Violations of the Law of One Price in Credit and Swap Markets During Market Distress

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The work presented in this thesis is my own.

M.C. Mengütürk

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ABSTRACT

This thesis is devoted to investigating the dynamic properties of Law of One Price (LOP) violations around periods of market distress. It studies the extent to which these violations are state-dependent and how they are related to different market conditions. The role of monetary policies and hedge funds in contributing to LOP equilibrium are also analysed. First part focuses on the construction of an LOP deviation proxy called $Basis_{\text{bond}}$, derived from the foreign-currency sovereign bond markets (in USD and Euro) of three main emerging economies (i.e. Brazil, Mexico and Turkey). It is observed that $Basis_{\text{bond}}$ moves close to zero (supporting LOP condition) during good states of economy (Pre-Crisis), whereas it becomes markedly large, persistent and volatile during bad states of economy (Credit Crisis). Second part delves deeper into why $Basis_{\text{bond}}$ deviated so markedly from zero during 2008-2009 Credit Crisis. We find strong evidence that rising funding costs, falling bond supply, intensified risk aversion and deteriorated default risk coupled with macroeconomic shocks are responsible in deterring arbitrageurs from exploiting the trading strategy, and inducing relative price divergence. Depending on the geography of bond issuance, there exist cross-sectional idiosyncrasies regarding the sign of deviation. While Turkey tends to pay smaller credit risk premium in Euro compared to USD, the opposite is true for Brazil and Mexico. When investors face discordant default risks across two equivalent securities, the underlying trading strategy is left unexploited. Moreover, there is strong evidence that different sets of monetary policies have different implications in resolving LOP disequilibrium. Third part investigates the impact of arbitrageurs (particularly hedge funds) in supplying liquidity to markets, and thus contributing to correct relative valuation of mispriced securities. It is confirmed that hedge fund withdrawal, due to severe capital reduction, contributes adversely to the growth of LOP deviations in credit and swap markets.

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Chapter 1

Introduction

It is good for a scientific enterprise, as well as for a society, to have well established laws. Physics has excellent laws, such as the law of gravity. What does economics have? The first law of economics is clearly the law of supply and demand, and a fine law it is. We would nominate as the second law "the law of one price".

Lamont and Thaler (2003a)

I. Law of One Price

The law of one price (LOP) requires that two assets generating equal cash-flows should trade at equal prices. Otherwise, there exists an LOP violation (as called in the finance literature), and potentially an arbitrage opportunity. This relationship plays a key role in financial economics, as quoted by Lamont and Thaler (2003b): "Arbitrage is the basis of much of modern financial theory, including the Modigliani-Miller capital structure propositions, the Black-Scholes option pricing formula, and the arbitrage pricing theory."

Violations of LOP are potentially easy for arbitrageurs to eliminate in "free-access" economies. If two identical securities A and B are trading at two different prices, say $101 and $100, respectively, then arbitrageurs could sell security A, and use the proceeds to simultaneously buy security B, locking-in a profit of $1. If access to capital markets is such that sufficient amount of liquidity can indeed be channeled into the trade (i.e. more arbitrageurs become aware of it, and implement the same strategy), the price of security B would eventually increase and the price of security A would eventually decrease, causing prices to converge, eliminating the arbitrage opportunity. Even though arbitrageurs are notoriously labeled as "free-riders" of the economy, they tend to play an essential role in eliminating mispricings by providing the required liquidity to capital markets, thus allowing asset prices to reflect correct relative valuation.

The paragraph above points to an important implication, that is, *if* LOP is violated, the violation is to be *temporary* (and small). This is simply due to the correcting mechanism that underlies the simultaneous buying/selling of arbitrageurs. The real mystery arises, however, when LOP violation becomes *persistent* (and large), since it implies that market participants are not willing (or capable) to exploit the implied arbitrage strategy. This phenomenon begs a series of important questions: What type of market constraints, costs or aversions *limit* an arbitrageur's active participation in arbitrage trades? Is this evidence of simple market irrationality, or is it rather linked to specific risk factors and institutional/geographical features that arise during certain states of the economy that make an arbitrage trade less and less feasible over time?

Understanding the role of markets in favoring (or limiting) the LOP equilibrium is an important endeavor in modern finance. The implications should be analyzed in a state-dependent approach: the LOP equilibrium may hold during the "good" states of the economy, but it may become violated during the "bad" states of the economy, when access to capital is limited, funding constraints are tightened, uncertainty suppresses risk appetite, and macroeconomic frictions are adversely binding.

It is important to note that, in real life, arbitrage trades are rarely risk-free. The associated risks can be either systematic, or idiosyncratic, or both. It could be reasonably conjectured that, when the perceived risk of arbitrage is higher than the return expected from it, the trade could go unexploited, causing relative prices to diverge further away from each other for an extended period of time. With a focus on different economic states, this thesis is dedicated to studying the structural and financial constraints that are responsible for LOP violations, and the role of monetary policies and hedge funds in contributing to price convergence.

II. Overview of Recent Financial Crisis

While significant deviations from LOP are certainly not common, the recent 2007-2009 financial crisis offers a unique laboratory to study this phenomenon across different markets. As stated by Borio (2008), the 2008 financial turbulence was preceded by a period called "Great Moderation" - a time when the world economy displayed a rapid growth and unusually strong financial-markets performance, particularly during 2004-2006 period that coincides with rising residential property prices and low risk premia. What was rather uncommon to previous decades was the unprecedented level of financial innovation in the credit risk transfer instruments (e.g. credit default swaps and structured credit products), coupled with high leverages and excessive risk-taking attitude. The credit risk inherent in assets was frequently re-bottled and sold off to capital markets. Credit regulations and rating methodologies were considerably relaxed, allowing banks and other financial institutions to over-extend their balance sheets, to pursue aggressive shadow-banking techniques through the use of complicated, off-balance sheet securitisations and derivatives, and to engage in various predatory lending activities. With the soothing promise of rising property prices whispered in the background, borrowers were given strong incentives to get committed to difficult mortgage loans - this was a time of credit and housing boom.

As of mid-2006, however, housing prices began to drop, and interest rates began to climb, giving the first signals of difficulty for borrowers to refinance their positions. The situation worsened in 2007, as housing prices continued to decline, consumer wealth continued to deteriorate, and number of defaults began to rise. On April 2, 2007, the subprime lender, New Century Financial Corp., filed for bankruptcy; and on June 20, 2007, a total of $4 billion of assets were sold by two Bear Stearns funds to cover the margin calls triggered by the subprime losses. Almost a month later, on July 10, 2007, Standard & Poor's declared that $12 billion of subprime debt may be subject to rating cuts. As of August 2007, the U.S. and Euro interbank markets experienced lending/borrowing dislocations, soon followed by tightened liquidity levels and downgraded structured products, writedowns and further subprime losses. As banks became increasingly reluctant to lend to each other, liquidity and counterparty risk premium soared in proportions that became increasingly difficult to relieve.

This "Liquidity Crisis", as often called in the finance literature, immediately called forth a regulatory response by the central banks that would soon provide large liquidity injections and positive public signaling to financial markets. In order to ease the pressure on short-term funding markets, for instance, Term Auction Facility (TAF) was launched on December 12, 2007. On the same day, the Federal Reserve (Fed) and the ECB agreed on the extension of USD swap lines to meet the dollar funding needs of the Euro Zone. Similarly, the creation of Term Securities Lending Facility (TSLF) was announced by the Fed on March 11, 2008. Borio (2008) emphasizes that, although these monetary policies proved effective in easing the funding pressures on interbank markets, they fell short of addressing the shifting nature of the turmoil, which was becoming more related to concerns over *credit risk* than liquidity risk.[1] On September 7, 2008, Fannie Mae and Freddie Mac were placed in government conservatorship by the Federal Housing Finance Agency. One week later, on September 15, 2008, Lehman Brothers filed for Chapter 11 bankruptcy. The following period, often called the "Credit Crisis" was characterized by the bankruptcy of major financial institutions, defaulted securities, government bailouts, reduction in consumer wealth, rise in credit risk and unemployment rates, and collapse of the stock markets around the globe.[2]

[1] Longstaff (2010) argues that Lehman's collapse changed the nature of the crisis, stating that, while the major concern previously had been the lack of market liquidity, the crisis became more affected by solvency risk.

[2] Some economists argue that the repeal of the Glass-Steagall Act of 1933 (under the Financial Services Modernization Act of 1999)

This thesis is focused on a time period that spans different economic states, and includes periods of market distress described above. To be more specific, our list of cross-sectional and time-series data cover July 2005 - April 2010 period, which is divided into three main stages (and two further sub-stages). The "Pre-Crisis" period covers July 1, 2005 - August 8, 2007; the "Crisis" period covers August 9, 2007 - March 31, 2009; the "Post-Crisis" period covers April 1, 2009 - April 30, 2010. We follow Taylor and Williams (2009) and Longstaff (2010) in our sampling procedure, and divide "Crisis" period further into two subsamples, such that the "Liquidity Crisis" covers August 9, 2007 - August 29, 2008, and the "Credit Crisis" covers September 1, 2008 - March 31, 2009.[3] The terminology introduced here, regarding the time periods, will be used throughout the thesis.

III. Overview of Thesis

This thesis studies the dynamic properties of LOP and near-LOP violations around periods of market distress. We investigate the extent to which these violations are time-varying, how they are related to specific market conditions, and how they have changed before, during, and after crisis periods. The brief summary of the thesis chapters follows:

Chapter 2: *Literature Review.* This chapter summarizes the related streams of literature.

Chapter 3: *Mispricing in Emerging Markets: Evidence from Cross-Sectional Data.* This chapter focuses on the construction and the dynamics of a near-LOP deviation proxy, $Basis_{\text{bond}}$, which we derive from the foreign-currency sovereign bond markets (in USD and Euro) of three main emerging economies (i.e. Brazil, Mexico and Turkey), whose domestic currencies are neither USD nor Euro. Two long-term bonds issued by the *same* sovereign across two $foreign$ currencies, under the ideal condition of identical cash-flows, must satisfy a no-arbitrage condition. In real life this would be extremely rare, if not impossible. So we start out by carefully selecting bond pairs issued by the same sovereign with *similar* cash-flow structure and time-to-maturity. We short the USD coupon-bond, convert the dollar proceeds into Euro in the FX spot market, and long the equivalent Euro coupon-bond of the same issuer. We simultaneously enter into a series of FX forward contracts to convert each future cash-flow (coupons and principal) of the Euro bond into dollars, and thus create a synthetic USD bond that consists only of dollar cash-flows. We define $Basis_{\text{bond}}$ as the yield of the synthetic USD bond minus the yield of the cash USD bond. According to LOP, $Basis_{\text{bond}}$, under

was one of the main reasons why the crisis escalated. Glass-Steagall Act commanded against an institution to act as a combination of a commercial bank, an investment bank and an insurance company, and thus, disallowing an investment bank, for instance, to "gamble" on the money of the depositors of the *affiliated* depository bank.

[3]Bernanke (2009) argues that during the first stage of the crisis, the Federal Reserve provided liquidity to solvent institutions with minimal credit risk. However, during the second stage of the crisis, the Federal Reserve accepted credit risk exposure by providing capital to some impaired borrowers in order to directly address counterparty credit risk.

this ideal setting, must equal zero, so that the arbitrageur would do no better than only perfectly meeting the dollar liability cash-flows on the USD bond side, using the dollar-converted asset cash-flows on the Euro bond side. However, due to structural cash-flow mismatches inherent in bond pairs, $Basis_{\text{bond}}$ could at best be a fair approximation of LOP, and therefore, a plausible proxy for near-LOP deviation. Several examples are discussed in the literature (see Chen and Knez (1995) and Gatev, Goetzmann, and Rouwenhorst (2006)). The rest of this chapter is devoted to testing whether $Basis_{\text{bond}}$ is indeed a good and reliable proxy for near-LOP deviation. The conclusion is affirmative. While $Basis_{\text{bond}}$ moves close to zero (supporting LOP condition) during the good states of the economy (Pre-Crisis), it becomes markedly large, strongly persistent and highly volatile during the bad states of the economy, far outstripping the total transaction cost threshold (Credit Crisis).

Chapter 4: *Determinants and Geography of Mispricing in Emerging Markets.* This chapter delves deeper into why $Basis_{\text{bond}}$ deviated so markedly from zero during Credit Crisis. We find strong evidence that deteriorated bond supply, tightened funding costs, macroeconomic shocks and exasperated default risk are jointly responsible in explaining the deviation. In addition, when the trading strategy is created by shorting the USD bond and longing the Euro bond, the sign of $Basis_{\text{bond}}$ displays cross-sectional idiosyncrasies, such that it is generally positive for Brazil and Mexico, and negative for Turkey.[4] This raises important discussions about the geographical nature of the financial frictions at hand: Turkey pays smaller credit risk premium in Euro compared to USD, while the opposite is true for Brazil and Mexico. We find evidence that the reason behind this could be related to reserve distribution dynamics of the given emerging market central banks, and the differing features of the interbank funding constraints across USD and Euro. This chapter also studies the impact of regulatory interventions and announcements in relieving $Basis_{\text{bond}}$ violations, and in contributing to price discovery. In order to understand the nature of the market frictions being targeted, we first categorize into different groups the monetary policies launched by the Fed and the U.S. Treasury. We then test whether any of these policies helped to reduce the size of $Basis_{\text{bond}}$. We find evidence that different sets of policies have different impacts and implications (positive and negative) on cross-sectional $Basis_{\text{bond}}$, such that at some points, the exclusion of one country from a certain policy (e.g. Turkey was excluded from the Fed's dollar swap line extensions, while Brazil and Mexico were included) can indeed open the cross-sectional gap of the LOP violation across different countries.

Chapter 5: *Supply of Risk Capital: Role of Arbitrageurs and Cross-Market Interactions.* This chapter investigates the impact of arbitrageurs (particularly hedge funds) in supplying liquidity to capital markets, and thus contributing to correct relative valuation of mispriced securities. In

[4] This means that the strategy should be reversed to make profit with Turkish bonds.

order to carry out the investigation, we generate a set of different LOP deviation proxies in credit and swap markets represented by $\vec{Basis}$, which is composed of (1) Emerging Market Eurobond Basis, $Basis_{\text{bond}}$, which we described in the above, (2) Developed Market CDS Basis, $Basis_{\text{cds}}$, (3) Swap Market CIRP Bases, $Basis_{\text{scirp}}$ and $Basis_{\text{lcirp}}$. Our findings suggest that the components of $\vec{Basis}$ fluctuate around zero during Pre-Crisis, but become large, volatile and persistent during Credit Crisis, when there is a level of commonality among them due to a systemic risk factor. Furthermore, we confirm the hypothesis that the withdrawal ("de-participation") of hedge funds from the markets, due to reduction in their capital, contributes significantly and adversely to $\vec{Basis}$ deviations, implying further LOP divergence. We show that both AuM depletion and deleveraging tends to exert a significant impact on LOP divergence. Supporting evidence is found that collateral constraints (captured by tightened requirements on loans and credit lines) have a significantly adverse impact on both hedge fund deleveraging and LOP disequilibrium.

Chapter 6: *Conclusions:* This chapter gives the summary results of all chapters.

IV. Remarks on Notation

Sections and Subsections: Chapters are ordered according to Arabic numbers. Sections are ordered according to Roman numbers (and they re-start from I. for each chapter). Subsections are alphabetically ordered (and they re-start from A. for each section).

Tables and Figures: Tables and Figures are represented in $C(n).T(n)$ and $C(n).F(n)$ format in the body of text, respectively, where $C(n)$ denotes the Chapter number, $T(n)$ denotes the Table number, and $F(n)$ denotes the Figure number. To give an example, Table C(3).T(1) is denoted as Table 3.1, which refers to Chapter 3, Table 1. Similarly, Figure C(4).F(2) is denoted as Figure 4.2, which refers to Chapter 4, Figure 2. Note that $T(n)$ and $F(n)$ re-start from 1 for each chapter $C(n)$. All tables and figures are given at the end of each corresponding chapter.

Appendices: Appendices are given at the end of each corresponding chapter.

Bibliography: Bibliography is given at the end of thesis.

Chapter 2

Literature Review

This thesis is related to seven main streams of literature, the relevance of which will be clear in the coming chapters.

Literature Stream 1: The first stream studies the economic reasons for observed deviations from the law of one price, and argues that arbitrage strategies, in practice, are very rarely risk-free. De Long, Shleifer, Summers, and Waldmann (1990) state that arbitrageurs with short horizons would be concerned about liquidating their mispriced assets, and hence act relatively less aggressive against the unpredictable behavior of unsophisticated investors who generate risks that make arbitrage trades less attractive. Shleifer and Vishny (1997) argue that a widening in the mispricing of an asset may lead arbitrageurs to unwind their positions, which may further amplify the initial mispricing. Such forced unwinding can be due to a suboptimal design of the capital structure of the arbitrageur. As he loses money on his positions, his investors ask earlier reimbursement. If the arbitrageur cannot compensate the demand shock of his investors (for instance by increasing his leverage), then deviations from the LOP can be persistent. Feeding from the potential implications of financial constraints on the equilibrium asset prices, this stream also focuses on different forms of frictions that may cause this persistence: (a) liquidity costs; (b) short-selling constraints; (c) leverage constraints; (d) other institutional frictions and macro shocks. Amihud and Mendelson (1986) investigate the impact of illiquidity on asset pricing, arguing that a strong measure of illiquidity can be captured by the spread between bid and ask prices. They theoretically show that asset returns are an increasing concave function of the measure of illiquidity (i.e. higher bid/ask spreads produce higher expected returns). Similarly, Garleanu and Pedersen (2007) find a link between risk management and liquidity and its effect on asset prices. They argue that an institution may choose to tighten its risk management and to reduce its security holdings, which leads to the reduction of liquidity in the market. Therefore, when every institution chooses a tight risk management, the market liquidity is severely impaired, and as a result, the asset prices drop significantly, given that liquidity risk is also priced in these assets. The authors highlight the multiplier effect of this phenomenon: the tighter the risk management, the higher the risk in the expected selling period, and thus even tighter the risk management. For the role of collateral value, Detemple and Murthy (1997) examine the frictions on portfolio weights limiting the short sale of assets. They argue that the existence of a collateral component suggests that all assets can deviate from the intertemporal MRS pricing in unrestricted trades. Similarly, Gromb and Vayanos (2002) explain how collateral may prevent the positions of an arbitrageur, such that the problems in asset liquidation (carried out by the hedge funds) lead to large drops in asset prices. For the role of limited risk capital, Gabaix, Krishnamurthy, and Vigneron (2007) give evidence for the existence of limited arbitrage in the mortgage-backed securities (MBS) markets. They argue that a marginal investor in a specific asset market is a specialized arbitrageur (not a diversified representative investor). Since specialized arbitrageurs constitute only a small set of investors, any distressed liquidation that they face is expected to have large effects on the asset prices. Therefore, the impact of limits to arbitrage are more pronounced in markets that need more expertise, such as the MBS market. The authors prove theoretically that liquidations have indeed a large effect in these markets, and limited capital (in the form of value-at-risk requirements) influences the price of prepayment risks. As a related work, on margin requirements, Brunnermeier and Pedersen (2009) provide a model where the capital of the speculator drives market liquidity and risk premiums. They define "market liquidity [as] the ease with which [an asset] is traded"and "funding liquidity [as] the ease with which [traders] can obtain funding". They show that under tight funding conditions, traders cannot open positions in high-margin securities, which in turn reduces market liquidity and increases volatility. Similarly, Gromb and Vayanos (2010) introduce a cross-asset arbitrage model driven by demand shocks that in turn generate mispricings across assets. Their theoretical framework gives strong evidence for the impact of holding costs, leverage and equity constraints on arbitrageur's ability to bring prices back to fundamentals. In context of margin constraints, Garleanu and Pedersen (2011) generate a dynamic general-equilibrium model with margin constraints, capturing the features of liquidity crises. They find that the price gaps between a security and a derivative (with identical cash flows) is a function of their margin requirements and funding costs. They also show that "negative shocks to fundamentals make margin constraints bind", which in turn decreases the risk-free rates and increases Sharpe ratios of risky securities.

Literature Stream 2: The second stream of the literature investigates market anomalies that appear to be unrelated to economic fundamentals. Within this literature several empirical studies focus on violations of the LOP. These include the Siamese-Twin stocks puzzle by Rosenthal and Young (1990), the closed-end discount puzzle by Klibanoff, Lamont, and Wizman (1998), the Palm-3Com spin-off puzzle by Lamont and Thaler (2003b), the put-call parity deviations by Ofek, Richardson, and Whitelaw (2004), the U.S. TIPS-Nominal Bonds puzzle by Fleckenstein, Longstaff, and Lustig (2010), and the CIRP violation puzzle by Coffey, Hrung, and Sarkar (2009), and Griffoli and Ranaldo (2011).[1] The American Depository Receipts (ADR) anomaly is discussed by Chung (2005) who investigates how changes in the Thai baht exchange rate during the period of the Asian financial crisis impacted prices, trading activity and the liquidity of ADRs. Gagnon and Karolyi (2010) use a vast data set to compare intraday prices and quotes of ADRs in the U.S. market with synchronous prices of their home-market shares, and find that while deviations from price parity are, on average, small, they can be volatile, and are related to country-level proxies for limits to arbitrage.

We are distinguished from many of these studies in terms of both the structure of our data and the type of questions we ask. Our empirical analysis is based on the data from large and liquid markets, where shorting costs are tiny and symmetrical across currency denominations, and the two assets converge in value at maturity. Moreover, the nature of our data set allows us to address a set of different questions than the previous literature: what are the cross-sectional and geographical differences in LOP deviations, and how are they correlated with the respective funding markets?

Literature Stream 3: The third stream of the literature investigates the role of institutional and credit frictions in the international provision of liquidity. Ivashina, Scharfstein, and Stein (2012) argue that, during credit crisis, shocks to U.S. money-market funds caused a sharp reduction to the funding provided to European banks, which created a wedge between the cost of USD and Euro funding. They suggest that a potential driver behind the persistent violations of covered interest rate parity, observed during 2008 market turmoil, can be found in a framework in which a European bank would cut USD lending more than Euro lending in response to a shock to its credit quality.

This stream also focuses on how systemic liquidity shocks that originate from one market are transmitted to local lending channels of other markets (Tong and Wei (2011); Schnabl (2012)); and how global banks contribute to the amplification of the international transmission of local liquidity shocks (Cetorelli and Goldberg (2012); Giannetti and Laeven (2012)). To the best of our knowledge, our work is the first to show the presence of a cross-sectional sign difference in the LOP deviations, which are related to different funding frictions across different geographies.

Literature Stream 4: The fourth stream of the literature is related to the literature on credit risk pricing. This stream has developed in two directions.

The first direction deals with the decomposition of yield spreads in a *single*-currency setting (Elton, Gruber, Agrawal, and Mann (2001); Collin-Dufresne, Goldstein, and Martin (2001); Longstaff, Neis, and Mithal (2005)). These studies show that yield spread levels and dynamics are difficult to reconcile with traditional structural credit risk models with additive preferences when calibrated

[1] Refer to Gromb and Vayanos (2010) for an excellent treatment of the main literature on market anomalies.

to historical default and recovery rates. Collin-Dufresne, Goldstein, and Martin (2001) argue the existence of a systematic factor that is not identifiable from traditional risk factors. Elton, Gruber, Agrawal, and Mann (2001) decompose corporate bonds into default risk, tax premium and risk premium, showing that the majority of the dynamics is explained by a systemic factor. Similarly, Collin-Dufresne, Goldstein, and Martin (2001) discuss the existence of a systematic factor, which is not identifiable from traditional priced risk factors. After decomposing the credit yield spreads, they argue that traditional models of default risk explain relatively a small portion of the change in credit yield spreads. Although both works focus on a single currency, they provide a useful insight into how credit risk premiums across different currencies would behave in the market. Their results support that the credit risk premium of a single issuer may not be explained only by the unit-free default risk, and may be related to other unit-bearing determinants, which may indeed differ across currencies. On the other hand, Longstaff, Neis, and Mithal (2005) decompose credit spreads into default and non-default components, and conclude that the majority of the bond yield spreads is actually explained by default risk.

The second direction deals with yield spreads of a single issuer in a *multi*-currency setting. Examples include studies on currency dependence in credit factor risk models (Kercheval, Goldberg, and Breger (2003)), the impact of the correlation between default variables and exchange rates (Jankowitsch and Pichler (2005)), and the impact of sudden devaluations (Ehlers and Schonbucher (2006)). To be more specific, Kercheval, Goldberg, and Breger (2003) derive a covered interest arbitrage condition, where the changes in the credit risk premiums of a single issuer, across two currencies, are expected to be highly correlated, and of the same sign and similar magnitude. Their findings suggest that the Euro, Sterling, and USD credit spreads of an issuer, (i.e. Toyota, Dresdner Bank, European Investment Bank), is weakly correlated during 1999 - 2001, and are highly currency-dependent, implying that the cross-currency risk premiums (of a single issuer) may not fully represent the perceived creditworthiness of that issuer. Furthermore, Ehlers and Schonbucher (2006) discuss a theoretical framework where the difference in cross-currency risk premiums is not only driven by the dependency between the default risk of the obliger and the exchange rate, but also by sudden devaluations (jumps) in the market. Jankowitsch and Pichler (2005) show that the risk premiums must be identical for a single issuer as long as the default variables and exchange rates are uncorrelated. Their findings point to the existence of currency dependence in international corporate bonds. Landschoot (2008) shows how corporate credit spreads in two different currencies (i.e USD and Euro) of two different issuers (i.e U.S. and Euro Zone) respond to various yield factors and market factors. The paper concludes that USD credit spreads, compared to their Euro counterparts, react more strongly to changes in the level and the slope of the risk-free term structure, the stock market returns and their volatility. These questions are important, since it is common market practice among investment banks, data suppliers (i.e. Reuters and Bloomberg) and rating agency companies (i.e. Moody's and Standard Poors) to employ USD as an input to price the credit risk of products that make reference to the same issuer, even across different currency denominations. The implicit assumption is that the FX market is liquid and deep enough to make the USD a perfect substitute for other currencies, and that yield spreads (across two currencies) are functions only of the underlying risk-free rates and the default credibility of the issuer.

Literature Stream 5: The fifth stream is related to the role of specialized institutions (particularly hedge funds) in ensuring market efficiency by trading assets with similar cash flows. Shleifer and Vishny (1997) argue that the ability of a specialized hedge fund in stabilizing prices can be substantially hindered by the behavior of performance-based, uninformed investors who could redeem capital after negative fund performance. As an empirical validation, Fleckenstein, Longstaff, and Lustig (2010) find strong evidence of the healing impact of arbitrage-related hedge funds on the convergence of TIPS-Treasury mispricing. The negativity of their slope coefficient shows that the corresponding mispricing indeed diminishes with increasing hedge fund returns, and thus with positive hedge fund performance and higher amounts of capital available. Moreover, Liu and Mello (2011) focus on how risk of coordination (i.e. uncertainty about behavior of other investors) might lead to the vicious cycle of capital withdrawals that would result in further LOP discrepancies. Furthermore, Mitchell and Pulvino (2012) establish the role of hedge fund rehypothecation in the widening of LOP deviations in the wake of 2008 crisis. They document that hedge fund deleveraging (due to rescission of prime brokerage debt financing) leads to a severe capital dry-up, which then forces hedge funds to reduce or liquidate their positions, eventually causing prices to diverge further away from their relative fundamentals. To the best of our knowledge, our work is the first to quantify the impact of hedge fund capital (from both equity and debt sides) on the growth of LOP deviations.

Literature Stream 6: The sixth stream is related to common factor models and their applications on large data sets of economic series (see Stock and Watson (2002a), Stock and Watson (2002b); Bai and Ng (2002), Bai and Ng (2006); Ludvigson and Ng (2009)). It is argued by Stock and Watson (2002b) that a factor model allows to capture the covariance of a large set of different economic series by a small number of unobserved common components, which can be consistently generated via principal components analysis. This approach has three main advantages: (1) structural instabilities and idiosyncratic shocks are ironed out in the process of common factor generation if they differ substantially among the given economic series (see Stock and Watson (2002a)), (2) predictability of real economic indicators is substantially improved when the forecasting is based on large data sets as opposed to low-dimensional regressions (see Stock and Watson (2004)), and (3) it can deal with a large set of variables without facing the scarce degrees of freedom problems (see Breitung and Eickmeier (2005)).[2] Although there is a growing stream of literature that finds strong links between LOP deviations and financial market risks, there is little evidence between the link of the former and macroeconomic shocks.

Literature Stream 7: The eighth stream is related to the literature that studies the policy implications on market anomalies. Regarding the defining features of the recent liquidity crisis, Borio (2008) highlights, first, the idiosyncratic attributes (e.g. financial innovation of credit structured products, and limitations of originate-and-distribute model), which led to excessive risk-taking under the illusion of security; and second, the common fundamental attributes (e.g. thirst for the expansion of credits and balance sheets during times of economic booms), which tend to build up in time to cause severe financial imbalances. Borio (2008) argues that both these attributes, though mostly the common factors, need to be addressed via the improvement of transparency and risk management systems, as well as the refinement of monetary policies that manage efficient liquidity funding to interbank markets. Furthermore, Gromb and Vayanos (2010) highlight the role of specialized institutions in the optimal allocation of capital, and their impact on socially optimal decisions. Krishnamurthy (2010) argues that financial crises, including the subprime and Lehman's collapse, provide a compelling example of how government intervention can play a role in the smooth functioning of financial markets. Geanakoplos and Polemarchakis (1986) show that in the presence of market frictions, market incompleteness creates the possibility of Pareto improvements triggered by public intervention. The research on LOP anomalies is no doubt linked to the debate on the optimal design of public policies during financial crises. However, the literature that specifically deals with this issue is limited, even though it deserves careful attention. This paper aims to deliver how important (or not) the role of regulation is on the dynamics of LOP deviations, as a possibly new stream of literature that might lead to further research.

