of $H_{ijk}$. We stop this iteration when the max-norm of $\hat{H}_{ijk}^{\text{opt}}$ and $\hat{H}_{ijk}^{\text{opt} - 1}$ is smaller than 0.01. Due to the high number of parameters in the factor matrix, we try many minimizations with different guessed values in order to compare the outputs and ensure that the global minimum is picked.

$$\hat{H}_{ijk}^{\text{opt}} = \arg \min M_{ijk}(H_{ijk})$$

(f) We use the true factor matrix $\hat{H}_{ijk}^{\text{opt}}$ and the new intensities $(\hat{\lambda}_{ijk}^{\text{opt}}, \hat{\gamma}_{ijk}^{b}, \hat{\gamma}_{ijk}^{a}, \hat{\gamma}_{ijk}^{b}, \hat{\gamma}_{ijk}^{g}, \hat{\gamma}_{ijk}^{b}, \hat{\gamma}_{ijk}^{g}, \hat{\gamma}_{ijk}^{b}, \hat{\gamma}_{ijk}^{g})(t)$ as new inputs, compute the difference between the theoretical and observed values and finally sum the differences across the time series.

$$S_{ij} = \sum_{t=1}^{T} \sum_{n=1}^{N} (P_{n}^{\text{mod}} - P_{n}^{\text{obs}})^2$$

(5.40)
We do the same operation across each grid point \( i \) in grid \( j \) and then take the minimum value of grid \( j \)^{39}.

\[
S_{j}^{opt} = \min \{S_{1,j}, S_{2,j}, \ldots, S_{I,j}\}
\]  

\((5.41)\)

(g) We pick the minimum value of step (f), use it as a finer local grid and move to the second grid. We do the same analysis until we reach grid 8. We stop this iteration across the grids when there is no further improvement in the fitting.

- As a robustness check instead of doing a grid search and changing individually each parameter in the vector \((\mu_{ij}, \beta_{ij}, \sigma_{ij}, \eta_{ij}^{b}, \eta_{ij}^{ask}, \eta_{ij}^{bid}, \eta_{ij}^{gb}, \eta_{ij}^{sys})\) as we have done above (from step(a) to step(g)), we take the optimal vector of parameters \((\hat{\mu}_{ij}, \hat{\beta}_{ij}, \hat{\sigma}_{ij}, \hat{\eta}_{ij}^{b}, \hat{\eta}_{ij}^{ask}, \hat{\eta}_{ij}^{bid}, \hat{\eta}_{ij}^{gb}, \hat{\eta}_{ij}^{sys})\) retrieved from step(g), put it as initial guess in a new optimization and run the algorithm in one go. In this procedure, each iteration will require the algorithm to come back to step(a) and redo the calibration by changing \((\mu_{ij}, \beta_{ij}, \sigma_{ij}, \eta_{ij}^{b}, \eta_{ij}^{ask}, \eta_{ij}^{bid}, \eta_{ij}^{gb}, \eta_{ij}^{sys})\) at the same time. This method ensures that our results are robust. The optimal parameters that we get are no different from the one obtained in step(g).

We fit the model to the data with a very small error. We obtain a mean error of 0.305,

^{39}Although grid search method is a robust technique because it allows to optimize non-linear problems, it suffers from the fact that one has to know the acceptable parameter space before starting the optimization, otherwise convergence is not guaranteed. Therefore, before initializing the vector \((\mu_{ij}, \beta_{ij}, \sigma_{ij}, \eta_{ij}^{b}, \eta_{ij}^{ask}, \eta_{ij}^{bid}, \eta_{ij}^{gb}, \eta_{ij}^{sys})\) at step(a), we first use trial values and estimate the model few times. This enables us to create a grid inside the acceptable parameter space.
0.35 and 0.369 bps for both bond and CDS spreads for rating A, BBB and BB respectively. In Figure 5.2, we plot the model-implied bond and CDS spreads with the actual data. Table 5.1 shows the values of the optimal parameters \((\hat{\mu}_{ij}, \hat{\beta}_{ij}, \hat{\sigma}_{ij}, \hat{\eta}_{ij}^{sk}, \hat{\eta}_{ij}^{bd}, \hat{\eta}_{ij}^{gb}, \hat{\eta}_{ij}^{sys})\). Rating BBB and BB have parameters that are in the same range. However rating A have higher volatility (i.e. \(\eta^l\)). Although in theory, rating A should have lower volatility we found that it does not converge at values that are in the same range as those of rating BBB and BB. Therefore, in our calibration exercise, we expand the grid by incrementing progressively the grid bounds of the volatility parameters \(\eta^l\). We stop increasing the grid when the inner iteration at step(e) retrieve the optimal factor sensitivity matrix \(\hat{H}_{ijk}^{opt}\).
5.7.3 Appendix 3: Dynamic Interactions Between CDS and Bond Markets: Long Run Relationship

In this section we study the dynamic interactions between the different components of CDS and bond markets presented in Table 5.4. The idea is to investigate whether there is a long run relationship between bond and CDS components for the subinvestment and investment grades\textsuperscript{40}.

The analysis is based on an econometric model that requires cointegration test between bond pure credit risk premium \( bd \) and CDS pure credit risk premium \( sdg, \ bla \) and \( sla \) where \( bla \) is the average of bond liquidity premium \( bl \) and bond market liquidity premium \( blg \), \( sla \) the average of CDS liquidity premium \( sl \) and systematic liquidity premium \( slg \), and finally the bond correlation premium \( bc \) and the CDS correlation premium \( sc \).

In case the premium are non-stationary\textsuperscript{41} and cointegrated, we estimate the Johansen Vector Error Correction Model (VECM) in order to study the long run relationship between premium and the short term deviations (i.e. adjustment speed). The VECM approach is very sensitive to the number of lags included in the estimation therefore in order to define the optimal lag number we use the Akaike Information Criterion (AIC) and pick the number of lags with the smallest AIC. In Table 5.5 we present the maximum likelihood estimation of the cointegrated vector (i.e. unnormalised vector) and the vector of adjustment parameters\textsuperscript{42}. Since our dataset covers the crisis period, we split the sample into two in order to be able to interpret the dynamics under different market conditions.

Table 5.5 reports the results of our estimation for the subinvestment and investment grade categories. We document that for the pre-crisis and crisis periods CDS pure credit risk premium \( sdg \) and bond pure credit risk premium \( bd \) are not cointegrated

\textsuperscript{40}Subinvestment grade represents the average of rating BBB and BB. Investment grade corresponds to rating A.

\textsuperscript{41}We apply the Augmented Dickey-Fuller (ADF) to test for the unit root effect.

\textsuperscript{42}Our interpretation of the cointegration relationship will be based on the normalised cointegration vector with respect to the first variable.
which implies that the effect of bond liquidity plays an important role in the defaultable leg of the CDS contract. On the other hand, liquidity premia $bla$ and $sla$ seems to be cointegrated at 1% level during the pre-crisis period. The liquidity of the bond and the CDS markets are cointegrated with positive sign indicating a negative relationship between the premia which indicates that low bond liquidity leads to a high liquidity in the CDS market. On the hand, the cointegration relationship doesn’t hold during crisis time which implies that the long run relationship between the liquidity premium of both markets is dependent on the magnitude of the default intensity.

The investment grade category displays different findings. In fact, there is no cointegration between the credit risk and liquidity premium. However the correlation premium of the bond and the CDS markets $bc$ and $sc$ respectively are cointegrated at 5% significance level for both the pre-crisis and crisis time with a negative sign revealing a positive relationship between the premium. This finding indicates that when default risk and liquidity risk are positively correlated in the bond market, the same applies to the CDS market. This scenario is likely if an increase in default probability increases bond liquidity which induce investors to use CDSs to hedge their position. This result is consistent with what we discussed in section 5.5.2.

In summary, the credit risk premium across both markets are not strongly related which infers that bond liquidity plays an important role in CDS spread movements and this is consistent with the results of Table 5.4 which show that liquidity plays a substantial role in the CDS market. The results clearly point to the fact that there is no stable or long run relationship between the premium of the sovereign CDS and bond market. This might constitute a possible explanation of the weak weight that the correlation risk premium carries.
Figures

Figure 5.1: Average Bond Spreads and CDS Mid Spreads for Ratings A, BBB and BB

The figures show the plot of the average bond and CDS mid spreads from November 2005 till September 2010 for rating A (top plot) and rating BBB and BB (bottom plot). We extract the bond spreads from the prices using the method described in section 5.3. The figures show that the bond and CDS spreads for rating A, BBB and BB track each other very closely although it seems that on average bond spreads are slightly higher than CDS spreads.
This figure shows the plot of the model implied bond and CDS bid/ask spreads for rating A (top plot), rating BBB (middle plot) and rating BB (bottom plot). The figures show that the model fits well the data. We obtain a mean error of 0.305, 0.35 and 0.369 bps for both bond and CDS spreads for rating A, BBB and BB respectively.
Tables

Table 5.1: **Latent Factors of Default and Liquidity Intensities**

In this table, we report the parameter values (in percent term) of the processes defining the default \( x \) and liquidity intensities \( y^l \) (where \( l=\text{b,ask,bid, gb or sys} \)) which are estimated using the calibration procedure defined in Appendix 5.7.2. \( \eta^l \) and \( \sigma \) are the volatility terms of the Gaussian and CIR processes respectively defined in equation (5.6) and (5.7). \( \beta \) and \( \alpha \) are the parameters specific to the drift of the CIR process.