[2] Other important applications of dynamic factors models show other benefits of the method in the investigation of a wide array of macroeconomic activities and policy analysis (see Bernanke and Boivin (2003); Stock and Watson (2005); Boivin and Giannoni (2005); Ludvigson and Ng (2007)).

Chapter 3

Mispricing in Emerging Markets: Evidence from Cross-Sectional Data

As a way of meeting long-term funding needs in international markets, it is common practice for sovereigns and multinational corporations to issue long-term bonds denominated in currencies that are strictly foreign to the local currency of the issuer. These bonds are called Eurobonds, which tend to offer fixed coupon flows over their lifetime, and are regarded as fairly attractive debt instruments, as they give issuers the versatility of financing themselves in any foreign currency they could issue. For instance, a large number of emerging sovereigns, such as Brazil, Mexico and Turkey, issue both USD- and Euro-denominated bonds with similar time-to-maturities, even though their local currency is neither USD nor Euro.

In this chapter we discuss that, in a frictionless market, the yields of emerging market Eurobonds (denominated in two foreign currencies) should approximately satisfy a simple LOP condition when their time-to-maturities, coupon structures, and expected recovery rates are very similar. We state that the price of a USD-denominated Brazilian bond, for instance, should be more or less equal to that of a synthetic USD bond that is constructed by swapping each future cash-flow of the Euro-denominated bond of the same issuer into dollars via the USD/EUR FX forward market. This means that traders, who short the USD-denominated bond and long the Euro-denominated bond, should do no better than meeting their dollar obligations by converting their Euro receivables into dollars, and should leave the trade with roughly zero profit/loss. The same logic applies to traders who long the USD-denominated bond and short the Euro-denominated bond. Otherwise, they would be in a position to extract a sizable return by exploiting the two nearly-identical debt securities of a single issuer.

During the 2007-2008 crisis, several institutional investors reported the existence of such an opportunity in the Eurobond markets, relating to the foreign bonds of emerging countries. But the question is whether the LOP was genuinely impaired in these markets after carefully accounting for transaction costs, exchange rate risks and structural limitations? This chapter investigates the dynamic properties of this specific case with a focus on emerging countries. We study the extent to which our constructed LOP proxy, called $Basis_{\text{bond}}$ is time-varying and state-dependent, and how it has changed before, during and after the 2007-2008 crisis. Indeed, while we find no evidence of a severe violation before 2007, a significant anomaly emerges during the 2008-2009 Credit Crisis, lasting not merely a few days but over three months. To be more precise, we find that, by mid-October 2008, $Basis_{\text{bond}}$ of the 2010-maturity Brazilian bonds reached 407 bps after hedging out the exchange rate risk and accounting for transaction costs. Around the same period, this deviation was 209 bps for 2015-maturity Brazilian bonds, 136 bps for 2020-maturity Mexican bonds, 169 bps for 2014-maturity Turkish bonds, and 201 bps for 2019-maturity Turkish bonds. These are large values indeed, given the liquid nature of these securities.

There is a flourishing literature studying such market anomalies, even though, to the best of our knowledge, a case of Eurobond mispricing has never been discussed in the literature before. Some of the most significant anomalies include the U.S. TIPS-Treasury Bond puzzle (Fleckenstein, Longstaff, and Lustig (2010)), the CIRP puzzle (Griffoli and Ranaldo (2011)), and the CDS-bond basis (Garleanu and Pedersen (2011), Bai and Collin-Dufresne (2011)) and the Siamese-Twin stocks puzzle (Rosenthal and Young (1990)). A differentiating feature of our work is that it provides both cross-sectional and time-series information across different emerging markets. Moreover, while the CDS-bond basis refers to a spread between two somewhat different assets, with substantially different liquidity and counterparty risks (a feature that is notoriously difficult to measure precisely), sovereign bond pairs are more homogeneous, even though they also suffer from certain structural limitations (to be discussed later). In addition, sovereign bond markets are substantially more liquid compared to twin stocks. Furthermore, bonds have a finite terminal resolution of uncertainty, so that the cash flows of the two legs of the trade must converge in finite time (either at maturity or at default).

In this chapter we proceed as follows. First, we extend the covered interest rate parity (i.e. CIRP) condition and derive an LOP relationship that should hold for the bonds denominated in two different currencies by the same issuer. Second, we select the three most important emerging sovereign bond markets (by notional amount outstanding) with bond issues denominated in both USD and Euro (i.e. Turkey, Brazil, and Mexico). These countries have four important features: (a) they have large and liquid Eurobond markets, in which trading costs were small before the crisis, (b) they were "remote" to the epicenter of the subprime crisis, as they were upgraded by credit rating agencies between 2007 and 2011, (c) their bond prices more or less satisfied the LOP prior to the crisis, and (d) they provide multiple pairs of tradable assets across different continents. Third, we identify specific bond pairs from the same issuer with nearly identical maturities in USD and Euro. Fourth, we construct an LOP proxy called $Basis_{\text{bond}}$ based on shorting the USD-denominated bond and longing the EUR-denominated bond of the same issuer, and converting the future cash flows of the Euro-denominated bond into USD in the forward FX markets. Fifth, we investigate the state-dependent dynamics of $Basis_{\text{bond}}$ before, during and after 2007-2008 crisis. Sixth, we quantify the impact of the structural limitations of the trade arising from the cash-flow mismatches.

We find a number of interesting results. There is strong evidence that, while $Basis_{\text{bond}}$ (net of transaction costs) across Brazil, Mexico and Turkey fluctuated close to zero during Pre-Crisis, it became markedly large, highly volatile, and strongly persistent during Credit Crisis. Multiple hypothesis tests reveal that the character of $Basis_{\text{bond}}$ changes substantially from Pre-Crisis to Credit Crisis across all countries, suggesting the presence of a severe distributional shock across different subsamples. It is also found that the sign of $Basis_{\text{bond}}$ deviations differ from one geography to another. When the trade is constructed by shorting the USD bond and longing the Euro bond for each country, it is mostly the case that Turkish $Basis_{\text{bond}} < 0$, whereas Mexican and Brazilian $Basis_{\text{bond}} > 0$. The negativity of the LOP deviation in Turkey, and positivity of it in Brazil and Mexico suggest the presence of potential frictions that operate at a geography-specific level. It also implies that Turkey often pays higher yield (and risk premium) in USD, whereas Brazil and Mexico often pay higher yield (and risk premium) in Euro. This casts doubt about whether the creditworthiness of a certain sovereign is truly universal across its debt-securities with different foreign currency denominations. Furthermore, our scenario-based assessments of structural limitations clearly show that the impact of cash-flow mismatches is extremely unlikely to explain the $Basis_{\text{bond}}$ deviations, which opens the door to Chapter 4 where we search for those exogenous state-dependent factors that are responsible for this pricing anomaly.

This chapter is organized as follows: Section I details the theoretical framework of the potential mispricing in emerging market sovereign bonds that are denominated in two foreign currencies to the issuer. Section II gives the data description on the constituents of $Basis_{\text{bond}}$. Section III details the construction of $Basis_{\text{bond}}$ as an LOP proxy, and Section IV discusses the dynamics of $Basis_{\text{bond}}$ and the associated multi-sample hypothesis tests during different subsamples. Section V quantifies the impact of structural limitations inherent in the $Basis_{\text{bond}}$ trade. Section VI prepares for the next chapter and concludes with a discussion on how to interpret the $Basis_{\text{bond}}$ anomaly. Section VII and Section VIII, respectively, give Appendix A and Appendix B.

I. LOP Restriction in Sovereign Bond Markets

A. Zero-Coupon Framework

In the absence of frictions, the Law of One Price suggests a simple link between contingent claims denominated in different currencies. This relationship, known in international finance as the covered interest rate parity (CIRP), requires that at time t=0 the returns of two riskless investments with maturity $T = 1$ year must satisfy:

$$[1 + R^a(t,T)] = \frac{X(t)}{F(t,T)}[1 + R^b(t,T)] \tag{3.1}$$

where $R^i(t,T)$ is the underlying annual risk-free rate in the two corresponding currencies $i = (a,b)$ - with a=USD and b=EUR, respectively - and $X(t)$ and $F(t,T)$ are the EUR/USD (EUR per unit of USD) spot and forward exchange rates, respectively.

An investor can borrow one dollar today, owing $[1 + R^a(t,T)]$ at maturity T, convert it to $X(t)$ Euros at time t, invest in a Euro deposit, and thus receive $X(t)[1 + R^b(t,T)]$ Euros at maturity T. If the forward exchange rate for time T is $F(t,T)$, the dollar value of this investment is $[X(t)/F(t,T)][1 + R^b(t,T)]$, which therefore needs to equal $[1 + R^a(t,T)]$ unless an arbitrage opportunity exists. If, for instance:

$$[1 + R^a(t,T)] < \frac{X(t)}{F(t,T)}[1 + R^b(t,T)] \tag{3.2}$$

such that $[1 + R^a(t,T)] = \$1.2$ and $X(t)[1 + R^b(t,T)]/F(t,T) = \$1.7$, the arbitrageur would lock-in a profit of \$0.5 at time T if he would borrow 1 USD at time t by shorting the given riskless USD security, and later convert the 1 USD into $X(t)$ Euros, and lend these Euros by longing the riskless Euro security, while committing simultaneously to a forward exchange contract that would convert the future Euro receivable into dollars via $F(t,T)$.

One may consider extending the CIRP from default-free zero-coupon bonds to defaultable zero-coupon bonds. Imagine, for instance, two pure discount bonds with maturity T, issued by Brazil, in two foreign currencies (i.e. USD and EUR). The arbitrageur has contemporaneous access to both spot and forward FX markets. Consider the following conditions:

- $\mathcal{C}1$ *Liquidity Constraints.* The two bonds are identical in terms of liquidity. Both bond markets are accessible by the arbitrageur at the same time.
- $\mathcal{C}2$ *Short-selling Constraints.* The two bonds are not subject to short-selling constraints, or the

inventory in the broker-dealer market is such that the two bonds have identical short-selling costs.

$\mathcal{C}3$ *Funding Constraints.* Each arbitrageur has free access to raise short-term and long-term capital in both USD and EUR.

$\mathcal{C}4$ *Simultaneous Default.* The two bonds have simultaneous default.

$\mathcal{C}5$ *Pari Passu.* The two bonds are pari-passu and the risk-adjusted recovery values are the same for both bonds.[1]

Proposition 1. *Let the credit yield spreads (paid over the risk-free rates) of the two bonds in USD and Euro be denoted by $S^a(t,T)$ and $S^b(t,T)$, respectively. When conditions $\mathcal{C}1$ - $\mathcal{C}5$ hold, the following holds:*

$$[1 + \underbrace{R^a(t,T) + S^a(t,T)}_{Y^a(t,T)}] = \frac{X(t)}{F(t,T)}[1 + \underbrace{R^b(t,T) + S^b(t,T)}_{Y^b(t,T)}] \tag{3.3}$$

where yield-to-maturity of the bonds in USD and Euro are denoted by $Y^a(t,T)$ and $Y^b(t,T)$, respectively.

Proof. See Appendix A to Chapter 3. □

Indeed, a trader with unlimited access to forward markets can replicate synthetically the USD bond with a EUR bond after hedging the future cash flows in the FX forward market. Notice that under the previous conditions, since bond cash-flows are identical state-by-state, the concepts of no-arbitrage, market integration and covered interest rate parity coincide.

Re-arranging Eq. (3.3), we can obtain the following decomposition:

$$\underbrace{\left[\frac{X(t)}{F(t,T)}[1 + R^b(t,T)] - [1 + R^a(t,T)]\right]}_{\text{CIRP Component}} + \underbrace{\left[\frac{X(t)}{F(t,T)}S^b(t,T) - S^a(t,T)\right]}_{\text{Spread Component}} = 0 \tag{3.4}$$

It can be stipulated that under LOP condition, both CIRP and Spread components must be equal to zero in a frictionless market. If LOP is violated, this might be due to (i) the violation of the CIRP component and not the Spread component; or (ii) the violation of the Spread component and not the CIRP component; or (iii) the violation of both components at the same time. This concept will be revisited in Section III, Chapter 4.

[1] This may not be the case when one of the two bonds is denominated in the domestic currency of the issuer. Since countries that do not peg their currency have control over their monetary policy, they can formally avoid default on their domestic bonds by printing local currency.

B. *Coupon Framework*

Our framework involves coupon-paying Eurobonds issued by the same emerging market sovereign in USD and Euro. Assume that both bonds have the same maturity, same coupon timing, and same coupon frequency. Consider that a trader shorts the USD bond of Brazil, for instance, and simultaneously longs Brazil's equivalent Euro bond, after converting the initially borrowed USD amount into Euro via the spot FX market. The trader must convert the Euro proceeds to dollars in the forward FX market at each cash-flow date, in order to meet the dollar obligations on the liability side.

Let us denote C_j^a as the j^{th} dollar cash-flow of the annual-coupon USD bond; C_j^b as the j^{th} Euro cash-flow of the annual-coupon EUR bond; and $[1/F_j]$ as the USD/EUR Forward FX rate exercised at j^{th} cash-flow date. Note that $C_j^b[1/F_j] = C_j^{a^*}$ across the lifetime of the given EUR bond would create a synthetic USD bond. The difference between the present values of the cash-flows of the synthetic USD bond and the original USD bond is:

$$D = \sum_{j=1}^{m} \frac{C_j^{a^*}}{(1+Y^a)^j} - \sum_{j=1}^{m} \frac{C_j^a}{(1+Y^a)^j} \tag{3.5}$$

where Y^a is the market yield of the USD bond, and m is the total number of cash-flows. As mentioned before, Y^a consists of the underlying risk-free rate plus the credit yield spread.

Let Y^{a^*} be the yield of the synthetic USD bond. Y^{a^*} is the yield that equates the present value of the synthetic USD bond's future cash-flows to the present value of the original USD bond's future USD cash-flows. Therefore:

$$\sum_{j=1}^{m} \frac{C_j^{a^*}}{(1+Y^{a^*})^j} = \sum_{j=1}^{m} \frac{C_j^a}{(1+Y^a)^j} \tag{3.6}$$

Substituting Eq. (3.6) into Eq. (3.5);

$$\begin{aligned} D &= \sum_{j=1}^{m} \frac{C_j^{a^*}}{(1+Y^a)^j} - \sum_{j=1}^{m} \frac{C_j^{a^*}}{(1+Y^{a^*})^j} \\ &= \sum_{j=1}^{m} C_j^{a^*} \left[\frac{1}{(1+Y^a)^j} - \frac{1}{(1+Y^{a^*})^j}\right] \end{aligned} \tag{3.7}$$

For no-arbitrage, we must have D=0, which implies $Y^{a^*} = Y^a$. For $D \neq 0$, we must have $Y^{a^*} \neq Y^a$. The logic here is that a potential trader, who shorts the USD-denominated bond and longs the Euro-denominated bond of a single issuer could do no better than meeting his dollar obligations by converting his Euro receivables into dollars, and leave the trade with zero profit/loss. If $Y^{a^*} > Y^a$, the expected return of the synthetic bond would be higher than the original cash USD bond.

Structural Limitations - Preview

In reality, however, the maturities of the bonds, as well as the coupon rates, timings and frequencies do not exactly match, and the forward FX rates are not constant. Under these limitations, there is no room for a guaranteed arbitrage setting. However, we hypothesize that any sizable deviation of $Y^{a^*} - Y^a$ from zero would nonetheless give us a plausible approximation and a useful insight about a potential anomaly in Eurobond markets. Part of this deviation would be traced to the structural mismatches in the cash-flows (discussed in Section V of this chapter), but part of it would depend on the economic risk factors that become increasingly pronounced and relevant during turmoil periods (discussed in Chapter 4). Therefore, if $Y^{a^*} - Y^a$ is unusually large relative to past trends (based on multi-sample hypothesis tests), it becomes reasonable to question as to whether there is indeed a reason for deviation *beyond* these structural limitations, and whether any state-dependent economic risk factors and geographical frictions could also be responsible for it. This is what we aim to investigate in this and the next chapter. We validate our hypothesis in the following sections, where we show that $Basis_{\text{bond}}$ differs greatly in magnitude and volatility during different economic periods, and that it is indeed affected by different economic risk factors and geographical frictions.

II. Data Description and Exploratory Analysis

A. *Bond Yield Data*

Covering the period between July 2005 to April 2010, we collect daily data on U.S. and Euro risk-free rates and EUR/USD spot and forward exchange rates (1 week to 10 years) using matching end-of-day Bloomberg data. From the same source, and for the same time period, we also obtain daily bid-ask prices and yields on Euro- and USD-denominated bonds of maturities up to 30 years for the three largest emerging market (i.e. EM) sovereign issuers: Turkey, Brazil, and Mexico. These countries have issued a large cross-section of bonds across both currencies in the ten years prior to the Crisis. Bid-ask prices and yields are retrieved as the end-of-day (17:00) weighted average of the quotes submitted by a minimum of five brokers and dealers (Bloomberg BGN).[2] This procedure does not pick the lowest (highest) price offer, but assigns a weight to each contributor based on

[2] See also Blanco, Brennan, and Marsh (2005), Chen, Lesmond, and Wei (2007), Landschoot (2008), Fleckenstein, Longstaff, and Lustig (2010), and Bao, Pan, and Wang (2011) for examples using BGN prices.

specific factors, such as the updating frequency. This allows for the minimization on the impact of measurement error from a specific broker dealer, and makes prices more reflective of market conditions. For particular currency pairs, BGN prices are adjusted to trading hours.

All bonds have fixed coupon rates and are neither callable, puttable, structured, or convertible. Brady Bonds are excluded.[3] We also exclude domestic bonds and/or bonds governed by domestic jurisdictions. After these filters, as of July 2005, Turkey has 10 Euro- and 22 USD-denominated bonds outstanding. Brazil has 6 Euro- and 22 USD-denominated bonds and Mexico has 5 Euro- and 10 USD-denominated bonds outstanding.[4] Our sample shows that the emerging market Eurobonds do not suffer from stale prices.[5]

From this sample, we pool and match the USD- and Euro-denominated bonds for Brazil, Mexico and Turkey with respect to their maturity dates. We define the maturity mismatch as the number of days between the maturities of USD- and Euro-denominated bonds for each country. Accordingly, we only include bond pairs with a maturity mismatch of less than or equal to 70 days (see also Fleckenstein, Longstaff, and Lustig (2010)). This is the case for the 2010-maturity Brazilian bonds (maturity mismatch of 70 days), the 2015-maturity Brazilian bonds (maturity mismatch of 32 days), the 2014-maturity Turkish bonds (maturity mismatch of 26 days), the 2019-maturity Turkish bonds (maturity mismatch of 22 days), and the 2020-maturity Mexican (maturity mismatch of 49 days). Table 3.1 displays the summary statistics of the given bond pairs used in our analysis.

The preliminary observations are worth discussing. The common pattern in all bonds is that the yields in both USD and Euro tend to increase from Liquidity Crisis to Credit Crisis, and then decrease during Post-Crisis period.[6] Given that the bond yield is a function of the underlying risk-free rate and the credit yield spread (i.e. credit risk premium), this very pattern alone suggests that the market perceives the emerging country bonds increasingly "risky" during Credit Crisis.

In Turkey, for instance, the average yield (volatility) of 2014 EUR-denominated bond, from Liquidity to Credit Crises, increases by 1.21% (0.92%), that is from 6.10% (0.48%) to 7.31% (1.40%), while the average yield (volatility) of the equivalent USD-denominated bond increases by 1.57%

[3]Claessens and Pennacchi (1996) argue that the price of a Brady bond, having a third-party guarantee, does not accurately reflect a country's fundamental creditworthiness, and hence require additional adjustments.

[4]Note that the number of bonds denominated in Euro is usually smaller than in USD. This is because the USD-based Eurobond market is still more popular among investors, although the Euro-based Eurobond market has been on the rise since the introduction of Euro in 2000.

[5]During Credit Crisis, there are at most two instances when prices are stale: (1) for one day, and (2) for two days. The instance (1) is observed only for 2015-maturity Brazilian EUR- and USD-denominated bond; and instance (2) is observed only for 2019-maturity Turkish EUR-denominated bond, and 2015-maturity Brazilian USD-denominated bond. Total number of days when prices are stale is only six across all five bond pairs (ten bonds) with 153 trading days for each bond (a total of 1530 trading days for all bonds) during Credit Crisis. Therefore, the rate of occurrence of stale prices is less than 0.4%.

[6]Note, however, that the average Pre-Crisis yield levels of 2010 and 2015 USD-denominated bonds of Brazil are higher than those of the Credit Crisis. This is the only exception in our entire cross-sectional sample (the same pattern does not hold for Brazil's EUR-denominated bonds, for instance.). Excluding Brazil's USD-denominated bonds, the Credit Crisis yield levels are always higher than the Pre-Crisis levels across all bonds in the corresponding emerging countries.

(1.19%), that is from 6.23% (0.40%) to 7.80% (1.59%). While the the average yield (volatility) of 2014 EUR-denominated bond, from Credit Crisis to Post-Crisis, decreases by 2.97% (0.66%), that is from 7.31% (1.40%) to 4.34% (0.74%), the average yield (volatility) of the equivalent USD bond decreases by 3.01% (0.71%), that is from 7.80% (1.59%) to 4.79% (0.88%), during the same period.

In Brazil, for instance, the average yield (volatility) of 2015 EUR-denominated bond, from Liquidity to Credit Crises, increases by 1.40% (0.96%), that is from 5.82% (0.33%) to 7.22% (1.29%), while the average yield (volatility) of the equivalent USD-denominated bond increases by 0.91% (0.81%), that is from 5.49% (0.26%) to 6.40% (1.07%). While the the average yield (volatility) of 2015 EUR-denominated bond, from Credit Crisis to Post-Crisis, decreases by 2.96% (0.60%), that is from 7.22% (1.29%) to 4.26% (0.69%), the average yield (volatility) of the equivalent USD bond decreases by 1.96% (0.44%), that is from 6.40% (1.07%) to 4.44% (0.63%), during the same period.

In Mexico, for instance, the average yield (volatility) of 2020 EUR-denominated bond, from Liquidity to Credit Crises, increases by 1.82% (0.36%), that is from 5.59% (0.39%) to 7.41% (0.75%), while the average yield (volatility) of the equivalent USD-denominated bond increases by 1.22% (0.69%), that is from 5.47% (0.22%) to 6.69% (0.91%). While the the average yield (volatility) of 2020 EUR-denominated bond, from Credit Crisis to Post-Crisis, decreases (increases) by 1.81% (0.13%), that is from 7.41% (0.75%) to 5.60% (0.88%), the average yield (volatility) of the equivalent USD bond decreases by 1.28% (0.47%), that is from 6.69% (0.91%) to 5.41% (0.44%), during the same period. This suggests that the funding costs and the credit riskiness of the given bonds tend to diminish once again as of Post-Crisis period.

Another interesting feature is that, between Liquidity Crisis and Credit Crisis, Turkey generally pays higher yields in USD than Euro, whereas Brazil and Mexico generally pay higher yields in Euro than USD. Moreover, during the same period, in Turkey, the increase in the average level and volatility of the USD yields is considerably steeper than that of the EUR yields. In Brazil and Mexico, the opposite is often the case (except for the volatility trend in Mexico). This suggests that the market tends to perceive Turkey comparably more "risky" in USD than Euro, whereas the exact opposite holds for Brazil and Mexico. This is an important observation, and is the first hint about the geographical difference of the funding markets across different emerging markets, which will be discussed in further detail in the next chapter.[7]

[7] Please also note that the trade could be constructed using CDSs rather than bonds across two currency denominations. Nevertheless, while USD-denominated CDSs are highly liquid, there is no healthy history on EUR-denominated CDSs in the emerging markets under study.

B. The Paris Club

Defaults of sovereign bonds denominated in foreign currencies are often governed by the debt treatment clauses of the Paris Club, an organization of creditors that coordinates the payment process of the debtor countries, and that enforces pari passu conditions when they apply. The main objective is to ensure the sustainability of equal conditions for all investors in terms of both bond maturity and recovery rates. This aim stems also from the "comparability of treatment" clause, under which "all external creditors must be subject to a balanced treatment for the outstanding debts of the debtor countries". The intent of this clause is to avoid instances of selective default and to ensure, in case of restructuring, equal exposure of all creditors irrespective of the applicable currency. The existence of this comparability clause confirms the widely held assumption that recovery rates of bonds of the same country are equal across different (foreign) currency denominations. To address concerns related to condition $\mathcal{C}5$, bonds included in our analysis are governed by similar jurisdictions, and are regulated by similar collective clause action rules. With two bonds being pari passu, the recovery rates should be the same.[8]

III. Construction of LOP Proxy: Basis(bond)

To construct our LOP proxy in sovereign Eurobond markets, we follow a similar procedure used by Fleckenstein, Longstaff, and Lustig (2010) who compute the TIPS-Treasury pricing anomaly. As discussed in the Data Description section, we use the pairs of bonds from the same issuer with nearly matching maturities: 2010- and 2015-maturity Brazilian bonds; 2014- and 2019-maturity Turkish bonds; and 2020-maturity Mexican bonds. For each bond pair for each country, the analysis is structured around carrying out the following steps.[9]

1. Short 100 USD of semi-annual coupon USD-denominated bond, convert the dollar proceeds into Euros in the spot FX market using the spot FX rate, X(t), and long the annual coupon EUR-denominated bond (by the same issuer) using the Euro proceeds.

[8] Ukraine's default provides a useful example of how equal conditions apply across currency denominations. Following its independence, Ukraine sustained its development by issuing large amounts of foreign denominated debt. In February 2000, however, its Finance Ministry declared that Ukraine would have failed to meet its coupon repayment for a specific Eurobond issue denominated in DM (i.e. the 16% DM bonds). In January, Ukraine also defaulted on the coupon payment for the 16.75% USD Eurobonds. After several rounds, a restructuring plan was coordinated to give bondholders the option of choosing between two 7-year coupon amortization bonds (with average terms of 4.5 years) denominated either in USD or Euro in exchange for the old debt. The terms of the restructuring were symmetric for both Euro and USD bond holders. A detailed calculation leads to estimates for the USD and Euro haircuts that differ only by a decimal of a percent (see Sturzenegger and Zettelmeyer (2005) for details), consistent with the "comparability of treatment" clause.

[9] Note that this analysis more general than that used in subsection IB in the sense that it incorporates the effect of accrued interest to allow for bonds traded on intermediate dates between two consecutive cash-flows.

2. Calculate the total face value (FV^b) corresponding to the total purchased amount of the EUR-denominated bond:

$$FV^b = \frac{PV^b}{A+B} \quad where \quad A = \sum_{j=1}^{m} \frac{CL^b}{(1+Y^b)^{k_j}} \text{ and } B = \frac{1}{(1+Y^b)^{k_m}} \tag{3.8}$$

where PV^b = 100*X(t) is the total present value of the purchased EUR-denominated bond; Y^b is the annual market yield of the EUR-denominated bond; CL^b is the Euro coupon rate given as a percentage of FV^b; and $k_j = [j^{th}$ Euro Coupon Date - Date $t]/365$, measured in years, for $j = [1, ...m]$ with m being the maturity point. Date t is the first day that the trade is launched by the arbitrageur. Note that the information of CL^b is publicly available for all bonds (as shown also in table 3.1).[10]

3. Having found the total face value corresponding to the total purchased amount of the EUR-denominated bond, generate the fixed coupon payment flows (i.e. C^b) for each coupon date for EUR-denominated bond, such that $C^b = CL^bFV^b$. In other words, find the physical coupon amounts by multiplying the coupon rate (in %) by the total face value.

4. Enter into a series of USD/Euro (USD per Euro) FX forward contracts to convert the calculated Euro coupon flows C^b at *each* coupon date, and the face value FV^b at the maturity date, into USD cash flows. If there are ten coupon payment dates, for instance, enter into ten different FX forward contracts so that each contract has the exact same maturity with each corresponding future cash-flow date.[11] This procedure constructs a synthetic USD bond that has variable coupons (due to variable forward rates), represented by:

$$\begin{aligned} PV^{a^*} &= \sum_{j=1}^{m} \frac{C^b/F_j}{(1+Y^{a^*})^{k_j}} + \frac{FV^b/F_m}{(1+Y^{a^*})^{k_m}} \\ &= \sum_{j=1}^{m} \frac{C_j^{a^*}}{(1+Y^{a^*})^{k_j}} + \frac{FV^{a^*}}{(1+Y^{a^*})^{k_m}} \end{aligned} \tag{3.9}$$

where PV^{a^*} denotes the initial cash-flow of the synthetic USD bond, which is obviously equal to PV^a = 100 USD; $[1/F_j]$ is the USD/EUR Forward FX rate to be implemented at j^{th} coupon date; $C_j^{a^*} = C^b/F_j$; $FV^{a^*} = FV^b/F_m$; and Y^{a^*} is the yield of the synthetic USD bond that satisfies this equation. The only unknown parameter in this equation is Y^{a^*}.

[10] Based on the previous notation, $Y^b = R^b + S^b$. Empirically, we use the market convention for the day-counts of USD-denominated bonds (30/360) and EUR-denominated bonds (ACT/ACT) and adjust for the accrued interests.

[11] First, interpolate a linear FX forward exchange rate curve using 1 week to 10 years maturity USD/EUR rates (retrieved from Bloomberg) for each corresponding date, so that the maturity date of the FX forward contracts will be identical to the corresponding cash-flow dates at each time t.

5. To calculate Y^{a^*} an iteration routine is developed. First, substitute a seed value into Eq. (3.9) to calculate the first guess for PV^{a^*}.[12] If $PV^{a^*} \neq 100$, then Y^{a^*} is iteratively changed until convergence ($PV^{a^*} = 100$).

6. Define:

$$Basis_{bond} = Y^{a^*} - Y^a \tag{3.10}$$

Example. To provide a specific example, let's take the USD- and Euro-denominated foreign bonds of Brazil. The USD bond matures on March 7, 2015. As an example, consider a trade executed on October 31, 2008. The quoted yield-to-maturity of Brazilian USD bond is $Y^a = 7.54\%$ and the quoted yield-to-maturity for its Euro counterpart is $Y^b = 9.46\%$. With approximately 6.3 years until maturity, the investor shorts 100 dollars-worth of USD-denominated bond, swaps the proceeds to 78.59 Euros in the spot FX market, and purchases 78.59 Euros-worth of the Euro-denominated bond, which pays seven coupons (7.375% of the face value) during the remainder of its lifetime. The calculated total face value corresponding to the total purchased amount of the EUR-denominated bond is 82.01 Euros, and thus the corresponding coupon payments are 6.05 Euros. Using the interpolated market USD/EUR FX forward rates $[1/F_j]$ for each coupon date (every 3rd of February from 2009 to 2015), all Euro cash-flows are converted into USD cash-flows. Since there are seven cash-flow periods, we execute seven forward contracts. This creates a synthetic USD bond consisting of only USD coupon flows, equal to \$7.69 on February 3, 2009, \$7.69 on February 3, 2010, \$7.70 on February 3, 2011, \$7.75 on February 3, 2011, \$7.81 on February 3, 2013, \$7.85 on February 3, 2014 and \$7.85 on February 3, 2015. Finally, the forward-converted face value is \$106.38. The yield-to-maturity of the synthetic bond Y^{a^*}, calculated based on the given USD flows, is 9.68%, after accounting for the bid-ask spreads in the execution of FX contracts. Hence, in terms of bps, $Basis_{\text{bond}} = Y^{a^*}$ - Y^a = 968 bps - 754 bps = 214 bps. Clearly, the synthetic USD bond, constructed from the EUR-denominated bond, generates a substantially higher yield than its original USD counterpart. At each time t and for every bond pair, the bid-ask spreads in the execution of FX contracts are integrated. We also need to account for the transaction costs based on the bond-specific bid-ask spreads involved in the trading of these bonds in the cash market. For this specific example, the total bond-specific bid-ask spread is 12 bps at this date. The $Basis_{\text{bond}}$ is therefore 214 bps - 12 bps = 202 bps, net of all transaction costs.

[12] MATLAB provides an in-built function (stepcpnyield) that calculates YTM for variable coupon bonds. This function, however, does not account for the accrued interest and is therefore not accurate enough for our purposes. In our calculations, therefore, the MATLAB predictions are taken as the seed (initial value) only.

IV. Dynamics of Basis(bond)

As mentioned before, all bonds in our study are coupon bonds. However, the coupons on the USD-denominated bonds have different dates, frequencies and rates than those on their EUR-denominated counterparts. For example, USD-denominated bonds carry semi-annual coupons while EUR-denominated bonds carry annual coupons. These structural mismatches could disrupt the theoretical relationship behind $Basis_{\text{bond}}$. Having said this, we nonetheless hypothesize that it would be legitimate to use our $Basis_{\text{bond}}$ as a *near*-LOP proxy despite structural mismatches.[13] Our main objective in this section boils down to testing this hypothesis (i.e. net $Basis_{\text{bond}}$ is an acceptable measure for LOP mispricing), which requires that (a) net $Basis_{\text{bond}}$ would display a low mean and variance during the disturbance-free Pre-Crisis period, and furthermore, (b) in the event of serious price disruptions, it would undergo statistically significant changes across one or more of the subsamples under study (i.e. Pre-Crisis, Liquidity Crisis, Credit Crisis, Post-Crisis). This section discusses the dynamics of $Basis_{\text{bond}}$ and tests the validity of this hypothesis. The extent to which structural mismatches affect the size and dynamics of $Basis_{\text{bond}}$ is analyzed in Section V.

A. Size of Basis(bond)

For all bond pairs, Figure 3.1 shows the evolution of the gross $Basis_{\text{bond}}$ calculated without transaction costs. It also shows transaction costs of the trade separately to allow for comparison.[14] Note that any sizable gross $Basis_{\text{bond}}$ value in excess of the transaction cost threshold (denoted by the red line in Figure 3.1) points to a mispricing that cannot be explained by transaction costs.

Two immediate results emerge. First, it can be observed that, while the gross $Basis_{\text{bond}}$ exceeds the transaction cost threshold only by small amounts (if at all) during Pre-Crisis, it far outstrips it during the Credit Crisis. This shows that after adjusting for the bid-ask spreads, there still remains significant mispricing in the underlying bonds. Second, the sign of $Basis_{\text{bond}}$ tends to be country-specific. When the trade is constructed by shorting the USD bond and longing the Euro bond, the gross Turkish $Basis_{\text{bond}}$ is generally negative during Credit Crisis, whereas for Mexico and Brazil, it is generally positive. This suggests that, with the interaction of the bond and FX markets, Turkey tends to pay a higher yield in USD, whereas Brazil and Mexico tend to pay a higher yield in Euro. It turns out, therefore, that the appropriate trade in Turkey would be to long the USD bond and short the Euro bond, whereas the exact opposite trade would be taken in Mexico and Brazil. This

[13] Similar concepts have been discussed by Chen and Knez (1995) and Gatev, Goetzmann, and Rouwenhorst (2006).

[14] All figures start from July 2005 for each $Basis_{\text{bond}}$, except for the $Basis_{\text{bond}}$ of Turkish 2019 bond pair, which begins from September 11, 2008, as this was the issuance date of the USD-denominated bond of the corresponding pair, and hence the first possible trading day of the strategy.

cross-sectional difference provides a good opportunity to learn about the nature of the geographical frictions that were responsible for these dynamics. The details of the sign puzzle will be discussed further in Chapter 4.

For the purpose of using in the analyses that follow (summary statistics and hypothesis tests), we re-calculate the "net" $Basis_{\text{bond}}$ by subtracting the total transaction costs of the trade from the absolute value of the gross $Basis_{\text{bond}}$. This approach, recommended by Fletcher and Taylor (1996), is adopted in order to eliminate any confusion arising from the different signs of gross $Basis_{\text{bond}}$. Hence,

$$\text{Net } Basis_{bond} = |\text{Gross } Basis_{bond}| - \text{Transaction Cost} \tag{3.11}$$

The subtraction of transaction cost from the absolute value of the gross $Basis_{\text{bond}}$ represents a "transaction-cost adjustment". According to Fletcher and Taylor (1996), the following should hold:

$$\begin{aligned} \text{Net } Basis_{bond} > 0 \quad &\Rightarrow \quad \text{LOP Deviation} \\ \text{Net } Basis_{bond} \leq 0 \quad &\Rightarrow \quad \text{No LOP Deviation} \end{aligned}$$

Therefore, while a positive net $Basis_{\text{bond}}$ is indicative of LOP deviation, a negative net $Basis_{\text{bond}}$ suggests that the return from the trading strategy is not large enough to compensate the cost, implying that there is no real LOP deviation. Hereafter, unless otherwise noted, all regressions in Chapters 4 and 5 use net $Basis_{\text{bond}}$, as defined in Eq. (3.11). In accordance with this representation (Eq. (3.11)), Table 3.2 shows (in its first three columns) the mean, maximum and standard deviation of net $Basis_{\text{bond}}$, for each analyzed bond pair, and for each subsample. The mean of the total bid-ask spreads is also given in the fourth column of this table. The following discussions are made.

During the Pre-Crisis, the mean (standard deviation) of net $Basis_{\text{bond}}$ is 4 bps (18 bps), 5 bps (14 bps), 18 bps (11 bps) and -5 bps (7 bps) for Brazil 2010, Brazil 2015, Mexico 2020 and Turkey 2014 bonds, respectively. It can be noticed that these values fluctuate close to zero with low mean and variance. This result supports the first requirement (a) of our hypothesis that $Basis_{\text{bond}}$ is a *near*-LOP proxy.

During the Liquidity Crisis, the mean (standard deviation) of net $Basis_{\text{bond}}$ tends to diverge further from zero (except for Brazil 2010 bond pair), being 17 bps (19 bps), 20 bps (23 bps) and 8 bps (17 bps) for Brazil 2015, Mexico 2020 and Turkey 2014 bonds, respectively. The mean of net $Basis_{\text{bond}}$ of Brazil 2010 bond pair, on the other hand, is negative (-15 bps), suggesting that LOP condition was satisfied at the time. Towards the end of the Liquidity Crisis, net $Basis_{\text{bond}}$ tends to grow in size, and reaches its maximum value of 52 bps, 74 bps, 75 bps and 66 bps for Brazil 2010, Brazil 2015, Mexico 2020 and Turkey 2014 bonds, respectively. It is observed that the size of net $Basis_{\text{bond}}$, however, is generally not large enough to designate this period as "anomalous". In fact, except for Mexico perhaps, the average size of net $Basis_{\text{bond}}$ is still reasonably low.[15] This suggests that the emerging countries used in our analysis stood relatively remote from the adverse impacts of the Liquidity Crisis originating from the U.S. and the Euro Zone. It is possible that funding constraints have not fully seeped into the cross-sectional dynamics of the sovereign Eurobonds.

During Credit Crisis, following the Lehman collapse in September 2008, however, the story changed distinctively. Displaying unprecedented dynamics, net $Basis_{\text{bond}}$ became markedly large, strongly persistent and highly volatile. The mean (standard deviation) of net $Basis_{\text{bond}}$ during this period is 54 bps (77 bps), 51 bps (48 bps), 32 bps (32 bps), 53 bps (30 bps) and 79 bps (43 bps) for Brazil 2010, Brazil 2015, Mexico 2020, Turkey 2014 and Turkey 2019 bonds, respectively. Similarly, by the same ordering, the maximum values are 407 bps, 209 bps, 136 bps, 169 bps and 201 bps, respectively.

Another important observation to be drawn from Figure 3.1 and Table 3.2 is that $Basis_{\text{bond}}$, though indicating increasing returns from Pre-Crisis to Credit Crisis, also displays increasing volatility (and therefore uncertainty) during the same period. The increased risk perception could deter arbitrageurs from exploiting the implied opportunity.

Examples of Dislocation. While one may expect pricing anomalies in small markets, it is puzzling, to say the least, to see them in such liquid sovereign markets. We note that the $Basis_{\text{bond}}$ refers to claims on cash flows of those emerging markets that are not directly exposed to subprime crisis. Therefore, any significant disruption gives us an indication of how sensitive emerging markets are to the economic shocks originating from developed markets.

To provide specific examples of the price disruption during Credit Crisis, on October 8, 2008, net $Basis_{\text{bond}}$ for the 2015 Brazilian pair was 104 bps. Two days later, on October 10, 2008, the anomaly was even larger for the 2010 Brazilian bonds, with a net deviation of 407 bps. While net $Basis_{\text{bond}}$ fluctuated between 163 bps and 209 bps for the 2015 Brazilian bonds from October 23 to 30, 2008, it varied between 250 bps and 345 bps for the 2010 Brazilian bonds within the same week. Similarly, on October 23, 2008, net $Basis_{\text{bond}}$ was 83 bps for the Mexican 2020 bonds, and reached 136 bps at the end of October. Once again, on October 23, 2008, net $Basis_{\text{bond}}$ equaled 98 bps for the 2014 Turkish pair, and 170 bps for the 2019 Turkish bonds.

The anomaly persisted over three months. A second round of disruption seems to have developed in mid-November. From 10 to 14 November, 2008, for instance, net $Basis_{\text{bond}}$ for the 2015 Brazilian bond pair fluctuated persistently between 115 bps and 151 bps. On November 20, 2008, net $Basis_{\text{bond}}$ for the 2014 and 2019 Turkish bond pairs widened to 169 bps and 201 bps, respectively. The

[15] $Basis_{\text{bond}}$ for Mexico gets elevated earlier than for Turkey and Brazil.

deviations continued to fluctuate between November and January, in particular for the 2019 Turkish bonds, for which the net deviation ranged between 155 bps and 195 bps.

During Post-Crisis, net $Basis_{\text{bond}}$ tends to subside for the majority of bonds with the exception of Mexico. The mean (standard deviation) of net $Basis_{\text{bond}}$ is -3 bps (13 bps), 4 bps (20 bps) and 16 bps (32 bps) for Brazil 2015, Turkey 2014 and Turkey 2019 bond pairs, respectively. The mean (standard deviation) of Mexico 2020 bonds is 49 bps (34 bps). This suggests that, while the bond pairs in Brazil and Turkey tend to to converge back to their relative equilibrium prices, $Basis_{\text{bond}}$ anomaly seems to intensify for Mexico 2020 bonds during the third quarter of 2009, when the net deviation reaches its highest peak of 155 bps on May 28, 2009. Although we observe that Mexican net $Basis_{\text{bond}}$ begins to dwindle from the last quarter of 2009, the finding suggests that the disruption in Mexico was not really over for an additional period of time.[16]

These results show that net $Basis_{\text{bond}}$ fluctuates close to zero during Pre-Crisis period, and hence supports the first requirement (a) of our hypothesis. During the Crisis period, net $Basis_{\text{bond}}$ becomes distinctly large and volatile, and hence gives a strong initial evidence in support of the second requirement (b) of our hypothesis. To see if this structural change is statistically significant, we move on to the next subsection.

B. *Hypothesis Tests*

To test the second requirement (b) that net $Basis_{\text{bond}}$ (calculated by using Eq. (3.11)) undergoes statistically significant changes across one or more of the subsamples, we conduct multi-sample hypothesis tests generated by using ANOVA (based on the strong 99% confidence level requirement). The null hypothesis states that there is no significant difference of means between the subsamples.

Figure 3.2 displays the results of the hypothesis tests for each subsample (i.e. period), and for three representative sovereign net $Basis_{\text{bond}}$ (i.e. Brazil 2015, Turkey 2014, and Mexico 2020 bond pairs).[17] The outcome of the hypothesis test is displayed in Panel A, and the p-values are given in Panel B.

To see how expectation (b) fares, we look at the results of the multi-sample hypothesis tests, and strongly reject the null hypothesis that there is no difference between the mean deviations across the subsamples. This holds for all given countries.[18] The important implication is that $Basis_{\text{bond}}$ is time-

[16] Prices of the two legs of the trade on Brazilian 2010-maturity bonds converge to the face value when approaching the maturity.

[17] Note that the analysis is based on net $Basis_{\text{bond}}$ calculated as the absolute values of gross $Basis_{\text{bond}}$ minus the transaction costs of the trade. Also note that for the 2019 USD-denominated Turkish bonds issued during Credit Crisis period, a two-sample hypothesis test is used instead of ANOVA, because the first two periods (i.e. Pre-Crisis and Liquidity Crisis) do not exist for this bond pair. Here, the null hypothesis similarly states that there is no difference of means between Credit Crisis and Post-Crisis periods.

[18] Although not shown in Figure 3.2, we also strongly reject the null hypothesis (with p-values = 0.000) for the 2010 Brazilian bonds and 2019 Turkish bonds.

variant and state-dependent. Moreover, as seen in Figure 3.2, Credit Crisis period is undeniably different from all other periods in all cases. Disruption in terms of mean and volatility seeps into the markets rapidly from Pre-Crisis to Credit-Crisis, as a clear sign of a severe distributional shock introduced into the system.[19] $Basis_{\text{bond}}$ becomes larger, more volatile and more persistent than any other subsample period, suggesting that our empirical proxy is subject to serious systemic breaks. This supports the second requirement (b) of our hypothesis.

V. Impact of Structural Limitations

What we have done in the preceding section was to obtain *a posteriori* confirmation that $Basis_{\text{bond}}$ was indeed a good measure of LOP deviation in the Turkish, Brazilian and Mexican bond pairs. Our next task is to test its predictive power as a near-LOP proxy. For this purpose, we use the same dataset but conduct *a priori* scenario-based assessment of the impact of the cash-flow mismatch in $Basis_{\text{bond}}$. We use a duration and convexity gap analysis for this purpose. The details of this analysis and the mathematical derivation are given in Appendix B to Chapter 3.

We denote the present value of the synthetic USD bond as A (asset), and the present value of the original USD bond as L (liability), both discounted with the annual yield Y^a of the original USD bond since that is the quoted yield in the market. The net present value generated from our strategy (i.e., profit) denoted by V is equal to $A - L$. For each bond pair in our study, it can be shown that (see Appendix B):

$$\begin{aligned} \frac{\Delta V}{V} &= -\frac{A}{A-L}\underbrace{\left[d_A - d_L\frac{L}{A}\right]}_{d_{gap}}\frac{\Delta Y}{(1+Y^a)} + \frac{1}{2}\frac{A}{A-L}\underbrace{\left[c_A - c_L\frac{L}{A}\right]}_{c_{gap}}\frac{(\Delta Y)^2}{(1+Y^a)^2} \\ &= \left(\frac{\Delta V}{V}\right)_{\text{Duration Component}} + \left(\frac{\Delta V}{V}\right)_{\text{Convexity Component}} \end{aligned} \tag{3.12}$$

where ΔY is a small increment representing the change in Y^a; d_A (and d_L) and c_A (and c_L) are the duration and convexity of A (and L), respectively; and ΔV is defined as $\Delta V = V_{\Delta Y} - V$, such that $V_{\Delta Y}$ denotes the present value of the profit when $\Delta Y \neq 0$ (i.e. with scenario analysis), and V denotes the present value of the profit when $\Delta Y = 0$ (i.e. without scenario analysis). The first component of $\Delta V/V$ is called the Duration Component, which captures the impact of the first-order duration gap between two bonds in reducing (or boosting) the profit; and the second component of $\Delta V/V$ is called the Convexity Component, which captures the impact of the second-order convexity gap between two bonds in reducing (or boosting) the profit V.

[19] Not all subsamples are statistically different from each other at the 0.01 level of significance. Notable exceptions are Pre-Crisis vs. Liquidity Crisis for Mexico 2020, and Liquidity Crisis vs. Post-Crisis for Turkey 2014.

Our original $Basis_{\text{bond}}$ calculation already prices the built-in coupon mismatches between USD and Euro bonds in the specific case where $\Delta Y = 0$. The USD shortages (in Brazil and Mexico) arising from these mismatches are *refinanced* with a constant dollar interest rate, and the Euro surpluses (in Turkey) are *reinvested* with a constant Euro interest rate, between each cash-flow point. Eq. (3.12) enables us to calculate how much of the profit V (and therefore $Basis_{\text{bond}}$) would be depleted (or enlarged) when the interest rates are no longer constant (i.e. $\Delta Y \neq 0$). Therefore, the size of ΔY, considered in each scenario, captures the interest rate shock to the market, and represents the cost (or gain) that the trader will endure (or benefit) due to underlying cash-flow mismatches.

In Brazil and Mexico, where the cash *inflows* of the synthetic USD bond (asset) is "less frequent" (by half a year) than the cash *outflows* of the original USD bond (liability), the trader must borrow dollars to finance the corresponding dollar gap until due dates for the coupon payments. Therefore, if dollar interest rates are to increase, the trader will have to borrow dollars "more expensively", and hence lose money from the refinancing. Any increase in the USD interest rates therefore implies that the profit V would be depleted, and hence $Basis_{\text{bond}}$ would decrease.

On the other hand, in Turkey, where the cash *inflows* of the synthetic EUR bond (asset) is "more frequent" (by half a year) than the cash *outflows* of the original EUR bond (liability), the trader must reinvest Euros to benefit from the corresponding Euro gap until due dates for the coupon payments. Therefore, if interest rates are to increase, the trader will get to lend "at higher rates", and hence gain more from the reinvestment. Any increase in the interest rates therefore implies that the profit V would be boosted, and hence the absolute value of $Basis_{\text{bond}}$ would increase.

Calculation Procedure

We consider two interest rate scenarios: (i) "one sigma" shock to dollar bond yield: $\Delta Y = \pm \sigma_Y$; and (ii) "2.32 sigma" shock to dollar bond yield: $\Delta Y = \pm\, 2.32\sigma_Y$. Scenario (i) captures an environment where there is 16% one-tail probability that the interest rate change will be greater than one standard deviation; whereas scenario (ii) captures a more extreme environment where there is 1% one-tail probability that the interest rate change will be greater than 2.32 standard deviations (in parallel with the parametric VaR approach widely used in banking).

The calculation steps follow below. To make the calculation procedure more clear, we give an example on the 2015-maturity Brazil bonds during Credit Crisis by considering scenario (i) where $\Delta Y = \sigma_Y = 0.96\%$.

1. **STEP 1 - Calculating ΔV:**

(a) Calculate A, L, d_A, d_L, c_A and c_L for each day from 1 September 2008 to 31 March 2009. In our example L=100 USD.

(b) For each day substitute the above data into Eq. (3.12), and calculate $\Delta V/V$. For Brazil 2015 bond pair, the average value of $\Delta V/V$ during Credit Crisis is:

$$\frac{\Delta V}{V} = -3.36\% + 0.02\% = -3.34\%$$

where -3.36% denotes the Duration Component, and 0.02% denotes the Convexity Component, as defined in Eq. (3.12). These components show how much of the total percentage change in profit V is attributed to the duration gap and convexity gap, respectively.

(c) Calculate ΔV for each day by multiplying both sides of Eq. (3.12) by $V = A - L$. For Brazil 2015 bond pair, the average value during Credit Crisis is:

$$\Delta V = -\$0.04$$

The negativity of ΔV is due to the fact that Brazil is in a *refinance* position. Hence, an increase of $\Delta Y = 0.96\%$ in the interest rates will decrease the present value of the profit V by \$0.04.

2. **STEP 2 - Calculating $\Delta Basis$:**

Define $\Delta Basis$ as the bps equivalent of ΔV:

$$\begin{aligned} \Delta Basis &= Basis_{\Delta Y} - Basis \\ &= [Y^{a*}_{\Delta Y} - Y^{a}_{\Delta Y}] - [Y^{a*} - Y^{a}] \end{aligned} \tag{3.13}$$

In the above $Basis_{\text{bond}}$ (calculated for $\Delta Y = 0$) is abbreviated as $Basis$ for notational convenience. $Basis_{\Delta Y}$ consists of $Y^{a*}_{\Delta Y}$ and $Y^{a}_{\Delta Y}$, which are the re-calculated yields of the synthetic and the original USD bond, respectively, after adjusting for $\Delta Y \neq 0$. Therefore, $\Delta Basis$ captures how much the trader would lose (or gain).

Note that there is a difference between the USD cash-flows corresponding to $\Delta Y = 0$ and those corresponding to $\Delta Y \neq 0$. But this difference in cash-flows boils down to ΔV in present value terms, since ΔV represents the present value of all the cash-flow changes in the disturbed state ($\Delta Y \neq 0$). Hence, $Y^{a*}_{\Delta Y}$ and $Y^{a}_{\Delta Y}$ are re-calculated by changing the initial cash-flow of the trading strategy by a total amount of ΔV, and keeping the remaining cash-flows the same.

(a) Based on the above, calculate Eq. (3.13). For Brazil 2015 bond pair, the average $\Delta Basis$

during Credit Crisis is:

$$\begin{aligned}\Delta Basis &= Basis_{\Delta Y} - Basis \\ &= [Y^{a*}_{\Delta Y} - Y^{a}_{\Delta Y}] - [Y^{a*} - Y^{a}] \\ &= (6.988\% - 6.486\%) - (6.992\% - 6.482\%) = -0.74\text{bps}\end{aligned}$$

Results

Table 3.3 displays the average values of both the Duration and Convexity components, the average percentage change in profit V (i.e. $\Delta V/V$) and the average change in $Basis_{\text{bond}}$ (i.e. $\Delta Basis$) during the Credit Crisis for each bond pair following the scenarios (i) and (ii).

1. In Brazil, the profit V decreases by 3.34% and 7.69%, corresponding to the scenarios with $\sigma_Y\%$ and $2.32\sigma_Y\%$ interest rate hikes, respectively. Similarly, the profit V in Mexico decreases by 15.38% and 32.84%, corresponding to the scenarios with $\sigma_Y\%$ and $2.32\sigma_Y\%$ interest rate hikes, respectively. $\Delta Basis$ in Brazil (Mexico) is -0.74 bps (-5.20 bps) and -1.78 bps (-11.13 bps) corresponding to the scenarios with $\sigma_Y\%$ and $2.32\sigma_Y\%$ interest rate hikes, respectively.

   Results for Mexico are notable in terms of the somewhat larger magnitude of the impact of ΔY. This is because of the longer maturity of the Mexican bond pair under study. It should be noted that the analysis assumes constant ΔY throughout the remaining lifetime of the bonds. In the case of Mexico 2020 bond pair, however, it is highly unlikely for the interest rates to remain at the elevated level of $Y^a + (2.32\sigma_Y\%)$ for 12 years after the onset of the Credit Crisis in 2008. Even in that extreme scenario, 67% of the profits are still retained. These results show that the cash-flow mismatch, even under extreme scenarios, falls way short of eliminating the $Basis_{\text{bond}}$ violation in Brazil and Mexico.

2. In Turkey, the profit V increases by 4.45% and 9.13%, corresponding to the scenarios with $\sigma_Y\%$ and $2.32\sigma_Y\%$ interest rate hikes, respectively. As opposed to Brazil and Mexico, the downside risk for Turkey is falling interest rates, which is due to the fact that Turkey is in reinvestment position. Therefore, the already negative value of the $Basis_{\text{bond}}$ will become more negative (or the absolute value will become larger). Our calculations show that $\Delta Basis$ is -1.78 bps and -3.59 bps corresponding to the scenarios with $\sigma_Y\%$ and $2.32\sigma_Y\%$ interest rate hikes, respectively. These results show that the cash-flow mismatch, even under extreme scenarios, will not alter the size of $Basis_{\text{bond}}$ violation in Turkey to any appreciable extent.

3. Due to the nature of the model in Eq. (3.12), the first-order duration component varies linearly with ΔY, whereas the second-order convexity component varies non-linearly. Table

3.3 shows that these two components act in offsetting directions in all cases. It is also clear that, at low values of ΔY, it is the duration component that is dominant. However, as ΔY increases, the relative weight of the convexity component becomes more pronounced.

The overall conclusion is that the impact of the cash-flow mismatch is way too far from wiping out the profits generated by our strategy. Once compared to the size of $Basis_{\text{bond}}$, the economic value of the duration and convexity gaps are a small fraction of the phenomenon that we want to explain.

VI. Concluding Remarks

It is common market practice among investment banks, data suppliers and rating agency companies to employ USD as a de-facto input to price the credit risk products that make reference to the same issuer across different currency denominations. Given that the bond yields are functions of the underlying risk-free rates and the *ubiquitous* default credibility of the issuer, the implicit assumption is that the issuer is subject to identical default probability across different currencies, and that the FX market is liquid and deep enough to make the USD-denominated product a perfect substitute for the EUR-denominated product. Based on our analysis, however, this assumption becomes questionable. Since Turkey generally pays higher yields in USD than Euro during Credit Crisis, it is possible to conjecture that the market assigns a higher credit risk, and thus, a higher default probability to Turkey's USD-denominated bonds compared to its Euro-denominated bonds. The exact opposite holds for Brazil and Mexico. This is why our results support the importance of accounting for the heterogeneity of funding markets in credit risk pricing.

It becomes evident that a part of the size of $Basis_{\text{bond}}$ deviation is traced back to cash-flow mismatches. However, after observing the highly volatile nature of $Basis_{\text{bond}}$ during different time periods, it becomes reasonable to ask whether these limitations really account for the entire story behind the mystery of $Basis_{\text{bond}}$ - a mispricing variable which acts more or less in accordance with the LOP restriction during Pre-Crisis (still in the presence of structural limitations), and becomes severely violated during Credit Crisis, and later converges back to Pre-Crisis levels during Post-Crisis. Unlike what most structural limitations suggest, this picture implies the presence of "state-dependent"risk factors at play. This is why we conjecture that a part of the deviation should depend also on a set of relevant "state-dependent" financial constraints (e.g. liquidity costs, funding costs, default risk, macroeconomic deterioration etc.) and geographical frictions that tighten during turmoil periods, and therefore, keep potential traders from fully exploiting the strategy. The validity of conditions $\mathcal{C}1$ - $\mathcal{C}5$ needs to be investigated in more depth. These issues will be discussed in further detail in the next chapter.