<table>
<thead>
<tr>
<th>( \eta^l )</th>
<th>A</th>
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<th>BB</th>
</tr>
</thead>
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<tr>
<td>( \eta_b )</td>
<td>50.0</td>
<td>1.0</td>
<td>2.0</td>
</tr>
<tr>
<td>( \eta_{ask} )</td>
<td>50.0</td>
<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>( \eta_{bid} )</td>
<td>50.0</td>
<td>1.0</td>
<td>1.0</td>
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<tr>
<td>( \eta_{gb} )</td>
<td>30.0</td>
<td>2.0</td>
<td>1.0</td>
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<tr>
<td>( \eta_{sys} )</td>
<td>10.0</td>
<td>1.0</td>
<td>2.0</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>10.0</td>
<td>8.7</td>
<td>8.0</td>
</tr>
<tr>
<td>( \beta )</td>
<td>20.0</td>
<td>20.8</td>
<td>20.5</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>10.0</td>
<td>10.3</td>
<td>5.0</td>
</tr>
</tbody>
</table>
Table 5.2: Independent Intensities

The table reports the descriptive statistics of the pure intensities (in percent term) where $x$ corresponds to the pure default risk, $y_b$ to the pure bond liquidity, $y_{ask}$ to the pure CDS ask liquidity, $y_{bid}$ to the pure CDS bid liquidity, $y_{gb}$ to the pure flight-to-liquidity and $y_{sys}$ to the pure systematic liquidity. The table shows that default intensity is positive across all the ratings however liquidity intensities have both negative and positive values. The signs are consistent with the assumptions made on the processes driving the intensities. The signs of the mean of the pure liquidity intensities combined with the signs of the parameters of the factor sensitivity matrix in Table 5.3 enables us to infer whether the impact on the correlated intensities is positive or negative (equation (5.4) and (5.5)).

<table>
<thead>
<tr>
<th></th>
<th>$x$</th>
<th>$y_b$</th>
<th>$y_{ask}$</th>
<th>$y_{bid}$</th>
<th>$y_{gb}$</th>
<th>$y_{sys}$</th>
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<tr>
<td>Mean</td>
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<td>8.16</td>
<td>8.14</td>
<td>3.26</td>
<td>-7.12</td>
</tr>
<tr>
<td>A Max</td>
<td>8.43</td>
<td>10.67</td>
<td>9.57</td>
<td>9.55</td>
<td>4.31</td>
<td>-5.12</td>
</tr>
<tr>
<td>Min</td>
<td>6.61</td>
<td>9.96</td>
<td>6.03</td>
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<td>2.70</td>
<td>-8.26</td>
</tr>
<tr>
<td>BBB Mean</td>
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<td>9.60</td>
<td>9.59</td>
<td>9.08</td>
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</tr>
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<td>10.51</td>
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</tr>
<tr>
<td>BB Mean</td>
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</tr>
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<td>-12.12</td>
</tr>
</tbody>
</table>
Table 5.3: Parameters of the Factor Sensitivity Matrix

The table presents the values of the parameters of the factor sensitivities matrix defined in equation (5.4). The matrix has been estimated using the calibration procedure defined in Appendix 5.7.2. \( f_b, f_{ask}, f_{bid}, f_{gb} \) and \( f_{sys} \) represent the impact of pure default risk \( x \) on bond liquidity \( \gamma^b(t) \), CDS liquidity ask \( \gamma^{ask}(t) \), CDS liquidity bid \( \gamma^{bid}(t) \), bond market liquidity \( \gamma^{gb}(t) \) and systematic liquidity \( \gamma^{sys}(t) \). The parameter \( g_b \) (or \( g_{ask}, g_{bid}, g_{gb}, g_{sys} \)) corresponds to the impact of pure liquidity intensity \( y^b(t) \) (or \( y^{ask}(t), y^{bid}(t), y^{gb}(t), y^{sys}(t) \)) on the credit risk premium \( \lambda(t) \). Finally, \( w \) represents the direct link between the different liquidity intensities. For example, \( w_{gb,ask} \) symbolizes the interaction between the flight-to-liquidity (or bond market liquidity) \( (gb) \) and the CDS ask quote \( (ask) \). The parameter \( w \) aims to capture all the possible liquidity shocks between bond and CDS markets.

<table>
<thead>
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<th>BB</th>
</tr>
</thead>
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<tr>
<td>( g_b )</td>
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<td>( g_{sys} )</td>
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<td>( w_{gb,b} )</td>
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<tr>
<td>( f_{gb} )</td>
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<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( f_{sys} )</td>
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<tr>
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<tr>
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<td>-0.0042</td>
<td>-0.1035</td>
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<td>( w_{gb,bid} )</td>
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</tr>
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<td>( w_{bid,sys} )</td>
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</table>
Table 5.4: Pure Credit Risk, Liquidity, Global Liquidity Risk and Correlation Premia

In this table, we report the results of our decomposition procedure defined in Sections 5.4.3 and 5.5.2. In Panel A, we show the percentage values of Bond Pure Credit Risk Premium (bd), Bond Pure Liquidity Premium (bl), Bond Pure Global Liquidity Premium (blg) and Bond Pure Correlation Premium (bc). In Panel B, we show the percentage values of CDS Pure Credit Risk Premium (sdg), CDS Pure Liquidity Premium (sl), CDS Pure Global Liquidity Premium (slg) and CDS Pure Correlation Premium (sc). We split our sample period into a pre-crisis and a crisis period and we do the same decomposition exercise as before. The row “BC” presents the magnitude (in percent term) of each component for the period before the crisis which is from November 2005 to January 2008. Likewise, “DC” introduces the magnitude (in percent term) of each component for the crisis period which is from January 2008 to September 2010.

<table>
<thead>
<tr>
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<th>BB</th>
</tr>
</thead>
<tbody>
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<td>Panel A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bd(%)</td>
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<td>71.2</td>
<td>74.0</td>
</tr>
<tr>
<td>BC bd(%)</td>
<td>74.1</td>
<td>72.3</td>
<td>74.1</td>
</tr>
<tr>
<td>DC bd(%)</td>
<td>73.64</td>
<td>70.45</td>
<td>73.97</td>
</tr>
<tr>
<td>bl(%)</td>
<td>19.49</td>
<td>13.90</td>
<td>5.0</td>
</tr>
<tr>
<td>BC bl(%)</td>
<td>19.78</td>
<td>13.77</td>
<td>3.99</td>
</tr>
<tr>
<td>DC bl(%)</td>
<td>19.2</td>
<td>14.06</td>
<td>5.88</td>
</tr>
<tr>
<td>blg(%)</td>
<td>6.6</td>
<td>14.7</td>
<td>20.90</td>
</tr>
<tr>
<td>BC blg(%)</td>
<td>6.1</td>
<td>13.88</td>
<td>21.89</td>
</tr>
<tr>
<td>DC blg(%)</td>
<td>7.08</td>
<td>15.48</td>
<td>20.1</td>
</tr>
<tr>
<td>bc(%)</td>
<td>0.00079</td>
<td>0.0031</td>
<td>0.00053</td>
</tr>
<tr>
<td>BC bc(%)</td>
<td>0.00065</td>
<td>0.0030</td>
<td>0.00047</td>
</tr>
<tr>
<td>DC bc(%)</td>
<td>0.00090</td>
<td>0.0032</td>
<td>0.00058</td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sdg(%)</td>
<td>54.5</td>
<td>55.7</td>
<td>56.6</td>
</tr>
<tr>
<td>BC sdg(%)</td>
<td>59.1</td>
<td>58.4</td>
<td>61.0</td>
</tr>
<tr>
<td>DC sdg(%)</td>
<td>50.8</td>
<td>33.6</td>
<td>33.2</td>
</tr>
<tr>
<td>sl(%)</td>
<td>24.1</td>
<td>16.1</td>
<td>16.4</td>
</tr>
<tr>
<td>BC sl(%)</td>
<td>21.6</td>
<td>14.4</td>
<td>13.8</td>
</tr>
<tr>
<td>DC sl(%)</td>
<td>26.0</td>
<td>17.4</td>
<td>18.5</td>
</tr>
<tr>
<td>slg(%)</td>
<td>21.5</td>
<td>28.1</td>
<td>26.8</td>
</tr>
<tr>
<td>BC slg(%)</td>
<td>19.3</td>
<td>27.1</td>
<td>25.1</td>
</tr>
<tr>
<td>DC slg(%)</td>
<td>23.2</td>
<td>28.9</td>
<td>28.2</td>
</tr>
<tr>
<td>sc(%)</td>
<td>0.0035</td>
<td>0.038</td>
<td>0.090</td>
</tr>
<tr>
<td>BC sc(%)</td>
<td>0.0028</td>
<td>0.037</td>
<td>0.088</td>
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<tr>
<td>DC sc(%)</td>
<td>0.0041</td>
<td>0.039</td>
<td>0.092</td>
</tr>
</tbody>
</table>
Table 5.5: VECM Analysis

In this table, we report our results of the cointegration analysis. We study the cointegration between \(bd\) and \(sdg\) (i.e. credit risk premium), \(bla\) and \(sla\) (i.e. liquidity premium) and finally \(bc\) and \(sc\) (i.e. correlation premium) where \(bla\) is the average of \(bl\) and \(blg\), \(sla\) is the average of \(sl\) and \(slg\). We first test for stationarity using the Augmented Dickey Fuller (ADF) test. If the series are non-stationary we estimate the Johansen Vector Error Correction Model (VECM) in order to study the long run relationship and the short term deviations between the premium. In the table below, we present the maximum likelihood estimation of the unnormalised cointegrated vector (Coint. Coeff) and the vector of adjustment (Speed Adj) parameters. On the other hand, if the series are not cointegrated we write NA ("Non Available"). In our analysis, we split our sample in two periods (before and during crisis). The period before the crisis runs from November 2005 to January 2008 and the crisis period goes from January 2008 to September 2010. Subinvestment Grade refers to the average of rating BBB and BB, investment grade to rating A. ‘∗’, ‘∗∗’ and ‘∗∗∗’ represent 1%, 5% and 10% significance level respectively.