VII. Appendix A to Chapter 3

The derivation below is based on the discrete version of the proof given in Jankowitsch and Pichler (2005). Assume that in a frictionless market, under conditions $C1 - C5$, a sovereign issues two zero-coupon bonds denominated in two foreign currencies (a=USD and b=EUR), both having identical time-to-maturity of 1 year. Today's price at $t = 0$ of the defaultable bonds are $C^a(t,T)$=1 USD and $C^b(t,T)$=1 Euro. Bonds are subject to simultaneous default at some random time $\tau^* \leq T$. Assuming zero recovery rates for both bonds, the final payoff of the bonds in the corresponding currencies are:

$$C^a(T,T) = (1 + R^a(t,T) + S^a(t,T))\mathbb{I}_{\tau^*>T} \tag{3.14}$$

$$C^b(T,T) = (1 + R^b(t,T) + S^b(t,T))\mathbb{I}_{\tau^*>T} \tag{3.15}$$

where $\mathbb{I}_{\tau^*>T}$ represents an indicator function so that it equals 1 if $\tau^* > T$, and 0 otherwise. $R^a(t,T)$ and $R^b(t,T)$ are the underlying risk-free rates in USD and Euro, respectively; and $S^a(t,T)$ and $S^b(t,T)$ are the credit yield spreads paid over the underlying risk-free rates, respectively. No-arbitrage implies the existence of a risk-adjusted measure $\mathbb{Q}$ such that the relative price of any tradable security with respect to the riskless money market account follows a martingale under the same $\mathbb{Q}$-measure. According to risk-neutral pricing, the following must hold for USD bond under $\mathbb{Q}$-measure:

$$\begin{aligned} 1 = C^a(t,T) &= \frac{1}{1+R^a(t,T)}\mathbb{E}^{\mathbb{Q}}[C^a(T,T) \mid \mathcal{F}_t] \\ &= \frac{1}{1+R^a(t,T)}\mathbb{E}^{\mathbb{Q}}\left[(1 + R^a(t,T) + S^a(t,T))\mathbb{I}_{\tau^*>T} \mid \mathcal{F}_t\right] \\ &= \left(1 + \frac{S^a(t,T)}{1+R^a(t,T)}\right)\mathbb{E}^{\mathbb{Q}}\left[\mathbb{I}_{\tau^*>T} \mid \mathcal{F}_t\right] \end{aligned} \tag{3.16}$$

where $\mathbb{E}^{\mathbb{Q}}\left[\mathbb{I}_{\tau^*>T} \mid \mathcal{F}_t\right]$ is the bond's "survival probability" under measure $\mathbb{Q}$ with respect to filtration $\mathcal{F}_t$. From Eq. (3.16), we can derive:

$$\frac{1 + R^a(t,T)}{1 + R^a(t,T) + S^a(t,T)} = \mathbb{E}^{\mathbb{Q}}\left[\mathbb{I}_{\tau^*>T} \mid \mathcal{F}_t\right] \tag{3.17}$$

According to risk-neutral pricing, the following must hold for EUR bond under $\mathbb{Q}$-measure:

$$\begin{aligned} \frac{C^b(t,T)}{X(t)} &= \frac{1}{1+R^a(t,T)}\mathbb{E}^{\mathbb{Q}}\left[\frac{1}{F(t,T)}C^b(T,T) \mid \mathcal{F}_t\right] \\ &= \frac{1}{1+R^a(t,T)}\mathbb{E}^{\mathbb{Q}}\left[\frac{1}{F(t,T)}(1 + R^b(t,T) + S^b(t,T))\mathbb{I}_{\tau^*>T} \mid \mathcal{F}_t\right] \\ &= \left(\frac{1}{F(t,T)}\frac{1 + R^b(t,T) + S^b(t,T)}{1 + R^a(t,T)}\right)\mathbb{E}^{\mathbb{Q}}\left[\mathbb{I}_{\tau^*>T} \mid \mathcal{F}_t\right] \end{aligned} \tag{3.18}$$

where $X(t)$ and $F(t,T)$ are the EUR/USD exchange rates (EUR per USD) in spot and forward markets at t and T, respectively. The trade is hedged against future FX volatility using $F(t,T)$. According to the covered interest rate parity condition, the following must hold:

$$\frac{1}{F(t,T)} = \frac{1}{X(t)} \frac{1+R^a(t,T)}{1+R^b(t,T)} \tag{3.19}$$

Substituting Eq. (3.17) and Eq. (3.19) into Eq. (3.18), we can derive:

$$\frac{1}{X(t)} = \frac{1}{X(t)} \left(\frac{1+R^a(t,T)}{1+R^b(t,T)}\right) \left(\frac{1+R^b(t,T)+S^b(t,T)}{1+R^a(t,T)}\right) \left(\frac{1+R^a(t,T)}{1+R^a(t,T)+S^a(t,T)}\right) \tag{3.20}$$

When the common terms are canceled, we have:

$$\frac{1+R^b(t,T)+S^b(t,T)}{1+R^b(t,T)} = \frac{1+R^a(t,T)+S^a(t,T)}{1+R^a(t,T)} \tag{3.21}$$

which can be rearranged as:

$$[1+R^a(t,T)+S^a(t,T)] = \frac{1+R^a(t,T)}{1+R^b(t,T)}[1+R^b(t,T)+S^b(t,T)] \tag{3.22}$$

Using the covered interest rate parity condition in Eq. (3.19), we can derive:

$$(1+\underbrace{R^a(t,T)+S^a(t,T)}_{Y^a(t,T)}) = \frac{X(t)}{F(t,T)}(1+\underbrace{R^b(t,T)+S^b(t,T)}_{Y^b(t,T)}) \tag{3.23}$$

VIII. Appendix B to Chapter 3

The present value of the synthetic USD bond, and the present value of the original USD bond are denoted as Asset A, and Liability L, respectively, each discounted with the annual yield Y^a of the original USD bond. Hence, we write:

$$A = \sum_{j=1}^{m} \left[\frac{C_j^A}{(1+Y^a)^{k_j}} \right] \quad \text{and} \quad L = \sum_{j=1}^{n} \left[\frac{C_j^L}{(1+Y^a)^{h_j}} \right] \tag{3.24}$$

where C^A denotes the dollar-converted cash-flows of asset A, and C^L denotes the dollar cash-flows of liability L. We also define $k_j = [j^{th}$ EUR Coupon Date - Date $t]/365$, measured in years, where $j = [1, ...m]$, and m is the total number of Euro coupon payments. Similarly, we define $h_j = [j^{th}$ USD Coupon Date - Date $t]/360$, measured in years, where $j = [1, ...n]$, and n is the total number of dollar coupon payments. Date t is the first day that the trade is launched. By second-order Taylor expansion, evaluated around Y^a, we can write:

$$A(Y^a + \Delta Y) = A + A'\Delta Y + A''\frac{(\Delta Y)^2}{2} \quad \text{and} \quad L(Y^a + \Delta Y) = L + L'\Delta i + L''\frac{(\Delta Y)^2}{2} \tag{3.25}$$

where ΔY is a small increment representing the change in Y^a. Note that A' and A'' are, respectively, the first and second derivatives of A with respect to Y^a. The same notational logic applies to L. Dropping Y^a in parentheses (for notational convenience), and taking out A and L, correspondingly, from both sides, and dividing both sides, correspondingly, by A and L, we get:

$$\frac{\Delta A}{A} = \frac{1}{A}A'\Delta Y + \frac{1}{A}A''\frac{(\Delta Y)^2}{2} \tag{3.26}$$

$$\frac{\Delta L}{L} = \frac{1}{L}L'\Delta Y + \frac{1}{L}L''\frac{(\Delta Y)^2}{2} \tag{3.27}$$

where $\Delta A = A(Y^a + \Delta Y) - A$, and similarly $\Delta L = L(Y^a + \Delta Y) - L$. On the asset side, the first and second derivatives of A can be expressed as:

$$\frac{1}{A}A' = -\underbrace{\left[\frac{1}{A}\sum_{j=1}^{m} k_j PG_j^A \right]}_{d_A} \frac{1}{(1+Y^a)} \tag{3.28}$$

$$\frac{1}{A}A'' = \underbrace{\left[\frac{1}{A}\sum_{j=1}^{m} (k_j)(k_j+1) PG_j^A \right]}_{c_A} \frac{1}{(1+Y^a)^2} \tag{3.29}$$

where d_A and c_A are known as the duration and convexity of A, respectively, and $PG_j^A = [C_j^A/(1+Y^a)^{k_j}]$ are the present values of C_j^A for each j. On the liability side, the first and second derivatives of L can be expressed as:

$$\frac{1}{L}L' = -\underbrace{\left[\frac{1}{L}\sum_{j=1}^{n} h_j PG_j^L\right]}_{d_L}\frac{1}{(1+Y^a)} \tag{3.30}$$

$$\frac{1}{L}L'' = \underbrace{\left[\frac{1}{L}\sum_{j=1}^{n}(h_j)(h_j+1)PG_j^L\right]}_{c_L}\frac{1}{(1+Y^a)^2} \tag{3.31}$$

where d_L and c_L are known as the duration and convexity of L, respectively, and $PG_j^L = [C_j^L/(1+Y^a)^{h_j}]$ are the present values of C_j^L for each j. Denoting the net present value generated from our strategy (i.e., profit) by $V = A - L$, the following holds:

$$\begin{aligned}\Delta V &= \Delta A - \Delta L \\ \frac{\Delta V}{A} &= \frac{\Delta A}{A} - \frac{\Delta L}{A} = \frac{\Delta A}{A} - \frac{\Delta L}{L}\frac{L}{A}\end{aligned} \tag{3.32}$$

From previous results, we can substitute:

$$\begin{aligned}\frac{\Delta V}{A} &= \left[-d_A\frac{\Delta Y}{(1+Y^a)} + c_A\frac{1}{2}\frac{(\Delta Y)^2}{(1+Y^a)^2}\right] - \left[-d_L\frac{\Delta Y}{(1+Y^a)} + c_L\frac{1}{2}\frac{(\Delta Y)^2}{(1+Y^a)^2}\right]\frac{L}{A} \\ &= -\underbrace{\left[d_A - d_L\frac{L}{A}\right]}_{d_{gap}}\frac{\Delta Y}{(1+Y^a)} + \underbrace{\left[c_A - c_L\frac{L}{A}\right]}_{c_{gap}}\frac{1}{2}\frac{(\Delta Y)^2}{(1+Y^a)^2}\end{aligned} \tag{3.33}$$

where d_{gap} is the duration gap, and c_{gap} is the convexity gap. The first and second terms therefore represent the corresponding contributions of duration and convexity gaps, respectively. To see the percentage change in V, we can write:

$$\begin{aligned}\frac{\Delta V}{V} &= -\frac{A}{A-L}\underbrace{\left[d_A - d_L\frac{L}{A}\right]}_{d_{gap}}\frac{\Delta Y}{(1+Y^a)} + \frac{1}{2}\frac{A}{A-L}\underbrace{\left[c_A - c_L\frac{L}{A}\right]}_{c_{gap}}\frac{(\Delta Y)^2}{(1+Y^a)^2} \\ &= \left(\frac{\Delta V}{V}\right)_{\text{Duration Component}} + \left(\frac{\Delta V}{V}\right)_{\text{Convexity Component}}\end{aligned} \tag{3.34}$$

where ΔV is defined as $\Delta V = V_{\Delta Y} - V$, such that $V_{\Delta Y}$ denotes the present value of the profit when $\Delta Y \neq 0$ (i.e. with scenario analysis), and V denotes the present value of the profit when $\Delta Y = 0$ (i.e. without scenario analysis). The first component of $\Delta V/V$ is called the Duration Component, which captures the impact of the duration gap between two bonds in reducing (or boosting) the profit; and the second component of $\Delta V/V$ is called the Convexity Component, which captures the impact of the convexity gap between two bonds in reducing (or boosting) the profit.

Figure 3.1:

Basis(bond) dynamics

The plots show the evolution of the gross $Basis_{\text{bond}}$ (in blue lines) for the 2010- and 2015-maturity Brazilian, the 2020-maturity Mexican and the 2014- and 2019-maturity Turkish bond pairs. the gross $Basis_{\text{bond}}$ by definition does not account for the total bid-ask spreads (i.e. transaction costs) of the trade. We plot the gross $Basis_{\text{bond}}$ in order to facilitate an easy comparison between the size of the total mispricing and the total transaction cost, which is calculated as the summation of the underlying FX bid-ask spreads and the bond-specific yield bid-ask spreads, and is shown separately in this figure (in red lines). The total bid-ask spreads represents a transaction cost threshold, such that any $Basis_{\text{bond}}$ value in excess of it represents a mispricing that cannot be explained by transaction costs. All values are denoted in percentages. All figures start from July 2005, except for Turkish 2019 $Basis_{\text{bond}}$, which begins from 11 September 2008, as this was the first possible trading day of the strategy. The sample is divided into corresponding subsamples by dashed vertical lines.

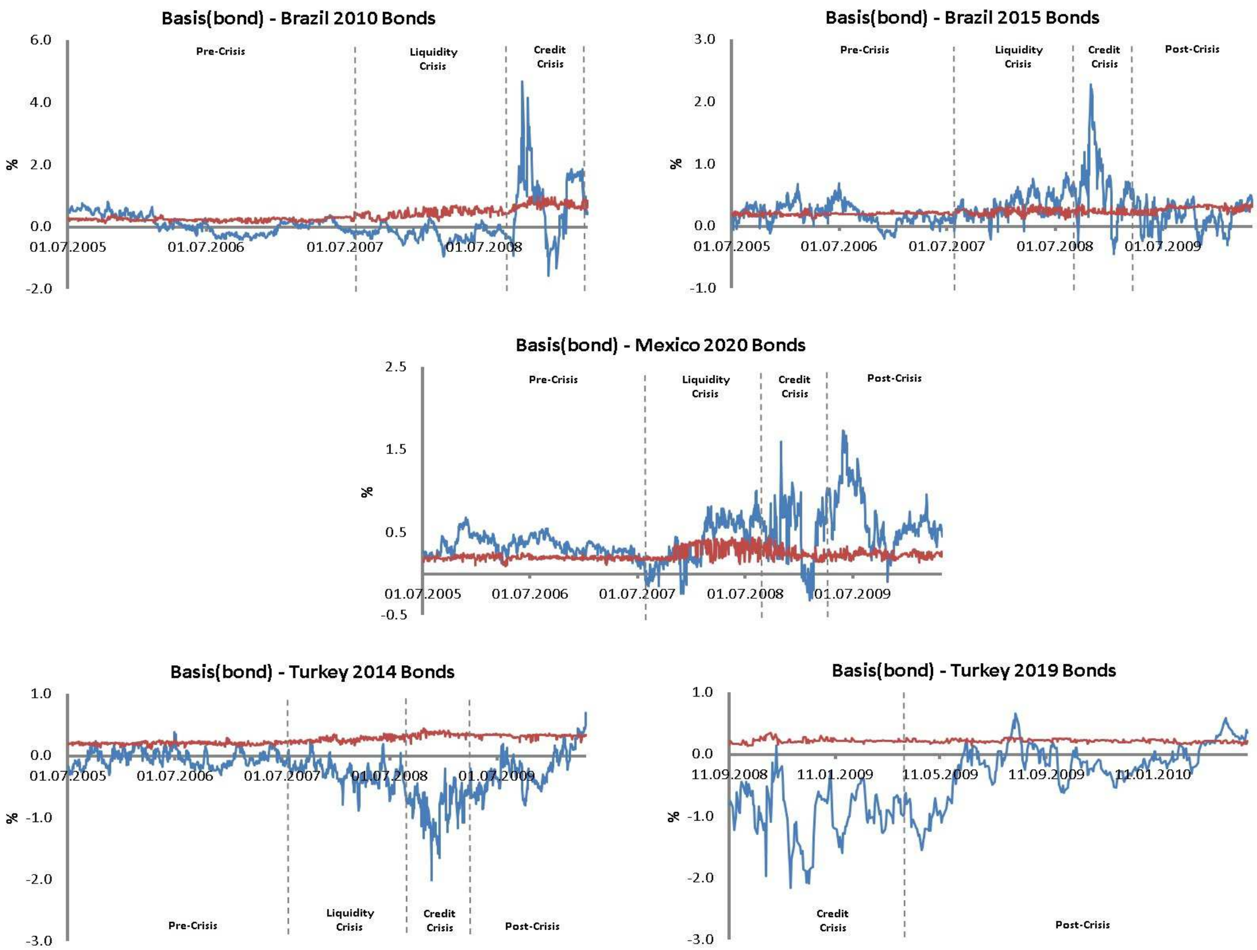

Figure 3.2:

Multi-sample hypothesis tests on Basis(bond)

We provide multi-sample hypothesis test results (using ANOVA) on $Basis_{\text{bond}}$ for the following bond pairs: 2015 Brazil, 2020 Mexico, and 2014 Turkey. The null hypothesis states that there is no difference between the mean deviations of $Basis_{\text{bond}}$ in one or more of the subsamples (i.e. Pre-Crisis, Liquidity Crisis, Credit Crisis and Post-Crisis). Panel A visualizes the mean of the net absolute $Basis_{\text{bond}}$ in the four sub-samples, and the corresponding red intervals of the statistical test. Panel B reports the p-values of the statistical test. It can be concluded that there are differences among the means at 0.01 level of significance (i.e. rejection of null hypothesis) if the red intervals in Panel A do not overlap, and if p-value < 0.01 in Panel B. The null hypothesis cannot be rejected if the red intervals in Panel A overlap, and if p-value > 0.01 in Panel B.

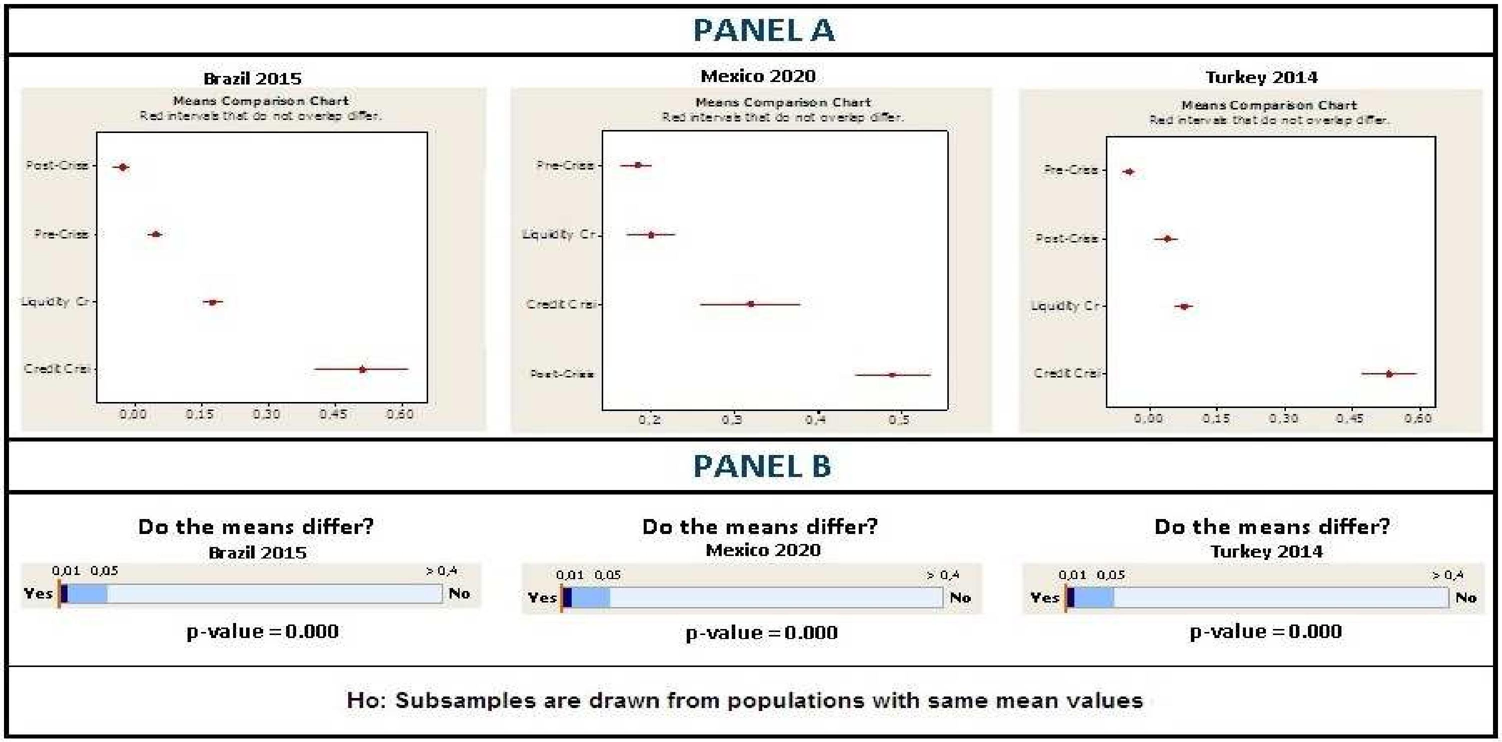

Table 3.1:

Summary statistics of emerging market bond pairs

This table reports the summary statistics of the bond pairs with nearly-matching maturities (at most 70 days mismatch) issued by Turkey, Brazil and Mexico. The table displays the ISIN number, the currency of denomination, issue date, maturity date, and annual coupon rate (in percentages) for each corresponding bond. The averages and the standard deviations (shown immediately below the averages) of the bond-specific yield-to-maturity are also reported for each subsample (i.e. Pre-Crisis, Liquidity Crisis, Credit Crisis and Post-Crisis).

Country	ISIN Number	Currency	Issue Date	Maturity Date	Coupon Rate (%)	Bond Yield Dynamics (%)			
						Pre-Crisis	*Liquidity*	*Credit*	*Post-Crisis*
Turkey	DE000A0AU933	EUR	10.02.2004	10.02.2014	6.5	5.37	6.10	7.31	4.34
						0.45	0.48	1.40	0.74
	US900123AS92	USD	24.09.2003	15.01.2014	9.5	6.66	6.23	7.80	4.79
						0.40	0.40	1.59	0.88
	XS0285127329	EUR	02.02.2007	02.04.2019	5.9	-	-	8.12	1.15
						-	-	5.55	0.66
	US900123BD15	USD	11.09.2008	11.03.2019	7.0	-	-	8.66	1.38
						-	-	6.14	0.69
Brazil	XS0106768608	EUR	04.02.2000	04.02.2010	11.0	4.61	4.95	5.30	-
						0.53	0.35	2.17	-
	US105756AV22	USD	16.04.2002	15.04.2010	12.0	5.79	4.20	4.01	-
						0.58	0.76	1.16	-
	XS0211229637	EUR	03.02.2005	03.02.2015	7.4	5.52	5.82	7.22	4.26
						0.54	0.33	1.29	0.69
	US105756BG46	USD	07.03.2005	07.03.2015	7.9	6.61	5.49	6.40	4.44
						0.71	0.26	1.07	0.63
Mexico	XS0206170390	EUR	22.11.2004	17.02.2020	5.5	4.95	5.59	7.41	5.60
						0.25	0.39	0.75	0.88
	US593048BN00	USD	30.03.2001	30.12.2019	8.1	5.91	5.47	6.69	5.41
						0.30	0.22	0.91	0.44

Table 3.2:

Summary statistics of net Basis(bond)

This table provides the summary statistics for the net $Basis_{\mathrm{bond}}$ of 2010- and 2015-maturity Brazil, 2020-maturity Mexico, and 2014- and 2019-maturity Turkey (obtained by subtracting from the absolute value of gross $Basis_{\mathrm{bond}}$ the total underlying bid-ask spreads). The total bid-ask spread is defined as the summation of the underlying FX bid-ask spread and the bond-specific yield bid-ask spread. The mean, maximum and standard deviation values are given in the first three columns of each net $Basis_{\mathrm{bond}}$ panel. The mean of the total bid-ask spreads is also given in the fourth column of each $Basis_{\mathrm{bond}}$ panel. All values are denoted in percentages. The sample periods are Pre-Crisis, Liquidity Crisis, Credit Crisis and Post-Crisis.

Summary Statistics of Net Basis(bond)

	Brazil 2010				**Brazil 2015**			
	Mean	*Max*	*St. Dev*	*Bid-Ask*	*Mean*	*Max*	*St. Dev*	*Bid-Ask*
Pre-Crisis	0.04	0.60	0.18	0.24	0.05	0.53	0.14	0.20
Liquidity Crisis	-0.15	0.52	0.20	0.43	0.17	0.74	0.19	0.22
Credit Crisis	0.54	4.07	0.77	0.72	0.51	2.09	0.48	0.23
Post-Crisis	-	-	-	-	-0.03	0.34	0.13	0.29

	Mexico 2020			
	Mean	*Max*	*St. Dev*	*Bid-Ask*
Pre-Crisis	0.18	0.53	0.11	0.19
Liquidity Crisis	0.20	0.75	0.23	0.27
Credit Crisis	0.32	1.36	0.32	0.23
Post-Crisis	0.49	1.55	0.34	0.23

	Turkey 2014				**Turkey 2019**			
	Mean	*Min*	*St. Dev*	*Bid-Ask*	*Mean*	*Min*	*St. Dev*	*Bid-Ask*
Pre-Crisis	-0.05	0.21	0.07	0.20	-	-	-	-
Liquidity Crisis	0.08	0.66	0.17	0.27	-	-	-	-
Credit Crisis	0.53	1.69	0.30	0.35	0.79	2.01	0.43	0.23
Post-Crisis	0.04	0.57	0.20	0.33	0.16	1.39	0.32	0.22

Table 3.3:

Duration and convexity analysis

This table reports the duration and convexity of the original USD bond and the synthetic USD bond. The change in interest rate levels (in terms of percentage) is represented by ΔY. The dollar-weighted net duration and convexity gaps are calculated based on shorting the original USD bond, and longing the synthetic USD bond for Brazil, Mexico and Turkey.

Bond Pairs	**Original USD Bond**		**Synthetic USD Bond**		**Duration Gap**
	Duration (d_L) (years)	*Convexity (c_L)*	*Duration (d_A) (years)*	*Convexity (c_A)*	*[d_A - d_L*(L/A)] (years)*
Turkey 2014	4.16	24.00	4.35	25.56	0.07
Brazil 2015	5.08	34.70	4.97	33.35	0.04
Mexico 2020	7.67	81.85	8.14	89.42	0.70

	Scenario ΔY *(%)*	**Duration Component (1st-Order)** *(%)*	**Convexity Component (2nd-Order)** *(%)*	**Impact on V** Δ *V / V* *(%)*	**Impact on Basis** Δ *Basis* *(bps)*
Turkey 2014	$\sigma_Y = 1.51$	4.84	-0.39	4.45	-1.78
	$2.32\sigma_Y = 3.51$	11.24	-2.11	9.13	-3.59
Brazil 2015	$\sigma_Y = 0.96$	-3.36	0.02	-3.34	-0.74
	$2.32\sigma_Y = 2.22$	-7.81	0.11	-7.69	-1.78
Mexico 2020	$\sigma_Y = 0.84$	-16.31	0.93	-15.38	-5.20
	$2.32\sigma_Y = 1.94$	-37.83	4.99	-32.84	-11.13

Chapter 4

Determinants and Geography of Mispricing in Emerging Markets

This chapter investigates the potential market determinants and the cross-sectional geographical features of $Basis_{\text{bond}}$ in emerging sovereign bond markets. The dynamics of $Basis_{\text{bond}}$, covered in the previous chapter, raises a series of fundamental financial economics questions related to the type of limitations that may prevent price convergence. We address four main sources of frictions suggested in the literature: (a) liquidity factors, (b) short-selling constraints, (c) funding costs, and (d) institutional frictions in the context of a large macro wealth shock affecting the demand for risky arbitrage. This investigation boils down to questioning the validity of conditions $\mathcal{C}1$ - $\mathcal{C}5$.

An interesting finding of our analysis is indeed the sign of $Basis_{\text{bond}}$, as introduced in the previous chapter. It is important to answer why our LOP proxy is positive in Brazil and Mexico, and negative in Turkey, when the trade is constructed by shorting the USD-denominated bond and longing the equivalent EUR-denominated bond. This suggests that Brazil and Mexico pay higher yields in Euro than USD, whereas the exact opposite holds for Turkey. Given that the Euro interest rates in general fluctuated at higher levels than USD interest rates around the globe, the sign is not surprising in the cases of Brazil and Mexico, but it is rather puzzling in the case of Turkey. This chapter delves deeper into the roots of this phenomenon, and provides potential explanations.

This chapter also investigates the impact of regulatory interventions and announcements in relieving the frictions on $Basis_{\text{bond}}$. In order to understand the nature of the market frictions being targeted, we categorize into different groups those monetary policies launched by the Fed and the U.S. Treasury. We later test whether any of these policies widened the cross-sectional gap between the Brazilian/Mexican $Basis_{\text{bond}}$ against the Turkish $Basis_{\text{bond}}$, given that Brazil and Mexico participated in some monetary policies that Turkey did not participate in.

Another important issue to highlight is the interpretation of the direction of our LOP deviation proxy. If $Basis_{\text{bond}}$ is persistently non-convergent to zero, a higher $Basis_{\text{bond}}$ surely means a bigger potential profit for the trader, while it also means a bigger *anomaly* in the underlying pricing mechanism. This double-meaning is essential to understanding the limits-to-arbitrage literature: bigger potential profit = bigger mispricing = bigger anomaly = tighter constraints in the market. In a frictionless market, $Basis_{\text{bond}}$ is expected to disappear instantly as traders are expected to exploit the so-called "riskless" arbitrage opportunity. If $Basis_{\text{bond}}$ is persistent, and even sometimes grows further in size, however, traders are unable (or unwilling) to participate in the trade (due to certain risks and limitations in the market), and therefore, are incapable of providing the sufficient demand and supply dynamics, eventually causing price convergence to remain unrealized. In other words, there should exist certain market constraints that are responsible for $Basis_{\text{bond}}$ to remain so large and volatile over an extended period of time. With the use of regression analyses, this chapter aims to identify these state-dependent financial constraints.

Results reveal that the sizable and persistent pricing anomaly encountered during Credit Crisis resulted from the strong interaction of a set of macroeconomic and market forces. On one side, sharply decreasing supply of funds, due to rising funding costs (captured by Secured and Unsecured), falling bond supply (captured by Inventory), and slowing macroeconomic activity (captured by LN-Macro); and on the other side, sharply decreasing appetite for risky arbitrage, due to deteriorating credit risk perception (captured by EM-CDSI) and increasing risk-aversion (captured by Closed End), jointly acted as binding constraints and/or deterring factors that kept arbitrageurs from exploiting the underlying opportunity, causing prices to diverge further and further away from equilibrium. This is consistent with the idea that the marginal arbitrageur is exposed to sources of risks that go above and beyond the risk factors affecting the local market of the issuing country.[1]

Supported by the price discovery analysis, calculations reveal that the way default risk is distributed among currencies depend directly on the geography of bond issuance. Turkey generally pays a higher default risk premium in USD than Euro ($S^a > S^b$), while the opposite is true for Brazil and Mexico ($S^a < S^b$). With forward FX markets being unable to correct this imbalance, $Basis_{\text{bond}}$ deviation becomes negative for Turkey, and positive for Brazil and Mexico. Under these circumstances, when investors face *discordant* default risks across two equivalent securities, $Basis_{\text{bond}}$ trade could indeed be left unexploited, causing prices to diverge further from each other. Furthermore, comparing central bank international reserve distributions of Turkey and Brazil, it is observed that Turkey, being a major trade partner with the Euro Zone, tends to hold more Euro than USD in its reserves, while Brazil, being closer to the USD-based trade geography, holds significantly less

[1] See Gromb and Vayanos (2010) for a model in which global arbitrageurs, who are present across different markets, are affected by common wealth shocks. When arbitrageurs find it difficult to absorb these shocks by accessing debt markets, this friction becomes a source of contagion across seemingly unrelated assets.

Euro than USD. Therefore, it could be argued that markets assign a relatively lower default risk premium to Euro-based assets in a Euro-strong country like Turkey, while they assign a relatively lower default risk premium to USD-based assets in a USD-strong country, like Brazil.[2]

An additional factor that contributes to sign puzzle arises from differences in accessibility of arbitrageurs to different loan markets. European banks, being major traders of Turkish bonds, have comparative advantage in funding in Euro (inside capital) than USD (outside capital). Our regression results indeed show that, in Europe, an increase in the spread between the unsecured USD funding relative to secured Euro funding, increases the size of net $Basis_{\text{bond}}$ of Turkey. This implies that in Europe, since EUR is comparatively easier to fund than USD, traders would tend to short the EUR bonds and long the USD bonds of Turkey. The opposite case is true for Brazil and Mexico. U.S. banks, being major traders of Brazilian and Mexican bonds, have comparative advantage in funding in USD (inside capital) than EUR (outside capital). Our regression results indeed show that, in the U.S., an increase in the unsecured EUR funding relative to secured USD funding, increases the size of net $Basis_{\text{bond}}$ of Brazil and Mexico. This indicates that in the U.S., since USD is comparatively easier to fund than EUR, traders would tend to short the USD bonds and long the EUR bonds of Brazil and Mexico.

An additional result is related to the impact of monetary policies in relieving the dislocation in the $Basis_{\text{bond}}$ trade. It is observed that Federal Open Market Committee (FOMC) has extended global dollar swap lines to Brazil and Mexico, but not to Turkey. This fact allows us to use Turkey as a control group in our event study analysis, and to identify the cross-sectional impact of the dollar swap lines on $Basis_{\text{bond}}$. Our findings suggest that the cross-sectional dispersion between the Turkish $Basis_{\text{bond}}$ vs. the Brazilian/Mexican $Basis_{\text{bond}}$ tends to widen further when these swap extensions are authorized. Following the announcement of swap extensions on October 29, 2008, the mispricing in the Brazilian and Mexican bonds begin to diminish almost immediately, whereas the mispricing in Turkey continues to rise. We also find that the geographical dispersion tends to increase following the announcements related to the Fed's Commercial Paper Funding Facility (CPFF), and the U.S. Treasury's Troubled Asset Relief Program (TARP). These results merit further research regarding the impact of monetary policy on pricing anomalies.

The chapter is organized as follows: Section I details the data description for the potential determinants of $Basis_{\text{bond}}$. Section II gives the regression analyses that test the significance of these determinants. Section III discusses the geographical aspects of $Basis_{\text{bond}}$ and offers explanations for the cross-sectional sign differences of the mispricing. Section IV conducts an event study analysis regarding the monetary policy implications on $Basis_{\text{bond}}$. Section V gives Appendix A.

[2] In case of Turkey, this would have a positive impact on the credit perception regarding Turkey's Euro-denominated risky assets, showing the extent to which Turkey can meet its Euro debt obligations in case of potential default. The opposite is true for Brazil.

I. Data Description and Exploratory Analysis

The constituents of the determinants of $Basis_{\text{bond}}$ are retrieved for July 2005 to April 2010 as the end-of-day weighted average of the quotes submitted by a minimum of five brokers and dealers from Bloomberg (BGN), unless otherwise noted. Other data sources include Data Explorers, Global Insights Basic Economics Database, the Conference Board's Indicators Database, Pastor and Stambaugh (2003) liquidity risk data, and Buraschi and Whelan (2012) disagreement in beliefs data, as detailed below. The determinants are divided into 7 main categories: (1) Liquidity Frictions, (2) Short-Selling Constraints, (3) Funding Costs, (4) Global Cash-Flow Factors, (5) Credit Risk Factor, (6) Risk Aversion Factors, and (7) Global Uncertainty. Each category consists of sub-categories. Details and discussions of the constituents of each category are given below. The summary statistics of each variable from Pre-Crisis to Post-Crisis are given in Table 4.1.

A. *Liquidity Frictions*

- *FX Latent Liquidity:* In an important study that investigates the role of FX liquidity on covered-interest rate violations, Griffoli and Ranaldo (2011) find that the first principal component of bid-ask spreads across different currency pairs explains no-arbitrage violations in FX markets during the crisis period. This result is interesting, since it suggests the existence of a latent liquidity variable helping to explain the deviations from the CIRP. Recall that the USD/EUR spot and forward FX markets make up an important part of our trading strategy, the trader converting the borrowed dollars into Euros via the spot FX market, and later converting each future Euro cash-flow into dollars via the forward FX market. Any illiquidity in the exchange rate markets is likely to hinder the ability of an arbitrageur to exploit the given transaction, which is likely to have an adverse impact on $Basis_{\text{bond}}$ deviation. Therefore, we replicate Griffoli and Ranaldo (2011) variable by using USD/EUR spot and forward exchange rates. Instead of using the bid ask spreads of different currency pairs, we focus on USD/EUR bid ask spreads for different maturities from one week to ten years. We compute the first principal component of the unit-root tested stationary bid-ask spreads (capturing liquidity cost) across given maturities, and call this variable Liq-FX.

  Table 4.1 shows that Liq-FX increases in size and volatility from Pre-Crisis to Credit Crisis, and drops once again during Post-Crisis. To be more precise, the average (standard deviation) of the principal component is -1.07 (0.61) in Pre-Crisis, 0.55 (0.70) in Liquidity Crisis, 3.48 (1.85) in Credit Crisis, and 0.91 (0.83) in Post-Crisis. These results imply that, during Credit Crisis, there was a severe systemic shock to FX markets, as the Liq-FX displays a large positive jump. FX forward markets suffered from widening bid-ask spreads, and thus became increasingly illiquid and costly for an arbitrageur to commit to the underlying $Basis_{\text{bond}}$ trade.

- *Stock Market Liquidity:* The U.S. equity market captures the pulse of the overall state of the economy, and is an indicative variable for the general drop of liquidity and the level of contagion across different asset classes. Kwan (1996) finds that while lagged stock returns have explanatory power for the contemporaneous bond yield changes, the vice versa is not true, suggesting that the dynamics of bonds are led by the dynamics of stocks through firm-specific information. Collin-Dufresne, Goldstein, and Martin (2001) and Campbell and Taksler (2003) argue that yield spread changes are significantly related to stock market returns. Moreover, Chordia, Sarkar, and Subrahmanyam (2005) find that the fluctuations in liquidity are correlated across stocks and bonds. Similarly, Landschoot (2008) finds a strong negative dependence among stock market return and credit quality. This is why it is a matter of curiosity whether any liquidity shock to stock markets have adverse impacts on bond markets, and on the seemingly unrelated emerging market $Basis_{\text{bond}}$. In this spirit, we control for the systematic properties of liquidity in the U.S. equity markets based on the work of Pastor and Stambaugh (2003) who compute an aggregate measure of liquidity from the cross-sectional average of individual stock liquidity, captured by the average effect of day t signed volume on day $t+1$ return. We call this variable Liq-PS, defined as the traded factor, which is computed as the value-weighted return on the 10-1 portfolio from a sort on historical liquidity betas that are generated as the estimated regression slope coefficients on daily stock returns and volume data of New York Stock Exchange and American Stock Exchange.[3] Pastor and Stambaugh (2003) state that by construction Liq-PS should be "negative in general and larger in absolute magnitude when liquidity is lower."

  Table 4.1 shows that, unlike other periods, Liq-PS is largest and most negative (about ten times more than Pre-Crisis levels in absolute value terms) during Credit Crisis. The levels tend to approach once again to their Pre-Crisis levels during Post-Crisis period. To be more precise, the average (standard deviation) of the Liq-PS is -0.01 (0.04) in Pre-Crisis, -0.09 (0.07) in Liquidity Crisis, -0.11 (0.08) in Credit Crisis, and -0.01 (0.05) in Post-Crisis.

B. *Short-Selling Constraints*

Saffi and Sigurdsson (2011) finds that the short-selling constraints (partly imposed by the regulatory acts, and measured by low lending supply), tend to maintain a negative impact on stock market efficiency. In other words, high-lending supply allows prices to reflect more information, helping

[3] The data is retrieved directly from $http://faculty.chicagobooth.edu/lubos.pastor/research$.

markets to become more efficient. To quote Saffi and Sigurdsson (2011): "[...] arbitrageurs cannot correct overvaluation as easily when short selling constraints are tighter."

We aim to investigate the impact of low lending supply on $Basis_{\text{bond}}$, since it is directly related to the ability of an arbitrageur to launch the trade at time t. If arbitrageur has little or no access to bonds (due to lending reluctance of bond owners), the trade might go unexploited. This is why we retrieve a unique dataset that includes detailed bond-specific information on the available inventory for lending of both the Euro- and USD-denominated bonds across the three EM countries used in our analysis (i.e. Brazil, Mexico and Turkey). The daily time-series data is obtained from Data Explorers and provides the most extensive coverage on sovereign bond security lending currently available on a bond-specific level from Liquidity Crisis to Post-Crisis period.[4] It includes the major prime brokers, custodians, and the lending desks of large firms that actually trade these securities. It captures bond-specific trading information from over 100 participants and covers approximately 85% of the OTC securities lending market.[5]

In order to capture the impact of short-selling constraints, we use the the sum of the bond-specific USD- and EUR-denominated actively lendable inventory values in dollar terms (filtered out from the inactive loans) for each bond pair at each point of time, and call this variable Inventory, which captures the dynamics of bond supply.[6]

Table 4.2 shows that Inventory tends to decrease from Liquidity Crisis to Post-Crisis across all given countries. For Brazil 2010-maturity pair, for instance, the average (standard deviation) of Inventory is \$27.15 mio (\$6.53 mio) in Liquidity Crisis, \$21.83 mio (\$7.23 mio) in Credit Crisis, and \$9.42 mio (\$5.03 mio) in Post-Crisis. This shows that Inventory decreased by 20% from Liquidity to Credit Crisis, and further decreased by 57% from Credit to Post-Crisis periods. Similarly, for Brazil 2015-maturity pair, the average (standard deviation) of Inventory is \$416.76 mio (\$38.69 mio) in Liquidity Crisis, \$343.24 mio (\$56.23 mio) in Credit Crisis, and \$354.60 mio (\$43.16 mio) in Post-Crisis. This shows that Inventory decreased by 18% from Liquidity to Credit Crisis, and slightly increased by 3% from Credit to Post-Crisis periods.

For Mexico 2020-maturity pair, the average (standard deviation) of Inventory is \$276.03 mio (\$36.46 mio) in Liquidity Crisis, \$156.95 mio (\$32.66 mio) in Credit Crisis, and \$164.09 mio (\$28.25 mio) in Post-Crisis. This shows that Inventory decreased by 43% from Liquidity to Credit Crisis, and slightly increased by 5% from Credit to Post-Crisis periods.

[4] Data Explorers, which is acquired by Markit on April 2012, covers \$12 trillion of securities over 20,000 institutional funds.

[5] All double-counted fields are eliminated.

[6] Total inventory can either be active or inactive. This is due to the fact that there is sometimes a difference between the total amount that could be lent out and the actual amount that was offered. Data Explorers state that this happens when "securities are held in too small parcels or have been restricted by the beneficial owner."

Furthermore, for Turkey 2014-maturity pair, the average (standard deviation) of Inventory is \$218.39 mio (\$59.97 mio) in Liquidity Crisis, \$169.56 mio (\$70.76 mio) in Credit Crisis, and \$78.73 mio (\$15.01 mio) in Post-Crisis. This shows that Inventory decreased by 22% from Liquidity to Credit Crisis, and further dropped by 54% from Credit to Post-Crisis periods. Likewise, for Turkey 2019-maturity pair, the average (standard deviation) of Inventory is \$176.05 mio (\$49.07 mio) in Credit Crisis, and \$150.99 mio (\$17.50 mio) in Post-Crisis. This shows that Inventory decreased by 14% from Credit to Post-Crisis periods.

Also in the aggregate level, using *all* retrieved outstanding Eurobonds issued by the given underlying countries (please see Section II of Chapter 1 for details), a similar pattern emerges. We find that during Liquidity Crisis, there were on average \$3,719; \$2030; and \$3,293 million worth of total active lendable Eurobonds a day in Brazil, Mexico, and Turkey, respectively. Between September 2008 and April 2009, however, there were on average \$3,441; \$1,251; and \$2,671 million worth of total active lendable Eurobonds a day in Brazil, Mexico and Turkey, respectively (see Figure 4.1). This suggests that the total available bond supply decreased in value by approximately 7% for Brazil, 38% for Mexico, and 19% for Turkey. After April 2009, the total active lendable Eurobonds started to grow in value by 8% in Brazil and 3% in Turkey, whereas they continued to drop by 43% in Mexico.

These observations suggest that the size of the emerging Eurobond markets shrunk notably during Credit Crisis, implying that the bond-holders became increasingly unwilling to trade. This may have hampered the flexibility of arbitrageurs to freely short/long the required bonds that underlie their strategy - a factor that could have an adverse impact on the dynamics of price efficiency, and on the size of $Basis_{\text{bond}}$.

C. *Funding Costs*

Funding costs depend on the level of capitalization and the risk of financial intermediaries. As Fontaine and Garcia (2012) suggest, the risk premia inherent in corporate bond yields increase with tighter funding conditions. In this context, it is important to capture how difficult it is to roll-over the arbitrage trades to take advantage of market dislocations, and fund large relative value positions. In our framework, the arbitrageur may be required to raise additional capital in order to fund the cash-flow mismatch, and to meet institutional costs that arise during the transactions. If funding conditions tighten (due to high funding costs), the arbitrageur could very well be driven away from the $Basis_{\text{bond}}$ trade.

Two types of traders are usually involved in such near-arbitrage opportunities: proprietary trading desks of investment banks and hedge funds. Although they go after similar trades, they usually operate under different funding markets. While hedge funds tend to borrow and lend against collateral on secured terms ("secured funding"), the prop desks of investment banks tend to participate in unsecured money market operations ("unsecured funding"). We use two main variables:

- *Secured Funding:* Similarly to Coffey, Hrung, and Sarkar (2009), we proxy "secured funding" with the spread between the Federal Agency cost of funding yield minus the U.S. Treasury yield. We use matching seven-years maturities for both variables.[7] Since both rates refer to a collateralized loan, this spread captures the difference in value between high-quality vs. relatively lower-quality collateral securities.[8] The higher this spread, the tighter the funding constraints in the secured markets, and thus lower the arbitrageur's ability to raise enough cash to fund the $Basis_{\text{bond}}$ trade.

  Table 4.1 shows that Secured variable increases in size and volatility from Pre-Crisis to Credit Crisis, and drops once again during Post-Crisis. The average (standard deviation) is 0.34% (0.06%) in Pre-Crisis, 0.57% (0.14%) in Liquidity Crisis, 0.51% (0.28%) in Credit Crisis, and 0.15% (0.12%) in Post-Crisis. The secured funding costs increased by more than 40% from Pre-Crisis to Credit Crisis. This implies that, during Credit Crisis, there was a severe funding constraint in the secured markets, which would have made it increasingly costly for a trader to fund the arbitrage trades.

- *Unsecured Funding:* We proxy "unsecured funding" with the spread between 3-month LIBOR and U.S. Overnight Index Swap (OIS) rates. Being one of the most active and liquid interest rates, LIBOR is the average interest rate of the leading banks in London if they are to borrow from other banks. OIS is the interest rate swap where the floating leg comprises of the geometric average of the daily overnight index rate (e.g. federal funds rate) throughout the payment period, and the fixed leg is based on a central bank rate that is less risky than LIBOR. The LIBOR-OIS spread captures the health of the interbank lending dynamics, and indicates the level of stress and funding costs in the money markets. A rise in the differential implies that financial institutions become less willing to lend to each other. The higher this spread, the tighter the funding constraints in the unsecured markets, and thus lower the arbitrageur's

[7] U.S. Treasury yields are interpolated by the U.S. Treasury, using the closing bid yields on the actively traded Treasury securities in the OTC market, based on the composite quotations obtained from Federal Reserve Bank of New York. The yield curve values that correspond to the securities' time-to-maturities, are retrieved only at fixed maturities. This means that even though there is no outstanding security with exactly seven-years remaining to maturity, seven-year maturity yields are read from the interpolated curve. Generic United States on-the-run government bond indices are used for Bloomberg rates. Federal Agency securities are instruments backed by the U.S. government guarantee and issued by the federal credit agencies (i.e. Federal Home Loan Bank, Federal Home Loan Mortgage Association (Freddie Mac), Federal National Mortgage Association (Fannie Mae), and Federal Farm Credit Bureau). These securities have high credit ratings (though still lower than U.S. Treasuries), and are used to fund public projects such as housing and urban renewal.

[8] See Gabaix, Krishnamurthy, and Vigneron (2007) for a discussion of the role of MBS as a funding markets.

ability to raise enough cash to fund the $Basis_{\text{bond}}$ trade through this channel (alternative to secured funding).

Table 4.1 shows that Unsecured variable increases in size and volatility from Pre-Crisis to Credit Crisis, and drops once again during Post-Crisis. To be more precise, the average (standard deviation) is 0.08% (0.02%) in Pre-Crisis, 0.68% (0.15%) in Liquidity Crisis, 1.51% (0.76%) in Credit Crisis, and 0.26% (0.26%) in Post-Crisis. The unsecured funding costs increased by more than 1787% from Pre-Crisis to Credit Crisis. This implies that, during Credit Crisis, there was a severe funding constraint in the unsecured markets as well, which may have limited an arbitrageur's chance of funding the $Basis_{\text{bond}}$ trade.

D. *Global Cash-Flow Factors*

- *Macro-Activity Risk:* A macro wealth shock that corresponds to aggregate-level consumption and production could have an adverse impact on the demand for risky arbitrage trades. The deterioration of economic activity would have direct implications on the general economic behavior of the agents involved. Individual agents would become much more risk-averse (as their economic utility function decreases due to lower consumption), and institutional agents (such as banks) would directly suffer from lower revenues and higher expenses (due to reluctance of lending against rising credit risk and falling industrial production). In an economic environment of such nature, interest rates would rise, liquidity would dry up, and financial markets would shrink, so that the implementation of any economic transaction, let alone a risky arbitrage transaction (e.g. $Basis_{\text{bond}}$ trade), could come to a temporary halt, having adverse impacts on the pricing mechanism.

  Our proxy for macroeconomic shocks to cash-flow factors is related to the sixth literature stream discussed in Chapter 2. We follow Ludvigson and Ng (2009), who estimate a set of common factors from a panel of 132 real, nominal, and monetary measures of economic activity. They show that a procedure which synthesizes information from macroeconomic activity possesses the ability to strongly predict excess bond returns, explaining 26% of the one-year-ahead variation. The monthly time-series used in our analysis are based on Ludvigson and Ng (2009) and are collected from the Global Insights Basic Economics Database and the Conference Board's Indicators Database. Unlike Ludvigson and Ng, we exclude price-based information from the panel in order to interpret this variable as a pure macro-activity factor, and to allow for an easier distinction between macro-activity and other risk factors. After removing price-based information from the panel, we end up with 99 cross-sectional economic series summarized under six main categories: (1) Consumption, Orders and Inventories, (2) Output and Income, (3) Labor Market, (4) Housing Market, (5) Money and Credit, (6) Prices and Inflation. Refer to Appendix A to Chapter 4 for the sources and the entire list of the data, accompanied by the coding system of how each variable is transformed for stationarity. Using the covariance matrix of 99 macroeconomic variables and the associated eigenvectors, we extract the first principal component (via principal component analysis), and label it LN-Macro.[9] The dataset includes industrial production and income, capacity utilization, manufacturing sale, labor force, employment, non-farm payroll, hourly earnings of production, housing starts, money stock and monetary base, outstanding commercial and industrial loans, producer and consumer price indices and others.

Table 4.1 shows that LN-Macro reflects a severe economic activity deterioration during Credit Crisis when it reaches its largest and most negative levels (about three times more than Pre-Crisis levels in absolute value terms). The levels tend to increase once again in Post-Crisis period, though with higher volatility compared to Credit Crisis. To be more precise, the average (standard deviation) of the LN-Macro in terms of principal component values is 3.04 (1.66) in Pre-Crisis, -0.37 (2.04) in Liquidity Crisis, -10.30 (3.56) in Credit Crisis, and 0.03 (4.73) in Post-Crisis. Since this variable captures the macro wealth shock in the economy, and the deterioration in general production, consumption and housing markets, it is likely to have impact on macroeconomic compression, and thus the validity of initiating a $Basis_{\text{bond}}$ trade in such an economy.

- *Term Premium:* A vast literature shows that the term premium of the U.S. yield curve is a forward looking proxy of macroeconomic activity. It has also been argued that arbitrageurs fund their activities rolling short maturity instruments. Estrella and Hardouvelis (1991) state that an upward sloping term structure is related to future rise in real economic activity. In addition, Landschoot (2008) empirically show that a rise in default-free term structure causes yield spreads to drop, given that, according to expectation hypothesis, an upward sloping term structure is associated with an increase in future short-term interest rates and a decrease in yield spreads. See also Vayanos and Vila (2009) for a model in which the slope of the term structure is informative about the relative cost of arbitrageurs funding risky arbitrage in bonds. We define the term premium as the difference between 10-year Treasury yield and 3-month Libor yield (see Landschoot (2008)). We label this factor as TP.

  Table 4.1 shows that TP increases from Pre-Crisis to Post-Crisis. The average (standard deviation) is -0.29% (0.40%) in Pre-Crisis, 0.20% (0.91%) in Liquidity Crisis, 0.93% (0.72%) in Credit Crisis, and 3.06% (0.50%) in Post-Crisis.

[9] Examples of price variables removed include: the S&P dividend yield, the Federal Funds (FF) rate, the 10-year T-bond, the Baa - FF default spread, and the Dollar-Yen exchange rate.

E. *Credit Risk Factors*

A high number of defaults tend to produce higher default expectations at times of recessions. To measure the impact of emerging market default risk, we use the Markit CDX Emerging Markets index price.[10] This index is used as a benchmark to study the changes in the credit quality of the underlying emerging markets, and reflect the default risk perception. The index price is inversely related to spread, and hence, the index tends to decrease when the credit spread (or default risk) increases. Since $Basis_{\text{bond}}$ trade is subject to the potential default of the underlying bonds, this variable captures the extent to which credit deterioration hinders arbitrageurs from participating in the strategy. We label this variable EM-CDSI starting from Liquidity Crisis.

Table 4.1 shows that EM-CDSI reaches its lowest index price (and hence its highest CDS spread levels) during Credit Crisis, giving a strong indication about the deteriorating default perception on emerging markets. This highlights the inherent riskiness of the underlying $Basis_{\text{bond}}$ trade, given that it consists of defaultable bonds. A significant fall in the general credit quality of the emerging market bonds would be a potential reason why an arbitrageur would be unwilling to participate in the strategy. The average (standard deviation) of the EM-CDSI index prices is 99.64 (1.74) in Liquidity Crisis, 87.49 (6.19) in Credit Crisis, and 107.94 (4.21) in Post-Crisis.

F. *Risk Aversion Factors*

- *Closed End Fund Discount Risk:* Closed-End Funds are investment companies (actively managed by an investment advisor) that initially raise fixed capital through IPO, and then trade like stocks on the exchange markets. They focus on specific industries or geographies (like emerging markets), and use leverage to increase returns. The stock price per share may be different than the net asset value (NAV) per share of the fund's investments. The stock price is said to be trading at a premium (discount) if it is above (below) the NAV. In other words, it is a premium when [Market Price]/[NAV] $>$ 1, and discount when [Market Price]/[NAV] $<$ 1. This is referred in the literature as a "closed-end fund puzzle", since it is difficult to explain this phenomenon. Technically, an investor can buy a sufficient amount of the under-priced shares from the market, gain the majority control of the company, and force investors to sell the fund at a higher market value, making an arbitrage profit. This is why a large body of the literature investigates the persistence of the closed-end fund discount as a potential pricing puzzle. The literature takes two different directions: (1) Rational models and (2) Behavioral models. Rational models tend to explain the anomaly by highlighting the importance of

[10]The CDX index is a standardised tradable credit security on its own. The credit event associated with the index is defined as bankruptcy or failure to pay. The determination of the new constituents follows the rule-based approach that takes into account liquidity (see http://www.markit.com for details).

frictions such as agency costs, managerial abilities and time variation in the discount factor (Malkiel (1977); Spiegel (1997); Ross (2002); Berk and Stanton (2007)), whereas behavioral models argue that it is due to irrational investment decisions and market sentiments (De Long, Shleifer, Summers, and Waldmann (1990); Lee, Shleifer, and Thaler (1991); Bodurtha, Kim, and Lee (1995); Baker and Wurgler (2007)).

We compute the arithmetic average of the closed-end funds discounts of three important emerging market debt funds (EDD, TEI and MSD).[11] We generate the closed-end fund premiums (discounts) by dividing the market prices to NAVs, and label it Closed End. We use this variable as a proxy for risk aversion against emerging market economies.

Note that the smaller the Closed End variable, the bigger the fund discount, and the bigger the mispricing anomaly. Table 4.1 indeed shows that this ratio reaches its lowest average and highest volatility during the Credit Crisis, even though closed end funds tend to trade at a discount throughout the given sample period. To be more precise, the average (standard deviation) of the given price ratio is 0.94 (0.03) in Pre-Crisis, 0.91 (0.03) in Liquidity Crisis, 0.79 (0.06) in Credit Crisis, and 0.88 (0.04) in Post-Crisis. This gives evidence for a potential fear against leverage and illiquidity, and a lack of confidence in the underlying emerging market securities during Credit Crisis.

- *Perceived Tail Event Risk:* In accordance with the studies of Bollerslev and Zhou (2006), and Bekaert, Harvey, Lundblad, and Siegel (2011), we use another measure of risk aversion with VIX option volatility index, which is the Chicago Board Options Exchange Market Volatility Index computed from the implied volatility of S&P 500 index options. Market practitioners use VIX as a representative of fear factor in the U.S. markets, as it captures the market's expectation of stock market volatility over the next 30 day period. It summarizes the cost of protection against major market tail event risk (see Pan and Singleton (2008) for an application in the context of credit markets). As further examples of empirical studies, Campbell and Taksler (2003) find a significant co-movement between the volatility of stock returns and credit risk premiums; and similarly, Landschoot (2008) highlights the significance of VIX (and VIX-squared for non-linearity effect) in corporate credit premiums across USD and Euro currencies. Finally, Cremers, Driessen, and Maenhout (2008) find that the jump risk premium, denoted by option-implied volatility, is an important component of credit spreads.

  Table 4.1 shows that VIX increases considerably from Pre-Crisis to Credit Crisis, and drops once again in Post-Crisis. The average (standard deviation) is 12.97% (2.55%) in Pre-Crisis, 23.05% (3.55%) in Liquidity Crisis, 48.20% (14.06%) in Credit Crisis, and 25.05% (5.93%)

[11] EDD stands for Morgan Stanley Emerging Markets. TEI stands for Templeton Emerging Markets Income Fund. MSD stands for Morgan Stanley Emerging Markets Debt Fund Inc.

in Post-Crisis. This implies that the forward-looking volatility and the tail event risk of the market rises by more than 270% from Pre-Crisis to Credit Crisis.