<table>
<thead>
<tr>
<th></th>
<th>(\Delta bd)</th>
<th>(\Delta sdg)</th>
<th>(\Delta bla)</th>
<th>(\Delta sla)</th>
<th>(\Delta bc)</th>
<th>(\Delta sc)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Subinvestment Grade (before crisis)</td>
<td>Coint. Coeff</td>
<td>NA</td>
<td>NA</td>
<td>0.0013∗</td>
<td>0.0051∗</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>Speed Adj</td>
<td>NA</td>
<td>NA</td>
<td>−0.48</td>
<td>−3.43</td>
<td>NA</td>
</tr>
<tr>
<td>Panel B: Investment Grade (before crisis)</td>
<td>Coint. Coeff</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>2.89∗∗</td>
</tr>
<tr>
<td></td>
<td>Speed Adj</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.022</td>
</tr>
<tr>
<td>Panel C: Subinvestment Grade (During crisis)</td>
<td>Coint. Coeff</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td></td>
<td>Speed Adj</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>Panel D: Investment Grade (During crisis)</td>
<td>Coint. Coeff</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.629∗∗</td>
</tr>
<tr>
<td></td>
<td>Speed Adj</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>0.01</td>
</tr>
</tbody>
</table>
Chapter 6

Implied Liquidity Risk in the Term Structure of the Sovereign Credit Default Swap Spreads

6.1 Introduction:

In this chapter, we extend the work of Chen, Fabozzi and Sverdlove (2010) and analyse the effect of liquidity risk in the term structure of sovereign CDS spreads. We differentiate ourselves from the authors by using the whole term structure of sovereign CDS spreads while they work on a dataset that contains mostly 5 year corporate CDSs.\(^1\) By using the information embedded in the time-series and cross section, we get more accurate measure of the credit and liquidity premium. Furthermore, because of data availability issues, Chen et al (2010) consider that bond and CDS liquidity risk are equal and use that assumption to explain liquidity of both bonds and CDSs. In fact, this might represent an issue because CDSs are more liquid than bonds, thus their method may not give a good representation of the liquidity frictions specific to the bond market. In our study we relax this assumption by using a separate liquidity factor for both sovereign bonds and CDSs.

In this chapter, we assume that illiquidity reduces the value of the asset. The idea is that the CDS spreads in the market contain liquidity risk and therefore are less than

\(^1\)Unlike the corporate CDS market where there is a significant trading activity at the five year point only, the sovereign CDS market is liquid at different maturities which provide us with a rich set of time-series and cross-sectional information.
hypothetical perfectly liquid CDS spreads. The perfectly liquid CDS spreads are not observable, however, their values can not be higher than the ask quotes. On the other hand, the traded CDSs should be relatively illiquid and therefore their values should be somewhere between the bid and the ask quotes. For convenience, we assume that the mid quote is a fair price for the traded CDSs. Thus, the ask-mid difference should represent an upper bound for liquidity risk.

By using a single factor model, we examine the time-series properties of the risk-neutral default arrival rate and liquidity risk implicit in the term structure of sovereign CDS spreads. Our focus on the one factor model is motivated by the high level of co-movements across maturities documented in the sovereign CDS market\(^2\). We choose to apply our framework to Brazil, Philippines and Turkey, three emerging countries with different credit history and for which a full term structure of sovereign CDS and bond spreads is available. Moreover, we use two different estimation techniques, the Maximum Likelihood method a la Chen and Scott (1993) and the Kalman filter approach, to approximate the liquidity premium and show that the Kalman filter provides robust results and give clearer insight on the identification of the liquidity premium.

Our study complements the paper of Pan and Singleton (2008) who focus on the dynamic properties of the risk neutral default arrival rate and recovery risk. We shed some light on the liquidity risk that may cause the variation over-time of the term structure of sovereign CDSs. While Pan and Singleton (2008) emphasize that a significant part of the co-movement among the term structures of sovereign CDS spreads is triggered by changes in investors appetites for credit exposure at a global level, rather than by a reassessment of the fundamental strengths of these specific sovereign economies, our results suggest that liquidity risk has a non-trivial role and participates directly to the variation over time of the term structure of sovereign CDS spreads. Moreover, our findings imply that CDS buyers benefited from the liquidity premium during the pre-crisis

\(^2\)Longstaff et al (2011) and others find that the first principal component can explain a large portion of the variation in the sovereign CDS market.
period. However, during crisis time, we observe an increase in the liquidity of the CDS market which shifted the balance of supply and demand of the CDS protections, thus CDS buyers were no longer able to earn the liquidity premium. Finally, we provide a complete picture of the co-movement of bond and CDS liquidity risk term structures and show empirical evidence that the CDS and bond liquidity ratio are mainly influenced by the magnitude of the default intensity. In fact, in case of high default risk, we observe that CDS liquidity risk increases more than bond liquidity risk.

Our chapter has important implications for risk managers and policy makers as it enhances our understanding of the movements along the term structure of sovereign CDS spreads.

In Section 6.2, we discuss the related literature and in Section 6.3 we provide an example to illustrate the methodology used to estimate liquidity risk. Section 6.4 introduces the data. Section 6.5 provides a rough estimation of the liquidity risk embedded in the CDS term structure and compare it with bond liquidity risk. Section 6.6 presents the theoretical framework. Section 6.7 and 6.8 explain the two estimation techniques utilised to estimate the model parameters. Finally, Section 6.9 discusses the results and Section 6.10 concludes.

6.2 Related Literature:

As we have discussed in the previous chapters, the literature of CDS liquidity has seen an important growth in the past years, however empirical studies that involve the modeling of the entire CDS curve is still quite rare. Zhang (2008) suggests a study that estimate the default risk using the entire credit curve of the sovereign CDSs for the Argentine case. The author suggests a model that takes into account the dynamic interaction between interest rate, default intensity, expected recovery rate and counterparty default risk. He finds that the risk neutral and physical default probabilities
increase substantially during the period of the sample when Argentina was close to default. Secondly, the author documents that the relation between default probability and default risk premium is not monotone. In fact, he finds that when the default probability is low, default risk premium plays an important role in CDS pricing. However, when the default probability is high, the default risk premium tends to decrease and the actual default probability becomes more important in the valuation of the CDS contract. Chen, Cheng and Lui (2008) extend the model of Chen–Cheng–Fabozzi–Liu (CCFL-thereafter) model (2006) to study the term structure of CDS spreads by using a matrix CDS dataset provided by JP Morgan. They find that the model fits well the data and captures most of the cross-sectional dynamics and time-series variation. Furthermore, they provide evidence of a negative relationship between the default risk and the risk free rate consistent with the finding of CCFL (2006). Chen, Chen and Wu (2011) provide a study that performs a joint analysis on the term structure of interest rate and credit spreads using CDS data. They mainly focus on the interactions between the aggregate credit condition of the market and the interest rate curve. They report interesting results. First, they find that unlike the one factor model, the two factors can price well the whole term structure of the credit spreads. Secondly, they document that the interest rate factors influence both the current and future changes of the credit risk factors. Finally, the authors also study the potential two way relationship between credit and interest rate factors and observe that the aggregate credit conditions impact both the short and the long end of the interest rate curve. Bedendo et al (2005) analyse whether the slope of the term structure of credit spreads can predict changes in future short and long-term credit spread levels. Using both bond and CDS data, they find significant predictive power for the short end of the term structure of credit spreads for both markets. Jarrow, Li and Ye (2009) explore the potential arbitrage opportunities in the term structure of the corporate CDS spreads. They construct a

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3Zhang (2008) defines the default risk premium as the difference between the actual and risk neutral default probability divided by the actual default probability.
portfolio of CDS contracts in order to test for the arbitrage profitability. Their results highlight that there are statistical arbitrage opportunities that could be exploited in the term structure of the corporate CDS spreads. Longstaff et al. (2011) use the sovereign CDS term structure to estimate the systematic distress risk premium embedded in the 5 years sovereign CDS spread. They find that on average distress risk represents a third of the sovereign CDS spreads. Pan and Singleton (2008) investigate the default intensity and the recovery rate using the term structure of CDS spreads and show that the first principal component captures 96% of the variation over-time of the term structure. Han and Zhou (2011) study the relationship between the slope of the term structure of CDS spreads\footnote{Han and Zhou (2011) define the slope as being the difference between five-year and one-year CDS spreads.} and the expected stock return and find that the slope predicts the cross-sectional returns of the stocks and signals deterioration in the firm’s credit quality. The authors emphasize that this negative relationship is consistent with the slow diffusion of the information, contained in the CDS slope, into stock prices. Truck, Laub and Rachev (2004) examine the term structure of bond and CDS spreads for different rating categories. They argue that although in theory lower credit quality tend to accompany high credit spreads, this empirical relationship can be rather controversial when we observe bonds with the same rating and different maturities. The authors provide evidence that there is a positive relationship between the maturity and the spreads for investment grade debt and this holds for both bond and CDS spreads. Bajlum and Larsen (2007) present a paper that estimates the impact of accounting transparency on the term structure of corporate CDS spreads. Typically the structural credit risk models are well known for under predicting the short end of the bond credit spreads. The authors argue that one of the reasons behind the model failure is the lack of information available to investors to assess fairly the firm value which give them an incentive to draw inference on delayed accounting data which in turn might be responsible for noisy estimates of the asset value. This phenomena might have an implication...
on the term structure of credit spreads and one of the aims of their paper is to capture
the component of credit spreads that is due to the lack of accounting transparency. To
this end, they utilise the term structure of corporate CDS spreads and find that the
transparency spread is significant at the short end and insignificant at the long end of
the CDS curve. Furthermore, they report that the accounting transparency effect is
large for the most risky firms and small for the others. As a conclusion, the authors
advance the idea that variables other than accounting transparency should be used to
capture the bias in the short end of the CDS curve. Finally, De Fronseca and Gottschalk
(2012) present a joint study of the term structure of the CDS spreads and the implied
volatility surface and analyse the information flow between credit and volatility factors.
The authors find that the credit market is the main responsible for the overall mar-
et shocks and thus emphasize the importance of the relationship between credit and
volatility markets.