G. *Global Uncertainty Factor*

An emerging body of literature uses dispersion in analyst forecasts as a proxy for ambiguity and uncertainty in financial markets, which could have an adverse impact on the risk aversion of the arbitrageurs, and hence on the $Basis_{\text{bond}}$ trade. They find that disagreement in beliefs helps to explain yield spreads. We incorporate subjective uncertainty using the Buraschi and Whelan (2012) dispersion factor, which is intended to capture the U.S.-based macroeconomic uncertainty. The heterogeneity in beliefs is obtained from market participant surveys regarding the expectations of future prices and macroeconomic fundamentals. The panel data on the expectations is provided by Blue Chip Economic Indicators (BCEI). Buraschi and Whelan (2012) focus on two types of forecasts (short-term and long-term), and three economic variables: (1) *Real* - Real GDP and Industrial Production (2) *Nominal* - Consumer Price Inflation and GDP deflator (3) *Monetary* - 3-Month and 10-year Treasury rates. The first principal component of the cross-sectional mean-absolute-deviation (MAD) in forecasts is computed for each category to proxy the macroeconomic disagreement. We directly use this first principal component as a proxy for the disagreement in beliefs, and label it as DiB. The variable is not available for the Post-Crisis period.

Table 4.1 shows that the disagreement in belief proxy increases as of Pre-Crisis, and reaches its maximum level during the Credit Crisis. The average (standard deviation) of the principal components is -0.22 (0.07) in Pre-Crisis, -0.10 (0.12) in Liquidity Crisis, and 0.25 (0.08) in Credit Crisis.

II. Determinants of Basis(bond)

In order to investigate the impact of various risk channels and constraints, we run weekly panel regressions on net $Basis_{\text{bond}}$ (based on absolute values, as defined by Eq. 3.11 in Chapter 3) for all bond pairs, and for all countries.[12] Regressions are based on White's heteroskedasticity-consistent estimators. The reason for using net $Basis_{\text{bond}}$ for all countries is to facilitate the economic interpretation of the analysis. Since net $Basis_{\text{bond}}$ is represented in absolute value terms, any rise in net $Basis_{\text{bond}}$ would directly indicate a rise in the pricing anomaly across any given emerging country. This way, a significantly positive/negative slope coefficient of an explanatory risk factor, when

[12] Monthly series (i.e. Liq-PS, LN-Macro and DiB) are weekly interpolated at end-of-week points to create matching data. For daily series (i.e. Inventory and Transaction), end-of-week days are used to create matching data. Inventory series are standardized.

regressed against net $Basis_{\text{bond}}$, could be unambiguously interpreted as increasing (or decreasing) the size of the anomaly, regardless of whether the actual $Basis_{\text{bond}}$ deviation is positive (Brazil and Mexico) or negative (Turkey). Therefore, a positive slope coefficient implies that the explanatory variable is positively correlated with net $Basis_{\text{bond}}$, such that any increase (decrease) in the explanatory variable increases (decreases) the pricing anomaly across all countries. On the other hand, a negative slope coefficient implies that the explanatory variable is inversely correlated with net $Basis_{\text{bond}}$, such that any increase (decrease) in the explanatory variable decreases (increases) the pricing anomaly across all countries.

As described in Fletcher and Taylor (1996), the main target is to understand the portion of the LOP mispricing that is in "excess" of the underlying bid-ask spreads. Once transaction costs are deducted, leading to net $Basis_{\text{bond}}$, there still remains a large time-variation unexplained. This is the portion that warrants investigation. This is why, in accordance with limits-to-arbitrage literature, we use net $Basis_{\text{bond}}$ on the LHS of regressions as the dependent variable. The only exception is Eq. (4.1) in section II.A, where we use gross $Basis_{\text{bond}}$. This is done to investigate the impact of bond-specific illiquidity (captured by bid-ask spreads). In all regressions, we focus on whether the following null hypothesis (H_0) holds for each independent variable:

$$\text{H}_0 : \text{No impact on the growth of } Basis_{\text{bond}}.$$

Hence, the rejection of the null hypothesis will give us statistical evidence that the corresponding risk factor has significant impact on $Basis_{\text{bond}}$. This section will help us pinpoint the risk factors that were responsible in deterring arbitrageurs from exploiting the $Basis_{\text{bond}}$ strategy, and consequently causing price convergence to remain unrealized in the market.

A. Liquidity Frictions

Liquidity is often argued to be an important priced state variable that captures the features of the investment environment and macroeconomy. An elevated mispricing could be evidence of liquidity frictions (Condition $\mathcal{C}1$). Either trading is costly or traders may be reluctant to take positions due to concerns about the potential future market impact of their trades. Amihud and Mendelson (1986), as well as a vast literature that followed, argue that bond-specific market liquidity is a significant factor in the pricing of corporate bonds. Longstaff, Neis, and Mithal (2005) point out the fact that a large portion of corporate spreads is due to default risk, but the time-varying nature of the non-default component is strongly related to bond-specific illiquidity. Furthermore, Perraudin and Taylor (2003) show that liquidity risk premium accounts for an important portion of credit spreads. Houweling, Mentink, and Vorst (2005) also find that liquidity risk premium is priced in corporate yield spreads. Starting in early 2007, a reduction of liquidity increased bid-ask spreads in several financial markets, leading commentators to refer to this period as a liquidity crisis. In this section, we investigate the link between the $Basis_{\text{bond}}$ and the reduced liquidity in the cash bond and FX markets.

First, we compare the dynamics of bid-ask spreads of both the cash bonds and the forward contracts required to build a long-short position in the $Basis_{\text{bond}}$ trade. Indeed, in the Liquidity Crisis, total bid-ask spreads increased by an average of 1.4x compared to the Pre-Crisis period. Bond bid-ask spreads, on average, account for 67% of the total transaction costs in the Pre-Crisis period, and 64% in the Liquidity Crisis period. From the Pre-Crisis to the Credit Crisis period, total bid-ask spreads increased by more than 1.8x; this is due to a 1.7x increase in the bond bid-ask spreads and a 2x increase in the FX bid-ask spreads. While transaction costs certainly increased, we find, however, that the increase in $Basis_{\text{bond}}$ far outstrips total transaction costs during the Credit Crisis (see Figure 3.1). $Basis_{\text{bond}}$ reaches levels that in some periods exceed total bid-ask spreads by 5x for Turkey 2014, 11x for Turkey 2019, 6x for Brazil 2010, 9x for Brazil 2015, and 5x for Mexico 2020 bonds.[13]

To investigate this link further, we regress the changes in the absolute value of gross $Basis_{\text{bond}}$ (without bid-ask adjustment), on changes in the bond-specific total bid-ask costs (denoted as BidAsk), Liq-FX and Liq-PS:

$$\Delta \left|\text{Gross } Basis(bond)_{j,t}\right| = \alpha_j + B_1 \left[\Delta BidAsk_{j,t}\right] + B_2 \left[\Delta Liq\ FX_t\right] + B_3 \left[\Delta Liq\ PS_t\right] + \epsilon_{j,t} \tag{4.1}$$

where α denotes the country-specific fixed effect, Δ denotes the first-difference, and j denotes the country-specific $Basis_{\text{bond}}$ of the bond pairs for Brazil 2010, Brazil 2015, Mexico 2020, Turkey 2014, and Turkey 2019. The idiosyncratic errors are captured by ϵ_t at time t. Table 4.3 details the regression specifications and summarizes the results in Column (A) by reporting the slope coefficients, White robust t-statistics and R-squared values.

Calculations reveal that during the Credit Crisis, BidAsk, Liq-FX and Liq-PS are all insignificant. The explanatory power is limited, never exceeding an R-squared of 3%.[14] Accordingly, the bond-specific transaction costs as well as the exchange rate costs arising from the spot and forward FX markets are not binding, suggesting that liquidity risk played a limited role in explaining the observed phenomenon.

[13] Note that the credit ratings of these countries have been upgraded by Fitch from 2007 to 2010: Brazilian treasuries from BB to BBB, Mexican treasuries from BB+ to BBB, and Turkish treasuries from BB- to BB+. This is consistent with the relatively small observed variations in bid-ask spreads for these bonds.

[14] To correct for the possibility that bid-ask spreads may be a function of the liquidity frictions (Liq-FX and Liq-PS), an additional test is conducted by running the effect of the given liquidity frictions on BidAsk, and using the residuals as a new liquidity measure against gross $Basis_{\text{bond}}$. These residuals would represent the portion of the bid-ask spreads that cannot be explained by Liq-FX and Liq-PS. We find that this new liquidity variable is also statistically insignificant.

B. *Short-Selling Constraints and Security Lending Frictions*

To implement our trading strategy, a trader needs to borrow a security from a broker dealer (Condition $\mathcal{C}2$). If this security is not available and/or the cost of borrowing is high, the trader can effectively face a short-selling constraint. Indeed, important literature has emerged that studies the implications of short-selling constraints (Harrison and Kreps (1978), Diamond and Verrecchia (1987), Scheinkman and Xiong (2003), Tuckman and Vila (1992)). To investigate this channel, we use bond-specific data on total lendable value adjusted to include the active availability for lending (i.e. Inventory), capturing the tightening of the loan supply and short-selling constraints in the Eurobond market.

Controlling for country-specific fixed effects, we run panel regressions for the changes in net $Basis_{\text{bond}}$ (after bid-ask adjustment) of the bond pairs included in the analysis on the changes in Inventory:

$$\Delta\left[\text{Net } Basis(bond)_{j,t}\right] = \alpha_j + \lambda_1 \left[\bar{\Delta} Inventory_{j,t}\right] + \epsilon_{j,t} \tag{4.2}$$

where α denotes the country-specific fixed effect, $\bar{\Delta}$ denotes the percentage difference, and other notations are as defined before. Table 4.3 details the regression specifications and summarizes the results in Column (B) by reporting the slope coefficients, White robust t-statistics and R-squared values.

Calculations reveal that Inventory is statistically significant at 95% confidence level, showing that during Credit Crisis the constraints in bond supply indeed help to explain net $Basis_{\text{bond}}$ deviations across all given bond pairs. The slope coefficient λ_1 is negative (with a t-stat of -2.99), implying that an increase in Inventory reduces net $Basis_{\text{bond}}$. This is consistent with recent findings on equity markets about the impact of the short-selling bans on price efficiency (see Saffi and Sigurdsson (2011)). The implication is that when the bond supply drops in the market (i.e. owners make bonds less available), the prices are less informative, and the initiation of the trade is jeopardized, preventing arbitrageurs from freely longing/shorting the required bonds, causing net $Basis_{\text{bond}}$ to diverge further away from zero. Nevertheless, our findings suggest that, when regressed alone, this channel has limited statistical explanatory power, having 3% R-squared.[15] The question is, if liquidity costs and short-selling constraints do not sufficiently enhance our understanding of $Basis_{\text{bond}}$ variation, then what does? A third source of friction investigated by the limits-to-arbitrage literature is related to funding constraints, which we explore in the next section.

[15] In addition, the impact of lending fees on $Basis_{\text{bond}}$ is investigated by Buraschi, Menguturk, and Sener (2013). Their findings show that lending fees are also not the main driver of the underlying pricing anomaly.

C. *Funding Costs in Debt Markets*

Consider a wealth shock that weakens the balance sheets of arbitrageurs. If external capital is still readily accessible then wealth shock could be absorbed by additional borrowing (Condition $\mathcal{C}3$). If access to external capital is limited, however, arbitrageurs may be forced to close their existing arbitrage positions, making the LOP equilibrium difficult to attain. Gromb and Vayanos (2002) and Gromb and Vayanos (2010) study a model in which arbitrageurs must collateralize their positions in each asset to implement an arbitrage. According to them, arbitrageurs cannot enforce the LOP condition unless their wealth is large relative to the demand shock and the margin requirement. Brunnermeier and Pedersen (2009), and Gromb and Vayanos (2010) extend this analysis to multiple assets. With multiple assets, they show that leverage constraints can generate contagion of shocks to seemingly unrelated assets. Shocks to one asset are transmitted to otherwise unrelated assets through changes in the arbitrageurs' balance sheets. Relating their argument to our analysis, trading desks operating simultaneously on multiple sovereign bond markets, cause international contagion of shocks and frictions across their assets.

Controlling for country-specific fixed effects, we run panel regressions for the changes in net $Basis_{\text{bond}}$ against the changes in Secured and Unsecured funding costs:

$$\Delta\left[\text{Net } Basis(bond)_{j,t}\right] = \alpha_j + \theta_1\left[\Delta Unsecured_t\right] + \theta_2\left[\Delta Secured_t\right] + \epsilon_{j,t} \tag{4.3}$$

where all notations are as defined before. Table 4.3 details the regression specifications and summarizes the results in Column (C) by reporting the slope coefficients, White robust t-statistics and R-squared values.

Calculations reveal that while Secured is statistically insignificant in this analysis, Unsecured is statistically significant at 90% confidence level, showing that during Credit Crisis the uncollateralized funding constraints indeed help to explain net $Basis_{\text{bond}}$ deviations across all given bond pairs. R-squared is 5%. The slope coefficient θ_1 is positive (with a t-stat of 1.67), implying that an increase in Unsecured funding cost increases net $Basis_{\text{bond}}$. This result is consistent with statements made by central bankers, before and during the crisis, underlying the importance of the unsecured interbank funding market. For example, Greenspan argued on various occasions that the LIBOR/OIS differential is a key characteristic of interbank lending and a key measure of the functioning of capital markets.[16]

[16] Greenspan consistently referred to this indicator as a key measure of policy effectiveness of the Fed interventions: "Lehman default [...] drove LIBOR/OIS up markedly. It reached a riveting 364 basis points on October 10th. The passage by Congress of the 700 billion dollar Troubled Assets Relief Programme (TARP) on October 3rd eased, but did not erase, the post-Lehman surge in LIBOR/OIS. The spread apparently stalled in mid-November and remains worryingly high." This convinced the Fed to intervene in the swap market in order to address the unusually wide LIBOR/OIS spreads in the initial stage of the crisis.

D. *The Macro Environment*

Subsections A, B and C above show that (a) liquidity frictions, (b) short-selling constraints, and (c) funding costs fail to offer a sufficiently convincing explanation when regressed in their own categories alone. But this is hardly surprising considering the truly global nature and the gargantuan scale of the economic disruption behind these price anomalies during the Credit Crisis. It would be overly simplistic to represent this highly interconnected, complex phenomenon within the categories of our own design. In the present section, therefore, we form various pools of distinct category variables, and investigate how they act jointly. In particular, we first control for the Liquidity Frictions and Short-Selling Constraints together with the Funding Costs, and run the following regression on net $Basis_{\text{bond}}$:

$$\begin{aligned}\Delta\left[\text{Net } Basis(bond)_{j,t}\right] = \alpha_j + \gamma_1\left[\Delta Liq\ FX_t\right] + \gamma_2\left[\Delta Liq\ PS_t\right] + \gamma_3\left[\bar{\Delta} Inventory_{j,t}\right] \\ + \gamma_4\left[\Delta Unsecured_t\right] + \gamma_5\left[\Delta Secured_t\right] + \epsilon_{j,t} \qquad (4.4)\end{aligned}$$

where all notations are as defined before. Table 4.3 details the regression specifications and summarizes the results in Column (D) by reporting the slope coefficients, White robust t-statistics and R-squared values. Results confirm that the unsecured funding channel retains its significance in the presence of short-selling constraints.

The joint role played by the short-selling constraints and funding costs may also be affected by the contemporaneous effect of other omitted state variables. For this reason, we extend the regression specifications in Table 4.3 and control for other potentially significant macro effects. We organize the control variables, for notational convenience, under: (i) Global Cash-Flow Factors, (ii) Credit Risk Factor, (iii) Risk Aversion Factors, and (iv) Global Uncertainty. See Section I of this chapter for the detailed explanation of each category. Controlling for country-specific fixed effects, we run the following panel regressions for the changes in net $Basis_{\text{bond}}$:

$$\begin{aligned}\Delta\left[\text{Net } Basis(bond)_{j,t}\right] = \alpha_j + \beta_1\left[\Delta Funding\ Costs_{t-v}\right] + +\beta_2\left[\Delta Short\ Selling\ Constraints_{j,t}\right] \\ + \beta_3\left[\Delta Global\ Cash\ Flow\ Factors_t\right] + \beta_4\left[\Delta Credit\ Risk\ Factor_t\right] \\ + \beta_5\left[\Delta Risk\ Aversion\ Factors_t\right] + \beta_6\left[\Delta Global\ Uncertainty_t\right] + \epsilon_{j,t} \qquad (4.5)\end{aligned}$$

where all notations are as defined before.[17] Table 4.4 details the regression specifications and summarizes the results by reporting the slope coefficients, White robust t-statistics and R-squared values for Liquidity Crisis, Credit Crisis and Post-Crisis periods.

Our findings reveal that, during the Liquidity Crisis, the most significant variable is Secured

[17] Funding Costs are regressed with the weekly lag parameter v = 0 for Unsecured Funding, and v = 1 for Secured Funding. This lag specification is chosen after observing that the impact of Secured Funding comes with a lag, possibly due to an inertia effect in the collateralized market.

funding with a positive slope coefficient (and a t-stat of 1.87). The tail event risk captured by VIX is also found statistically significant with a positive slope coefficient (and a t-stat of 1.74). Nevertheless, no other factor linked to economic activity is significant. R-squared is 7%.

During Credit Crisis, however, a completely different picture emerges. Variables within the categories of Global Cash-Flow Factors, Risk Aversion Factors and Credit Risk Factor become highly and statistically significant. This suggests that during the market turmoil, $Basis_{\text{bond}}$ was not simply the outcome of a security-specific phenomenon but was in fact correlated with market-wide systematic factors. To be more precise, shocks to macroeconomic activity (represented by LN-Macro) are found statistically and economically significant with a negative slope coefficient (and a t-stat of -2.03) during Credit Crisis, whereas they are insignificant during Liquidity Crisis. This result suggests that, the lower the level of macroeconomic activity, the higher the net $Basis_{\text{bond}}$ across the given bond pairs. Therefore, the impact of the macro wealth shock (affecting aggregate consumption and production) indeed matters, especially in an environment when arbitrageurs are unable to compensate it by leveraged borrowing. The shrinkage of the economy seeps into the trading behavior of all economic agents, some of whom are unwilling to lend, and some of whom are unwilling to borrow. The deadlock of the transaction markets would surely *limit* the arbitrageurs to freely short/long the corresponding bonds, and to provide the necessary liquidity into the dislocated markets.

Second, the risk-aversion proxy based on the average discount of a portfolio of EM closed-end funds (represented by Closed End) is also found statistically and economically significant with a negative slope coefficient (and a t-stat of -4.55). This result suggests that, as the closed end discount decreases by diverging further away from one towards zero (and thus the size of mispricing anomaly increases in the underlying emerging market funds), net $Basis_{\text{bond}}$ increases. The implication is that, in this period, the arbitragers being relatively more risk-averse to trade emerging market funds (due to lack of confidence) would be withdrawing (or liquidating) their positions in other emerging market asset classes (such as Eurobonds) as well. The growing negativity of Closed End during Credit Crisis implies that there is a severe problem in the asset valuation dynamics in emerging markets.

Third, the default risk proxy (represented by EM-CDSI) is also found statistically and economically significant with a negative slope coefficient (and a t-stat of -3.51). The result suggests that a decrease in the CDS index (i.e. an increase in EM default risk) increases net $Basis_{\text{bond}}$. The implication is similar to that of Closed End. Arbitrageurs becoming increasingly risk-averse against default, in this period, would be withdrawing (or liquidating) their positions in emerging market asset classes that tend to pose a serious credit risk. If the bonds default indeed, the arbitrageurs' profits would dwindle away proportionally by the recovery rate. Therefore, if the perception of default risk is greater than the return, the opportunity indicated by $Basis_{\text{bond}}$ would be left unexploited.

Fourth, after controlling for the additional exogenous factors above, both the Unsecured and one-week lagged Secured funding channels are found highly and statistically significant with positive slope coefficients (and t-stats of 2.08 and 2.47, respectively, higher than in Table 4.3). This result highlights the role of both hedge funds and investment banks in ensuring the LOP condition as long as the funding constraints that they face are not binding (to be discussed in further detail in Chapter 5). It can thus be argued that Funding Costs help to capture the tightness of leverage constraints, which might limit the demand for risk capital needed to carry arbitrage trades and absorb deviations from the LOP.[18] Furthermore, Inventory also retains its statistical significance with a negative slope coefficient (and a t-stat of -3.66, again higher than in Table 4.3). The conclusion is that when Short-Selling Constraints and Funding Costs are controlled with exogenous macro shocks related to macroeconomic deterioration, risk aversion and default risk, the majority of net $Basis_{\text{bond}}$ deviation can indeed be explained accurately during Credit Crisis. This suggests that net $Basis_{\text{bond}}$ is strongly and adversely affected by the interaction between deteriorated supply dynamics, leverage constraints and funding costs in the presence of a massive macroeconomic shock restraining the supply of risk capital extensively. Jointly, these factors account for 43% of the total variation.[19]

To ensure robustness, we finalize our investigation by regressing each category individually against net $Basis_{\text{bond}}$. Table 4.5 details the regression specifications and summarizes the results by reporting the slope coefficients, White robust t-statistics and R-squared values for Credit Crisis. Our findings show that the market constraints that are found significant jointly are also found significant individually. This strengthens our claim that the conclusions are robust.

These results show that on one side, sharply decreasing supply of funds, due to rising funding costs (captured by Secured and Unsecured), and falling bond supply (captured by Inventory), and slowing macroeconomic activity (captured by LN-Macro); and on the other side, sharply decreasing appetite for risky arbitrage, due to deteriorating credit risk perception (captured by EM-CDSI) and increasing risk-aversion (captured by Closed End), acted jointly and individually as binding constraints and/or deterring factors that kept arbitrageurs from exploiting the underlying opportunity, causing prices to diverge further and further away from equilibrium.

During Post-Crisis, on the other hand, most of these factors are no longer significant, and R-squared drops down to 5%. The only significant explanatory variable is Inventory with the expected

[18] See also Bernanke and Gertler (1989) for earlier related work.

[19] Other factors, such as TP, VIX and DiB are found statistically insignificant.

negative slope coefficient (and a t-stat of -3.65). Funding Costs, Risk Aversion Factors, Global Cash-Flow Factors and Credit Risk Factor are no longer relevant in the dynamics of net $Basis_{\text{bond}}$, which tends to give strong signs of price convergence for most bond pairs during this period.

III. Geography of Basis(bond)

One of the most intriguing findings is that the *sign* of the $Basis_{\text{bond}}$ is country-specific. $Basis_{\text{bond}}$ of Turkey is generally negative, whereas $Basis_{\text{bond}}$ of Mexico and Brazil is generally positive. This sign puzzle implies that arbitrageurs in Turkey would long the USD bond and short the Euro bond, whereas those in Brazil and Mexico would make the opposite trade. This result is of interest to us since it provides additional important clues as to the type of frictions that are at the source of the pricing dynamics.

A. *Price Discovery of Credit Yield Spreads*

If institutional frictions create asymmetries in the relative cost of funding for different sovereign bonds, this asymmetry would be visible in terms of the relative difference in the information content of each bond. We use a price discovery analysis to learn about the potential effects of the geographical frictions that relate to the cross-sectional differences in information content.

There are two traditional ways to conduct a price discovery analysis. The first one is based on the information share (IS) measure, as suggested by Hasbrouck (1995). The second one is based on the component share (CS) measure, as suggested by Gonzalo and Granger (1995). Both measures rely on vector error-correction models (VECM). IS assumes that price volatility reflects new information, and allows for the correlation among multiple markets via the variance and covariance of price innovations. Following Blanco, Brennan, and Marsh (2005), we calculate the IS measures and find the contribution of USD credit yield spreads (i.e. S_t^a) to Euro credit yield spreads (i.e. S_t^b). Using the interpolated riskless USD and EUR government yields (R^a and R^b, respectively), and the actual USD and EUR yields (Y^a and Y^b, respectively), of the underlying bonds in Turkey 2014-maturity bond pairs, Brazil 2015-maturity bond pair, and Mexico 2020-maturity bond pair, for each time t, we first calculate the credit yield spreads, $S^i(t,T) = Y^i(t,T) - R^i(t,T)$ for each currency i=[a, b], where a=USD and b=EUR, as defined before.[20] Our calculations reveal that:

$$\text{In Brazil and Mexico} : S^a < S^b \tag{4.6}$$

$$\text{In Turkey} : S^a > S^b \tag{4.7}$$

Applying the Johansen cointegration test, we find that S_t^a and S_t^b are highly cointegrated during the sample period across the given bond pairs. We define $z_{t,T} \equiv [S_{t,T}^a - k_1 \times S_{t,T}^b]$. Dropping subscript T for notational convenience, we estimate the following VECM for the credit yield spreads of each country:

$$\Delta S_t^a = A_1 z_{t-1} + \sum_{n=1}^{N} \phi_{1n} \Delta S_{t-n}^a + \sum_{n=1}^{N} \gamma_{1n} \Delta S_{t-n}^b + u_{1t} \tag{4.8}$$

$$\Delta S_{c,t}^b = A_2 z_{t-1} + \sum_{n=1}^{N} \phi_{2n} \Delta S_{t-n}^a + \sum_{n=1}^{N} \gamma_{2n} \Delta S_{t-n}^b + u_{2t} \tag{4.9}$$

where the optimal lag structure $N = 2$ is determined by Akaike Information Criteria (AIC). To estimate the cointegration parameter k_1, we use directly the restrictions implied by the LOP and set it equal to the average of $X(t)/F(t,T)$ for each bond pair. We are interested in exploring two properties of this dynamic system: (a) the existence of an asymmetric structure in the vector $A = [A_1, A_2]$, and (b) the Hasbrouck information-share coefficient.

Following the detailed explanation in Blanco, Brennan, and Marsh (2005), it is argued that, in the presence of frictions, S^b contributes more to the price discovery if A_1 is statistically significant and negative. On the other hand, S^a contributes more to the price discovery if A_2 is statistically significant and positive. If both coefficients are significant, then both currencies are jointly important in the price discovery process.

Note also that Stock and Watson (1988) decomposition forms the basis for Hasbrouck (1995) measure of "information share". The maintained assumption is that new information is reflected by price volatility. Let σ_1 and σ_2 be the volatility of the estimated residuals u_1 and u_2, respectively, and let σ_{12} be the covariance. Blanco, Brennan, and Marsh (2005) states that "market that contributes the most to the variance of the innovations to the common factor is presumed to be the one that contributes the most to the price discovery." When $\sigma_{12} = 0$, Hasbrouck's measure is defined

[20] As discussed in the previous chapter, $S_{t,T}^a$ and $S_{t,T}^b$ must satisfy a long-run LOP restriction, namely $[S_{t,T}^a - k_{t,T} \times S_{t,T}^b] = 0$, with $k_{t,T} = X(t)/F(t,T)$.

uniquely; when $\sigma_{12} \neq 0$, this measure provides two bounds, H_l and H_u, expressed as follows:

$$H_l = \frac{A_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{A_2^2\sigma_1^2 - 2A_1A_2\sigma_{12} + A_1^2\sigma_2^2}, \qquad H_u = \frac{\left(A_2\sigma_1 - A_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{A_2^2\sigma_1^2 - 2A_1A_2\sigma_{12} + A_1^2\sigma_2^2} \tag{4.10}$$

where $A = [A_1, A_2]$ are the estimated slope coefficients from Eq. (4.9). In order to find the decomposition of the price discovery process, Baillie, Booth, Tse, and Zabotina (2002) suggest using the average of H_l and H_u, namely H_m. Based on Eq. (4.10), H_m estimates how much S^a contributes to the price discovery process. Therefore, $1 - H_m$ shows how much S^b contributes to the price discovery process. If $H_m > 50\%$, then S^a is the greater contributor; if $H_m < 50\%$, then S^b is the greater contributor; and if $H_m = 50\%$, both credit yield spreads are equally important in the price discovery process.

Table 4.6 summarizing our results, indicate a clear pattern. For Brazil and Mexico, A_2 is positive and statistically significant, showing that S^a contributes more to the price discovery process. On average, H_m is 66% for Brazil, and 84% for Mexico. On the other hand, the exact opposite is true for Turkey. We find that A_1 is negative and statistically significant, showing that S^b contributes more to the price discovery process. On average, H_m is 29%, so that the contribution of S^b is 1- H_m = 71%. These results show the geographical differences in the information content of sovereign bonds, and implies that different funding channels may be at work to create a cross-sectional dispersion in the price discovery process.

B. *Currency Composition of Central Bank International Reserves*

Is the evidence in the previous section consistent with capital hoarding at the country-specific level? This phenomenon, perhaps triggered by a precautionary motive in anticipation of future expected losses from security write-downs, might have played a role in the geography of funding capital. To investigate this issue in greater detail, we study the evolution of capital at aggregate level, in terms of central bank foreign currency reserve distributions of Turkey and Brazil.[21] Table 4.7 displays the reserve distribution on the following currencies: the U.S. dollar (USD), Euro (EUR), and others (e.g. Japanese Yen (JPY), British Pound (BGP), Canadian Dollars (CAD), Australian Dollars (AUD)).

Interesting geographical patterns emerge. It is observed that 51% (46%) of the total international reserves of Turkey was attributed to USD (EUR) during 2008.[22] Similarly, the same proportion was

[21] The data for Turkish Central Bank reserve distribution is retrieved from the central bank official website (www.tcmb.gov.tr). The data for Brazilian Central Bank reserve distribution is retrieved from a Senior Economist of HSBC Bank Brazil. No data is available for Mexico's central bank foreign reserve distribution.