The literature review presented above shows that there are few studies that are
closely related to ours which are those of Zhang (2008), Pan and Singleton (2008) and
Longstaff et al (2011). All of these studies estimate default risk using the entire credit
curve of sovereign CDS spreads. One important contribution of our chapter, however,
is the analysis of the dynamic properties of the liquidity risk embedded in the sovereign
CDS curve. In the following section, we provide an example to illustrate the main idea
of this study.

6.3 A Quick Illustration:

The chapter postulates that illiquidity reduces the value of the asset. This idea can be
clearly illustrated with the following example.

We assume $V_{Bond}$ to be the value of a perfectly liquid sovereign bond (i.e. free of
liquidity risk). The full bond pricing formula can be expressed as follows:
\[ V_{\text{Bond}} = c \sum_{j=1}^{n} P_j Q_j + P_n Q_n + w \sum_{t=0}^{T} P_t (\Delta Q_t) \quad (6.1) \]

with

\[ Q_t = e^{-h^* t} \quad (6.2) \]

and

\[ \Delta Q_t = Q_{t-1} - Q_t \quad (6.3) \]

\( P_t, Q_t, h \) and \( w \) represent the risk-free discount factor, the survival probability, the hazard rate factor and the recovery rate respectively. \( T \) corresponds to the time of default and \( \Delta Q_t \) to the probability of surviving till \( t - 1 \) and defaulting between \( t - 1 \) and \( t \).

We now define \( V_{\text{Bond}}^* \) to be the value of a bond with liquidity risk and introduce a liquidity discount factor in the pricing formula.

\[ V_{\text{Bond}}^* = c \sum_{j=1}^{n} P_j Q_j L_t + P_n Q_n L_n + \sum_{t=0}^{T} P_t (\Delta Q_t) L_t \quad (6.4) \]

with

\[ L_t = e^{-y^* t} \quad (6.5) \]

representing the liquidity discount factor and \( y \) the liquidity risk.

Because of the additional discount factor \( L_t \), \( V_{\text{Bond}}^* < V_{\text{Bond}} \). Therefore the liquidity risk reduces the value of the asset.

The same idea can be applied to the value of the CDS contract \( V_{\text{CDS}} \).

\[ V_{\text{CDS}} = s_T(\sum_{j=1}^{n} P_j Q_j) = (1 - w) \sum_{t=0}^{T} P_t (\Delta Q_t) \quad (6.6) \]

where \( s_T \) represents the CDS premium (free of liquidity) paid on a semi-annual basis. The term \( s_T(\sum_{j=1}^{n} P_j Q_j) \) in equation (6.6) corresponds to premium leg and
\((1 - w) \sum_{t=0}^{T} P_t(\Delta Q_t)\) to the defaultable leg. We postulate that the CDS spread in the market contains liquidity risk and should be less than the perfectly liquid CDS spread \(s_T\). Therefore, \(s_T^* < s_T\) where \(V_{CDS}^*\) is defined as:

\[
V_{CDS}^* = s_T^* \left( \sum_{j=1}^{n} P_j Q_j \right) = (1 - w) \sum_{t=0}^{T} P_t(\Delta Q_t) L_t
\]  

(6.7)

In order to estimate the credit and the liquidity risk, we will fit equation (6.6) and (6.7) to the ask quote and mid quotes respectively. In what follows, we describe our dataset.

### 6.4 Data Description:

Similarly to the previous chapter, we focus on emerging market countries to run our analysis. We download bid, ask and mid quotes for the 1, 3, 5, 7 and 10 years CDS spreads on a daily basis from Datastream Reuters for the following countries: Brazil, Philippines and Turkey. These countries have different geopolitical characteristics and have a rich set of sovereign bonds which enable us to study the liquidity of the term structure of their sovereign bond markets. We use the same bond data as Section 5.3 of Chapter 5.

Table 6.2 presents a description of our bond dataset with information on the average mid yield, maturity dates, coupon payment rates and issue dates. The diversity in bond maturities will help us match as closely as possible the different maturities of the CDS contracts.

In the following section, we use our dataset to estimate the liquidity premium for both CDS and bond spreads.
6.5 A Rough Estimation of the Liquidity Risk:

In this section, we assume that the default intensity $h$ and the liquidity risk $y$ defined in equation (6.2) and (6.5) are constant. We then perform a simple exercise in order to estimate the liquidity risk in the sovereign CDS term structure and compare it with bond liquidity risk.

6.5.1 CDS Discretization:

We compute the default and liquidity intensity $h$ and $y$ respectively, directly from the CDS spreads by using a discrete-time approximation of the CDS pricing formula defined below.

Equation (6.6) defined above does not have any liquidity adjustment and includes only a default component. Since we postulate that the ask quote is an upper bound for the perfectly liquid CDS spreads, we use it to retrieve the implied default intensity $h$. The idea can be illustrated as follows:

$$V_{CDS}^{\text{ask}} = s_{T}^{\text{ask}} \left( \frac{1}{2} \sum_{j=1}^{2K} P(j/2)Q(j/2) \right) = (1-w) \left[ \frac{1}{2} \sum_{j=1}^{2K} P(j/2)[Q(j-1/2)-Q(j/2)] \right]$$

(6.8)

$P(j/2)$ and $Q(j/2)$ represent the risk free discount factor and the risk-neutral survival probability respectively, $K$ corresponds to the maturity of the CDS and $w$ to the recovery rate. Both variables are divided by two in order to account for the semi-annual payment. We assume a constant risk neutral default intensity $h$ which leads to a survival probability equal to:

$$Q(j/2) = e^{-h/2}$$

(6.9)

\*\*In this study, we use the terms hazard rate and default intensity interchangeably.\*\*
\( L = (1 - w) \) is the risk neutral loss rate in the event of default and is equal to 75\% (Pan and Singleton(2008)). The left hand side of equation (6.8) represents the value of the protection-buyer leg and the right hand side the value of the protection seller at the initiation of the contract. By rearranging equation (6.8), we can infer the default intensity \( s_{T/2} = L(e^{h/2} - 1) \) which leads to:

\[
h = 2 \times \log\left(1 + \frac{s_{T}^{ask}}{2 \times (1 - w)}\right)
\]

Equation (6.10) represents the implied default intensity implied from the CDS ask quote.

On the other hand, equation (6.7) contains a penalty for illiquidity and a default adjustment. Since we assumed that all the CDS spreads in the market are illiquid (or not perfectly liquid) and therefore less than the ask quote, we use the CDS mid\(^a\) to retrieve the implied default and liquidity intensity (\(h\) and \(y\) respectively). Thus, we can rewrite the discretized CDS pricing formula as follows:

\[
V_{CDS}^{mid} = s_{T}^{mid} \times \left( \frac{1}{2} \sum_{j=1}^{2T} P(j/2) \times Q(j/2) \right) = (1 - w) \times \frac{1}{2} \sum_{j=1}^{2T} P(j/2) \times [Q(j-1/2) - Q(j/2)] \times L(j/2)
\]

where

\[
L(j/2) = e^{-y/2}
\]

which leads to:

\[
h + y = 2 \times \log\left(1 + \frac{s_{T}^{mid}}{2 \times (1 - w)}\right)
\]

Equation (6.13) corresponds to the credit and liquidity intensity implied from the CDS mid quote. Finally, we take the difference between equation (6.13) and (6.10) to

\(^a\)In this study, we assume that the CDS mid quote is a fair price for the CDS.
isolate the implied default intensity and focus only on the liquidity intensity $y$ which provide us with a rough liquidity risk estimate.

We redo the same analysis across the term structure of sovereign CDS spreads (i.e for the 1y, 3y, 5y, 7y and 10y maturity) and we plot the time series of the CDS liquidity risk term structure of Brazil (Figure 6.1), Philippines (Figure 6.2) and Turkey (Figure 6.3).

Overall, the figures show that for the period preceding the crisis the term structure of CDS liquidity risk has a flat behavior especially for Turkey and Philippines, although we observe that the liquidity risk is slightly higher for the short and the long end of the term structure. The case of Brazil is different as we see that the first part of the sample is characterized by few spikes in the liquidity risk and after that the term structure flattens similarly to Philippines and Turkey. During the crisis period and for all the countries, we observe spikes in the liquidity risk and the shape of liquidity risk term structure is inverted with the short end having higher values than the long end of the curve. This result points to the fact that liquidity risk is pressurizing more at the short end of the CDS curve. In their study Pan and Singleton (2008) find that their log-normal one factor model captures quite well the behavior of the sovereign CDS term structure but misprices the 1 year CDS contract. The authors provide as a possible explanation the liquidity and/or the effects of supply and demand pressure. We add to their explanation an empirical evidence showing that illiquidity plays an important role in the short end of the curve\(^7\).

In this following, we analyse CDS liquidity behavior with respect to bond liquidity. The liquidity of the underlying bond market is also important to consider because CDS traders hedge their positions with cash market instruments and the higher the liquidity risk in the bond the higher would be the impact on CDS spreads.

\(^7\)We redo the same analysis by trying different values for the loss rate (50\%, 60\%, 90\%) and although it influences the magnitude of the hazard rate and liquidity premium it doesn't change the results described above.
6.5.2 The Term Structure of Bond and CDS Liquidity Risk: A Comparative Analysis

We do a comparative analysis between bond and CDS liquidity risk at both term structure and time series levels. To this end, we need to match bond and CDS maturities (i.e. 1, 3, 5, 7 and 10 years), therefore for the 1 year CDS we should have bonds that mature between 2006 and 2011, for the 3 year CDS we need bonds that mature between 2008 and 2013, for the 5 year CDS we require bonds maturing between 2010 and 2015, for the 7 year CDS we should use bonds maturing between 2012 and 2017 and finally for the 10 year CDS we should have bonds maturing between 2010 and 2020. Although the countries we picked have a large amount of bonds issued at different dates\(^8\), it is not enough to match all the CDS maturities, however for each CDS maturity we pick bond that fall into the maturity intervals mentioned above. Therefore, in order to proxy for the 1 year bond liquidity risk we use the difference between the mid and ask yields of the shortest maturity we have for each country (i.e. 02/2013 for Philippines, 08/2011 for Brazil and 06/2011 for Turkey). Likewise, we proxy the liquidity risk of the 3 year bond by taking the difference between the mid and ask yields of bonds that expire right after the shortest maturity (i.e. 01/2014 for Philippines, 01/2012 for Brazil, 01/2013 for Turkey). For the 5 year bond, we choose bonds with maturity dates that do not exceed 2015 (i.e. 03/2015 for Philippines, 03/2015 for Brazil and 03/2015 for Turkey). For the 7 year bond, we pick bonds that have maturity dates that are around 2017 (i.e. 01/2017 for Philippines, 01/2018 for Brazil and 07/2017 for Turkey) and finally we do the same thing for the 10 year bond and collect bonds that have maturities that are as close as possible to 2020 (i.e. 10/2024 for Philippines, 01/2020 Brazil and 02/2025 Turkey).

Table 6.1 presents the descriptive statistics of bond and CDS liquidity risk and shows that overall the mean of the term structure of bond liquidity risk over the sample period

\(^8\)Table 6.2 presents a description of our bond dataset with information on the average mid yield, maturity dates, coupon payment rates and issue dates.
is slightly higher than that of the CDS liquidity risk for Brazil, Philippines and Turkey. Finally, we plot the ratio of bond and CDS liquidity term structures in order to analyse their joint behavior. The results are shown in Figure 6.4, 6.5 and 6.6.

For Brazil, Figure 6.4 shows that at short-end of the curve we have a low CDS/bond liquidity ratio which implies that bond liquidity risk is higher than the CDS liquidity risk. However during the crisis, we observe an increase in the default intensity pushing up the CDS/bond liquidity ratio which indicates that the CDS liquidity risk increases more strongly than the bond liquidity risk. Furthermore, during the crisis the magnitude of the increase in the CDS/bond liquidity ratio is higher for the long end of the curve than for the short end which implies that longer maturities are more sensitive to the default intensity. This result is intuitive as there is more uncertainty for longer maturities.

As far as Philippines is concerned, Figure 6.5 exhibits a different behavior. Before the crisis, we see that the bond liquidity risk is higher than the CDS liquidity risk across the whole term structure. On the other hand, during the crisis, the increase in the default intensity impacts the ratio of CDS/Bond liquidity in the same manner across the whole term structure with CDS liquidity risk increasing more strongly than the bond liquidity risk.

Finally for Turkey we observe in Figure 6.6 that the short end of curve has a stable CDS/bond liquidity ratio (of about 1) and that this value is not significantly influenced by the changes of the default intensity. During the crisis the ratio stays at around 1 which indicates that both bond and CDS liquidity risk increase with the same intensity. On the other hand, the long end of the curve shows a high value of the CDS/bond liquidity ratio implying that the CDS liquidity risk is higher than the bond liquidity risk.

---

9In the long end curve we observe few spikes in the CDS liquidity risk which push the ratio CDS/Bond liquidity to a high level.

10When we plot the time series of bond liquidity we see that bond liquidity risk increases during the crisis time, this is valid for Brazil, Philippines and Turkey.

11When we plot the bond and CDS liquidity individually we observe a sharp increase in liquidity risk in both markets.
risk. Furthermore, during the crisis, the ratio decreases in value meaning that bond liquidity risk increased substantially during that period, though CDS liquidity risk still seems to be higher.

In summary, the results show that CDS/bond liquidity relationship is largely influenced by liquidity issues relevant to each country, however we report that an increase in the default intensity changes dramatically the relationship between bond and CDS liquidity as we see a surge in liquidity risk in both markets with a stronger increase from the CDS side.

6.6 Exponential Affine Framework: Credit and Liquidity Factors

In this section, we model the dynamics of the credit and liquidity factors using a stochastic process. We use one single factor model in our study as Pan and Singleton (2008) find that one principal component can explain over 96% of the variation over time of the sovereign CDS term structure. Moreover, we assume that both the hazard rate \( h_t \) and the liquidity risk \( y_t \) follow a CIR process. The reason is because in our model we are assuming that both default and liquidity risk reduce the price of the asset, this implies that both discount factors have to be positive.

\[
\begin{align*}
    dh_t &= (\alpha_1 \mu_1 - (\alpha_1 + \lambda_1) \cdot h) \cdot dt + \sigma_1 \sqrt{h} \cdot dW_1 \\
    dy_t &= (\alpha_2 \mu_2 - (\alpha_2 + \lambda_2) \cdot y) \cdot dt + \sigma_2 \sqrt{y} \cdot dW_2
\end{align*}
\]

(6.14) \hspace{1cm} (6.15)

where \( h \) and \( y \) represent the risk neutral hazard rate and liquidity risk respectively, \( \alpha_i \) corresponds to the mean reversion speed, \( \mu_i \) the mean reversion level, \( \sigma_i \) the volatility and \( \lambda_i \) the risk premium with \( i = 1, 2 \). \( dW_1 \cdot dW_2 = 0 \).

Following Longstaff et al (2005), we derive a closed form solution for the expected
values of the default $h_t$ and liquidity risk $y_t$. We have:

$$Q_t = E[\exp(-\int_0^t h_u du)] \quad (6.16)$$

We solve for $h$ using the following expression:

$$Q_t = A(t, s) * \exp(-h_t * B(t, s)) \quad (6.17)$$

where

$$A(t, s) = \left[ \frac{2 * \phi * \exp(0.5 * (\alpha_1 + \lambda_1 + \phi) * (s - t))}{2 * \phi + (\alpha_1 + \lambda_1 + \phi)(\exp(\phi(s - t)) - 1)} \right]^{\frac{2 * \alpha_1 * \mu_1}{\sigma_1^2}} \quad (6.18)$$

with $s > t$ and

$$B(t, s) = \left[ \frac{2 * \exp(\phi(s - t)) - 1}{2 * \phi + (\alpha_1 + \lambda_1 + \phi)(\exp(\phi(s - t)) - 1)} \right] \quad (6.19)$$

with

$$\phi = \sqrt{(\alpha_1 + \lambda_1)^2 + 2 * \sigma_1^2} \quad (6.20)$$

In the same way we solve for the liquidity risk $y$:

$$L_t = E[\exp(-\int_0^t y_u du)] \quad (6.21)$$

$$L_t = A(t, s) * \exp(-y_t * B(t, s)) \quad (6.22)$$

where $A(t, s)$ and $B(t, s)$ are similar to the expressions defined in equation (6.18) and (6.19) but differ by having new parameters $\alpha_2, \mu_2, \sigma_2$ and $\lambda_2$.

In the following section, we estimate the affine model using the maximum likelihood
6.7 Estimation Method: Maximum Likelihood (ML)

6.7.1 Hazard Rate and Liquidity Risk:

In order to implement the maximum likelihood method, we need to use the density function implied by the CIR process. The density function of both the hazard rate and liquidity risk is the non central chi-squared distribution. Since liquidity and hazard rate follow the same process we only discuss the hazard rate process. We define the hazard factor in the following way:

\[ Q(t) = A + B * h(t) \]  \hfill (6.23)

where \( B \) and \( A \) are scalars.

\[ f(Q_t | Q_{t-1}) = \frac{1}{\text{det}(B)} * f(h_t | h_{t-1}) \]  \hfill (6.24)

where \( f(h_t | h_{t-1}) \) is defined as follows:

\[
\begin{align*}
    f(h_t | h_{t-1}) &= c * \exp(-c * h_t - c * e^{(-\alpha_1 * \Delta t) * h_{t-1}}) * h_t \\
 &\quad * \frac{h_t}{\exp(-\alpha_1 * \Delta t) * h_{t-1}}^{0.5 \cdot q} \\
 &\quad * I_q(2 * c * \sqrt{h_t} * \exp(-\alpha_1 * \Delta t) * h_{t-1})
\end{align*}
\]  \hfill (6.25)

where

\[
c = \frac{2 * \alpha_1}{\sigma_1^2 * (1 - \exp(-\alpha_1 * \Delta t))} \]  \hfill (6.26)
and

\[ q = \frac{2 \cdot \alpha_1 \cdot \mu_1}{\sigma_1^2} - 1 \quad (6.27) \]

\( I_q \) is the modified Bessel function of the first kind of order \( q \).