[22] No data is available for years preceding 2008.

52.6% (44.6%) in 2009, and 51.3% (46.5%) in 2010, respectively. Note that the USD reserves also include gold and SDR, implying that it is not pure dollar currency. Even under these circumstances, however, the proportion of EUR assets is highly close to that of USD assets. Since there is not a great deal of movement in the reserves (the proportion is "sticky" over time), Turkey, being also major trade partner with the Euro Zone, have the features of being a Euro-strong country, which would bring about a positive impact on the credit perception of its Euro-denominated liabilities vis-a-vis USD-denominated ones. In addition, if gold and SDR reserves are deducted from the USD reserves, it is very likely that Turkey holds more Euro reserves than USD reserves. This would mean that Turkey is better equipped to meet its Euro-denominated obligations than its USD-denominated ones, suggesting that a lower default probability (and a lower credit yield spread) would be assigned to its Euro-denominated assets. This is a plausible reason for $S^a > S^b$ in Turkey.

The situation is different for Brazil. In Table 4.7, it is noted that the weight of the dollar reserves rose from 55% in 2004 to 89% in 2008, whereas the weight of the Euro reserves during the same period fell from 35% to 9%. It is evident that Brazil is predominantly a USD-strong country. Share of Euro in Brazil's international reserves, being small and falling, would generate a negative impact on the credit perception of its Euro-denominated liabilities, offering a plausible reason for $S^a < S^b$ in Brazil (and possibly Mexico for that matter).

C. *Decomposing Basis(bond)*

While Eq. (3.3) (in Section I, Chapter 3) served as an initial stepping-board to construct $Basis_{\text{bond}}$ under a coupon framework (in Section III, Chapter 3), Eq. (3.4) (in Section I, Chapter 3) similarly provides us with a strong intuition to decompose $Basis_{\text{bond}}$ into its CIRP and Spread components. Following the procedure described in Section III, Chapter 3, and assuming that the Eurobond pairs used in our study are issued by risk-free sovereigns (e.g. U.S. and Germany), we construct a hypothetical risk-free bond pair and calculate the CIRP component that we call $Basis_{\text{cirp}}$. We do this by replacing the Eurobond market yields (Y^a and Y^b) with the risk-free government bond yields (R^a and R^b) in USD and EUR.[23] We define $Basis_{\text{cirp}} = R^{a^*} - R^a$, where R^{a^*} is the yield of the synthetic USD riskless bond, and R^a is the yield of the original USD riskless bond. Any difference between $Basis_{\text{bond}}$ and $Basis_{\text{cirp}}$ therefore represents the additional Spread component in the trading strategy, calculated as:

$$Basis_{\text{spread}} = Basis_{\text{bond}} - Basis_{\text{cirp}} \tag{4.11}$$

[23] USD and EUR riskless government yields are retrieved from Bloomberg (BGN). These yields are linearly interpolated using fixed maturity points (2-years to 10-years) at each time t to come up with such R^a and R^b that exactly correspond to Eurobonds' actual time-to-maturities.

Note that while $Basis_{\text{cirp}}$ captures the proportion of $Basis_{\text{bond}}$ due to CIRP violation, $Basis_{\text{spread}}$ captures the proportion due to the mispricing in the underlying country-specific credit yield spreads.[24] While it is difficult to identify the fundamental source of the anomaly, this analysis will give us a useful insight about the link between the $Basis_{\text{bond}}$ at the level of the individual issuing countries and the CIRP violation in the global FX markets. A good understanding of the relative magnitudes of the two components can shed light on geographical dispersion of frictions.

Figure 4.2 shows the proportion of $Basis_{\text{spread}}$ and $Basis_{\text{cirp}}$ components of total $Basis_{\text{bond}}$ of Brazil, Mexico and Turkey. We select 2014-maturity Turkey, 2015-maturity Brazil and 2020-maturity Mexico bond pairs as representatives. The top left panel of the figure presents the average proportions of each component in terms of the percentage of total $Basis_{\text{bond}}$. The remaining panels show the time evolution of each component (in terms of bps) for each country separately during the last four months of 2008 (representing the peak of Credit Crisis). Our calculations reveal that $Basis_{\text{cirp}}$ is positive. This means that in Mexico and Brazil, $Basis_{\text{bond}}$ and $Basis_{\text{cirp}}$ have the same signs, but in Turkey $Basis_{\text{bond}}$ and $Basis_{\text{cirp}}$ have the opposite signs. In other words, CIRP component tends to contribute further to the total positive $Basis_{\text{bond}}$ of Brazil and Mexico; whereas it works against the total negative $Basis_{\text{bond}}$ of Turkey (pulling it closer to zero). The difference in deviation signs may require additional explanation for Turkey. Since $Basis_{\text{bond}} < 0$ for Turkey, and $Basis_{\text{cirp}} > 0$, Eq. (4.11) indicates that $Basis_{\text{spread}}$ for Turkey must have a larger negative value than $Basis_{\text{bond}}$. Therefore, the proportion of $Basis_{\text{spread}}$ exceeds 100%, and the proportion of $Basis_{\text{cirp}}$ becomes negative, even though $Basis_{\text{cirp}}$ itself is positive. This can be seen clearly in the top left panel of Figure 4.2.

The analysis unearths important results. The country-specific $Basis_{\text{spread}}$ component, compared to the universal $Basis_{\text{cirp}}$ component, is indeed the dominant factor in $Basis_{\text{bond}}$, and is a key component of the large mispricing in the corresponding emerging markets during Credit Crisis. Frictions that are specific to global CIRP markets cannot entirely explain the large deviation. The top left panel of the figure shows that, on average, 66% (34%) of Brazilian $Basis_{\text{bond}}$ is attributed to $Basis_{\text{spread}}$ ($Basis_{\text{cirp}}$) components. In Brazil, $Basis_{\text{spread}}$ reaches a maximum of 178 bps. Similarly, 80% (20%) of Mexican $Basis_{\text{bond}}$ is attributed to $Basis_{\text{spread}}$ ($Basis_{\text{cirp}}$) components. In Mexico, $Basis_{\text{spread}}$ reaches a maximum of 153 bps. On the other hand, we find that 145% (-45%) of Turkish $Basis_{\text{bond}}$ is attributed to $Basis_{\text{spread}}$ ($Basis_{\text{cirp}}$) components. This implies that the negativity of $Basis_{\text{spread}}$ is so large that even the positivity of the CIRP component is insufficient to pull it back to zero. In Turkey, $Basis_{\text{spread}}$ reaches a maximum of -267 bps.[25]

[24] Refer also to Kercheval, Goldberg, and Breger (2003), Jankowitsch and Pichler (2005), and Ehlers and Schonbucher (2006) for the no-arbitrage condition on the credit yield spreads of a single issuer across two foreign currencies.

[25] Baba (2009) argues that the CIRP violations can also be captured by using cross-currency basis swap spreads. Indeed, Buraschi, Menguturk, and Sener (2013) conduct the same analysis above by using cross-currency basis swap spreads to denote the $Basis_{\text{cirp}}$ component. The main results of the thesis are strongly in line with those found in the paper.

It can thus be argued that a significant component of the frictions are compatible with models in which the credit quality of an issuer differs across USD and EUR. This is indeed one of the most important findings of this study, providing a key explanation behind the sign mystery, since it implies that, unlike commonly assumed, investors during times of market turmoil tend to assign different default risks to different foreign-currency securities, even though both securities are issued by the same sovereign. The way default risk is distributed among currencies depend directly on the geography of the issuing country. Therefore, default risk is not only country-specific, but is also currency-specific in *each* country, casting doubts on condition $\mathcal{C}4$ in Chapter 3. Under these circumstances, when investors face *discordant* default risks across two equivalent securities, $Basis_{\text{bond}}$ trade could indeed be left unexploited, causing prices to diverge further from each other.

D. *Bank Funding Frictions*

Ivashina, Scharfstein, and Stein (2012) suggest an interesting hypothesis. To illustrate the idea, suppose that a large part of Turkey's lending activity is carried out by European banks. These banks can fund their Euro-lending activity by raising cash from their domestic retail base with (insured) Euro-denominated deposits. On the other hand, since they are unable to raise dollars using the insured channel,[26] a large portion of the funding of their USD lending activity takes place either by issuing (unsecured) USD-denominated commercial paper or by synthetically converting a portion of their Euro deposits into dollars. When credit risk levels are small, costs of direct and synthetic dollar funding are similar. However, if global credit risk perception deteriorates, the cost of funding dollar assets through commercial paper would increase, as U.S. money-market funds would reduce their exposure to most European banks. In the absence of other frictions, European banks could still raise capital in Euro, taking advantage of the insurance subsidy, and convert it to dollars, but in the presence of limited capacity in the foreign exchange markets (where there is an increasing reluctance in dollar supply), the cost of dollar conversion would rise.

In this light, European banks, being major traders of Turkish bonds, have comparative advantage in funding in Euro (inside capital) than USD (outside capital). Therefore, in Europe, traders would short the EUR-denominated bonds and long the USD-denominated bonds of Turkey. On the other hand, U.S. banks, being major traders of Brazilian and Mexican bonds, have comparative advantage in funding in USD (inside capital) than EUR (outside capital). Therefore, in the U.S., traders would long the EUR-denominated bonds and short the USD-denominated bonds of Brazil and Mexico.

First of all, to see if there is any tightness in the dollar deposit market in Turkey, we use the data retrieved from the official website of Turkish Central Bank for 3-month average USD and

[26] Only the capitalized U.S. subsidiary of a European headquartered bank can issue FDIC-insured deposit in the U.S.

Euro deposit rates of Turkish banks.[27] Indeed, after Lehman's collapse, we find that the 3-month USD deposit rates in Turkey increased well above the 3-months Euro deposit rates, such that the difference of USD rates minus Euro rates increased from -10 bps to 90 bps between May 2008 to October 2008 (see Figure 4.3). This evidence supports the hypothesis of country-specific capital imbalances that made the cost of funding via inside capital (insured deposits) substantially cheaper than unsecured outside funding in the foreign market.

Second, to test the existence and nature of bank funding frictions operating at the geography-specific level, we execute two sets of regressions analysis: (1) Geography-Specific Cost of Funding, and (2) Relative Cost of Funding. Details are explained below.

Geography-Specific Cost of Funding

Depending on the geographical location of the issuer, we regress the absolute value of net $Basis_{\text{bond}}$ either on [USD CP - EUR Depo] or on [EUR CP - USD Depo]. We retrieve 3-months USD and Euro CP rates from Bloomberg, and 3-month USD Deposit rates (as certificate of deposits) from Fed, and 3-month Euro Deposit rates from ECB.[28] We also control for the interbank borrowing rates in USD and Euro by using 3-month USD Libor and 3-month Euribor, (since they are highly correlated, we lag one of the two rates to avoid multicollinearity), and run the following panel regressions for the changes in net $Basis_{\text{bond}}$:

$$\begin{aligned} \Delta\,[\text{Net } Basis(bond)_{TR,t}] &= \alpha + \beta_{1,1}\,[\Delta(USD\ CP - EUR\ Depo)_t] + \beta_{1,2}\ \Delta Euribor_t + \beta_{1,3}\ \Delta Libor_{t-1} \\ &\quad + \beta_{1,4}\ \Delta L_{t-1} + \epsilon_{TR,t} \qquad (4.12) \\ \Delta\,[\text{Net } Basis(bond)_{j,t}] &= \alpha_j + \beta_{2,1}\left[\bar{\Delta}(EUR\ CP - USD\ Depo)_t\right] + \beta_{2,2}\ \Delta Euribor_t + \beta_{2,3}\ \Delta Libor_{t-1} \\ &\quad + \beta_{2,4}\ \Delta L_{t-1} + \epsilon_{j,t} \quad \text{with } j = MX, BR \qquad (4.13) \end{aligned}$$

where Δ denotes first-difference, $\bar{\Delta}$ denotes percentage difference, and j denotes the specific $Basis_{\text{bond}}$ of the bond pairs for j=[BR,MX]. TR, MX and BR represent Turkey, Brazil and Mexico, respectively. The variable L_{t-1} denotes the one-week lag of the dependent variable of each given regression. Table 4.8 reports the slope coefficients, White robust t-statistics and R-squared values of each regression.

We find that the difference of [USD CP - EUR Depo] rates is highly and statistically significant in explaining net $Basis_{\text{bond}}$ of Turkey. The slope coefficient $\beta_{1,1}$ has the expected positive coefficient sign and a t-stat of 2.34, suggesting that an increase in the unsecured USD funding (outside

[27] To be more precise, the data for the foreign-currency denominated bank deposit rates of Turkish banks is retrieved from http://evds.tcmb.gov.tr.

[28] To be more specific, USD deposit rates are retrieved from http://www.federalreserve.gov. Euro deposit rates are retrieved from http://sdw.ecb.europa.eu.

capital) relative to secured Euro funding (inside capital) increases net $Basis_{\text{bond}}$ of Turkey. The slope coefficient on Euribor is statistically significant and negative with a t-stat of -3.00, while the slope coefficient on Libor is statistically insignificant and positive. This suggests that, as interbank funding in Euro becomes less expensive, the Euro yield of Turkey's EUR-denominated bond decreases as well, increasing in turn the size of net $Basis_{\text{bond}}$ of Turkey. The lagged dependent variable is also found highly and statistically significant with a t-stat of -1.87. R-squared is 21%. These results confirm the expectation that in Europe, since EUR is comparatively easier to fund than USD, traders would tend to short the EUR bonds and long the USD bonds of Turkey.

The opposite mechanism is true for Brazil and Mexico. The percentage difference of [EUR CP - USD Depo] rates is highly and statistically significant in explaining net $Basis_{\text{bond}}$ of Brazil and Mexico. The slope coefficient $\beta_{2,1}$ has the expected positive coefficient sign with a t-stat of 10.86, suggesting that an increase in the unsecured EUR funding (outside capital) relative to secured USD funding (inside capital) increases net $Basis_{\text{bond}}$ of Brazil and Mexico. The slope coefficient on Euribor is statistically significant and positive with a t-stat of 5.86, while the slope coefficient on Libor is statistically significant and negative with a t-stat of -1.90. This is the opposite of what we find for Turkey. This suggests that, as interbank funding in Euro becomes more expensive, net $Basis_{\text{bond}}$ of Brazil and Mexico widens. The lagged dependent variable is also found highly and statistically significant with a t-stat of -4.05. R-squared is 47%. These results confirm the expectation that in the U.S., since USD is comparatively easier to fund than EUR, traders would tend to short the USD bonds and long the EUR bonds of Brazil and Mexico. This evidence is consistent with the existence of a geographical effect in funding liquidity.

Relative Cost of Funding

With the objective of understanding if and how relative costs of funding by USD banks versus European banks affected $Basis_{\text{bond}}$, we use one country (Turkey) as a control group, and run a "diff-in-diff" analysis by computing the ratio between net Mexico (and Brazil) $Basis_{\text{bond}}$ over net Turkish $Basis_{\text{bond}}$. The assumption is that most Turkish sovereign bonds were funded by European-based banks while Brazilian and Mexican bonds by U.S.-based banks. We run the following regression:

$$\Delta\left[\frac{[\text{Net } Basis(bond)_{j,t}]}{[\text{Net} Basis(bond)_{TR,t}]}\right] = \alpha_j + \beta_{3,1}\,\Delta\left[\frac{(EUR\ CP - USD\ Depo)_t}{(USDCP\ - EUR\ Depo)_t}\right] + \beta_{3,2}\,\Delta L_{j,t-1} + \epsilon_{j,t} \quad \text{with } j = MX, BR \tag{4.14}$$

where Δ denotes first-difference, and j denotes the specific bond pairs for j=[BR,MX]. The variable L_{t-1} denotes the one-week lag of the dependent variable of each given regression. Table 4.8 reports the slope coefficients, White robust t-statistics and R-squared values of the regression. We find that the $\beta_{3,1}$ coefficient is positive and strongly significant, with a t-stat of 6.45. This implies that a relative increase in the cost of unsecured Euro funding of US banks contributes to a widening on the Mexico and Brazil net $Basis_{\text{bond}}$ relative to the Turkey net $Basis_{\text{bond}}$. R-squared is 18%. This supports explanations based on a distinction between inside and outside capital, as in Ivashina, Scharfstein, and Stein (2012).

IV. Monetary Policy Implications on Basis(bond)

What is the extent to which monetary policies may have eased some of the market frictions? If arbitrageurs are contemporaneously present on multiple asset markets, Gromb and Vayanos (2010) argue that balance sheet shocks can give rise to contagion effects even across seemingly unrelated assets. The idea is that when the burden of market constraints is partly lifted from the shoulders of arbitrageurs, then arbitrageurs would find it relatively easier to operate in mispriced markets. This would have a positive impact on price convergence. In this context, it is possible that some of the monetary policies with the objective of relieving funding conditions on the U.S. markets, in times of crisis, might relax some of the constraints in EM bonds, thus affecting $Basis_{\text{bond}}$. We design this last part of the analysis as an event study and quantify the impact of different monetary interventions on the dynamics of $Basis_{\text{bond}}$.

A. *Description of Monetary Policies*

We define two main monetary policy phases: "Funding Relief Policies", which took place both with conventional funding liquidity measures (mainly during the first phase of the Crisis) and unconventional asset purchases, and "Uncertainty Relief Policies", which consists of the publication of the results of stress test analysis on a number of U.S. banks, aimed to address financial uncertainty via public signaling.

Policy Phase 1: Funding Relief Policies

This phase of "Funding Relief Policies" unfolded in two parts. In the first part, the Fed became increasingly concerned about market illiquidity, and executed a series of the so-called Liquidity Risk Interventions. On December 12, 2007, the Fed introduced a Term Auction Facility (TAF), designed to lend funds directly to depository institutions for a fixed term (28 or 84 days), and to relieve the frictions related to interbank borrowing. Two important restrictions applied: (a) funds were in fixed terms and in limited supply; and (b) foreign banks could bid through their U.S. branches (or agencies) if they maintained reserves with the Fed; otherwise, they needed to borrow in their own jurisdictions. Moreover, to facilitate the provision of USD liquidity to other central banks around the globe, the Federal Open Market Committee (FOMC) authorized bilateral currency swap lines with the European Central Bank (ECB) and the Swiss National Bank (SNB) in the amounts of $20 billion and $4 billion, respectively, on December 12, 2007. On September 29, 2008, the FOMC expanded the swap line program with the Bank of England, the Bank of Canada, SNB, ECB, Norges Bank, Danmarks Nationalbank, Sveriges Riksbank, the Bank of Japan, and the Reserve Bank of Australia to $330 billion. One month later, on October 29, 2008, the FOMC established new swap lines to the central banks of emerging markets that are major U.S. partners, such as Banco Central do Brasil, Banco de Mexico, the Monetary Authority of Singapore, and the Bank of Korea in the amount of $30 billion each. Mexico used it on three occasions with tenors of 88 days and 3.22 billion each. The Turkish Central Bank, on the other hand, never had access to this facility. Aizenman and Pasricha (2010) argue that the high concentration of US banks' lending exposure to Brazil and Mexico was the key selection criteria used by the Fed to extend the swap lines.

In the second part of "Funding Relief Policies", the Fed and U.S. Treasury shifted the nature of their interventions to directly address credit risk concerns. Three unconventional policies followed: (1) The Troubled Asset Relief Program (TARP) by the U.S. Treasury, aimed at compensating for the lost capital of U.S. banks and restarting their lending activities,[29] (2) The Term Asset-Backed Securities Loan Facility (TALF) by the Fed, aimed at increasing credit availability and supporting economic activity by facilitating renewed issuance of consumer and business asset-backed securities (ABS) at normal interest rate spreads,[30] and (3) The Commercial Paper Funding Facility (CPFF) by the Fed, aimed at relieving short-term funding frictions and thereby contributing to greater availability of credit for businesses and households.[31] A key difference between the U.S. Treasury and the Fed programs was that while the Treasury's balance sheet interventions mainly addressed secured markets via purchasing large amounts of bank preferred stocks and taking on credit risk exposure (by providing capital), the Fed's interventions tended to focus on unsecured markets (i.e. interbank funding markets via new term auction facilities).

[29] The program was signed into law on October 3, 2008, and involved the mass purchasing of troubled assets, such as mortgage-backed securities, from U.S. banks and other financial institutions (initially up to $700 billion). The Capital Purchase Program (CPP) was a part of TARP that involved the purchase of preferred stocks of U.S. banks.

[30] The program was announced on November 25, 2008, and involved the lending of up to $1 trillion to holders of AAA-rated asset-backed securities.

[31] The program was created on October 27, 2008, and allowed the Fed to finance the purchase of highly rated unsecured and asset-backed commercial paper.

Policy Phase 2: Uncertainty Relief Policy

This second phase is quite different compared to the first one or to any previous experience. In 2009, the Federal Reserve Board decided to more directly address market uncertainty and tail risk perception by implementing explicit economic assessments and stress tests on a broad set of banks and financial institutions. On February 25, 2009, the Federal Reserve Board - together with the Federal Deposit Insurance Corporation, the Office of Thrift Supervision and the Office of the Comptroller of the Currency - announced that they will conduct stress tests on eligible U.S. banks. An initial set of stress test results was released on May 7, 2009. The goal of this exercise was to reduce uncertainty about the true fundamental value of major financial institutions and to regain the trust of market participants via public signals on the value-at-risk measures of a series of banks.[32]

B. *Event Study Analysis*

Which, if any, of these policy measures have been significant in reducing $Basis_{\text{bond}}$? We investigate this question in the context of an event study. For our purposes, we aggregate and classify the policy events above into four groups: (a) Policy announcements of the Fed (PAF), (b) Policy announcements of the U.S. Treasury (PAT), (c) USD Swap Lines to developed and emerging markets (SWAP), and (d) stress tests announcements on U.S. financial institutions (STRESS). As a key feature of this study, we use the fact that Turkey did not have access to global swap and liquidity lines by the Fed and ECB. This allows us to use Turkey as a control group to identify the cross-sectional impact of different relief programs using a "diff-in-diff" approach.[33] This approach has the advantage of controlling for events that affected all bond markets at the same time. The calculation procedure we use is as follows: (i) we compute forward-looking three-week rolling averages of net $Basis_{\text{bond}}$, namely $3WBasis_{\text{bond}}$, for each of the three countries; (ii) we calculate the spread of the $3WBasis_{\text{bond}}$ between Turkey and the other two countries as an endogenous variable, which we call $Disp_t$; (iii) we collect an extensive database of 211 economic news and announcements from the Federal Reserve Bank of Saint Louis and Bloomberg, and use them as control variables in multivariate regressions. The dataset includes the policy events described above (PAF, PAT, SWAP and STRESS), as well as other financial news originating from the U.S., Europe, and the rest of the

[32] To highlight the positive assessment results, Bernanke pointed out to the Joint Economic Committee: "I've looked at many of the banks and I believe that many of them will be able to meet their capital needs without further government capital." (Reuters News Agency on May 5, 2009).

[33] For a related study, see Ashcraft, Garleanu, and Pedersen (2010), who study the differential impact of the Term Asset-Backed Securities Loan Facility (TALF) on the spread between eligible versus non-eligible bonds. They find evidence of a significant drop in the yield of eligible bonds with respect to non-eligible ones.

world (e.g. China). Each financial news is grouped according to whether it is positive (e.g. China's two-year, \$586 billion stimulus plan) or negative (e.g. MBIA and Ambac losing their S&P AAA rating after disclosing \$1 trillion in debt). Among the news variables we include announcements of significant write-downs and subprime losses of financial institutions (see Table 4.9 for specific dates and examples of these events). Each news or policy announcement is used as an explanatory variable and treated as a dummy variable.

The conjecture of this analysis is that Brazil and Mexico, being geographically and economically closer to U.S. (and to the relief policies that mainly address U.S. banks being exposed to Brazil and Mexico), would tend to benefit relatively more from these policy measures compared to Turkey. Before we proceed with the discussion of the results of our multivariate regression analysis, Figure 4.4 shows the dynamics of the dispersion among the $Basis_{\text{bond}}$ of Turkey, Brazil and Mexico, following a set of PAF, PAT and SWAP events. The figure reveals that the cross-sectional dispersion between Turkey vs. Brazil and Mexico $Basis_{\text{bond}}$ tended to widen considerably following these events.[34]

The first significant set of interventions occurred on October 7, 2008 when the Fed announced the introduction of the Commercial Paper Funding Facility (CPFF). This program is potentially important for us since it was intended to provide "a liquidity backstop to U.S. issuers of commercial paper through a special purpose vehicle that purchases three-month unsecured and asset-backed commercial paper directly from eligible issuers"as quoted by the Fed. The next day, (on October 8, 2008) the ECB changed the tender procedure for Euro area banks in the weekly main refinancing operations to fixed rate tender with full allotment, which means that the allotment at the refinancing operations is adjusted to fully match the level of demand. A week later, on October 14, 2008, the U.S. Treasury announced the creation of the Troubled Asset Relief Program (TARP).[35] Following these events, net $Basis_{\text{bond}}$ of Brazil and Mexico dropped by 63 bps and 27 bps, respectively, in the two weeks following, whereas during the same period net $Basis_{\text{bond}}$ of Turkey rose by 34 bps.

The largest effect, however, follows the decision on October 29th, 2008, by the Fed to extend the foreign currency swap facilities to Brazil and Mexico. Importantly, the Turkish Central Bank did not participate. Moreover, starting October 30th, 2008, the Governing Council of the European Central Bank (ECB) decided: (a) to extend the offering of U.S. dollar liquidity by expanding the list of assets eligible as collateral in Eurosystem credit operations to include marketable debt instruments denominated in currencies other than Euro - namely USD, British pound, and Japanese yen; (b) to lower the credit threshold for marketable and non-marketable assets from A- to BBB-,

[34] As mentioned earlier, PAF consists of events such as Term Auction Facility and The Term Asset-Backed Securities Loan Facility, and PAT consists of events such as The Troubled Asset Relief Program and Capital Purchase Programs.

[35] To quote the Fed, this program was designed to "purchase capital in financial institutions under the authority of the Emergency Economic Stabilization Act of 2008. The U.S. Treasury will make available \$250 billion of capital to U.S. financial institutions. This facility will allow banking organizations to apply for a preferred stock investment by the U.S. Treasury. Nine large financial organizations announce their intention to subscribe to the facility in an aggregate amount of \$125 billion."

with the exception of asset-backed securities (ABS). Since Turkish bonds were BB, they were not eligible collateral; on the other hand, Mexican and Brazilian bonds were BBB rated and were eligible collateral.[36] Indeed, after the Fed's swap line decision, we note that net $Basis_{\text{bond}}$ of Brazil and Mexico compressed by 160 bps and 113 bps, respectively, whereas net $Basis_{\text{bond}}$ of Turkey continued to rise by 99 bps during the same period. The average dispersion in the $Basis_{\text{bond}}$ reached its highest value of 150 bps on November 20, 2008.

We also note that the decision by the U.S. Treasury, after December 5, 2008, to purchase $38 billion in preferred stocks in more than 49 U.S. banks under the Capital Purchase Program had an impact on the average dispersion. Indeed, in the two weeks following these decisions, net $Basis_{\text{bond}}$ of Brazil and Mexico dropped by 66 bps and 34 bps, respectively, whereas net $Basis_{\text{bond}}$ of Turkey continued to rise by 32 bps during the same period. Finally, on December 30, 2008, the Fed announced the purchase of mortgage-backed securities backed by Fannie Mae, Freddie Mac, and Ginnie Mae; a day later, on 31 December, 2008, the U.S. Treasury purchased $1.91 billion worth of preferred stocks in 7 U.S. banks under Capital Purchase Program. Following these decisions, net $Basis_{\text{bond}}$ of Brazil and Mexico dropped by 41 bps and 67 bps, respectively, in two weeks, whereas net $Basis_{\text{bond}}$ of Turkey continued to rise by 53 bps during the same period.

While Figure 4.4 is revealing, the standard concern in any event study is the potential contemporaneous effect of other economic variables. To address this issue, we run the following multivariate regressions:

$$\begin{aligned}
\Delta\text{Disp(TRBR)}_{t+1} &= \rho + \pi_1 PAF_t + \pi_2 PAT_t + \pi_3 SWAP_t + \pi_4 STRESS_t \\
&\quad + \pi_5[\text{Positive News}]_t + \pi_6[\text{Negative News}]_t + \pi_7\Delta\text{Disp(TRBR)}_t + \epsilon_t \\
\Delta\text{Disp(TRMX)}_{t+1} &= \rho + \pi_1 PAF_t + \pi_2 PAT_t + \pi_3 SWAP_t + \pi_4 STRESS_t \\
&\quad + \pi_5[\text{Positive News}]_t + \pi_6[\text{Negative News}]_t + \pi_7\Delta\text{Disp(TRMX)}_t + \epsilon_t
\end{aligned}$$

where the dispersion variables for Turkey vs. Brazil and Mexico are denoted by:

$$\begin{aligned}
Disp(TRBR) &= |3WBasis(bond)_{TR}| - |3WBasis(bond)_{BR}| \\
Disp(TRMX) &= |3WBasis(bond)_{TR}| - |3WBasis(bond)_{MX}|
\end{aligned}$$

where $3WBasis(bond)$ denotes the three-week forward-looking rolling average of net $Basis_{\text{bond}}$ of each country.[37] Explanatory variables are the policy and news events, each treated as a dummy

[36] Jose Manuel Gonzalez-Paramo, Member of the Executive Board of the ECB, stated that: "As a result of such decisions, euro area banks can now borrow from the ECB as much euro and USD liquidity as they wish, also at some key term maturities, of course against eligible collateral. The new set of temporary measures provide an important contribution to mitigating the funding risks of solvent banks in the euro area [...]." (Speech at Universidad de Alcala de Henares, Madrid, January 16, 2009).