The log-likelihood function for a sample of observations on a state variable \( h_t \) for \( t=1,\ldots,T \) is:

\[ \ln L(h_{i,t}, \ldots, h_{i,T}) = \sum_{t=2}^{T} \ln(f(h_{i,t} \mid h_{i,t-1})) \quad (6.28) \]

Given a set of observations\(^{12}\) at time \( t=2,\ldots,T \).

\[ \mathcal{L} = \sum_{t=2}^{T} \log(f(Q_t \mid Q_{t-1})) = \sum_{t=2}^{T} \left\{ \log \left( \frac{1}{\det(B)} \cdot f(h_t \mid h_{t-1}) \right) \right\} \quad (6.29) \]

\[ = \sum_{t=2}^{T} \left\{ -\ln |B| + \ln(f(h_t \mid h_{t-1})) \right\} \]

We use the method of maximum likelihood defined in Chen and Scott (1993) to estimate the parameters of the model. Therefore, we assume that the discount factor \( Q \) is perfectly priced at 5 year maturity and observed with some errors for the other maturities (i.e. 1, 3, 7 and 10 years):

\(^{12}\)We maximize the log-likelihood function conditioned on the first observation being deterministic.
\[
\begin{aligned}
-\ln Q_t^1(t) &= -\ln A_1(t, s_1) + B_1(t, s_1) * h_t + u_{1,t} \\
-\ln Q_t^2(t) &= -\ln A_3(t, s_3) + B_3(t, s_3) * h_t + u_{3,t} \\
-\ln Q_t^3(t) &= -\ln A_5(t, s_5) + B_5(t, s_5) * h_t \\
-\ln Q_t^4(t) &= -\ln A_7(t, s_7) + B_7(t, s_7) * h_t + u_{7,t} \\
-\ln Q_t^{10}(t) &= -\ln A_{10}(t, s_{10}) + B_{10}(t, s_{10}) * h_t + u_{10,t}
\end{aligned}
\]  

(6.30)

where \(A_i\) and \(B_i\) are defined above and \(i = 1, 3, 5, 7, 10\) correspond to the maturities chosen for our study (1, 3, 5, 7 and 10 years). The errors \(u_t\) follow a normal distribution

\[u_t \sim N(0, \sigma^2)\]  

(6.31)

\[f(u_{j,t} \mid u_{j,t-1}) = \frac{1}{\sqrt{2\pi} \sigma^2} * \exp\left(-\left(\frac{u_{t,j}}{2 * \sigma^2}\right)^2\right)\]  

(6.32)

Therefore, the final log-likelihood function can be rewritten in the following way:

\[\mathcal{L}^* = \mathcal{L} + \sum_{i=1}^{T} \log(f(u_t \mid u_{t-1}))\]  

(6.33)

which gives:

\[\mathcal{L}^* = \ln L(h_{i1}, \ldots, h_{iT}) - T \ln |B| - \frac{M \times T}{2} \ln (2\pi) - \frac{T}{2} \ln (|\Omega|) - \frac{1}{2} \sum_{t=2}^{T} u_{t}^{'} \Omega^{-1} u_{t}\]  

(6.34)

To estimate the liquidity risk \(y\) we follow exactly the same steps.
6.7.2 ML Results:

Following the assumption of Chen, Fabozzi and Sverdlove (2010), we retrieve the credit parameters using the mid quote and the liquidity parameters using the ask quote\textsuperscript{13}. Table 6.3, shows the results of the credit parameters. We see that credit premium $\lambda_1$ is not significant for all the countries for both the pre-crisis and crisis time which implies that the credit premium is not priced in the market. However the table shows that $\lambda_1$ is priced during the crisis period for Turkey. Table 6.3, indicates that the half life\textsuperscript{14} is shorter during the pre-crisis than the crisis period which means that there is a strong mean reversion during the pre-crisis period across all the countries. This result is consistent with our time series plot of the default intensity (Figure 6.4, 6.5 and 6.6), but is in large contrast with the findings of Pan and Singleton (2008) and Longstaff et al (2011) who report that the parameters governing the default intensity under the risk neutral measure show very slow mean reversion (and even explosive behavior). We argue that this difference in due to the fact that we are assuming a CIR process for default intensity while Pan and Singleton (2008) and Longstaff et al (2011) assume a lognormal process.

Moreover, Table 6.3 shows that the pricing errors $\sigma_{\epsilon}(i)$ for the CDS contracts with the maturities of one, three, seven and ten years, are quite small. The parameters $\sigma_{\epsilon}(i)$ represent the standard deviations (in percentage term) of the pricing errors where $i$ is the maturity of the contract. Overall, the magnitude of the standard deviations supports our choice of using the one factor model. Furthermore, the errors seem to be larger in the short end of CDS curve which indicate that the model fits better $i=7$ and $10$ than the shorter maturities $i=1$ and $3$. This result is in line with Pan and Singleton (2008) who emphasize that there are some components of the short end of CDS curve

\textsuperscript{13}The prices in the OTC market for CDSs are set by the dealers, who want to protect themselves against illiquidity. Therefore the price that a CDS buyer pays, namely the ask price, will be an illiquid price. When the investor wants to sell to the dealer, the dealer will pay an (illiquid) bid price. In other words the dealer protects himself against illiquidity risk by making the bid-ask spread larger. The liquid price would then be somewhere in between the bid and the ask. For convenience of calculation, we use the midpoint as our estimate of the liquid price.

\textsuperscript{14}The half life gives the slowness of mean reversion process and is computed as follows: $t = -\ln(0.5)/\alpha$
that are not well captured by the one factor model.

On the other hand, Table 6.4 presents the estimation of the liquidity parameters. We observe that liquidity premium $\lambda_2$ is not significant across all the periods and countries. Furthermore, the results have some similarity with Table 6.3 and show that the pricing errors are higher in both the short and long end of the CDS curve ($\sigma_c(1)$ and $\sigma_c(10)$ respectively). Finally, the result reveals stronger mean reversion during the pre-crisis than the crisis period.

Both Table 6.3 and 6.4 point that the pricing errors are higher during the crisis period for $\sigma_c(1)$ and $\sigma_c(10)$, implying the difficulty of fitting a highly volatile time series.

Overall, it seems that Chen and Scott (1993) method does not provide us with encouraging results. In fact, although we find that the one factor model produces small errors in the fitting of the term structure, the credit and liquidity premium are insignificant. As we described earlier, Chen and Scott (1993) method assumes that one maturity (5 year) is perfectly priced, this enables us to invert the function and estimate the factor $h_t$ and/or $y_t$. The choice of the maturity can be rather arbitrary and the results of the model will depend on that particular choice. In order to double check our results, we introduce a pricing error to all the maturities and we reestimate the model using the Kalman filter technique.

6.8 Kalman Filter Estimation:

In the estimation described below, we allow measurement errors on all the CDS maturities. This estimator differs from the Maximum Likelihood a la Chen and Scott (1993) because we do not use the non-central chi-squared distribution and we do not restrict the measurement errors to follow a normal distribution. In fact, the likelihood function remains relatively simple and tractable.

By adding measurements errors, we improve the precision of the risk premium es-
timation. Therefore, we believe that the Kalman filter estimation will give us a good robustness check on the results discussed above.

6.8.1 State Space Representation:

The model can be expressed in the state space form by adding measurement errors to the equation of the observable CDS prices.

\[ h_t = a + \Phi * h_{t-1} + v_t \]  \hspace{1cm} (6.35)

\[-\ln Q_t = -\ln A(t, s_i) + B(t, s_i) * h_t + \varepsilon_t \]  \hspace{1cm} (6.36)

where \( \varepsilon_t = (\varepsilon_1, \varepsilon_3, \varepsilon_5, \varepsilon_7, \varepsilon_{10}) \). \( \varepsilon_i \) represents the measurement error term introduced to allow for imperfections and small errors in each maturity \( i \). Since \( h_t \) follows a CIR process, we can rewrite it as follows:

\[ h_t = \mu_1(1 - \exp(-\alpha_1 \Delta t)) + \exp(-\alpha_1 \Delta t) * h_{j,t-1} + v_{1t} \]  \hspace{1cm} (6.37)

\[-\ln Q_t = -\ln A(t, s_i) + B(t, s_i) * h_t + \varepsilon_t \]  \hspace{1cm} (6.38)

where \( i = 1, ..., 5 \) represents the number of maturities considered.

The error term \( v_t \) represents the unanticipated change (or innovation) in the state variable \( h_t \) and has a conditional expected mean of zero and conditional variance equal to:

\[ \text{var}(v_t \mid v_{t-1}) = \sigma_1 * \left( \frac{1 - \exp(-\alpha_1 \Delta t)}{\alpha_1} \right) (0.5 * \mu_1 * (1 - \exp(-\alpha_1 \Delta t)) + \exp(-\alpha_1 \Delta t) * h_{t-1} \]  \hspace{1cm} (6.39)
We adopt the standard assumption in Kalman filter and we assume that there is no serial or cross sectional correlation between the measurement errors. Therefore, we can write the covariance matrix as follows:

\[
E_{t-1} \begin{pmatrix} v_t \\ \varepsilon_t \end{pmatrix} \begin{pmatrix} v_t \\ \varepsilon_t \end{pmatrix}' = \begin{pmatrix} H_t & 0 \\ 0 & U \end{pmatrix} 
\]

(6.40)

where \(H_t\) and \(U\) are the conditional variances of the state variable and the variances of the measurement errors on the diagonal respectively.

6.8.2 Quasi Maximum Likelihood (QML) Estimation:

The fixed parameters of the state space representation described above are typically estimated using the maximum likelihood method. In our case, we are assuming that \(h_t\) and \(y_t\) are following a CIR process, therefore the innovations of the state variables are not normally distributed which make the standard linear Kalman filter a biased estimator of the unobservable state variables. However, De Jong (2000) and Chen an Scott (2002) perform Monte-carlo exercise and show that there is no evidence of significant bias in the parameter estimates. Therefore, by using the QML estimator the authors prove that it is possible to obtain consistent estimators. We follow their approach and estimate the parameters using the QML as follows:

\[
max_\theta \ln L = \sum_{t=1}^{T} L_t = \sum_{t=1}^{T} -0.5 \ast (\ln |H_t| + u_t' \ast F_t^{-1} \ast u_t) 
\]

(6.41)

where \(\theta\) represents the vector of parameters to optimize \(\theta = (\alpha_1, \mu_1, \sigma_1, \lambda_1, \varepsilon_1(1), \varepsilon_1(3), \varepsilon_1(5), \varepsilon_1(7), \varepsilon_1(10))\) and \(u_t\) and \(F_t\) are defined as

\[
u_t = -\ln Q_t - (A + B \ast (a + \Phi \ast \hat{h}_{t-1})) \]

(6.42)
\[ F_t = E(u_t \ast u_t') \] (6.43)
if the CDS market is illiquid\(^{15}\), this is equivalent to say that the protection buyer will earn the liquidity premium\(^{16}\). Table 6.6 reveals that during the pre-crisis period the liquidity premium is positive and significant for all the countries, this indicates that the price of liquidity risk has significant impact on the defaultable leg of the CDS contract and does reduce CDS spreads in line with our model assumption. However, we observe that liquidity premium \(\lambda_2\) decreases in magnitude and even disappears during crisis time. In fact, this situation is possible if, in crisis time, there is a high demand of CDS protection to hedge against default risk. If the demand of protection is strong then protection buyers are not able to demand any compensation for liquidity risk because the CDS market is more liquid. Therefore, protection sellers are able to benefit from the shift in the demand and supply to either lower the liquidity premium earned by protection buyers (i.e. case of Brazil, we observe that \(\lambda_2\) has low significance level) or to remove it (i.e. case of Philippines and Turkey, we observe that \(\lambda_2\) is insignificant).

6.9 Interpretation of the Results:

Overall, it seems that our findings suggest mixed interpretations. While the first method used (i.e ML a la Chen and Scott (1993)) shows that neither the credit nor the liquidity premium are priced in the term structure of sovereign CDS curve\(^{17}\). The other technique (i.e. Kalman filter) provides stronger evidence of a liquidity premium priced in the term structure of sovereign CDS spreads especially during the pre-crisis period.

The fact that the measurement error was highly significant (at 1\% significance level) at 5 year maturity across all the countries and during both the pre and the crisis period implies that the assumption that the 5 year contract is perfectly priced may not give an accurate measure of the state variable and this may explain why the results obtained

\(^{15}\)If the CDS sellers sell an illiquid protection to the protection buyer, the latter will incur costs if he decides to trade it therefore he will require a discount as a compensation for that.

\(^{16}\)This assumption is different from that of Buhler and Trapp (2010) where the liquidity premium enters both defaultable and premium leg of the CDS contract.

\(^{17}\)The credit premium is priced during the crisis period for Turkey only.
from the ML a la Chen and Scott (1993) are different from those of the Kalman filter.

It seems that using the state space form to allow for measurement errors across all the maturities provides clearer insight on the identification of the market price of risk. It also has the advantage of simplifying the likelihood function and making it easier to optimize. Therefore, we believe that the Kalman filter technique gives more accurate measure and its results suggest that, during some subperiods (i.e., during the pre-crisis period), a part of the time-series variation of term structure of the sovereign CDSs was caused by changes in liquidity risk rather than changes in the default risk only. We argue that during the pre-crisis period, the CDS market is relatively less liquid than during the crisis period therefore CDS buyers earn the liquidity premium and pay less spreads. However, during crisis period, because of high risk aversion there are more buyers in the market which increase the liquidity of the CDS market and therefore cancel the earned liquidity premium.

While Pan and Singleton (2008) emphasize that a significant part of the co-movement among the term structures of sovereign CDS spreads is triggered by changes in investors appetites for credit exposure at a global level, rather than by the reassessments of the fundamental strengths of these specific sovereign economies, our results suggest that liquidity risk has a non-trivial role and participates to the variation over time of the term structure of the sovereign CDS spreads.

6.10 Conclusion:

In this chapter, we provide the first study that analyses the dynamic properties of the risk neutral liquidity premium embedded in the term structure of the sovereign credit default swap spreads. In order to carry out this analysis, we extend the work of Chen, Fabozzi and Sverdlove (2010) and assume that mid-ask quote provide an upper bound for the liquidity risk. However, we differentiate ourselves from the authors by using the
term structure of sovereign CDS spreads to do our analysis. By using the time series and cross sectional information, we are able to provide more accurate measure of the credit and liquidity premium. We choose to apply our framework to Brazil, Philippines and Turkey, three emerging countries with different credit history and for which a full term structure of sovereign CDS and bond spreads is available. Using a single factor model, we use two estimation techniques, the Maximum Likelihood a la Chen and Scott (1993) and the Kalman filter, to approximate the credit and the liquidity premium. Although both estimations suggest mixed interpretations, we argue that the Kalman filter provides robust results and give clearer insight on the identification of the liquidity premium.

Our results suggest that liquidity risk has a non-trivial role and participates to the variation over time of the term structure of sovereign CDS spreads, especially during the period preceding the crisis. Since in our model assumption liquidity risk enters only the defaultable leg of the CDS contract, our findings imply that CDS buyers earn the liquidity premium during the pre-crisis period. However, during crisis time, we observe an increase in the CDS market liquidity which shifts the balance of supply and demand of CDS protections, thus CDS buyers are not able to earn the liquidity premium anymore. Moreover, using the mid-ask yield bond spread, we provide a complete picture of the co-movement of the bond and CDS liquidity risk term structures. We show that the co-movement of CDS and bond liquidity ratio is mainly influenced by the magnitude of the default intensity. In fact, in case of high default risk, we observe that CDS liquidity risk increases more than bond liquidity risk. Finally, our findings complete that of Pan and Singleton (2008) and give clear indication that the movements along the term structure of sovereign CDS spreads is driven by (liquidity) factors that do not necessarily reflect the reassessment of the fundamental strength of the countries. Finally, we believe that further research should be done to better understand the mispricing that occurs at the one year CDS contract.
Tables

Table 6.1: Descriptive Statistics of the Bond and CDS Liquidity Risk Term Structure

In this table, we present descriptive statistics of the bond and CDS liquidity risk term structure for the 1, 3, 5, 7 and 10 years maturity for Brazil, Philippines and Turkey. The table shows the min, max, mean and the standard deviations of the bond yield and CDS spreads.

<table>
<thead>
<tr>
<th></th>
<th>1Y</th>
<th>3Y</th>
<th>5Y</th>
<th>7Y</th>
<th>10Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>0</td>
<td>0.0001</td>
<td>0.002</td>
<td>0.001</td>
<td>0.0001</td>
</tr>
<tr>
<td>Max</td>
<td>0.0071</td>
<td>0.0039</td>
<td>0.0072</td>
<td>0.0026</td>
<td>0.0042</td>
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<tr>
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<td>0.0006</td>
<td>0.0011</td>
<td>0.0005</td>
<td>0.0006</td>
</tr>
<tr>
<td>Std</td>
<td>0.001</td>
<td>0.0004</td>
<td>0.0008</td>
<td>0.0003</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
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<td>7Y</td>
<td>10Y</td>
</tr>
<tr>
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<td></td>
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</tr>
<tr>
<td>Philip</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
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<td>0.0003</td>
<td>0.0024</td>
<td>0.0021</td>
<td>0.0008</td>
</tr>
<tr>
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<td>Turkey</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
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<td>0.0011</td>
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Table 6.2: Description of Bond Data for Brazil, Philippines and Turkey

This table presents the description of the bond dataset downloaded from Datastream. We provide information on the average mid yield, maturity dates, coupon payment rates and issue dates. After computing bond yields, we take the average mid yield (i.e. sum of ask and bid divided by 2) over the entire sample period (from November 2005 to September 2010).

<table>
<thead>
<tr>
<th>Brazil</th>
<th>Maturity</th>
<th>07/06/2011</th>
<th>11/01/2012</th>
<th>17/06/2013</th>
<th>14/07/2014</th>
<th>07/03/2015</th>
<th>17/01/2017</th>
<th>15/01/2018</th>
<th>15/01/2019</th>
<th>14/10/2019</th>
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<th>15/04/2024</th>
<th>15/04/2024</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coupon</td>
<td>10%</td>
<td>11%</td>
<td>4%</td>
<td>2%</td>
<td>8%</td>
<td>6%</td>
<td>8%</td>
<td>8%</td>
<td>4%</td>
<td>8%</td>
<td>8%</td>
<td>8%</td>
</tr>
<tr>
<td></td>
<td>Average Mid Yield</td>
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<td>0.041</td>
<td>0.042</td>
<td>0.0514</td>
<td>0.051</td>
<td>0.062</td>
<td>0.047</td>
<td>0.0614</td>
<td>0.061</td>
<td>0.064</td>
<td>0.064</td>
<td>0.064</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Philippines</th>
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Table 6.3: Parameter Estimation of the CIR Process for the Credit Premium: Maximum Likelihood Method

In this table, we present the estimation of the parameters (in percentage term) of the CIR process relevant to the hazard rate (or default intensity) $h$ (i.e., using the mid quote data). $\alpha_1$ corresponds to the mean reversion speed, $\mu_1$ the mean reversion level, $\sigma_1$ the volatility and $\lambda_1$ the credit premium. The estimation is performed using the Maximum Likelihood method a la Chen and Scott (1993). We split our sample period in two periods: Before Crisis (BC) and During Crisis (DC). We compute the standard errors using the BHHH method. The parameters $\sigma_{\epsilon}(i)$ represent the standard deviations (in percentage term) of pricing errors where $i$ is the maturity of the CDS contract. Finally, ‘*’, ‘**’ and ‘***’ represent 1%, 5% and 10% significance level respectively.

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Table 6.4: Parameter Estimation of the CIR Process for the Liquidity Premium: Maximum Likelihood Method

In this table, we present the estimation of the parameters (in percentage term) of the CIR process relevant to the liquidity risk $y$ (i.e. using the ask quote data). $\alpha_2$ corresponds to the mean reversion speed, $\mu_2$ the mean reversion level, $\sigma_2$ the volatility and $\lambda_2$ the liquidity premium. The estimation is performed using the Maximum Likelihood method a la Chen and Scott (1993). We split our sample period in two periods: Before Crisis (BC) and During Crisis (DC). We compute the standard errors using the BHHH method. The parameters $\sigma_\epsilon(i)$ represent the standard deviations (in percentage term) of pricing errors where $i$ is the maturity of the CDS contract. Finally, ‘*, **’ and ‘***’ represent 1%, 5% and 10% significance level respectively.

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Table 6.5: Parameter Estimation of the CIR Process for the Credit Premium: Kalman Filter

In this table, we present the estimation of the parameters (in percentage term) of the CIR process relevant to the hazard rate (or default intensity) $h$ (i.e. using the mid quote data). $\alpha_1$ corresponds to the mean reversion speed, $\mu_1$ the mean reversion level, $\sigma_1$ the volatility and $\lambda_1$ the credit premium. The estimation is performed using the Kalman filter Method. We split our sample period in two periods: Before Crisis (BC) and During Crisis (DC). The parameters $\varepsilon_1(i)$ represent the measurement errors introduced for each maturity $i$ of the CDS contract. We compute the standard errors using the White method (1982). Finally, ‘*’, ‘**’ and ‘***’ represent 1%, 5% and 10% significance level respectively.

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Table 6.6: Parameter Estimation of the CIR Process for the Liquidity Premium: Kalman Filter

In this table, we present the estimation of the parameters (in percentage term) of the CIR process relevant to the liquidity intensity \( y \) (i.e using the ask quote data). \( \alpha_2 \) corresponds to the mean reversion speed, \( \mu_2 \) the mean reversion level, \( \sigma_2 \) the volatility and \( \lambda_2 \) the liquidity premium. The estimation is performed using the Kalman filter Method. We split our sample period in two periods: Before Crisis (BC) and During Crisis (DC). The parameters \( \varepsilon_2(i) \) represent the measurement errors introduced for each maturity \( i \) of the CDS contract. We compute the standard errors using the White method (1982). Finally, \('*\)', \('**\)' and \('***\)' represent 1%, 5% and 10% significance level respectively.

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Figure 6.1: CDS Liquidity Risk Term Structure Brazil

This figure shows the time series plot of the estimated CDS liquidity risk (in decimals) of the 1, 3, 5, 7 and 10 year maturity for Brazil. We estimate the liquidity risk $y$ by using a discrete-time approximation of the CDS pricing formula defined in Section 6.5.1.
Figure 6.2: CDS Liquidity Risk Term Structure Philippines

This figure shows the time series plot of the estimated CDS liquidity risk (in decimals) of the 1, 3, 5, 7 and 10 year maturity for Philippines. We estimate the liquidity risk $y$ by using a discrete-time approximation of the CDS pricing formula defined in Section 6.5.1.
Figure 6.3: CDS Liquidity Risk Term Structure Turkey

This figure shows the time series plot of the estimated CDS liquidity risk (in decimals) of the 1, 3, 5, 7 and 10 year maturity for Turkey. We estimate the liquidity risk by using a discrete-time approximation of the CDS pricing formula defined in Section 6.5.1.
Figure 6.4: **Bond and CDS Liquidity Risk Term Structure: Brazil**

The (top) figure shows the time series plot of the estimated hazard rate (or default intensity) of the 1, 3, 5, 7 and 10 year maturity for Brazil. We estimate the hazard rate \( h \) by using a discrete-time approximation of the CDS pricing formula defined in Section 6.5.1. The (bottom) figure shows the time series plot of the ratio of CDS over bond liquidity for Brazil. We estimate the CDS liquidity risk \( y \) by using the same discrete-time approximation of the CDS pricing formula defined in Section 6.5.1. However, bond liquidity risk is approximated by taking the difference between the mid and ask yield of the relevant maturity.
Figure 6.5: Bond and CDS Liquidity Risk Term Structure: Philippines

The (top) figure shows the time series plot of the estimated hazard rate (or default intensity) of the 1, 3, 5, 7 and 10 year maturity for Philippines. We estimate the hazard rate \( h \) by using a discrete-time approximation of the CDS pricing formula defined in Section 6.5.1. The (bottom) figure shows the time series plot of the ratio of CDS over bond liquidity for Philippines. We estimate the CDS liquidity risk \( y \) by using the same discrete-time approximation of the CDS pricing formula defined in Section 6.5.1. However, bond liquidity risk is approximated by taking the difference between the mid and ask yield of the relevant maturity.
Figure 6.6: Bond and CDS Liquidity Risk Term Structure: Turkey

The (top) figure shows the time series plot of the estimated hazard rate (or default intensity) of the 1, 3, 5, 7 and 10 year maturity for Turkey. We estimate the hazard rate $h$ by using a discrete-time approximation of the CDS pricing formula defined in Section 6.5.1. The (bottom) figure shows the time series plot of the ratio of CDS over bond liquidity for Turkey. We estimate the CDS liquidity risk $y$ by using the same discrete-time approximation of the CDS pricing formula defined in Section 6.5.1. However, bond liquidity risk is approximated by taking the difference between the mid and ask yield of the relevant maturity.
Chapter 7

Concluding Remarks

In this thesis, we study the determinants of the sovereign credit default swap spreads. As a first step, we utilise a panel regression model in order to investigate the effect of CDS and bond liquidity on sovereign CDS spreads. Using different liquidity proxies, we find that, during crisis time, search frictions and inventory costs do not represent a constraint to market participants, however bond liquidity has a significant effect on sovereign CDS spreads.

Secondly, we explore the effect of commonality in liquidity. To this end, we extend the Liquidity-Adjusted CAPM model of Acharya and Pedersen (2005) and construct beta risk factors that aim to capture both CDS and bond systematic liquidity risk. We find that market liquidity plays an important role in CDS spread movements. We conclude the chapter by advancing the idea that speculation may participate to the widening of bid-ask spreads and that funding liquidity risk is more constraining during crisis time.

As a further step in our analysis, we concentrate on the pricing issues and use a factor model in order to decompose sovereign CDS spreads into a pure default risk, pure liquidity and correlation components. The main objective is to measure the weight of liquidity in sovereign CDS spreads not by using liquidity proxies such as bid-ask spreads or volumes but by jointly calibrating the model to both bonds and CDSs. By doing so, we are able to use a large amount of information on sovereign default risk and thus
present a better decomposition and estimate the components more precisely.

Overall, our results reveal that sovereign CDS spreads are highly driven by liquidity and that sovereign bond spreads are less subject to liquidity frictions and therefore could represent a better proxy for sovereign default risk. This finding is consistent with the results of Chapter 4, where we demonstrate empirically that market liquidity risk is a priced state variable. Finally, our decomposition exercise puts forward the idea that the increase in the CDS spreads observed during the crisis period was mainly due to a surge in liquidity rather than to an increase in the default intensity.

Last but not the least, we analyse the dynamic properties of the risk-neutral liquidity premium embedded in the term structure of the sovereign CDS spreads. As a main assumption, we postulate that mid-ask quotes provide an upper bound for liquidity risk. Our results suggest that liquidity risk participates directly to the variation over time of the term structure of sovereign CDS spreads. Moreover, using the mid-ask yield bond spreads, we provide a complete picture of the co-movement of the bond and CDS liquidity risk term structures and show that CDS and bond liquidity ratio is mainly influenced by the magnitude of the default intensity.

In summary, all our results underline that liquidity is one of the important driving factors of the sovereign CDS spreads. Our findings give clear indication that liquidity influences asset prices by drifting them away from their fundamental values. We thus believe that this thesis enhances our understanding of the sovereign CDS market and its results have important implications for practitioners and policy makers.

More research is warranted to understand the effect of speculation on CDS spreads. Moreover, further investigation is required to interpret the mispricing that occurs at the one year CDS contract.
Bibliography


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