[37] By taking three-week averages, we aim to better capture the inertia effect of monetary policies.

variable that is equal to 1 on the dates of the announcements. Table 4.10 summarizes the results by reporting the slope coefficients, t-stats and R-squared values.

Our findings reveal that the slope coefficient of SWAP is highly significant and positive with a t-stat 3.38 and 3.41 for the dynamics of $Disp(TRBR)$ and $Disp(TRMX)$, respectively, validating the hypothesis that the extension of swap lines indeed helped to relieve the liquidity frictions on sovereign bonds of the participants (Brazil and Mexico) and not those of the non-participating country (Turkey). This suggests the existence of cross-sectional differences in the characteristics of the marginal investors in these markets, and how they were affected differently by these measures. We also find that the slope coefficient of PAF is highly significant and positive with a t-stat 1.74 and 1.99 for the dynamics of $Disp(TRBR)$ and $Disp(TRMX)$, respectively. Within the PAF variable, we note that CPFF's introduction was followed by a particularly significant widening of the dispersion measure. The evidence for PAT is mixed and is significant mainly for $Disp(TRBR)$ with a t-stat of 2.14.

Last, we find that the announcement of the stress tests helped to reduce the cross-sectional dispersion variable. This may be either because it took relatively longer before the effects of the previous policies were felt by the marginal agents in the Turkey, or because the information content of the stress tests was more global in nature, and relieved the systemic uncertainty among intermediaries on a broader scale, thus reducing cross-sectional differences in $Basis_{\text{bond}}$. This is consistent with Acharya and Merrouche (2010)'s argument that "[...] regulatory attempts to thaw the money market stress and reduce variability of inter-bank rates [...] should involve addressing insolvency concerns (for example, early supervision and stress tests, and recapitalization of troubled banks) and not just provisions of emergency liquidity."

This evidence is consistent with the interpretation that constraints of arbitrageurs were binding both because of an initial balance sheet shock and also because of economic uncertainty that monetary polices helped to reduce. This work might induce future research regarding the impact of monetary policies and regulatory actions in helping to correct price disequilibrium in dislocated markets.

V. Appendix A to Chapter 4

Appendix A

Data description and transformations

This table includes the descriptions of the economic series, their categories and the required stationarity transformations. The table is based on Ludvigson and Ng (2009). There are six categories: (1) Output and Income, (2) Consumption, Orders and Inventories, (3) Labor Market, (4) Housing, (5) Money and Credit, and (6) Prices and Inflation. All series are retrieved from the Global Insights Basic Economics Database, unless otherwise stated, where The Conference Board's Indicators Database (TCB) are shown in (parentheses). In the transformation column, the levels and the first-differenced levels of the series are denoted as *lev*, and *dlev*, respectively. The logarithms of the series are denoted as *log*; the first- and second-differenced logarithms are denoted as *dlog* and *d2log*, respectively.

Description	**Transformation**	**Category**
Personal Income (AR, Bil. Chain 2000 USD) (TCB)	dlog	Output and Income
Personal Income Less Transfer Payments (AR, Bil. Chain 2000 USD) (TCB)	dlog	Output and Income
Industrial Production Index -Total Index	dlog	Output and Income
Industrial Production Index - Products, Total	dlog	Output and Income
Industrial Production Index - Final Products	dlog	Output and Income
Industrial Production Index - Consumer Goods	dlog	Output and Income
Industrial Production Index - Durable Consumer Goods	dlog	Output and Income
Industrial Production Index -Nondurable Consumer Goods	dlog	Output and Income
Industrial Production Index - Business Equipment	dlog	Output and Income
Industrial Production Index -Materials	dlog	Output and Income
Industrial Production Index - Durable Goods Materials	dlog	Output and Income
Industrial Production Index - Nondurable Goods Materials	dlog	Output and Income
Industrial Production Index -Manufacturing	dlog	Output and Income
Industrial Production Index - Residential Utilities	dlog	Output and Income
Industrial Production Index - Fuels	dlog	Output and Income
Napm Production Index (Percent)	lev	Output and Income
Capacity Utilization (Manufacturing) (TCB)	dlev	Output and Income
Manufacturing and Trade Sales (Mil. Chain 1996 USD) (TCB)	dlog	Consumption, Orders and Inventories
Sales of Retail Stores (Mil. Chain 2000 USD) (TCB)	dlog	Consumption, Orders and Inventories
University of Michigan Index of Consumer Sentiment	dlev	Consumption, Orders and Inventories
Purchasing Managers' Index (Sa)	lev	Consumption, Orders and Inventories
Napm New Orders Index (Percent)	lev	Consumption, Orders and Inventories
Napm Vendor Deliveries Index (Percent)	lev	Consumption, Orders and Inventories
Napm Inventories Index (Percent)	lev	Consumption, Orders and Inventories
Manufacturers' New Orders, Consumer Goods and Materials (Bil. Chain 1982 USD) (TCB)	dlog	Consumption, Orders and Inventories
Manufacturers' New Orders, Durable Goods Industries (Bil. Chain 2000 USD) (TCB)	dlog	Consumption, Orders and Inventories
Manufacturers' New Orders, Nondefense Capital Goods (Mil. Chain 1982 USD) (TCB)	dlog	Consumption, Orders and Inventories
Manufacturers' Unfilled Orders, Durable Goods Industries (Bil. Chain 2000 USD) (TCB)	dlog	Consumption, Orders and Inventories

Appendix A (cntd.)

Data description and transformations

This table includes the descriptions of the economic series, their categories and the required stationarity transformations. The table is based on Ludvigson and Ng (2009). There are six categories: (1) Output and Income, (2) Consumption, Orders and Inventories, (3) Labor Market, (4) Housing, (5) Money and Credit, and (6) Prices and Inflation. All series are retrieved from the Global Insights Basic Economics Database, unless otherwise stated, where The Conference Board's Indicators Database (TCB) are shown in (parentheses). In the transformation column, the levels and the first-differenced levels of the series are denoted as *lev*, and *dlev*, respectively. The logarithms of the series are denoted as *log*; the first- and second-differenced logarithms are denoted as *dlog* and *d2log*, respectively.

Description	**Transformation**	**Category**
Index of Help-Wanted Advertising in Newspapers (1967=100; Sa)	dlev	Labor Market
Employment: Ratio; Help-Wanted Ads: No. Unemployed Civilian Labour Force	dlev	Labor Market
Civilian Labor Force: Employed, Total (Thous., Sa)	dlog	Labor Market
Civilian Labor Force: Employed, Nonagriculture Industries (Thous., Sa)	dlog	Labor Market
Unemployment Rate: All Workers, 16 Years and Over (%, Sa)	dlev	Labor Market
Unemploy. By Duration: Average (Mean) Duration in Weeks (Sa)	dlev	Labor Market
Unemploy. By Duration: Persons Unemployed Less than 5 Weeks (Thous., Sa)	dlog	Labor Market
Unemploy. By Duration: Persons Unemployed 5 to 14 Weeks (Thous., Sa)	dlog	Labor Market
Unemploy. By Duration: Persons Unemployed 15 Weeks + (Thous.,Sa)	dlog	Labor Market
Unemploy. By Duration: Persons Unemployed 15 to 26 Weeks (Thous., Sa)	dlog	Labor Market
Unemploy. By Duration: Persons Unemployed 27 Weeks + (Thous., Sa)	dlog	Labor Market
Average Weekly Initial Claims, Unemployed Insurance (Thous.) (TCB)	dlog	Labor Market
Employees on nonfarm Payrolls: Total Private	dlog	Labor Market
Employees on nonfarm Payrolls: Goods-Producing	dlog	Labor Market
Employees on nonfarm Payrolls: Mining	dlog	Labor Market
Employees on nonfarm Payrolls: Construction	dlog	Labor Market
Employees on nonfarm Payrolls: Manufacturing	dlog	Labor Market
Employees on nonfarm Payrolls: Durable Goods	dlog	Labor Market
Employees on nonfarm Payrolls: Nondurable Goods	dlog	Labor Market
Employees on nonfarm Payrolls: Service-Providing	dlog	Labor Market
Employees on nonfarm Payrolls: Trade, Transportation and Utilities	dlog	Labor Market
Employees on nonfarm Payrolls: Wholesale Trade	dlog	Labor Market
Employees on nonfarm Payrolls: Retail Trade	dlog	Labor Market
Employees on nonfarm Payrolls: Financial Activities	dlog	Labor Market
Employees on nonfarm Payrolls: Government	dlog	Labor Market
Avg Weekly Hrs of Prod or Nonsup Workers on Private Nonfarm Payrolls: Goods-Producing	lev	Labor Market
Avg Weekly Hrs of Prod or Nonsup Workers on Private Nonfarm Payrolls: Mfg Overtime Hours	dlev	Labor Market
Average Weekly Hours in Manufacturing (Hours) (TCB)	lev	Labor Market
Napm Employment Index (Percent)	lev	Labor Market
Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls: Goods-Producing	d2 log	Labor Market
Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls: Construction	d2 log	Labor Market
Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls: Manufacturing	d2 log	Labor Market

Appendix A (cntd.)

Data description and transformations

This table includes the descriptions of the economic series, their categories and the required stationarity transformations. The table is based on Ludvigson and Ng (2009). There are six categories: (1) Output and Income, (2) Consumption, Orders and Inventories, (3) Labor Market, (4) Housing, (5) Money and Credit, and (6) Prices and Inflation. All series are retrieved from the Global Insights Basic Economics Database, unless otherwise stated, where The Conference Board's Indicators Database (TCB) are shown in (parentheses). In the transformation column, the levels and the first-differenced levels of the series are denoted as *lev*, and *dlev*, respectively. The logarithms of the series are denoted as *log*; the first- and second-differenced logarithms are denoted as *dlog* and *d2log*, respectively.

Description	**Transformation**	**Category**
Housing Starts: Nonfarm(1947-58); Total Farm and Nonfarm(1959-) (Thous., Saar)	dlev	Housing
Housing Starts: Northeast (Thous.U.) S.A.	dlev	Housing
Housing Starts: Midwest (Thous.U.) S.A.	dlev	Housing
Housing Starts: South (Thous.U.) S.A.	dlev	Housing
Housing Starts: West (Thous.U.) S.A.	dlev	Housing
Housing Authorized: Total New Private Housing Units (Thous., Saar)	dlev	Housing
Houses Authorized by Build. Permits: Northeast (Thou.U.) S.A.	dlev	Housing
Houses Authorized by Build. Permits: Midwest (Thou.U.) S.A.	dlev	Housing
Houses Authorized by Build. Permits: South (Thou.U.) S.A.	dlev	Housing
Houses Authorized by Build. Permits: West (Thou.U.) S.A.	dlev	Housing
Money Stock: M1 (Bil USD,Sa)	d2 log	Money and Credit
Money Stock: M2 (Bil USD,Sa)	d2 log	Money and Credit
Monetary Base, Adjusted for Reserve Req Changes (Mil USD, Sa)	d2 log	Money and Credit
Depository Inst Reserves: Total, Adj. for Reserve Req Changes (Mil USD, Sa)	d2 log	Money and Credit
Depository Inst Reserves: Nonborrowed, Adj. Res Req Changes (Mil USD, Sa)	d2 log	Money and Credit
Commercial and Industrial Loans Outstanding in 1996 Dollars	d2 log	Money and Credit
Net Change Commercial and Industrial Loans (Bil USD, Saar)	d2 log	Money and Credit
Consumer Credit Outstanding - Nonrevolving (G19)	d2 log	Money and Credit
Consumer Installment Credit to Personal Income, Ratio (TCB)	dlev	Money and Credit

Appendix A (cntd.)

Data description and transformations

This table includes the descriptions of the economic series, their categories and the required stationarity transformations. The table is based on Ludvigson and Ng (2009). There are six categories: (1) Output and Income, (2) Consumption, Orders and Inventories, (3) Labor Market, (4) Housing, (5) Money and Credit, and (6) Prices and Inflation. All series are retrieved from the Global Insights Basic Economics Database, unless otherwise stated, where The Conference Board's Indicators Database (TCB) are shown in (parentheses). In the transformation column, the levels and the first-differenced levels of the series are denoted as *lev*, and *dlev*, respectively. The logarithms of the series are denoted as *log*; the first- and second-differenced logarithms are denoted as *dlog* and *d2log*, respectively.

Description	**Transformation**	**Category**
Producer Price Index: Finished Goods (1982=100, Sa)	d2 log	Prices and Inflation
Producer Price Index: Finished Consumer Goods (1982=100, Sa)	d2 log	Prices and Inflation
Producer Price Index: Intermed Material Supplies and Components (1982=100, Sa)	d2 log	Prices and Inflation
Producer Price Index: Crude Materials (1982=100, Sa)	d2 log	Prices and Inflation
Spot market price index: All commodities (1967=100)	d2 log	Prices and Inflation
Index Of Sensitive Materials Prices (1990=100)	lev	Prices and Inflation
Napm Commodity Prices Index (Percent)	d2 log	Prices and Inflation
Cpi-U: All Items (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: Apparel and Upkeep (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: Transportation (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: Medical Care (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: Durables (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: Services (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: All Items Less Food (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: All Items Less Shelter (1982-84=100, Sa)	d2 log	Prices and Inflation
Cpi-U: All Items Less Medical Care (1982-84=100,Sa)	d2 log	Prices and Inflation
Personal Consumption Expenditure (1987=100)	d2 log	Prices and Inflation
Personal Consumption Expenditure: Durables (1987=100)	d2 log	Prices and Inflation
Personal Consumption Expenditure: Nondurables (1987=100)	d2 log	Prices and Inflation
Personal Consumption Expenditure: Services (1987=100)	d2 log	Prices and Inflation

Figure 4.1:

EM total active lendable values

The three panels show the Total Active Lendable Value (i.e. the aggregate amount available for lending) for all outstanding Eurobonds of Brazil, Mexico, and Turkey, respectively, in millions of USD. The sample includes the Credit Crisis, where the dashed vertical lines denote the start of Credit Crisis in September 2008 (e.g. Lehman's default).

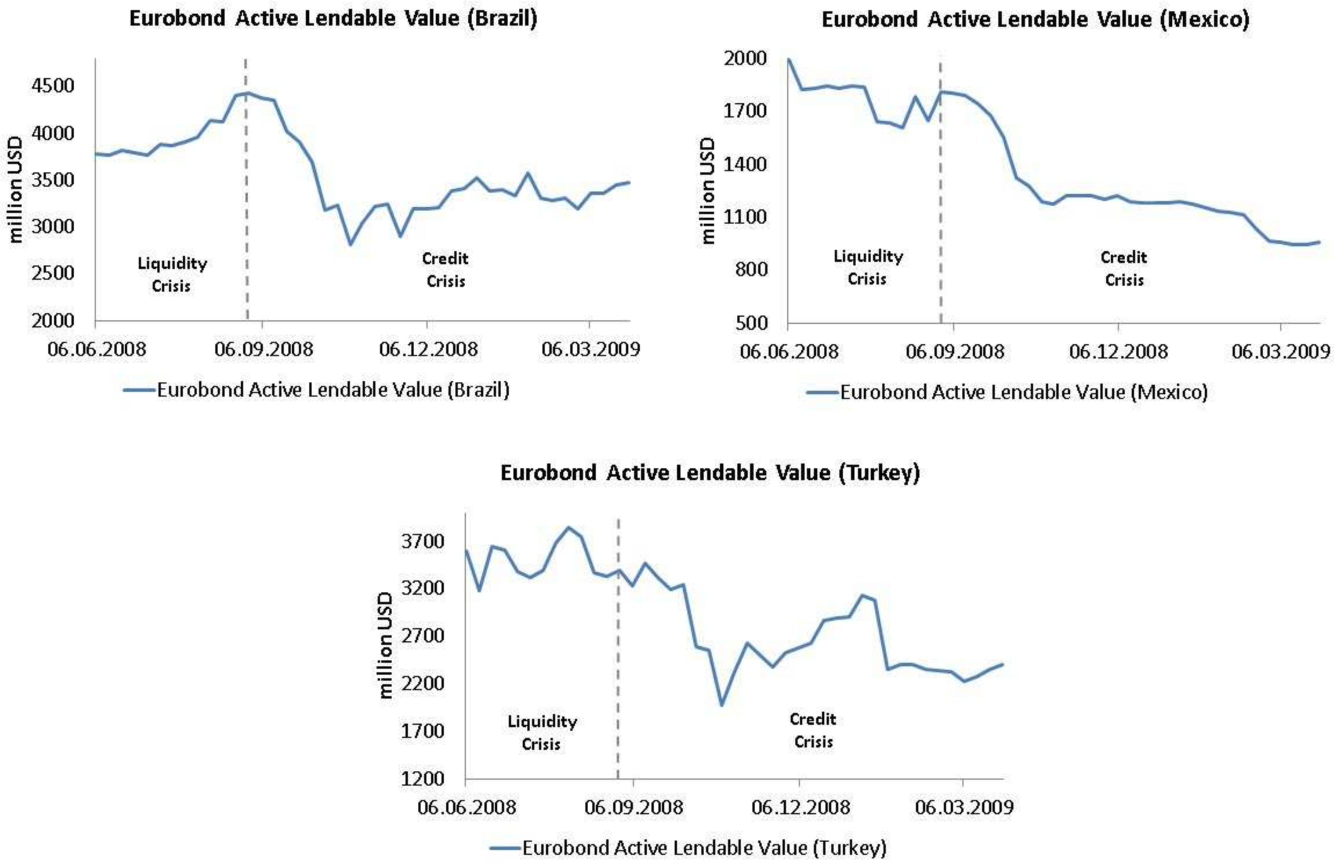

Figure 4.2:

Basis(bond) decomposition
The four panels show the decomposition $Basis_{\text{bond}}$ (blue bars) into its underlying $Basis_{\text{spread}}$ component (red bars) and $Basis_{\text{cirp}}$ component (green bars) for 2014-maturity Turkey bond pair, 2015-maturity Brazil bond pair, and 2020-maturity Mexico bond pair. The top left panel of the figure presents the average proportions of each component in terms of the percentage of total $Basis_{\text{bond}}$. The remaining panels show the time evolution of each component (in terms of bps) for each country separately during the last four months of 2008 (representing the peak of Credit Crisis).

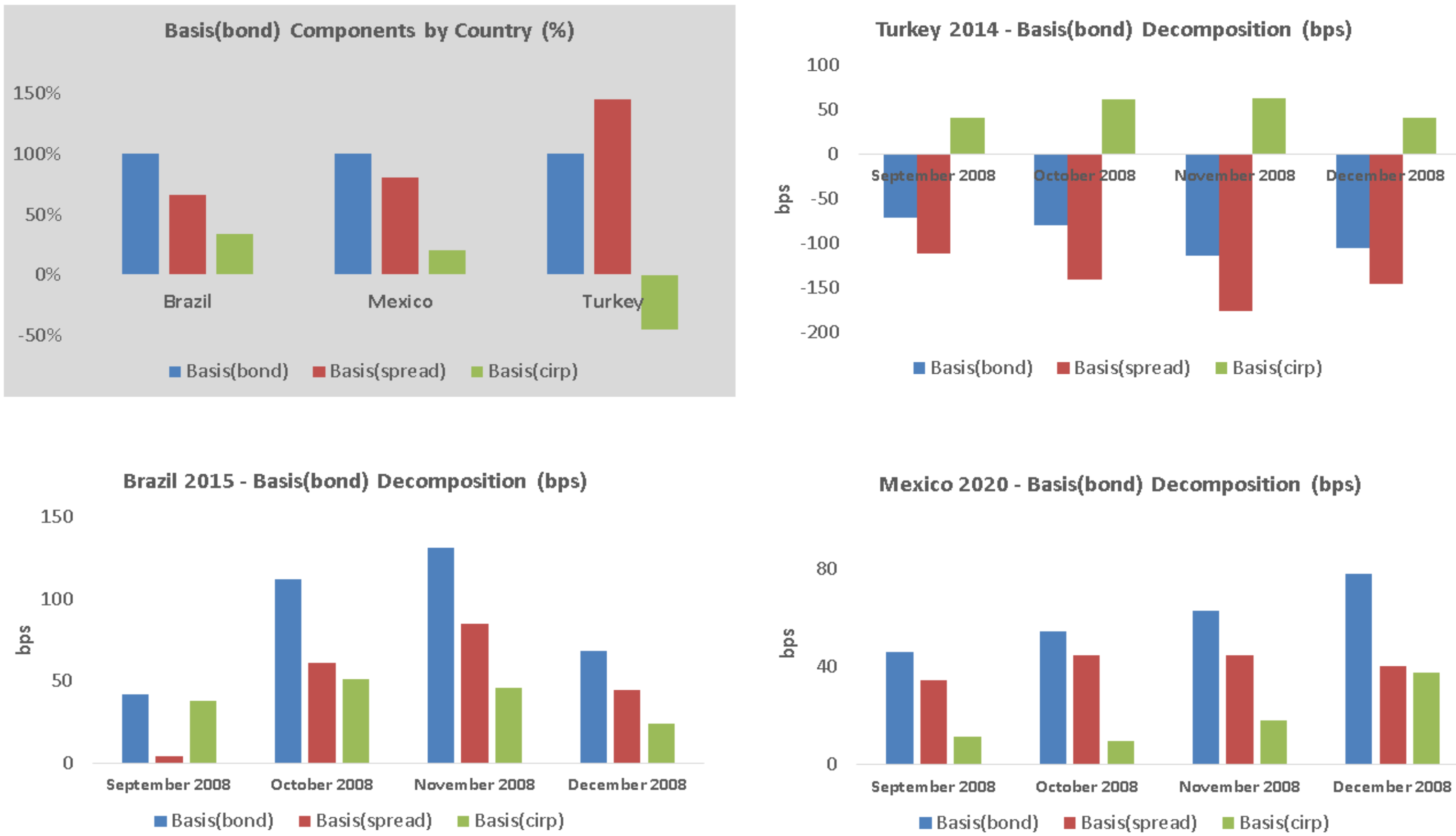

Figure 4.3:

Differential of foreign deposit rates of Turkish banks
The figure shows the difference between the 3-month average USD minus Euro deposit rates (in bps) of Turkish banks, between March 2008- September 2009.

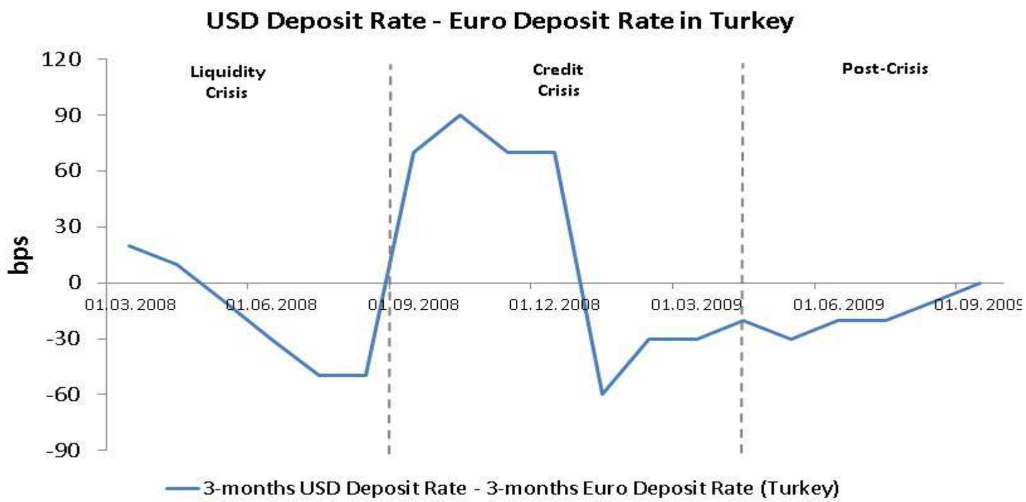

Figure 4.4:

Impact of PAF, PAT and SWAP on Basis dispersion
The figure shows the evolution of the Dispersion Variable defined as net $Basis_{\text{bond}}$ of Turkey minus the average of net $Basis_{\text{bond}}$ of Brazil and Mexico during the Credit Crisis. The policy announcements of the Fed (PAF) are indicated by the green vertical lines; the policy announcements of the US Treasury (PAT) are indicated by the black vertical lines; the dollar swap line extended to Brazil and Mexico (SWAP) is indicated by the red vertical line.

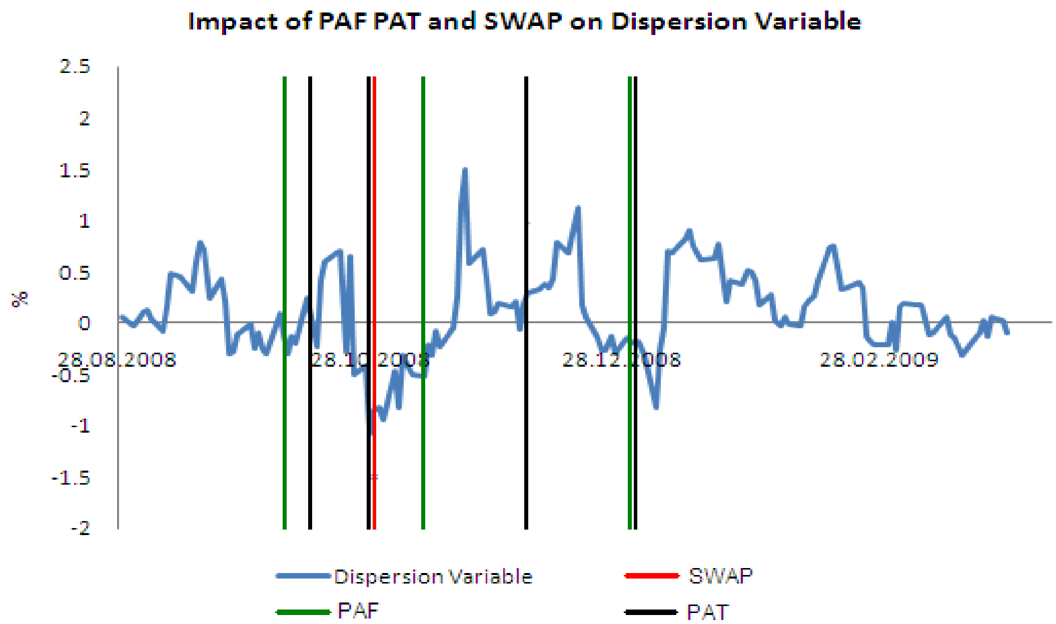

Table 4.1:

Potential determinants of $Basis_{\textbf{bond}}$

Summary statistics of the potential determinants of $Basis_{\text{bond}}$ of Turkey, Brazil and Mexico, during Pre-Crisis, Liquidity Crisis, Credit Crisis and Post-Crisis periods. The average value of each variable is shown on corresponding top rows, and the associated standard deviations are shown immediately below. The unit of each variable is also presented. Liquidity Risks include [Liq-FX, Liq-PS]; Funding Costs include [Unsecured, Secured]; Global Cash-Flow Factors include [LN-Macro, TP]; Credit Risk Factor includes [EM-CDSI]; Risk Aversion Factors include [Closed End, VIX]; Global Uncertainty factor includes [DiB]. Summary statistics of the variable Inventory is presented in Table 4.2.

Categories	**Determinant**	**Unit**	**Period**			
			Pre-Crisis	*Liquidity Crisis*	*Credit Crisis*	*Post-Crisis*
Liquidity Risks	*Liq-FX*	Principal	-1.07	0.55	3.48	0.91
		Component	0.61	0.70	1.85	0.83
	Liq-PS	Historical Beta	-0.01	-0.09	-0.11	-0.01
		Coefficient	0.04	0.07	0.08	0.05
Funding Costs	*Secured*	Percentage	0.34	0.57	0.51	0.15
			0.06	0.14	0.28	0.12
	Unsecured	Percentage	0.08	0.68	1.51	0.26
			0.02	0.15	0.76	0.26
Global Cash-Flow	*LN-Macro*	Principal	3.04	-0.37	-10.30	0.03
Factors		Component	1.66	2.04	3.56	4.73
	TP	Percentage	-0.29	0.20	0.93	3.06
			0.40	0.91	0.72	0.50
Credit Risk	*EM-CDSI*	Index Price	-	99.64	87.49	107.94
Factor			-	1.74	6.19	4.21
Risk Aversion	*Closed End*	Price Ratio	0.94	0.91	0.79	0.88
Factors			0.03	0.03	0.06	0.04
	VIX	Percentage	12.97	23.05	48.20	25.05
			2.55	3.55	14.06	5.93
Global Uncertainty	*DiB*	Principal	-0.22	-0.10	0.25	-
Factor		Component	0.07	0.12	0.08	-

Table 4.2:

Short-selling constraints on $Basis_{\mathbf{bond}}$

Summary statistics of the short-selling constraints on $Basis_{\text{bond}}$ of Turkey, Brazil and Mexico, during Pre-Crisis, Liquidity Crisis, Credit Crisis and Post-Crisis periods. The average value of each variable is shown on corresponding top rows, and the associated standard deviations are shown immediately below. The unit of each variable is also presented. Inventory represents the the pair-specific value of total actively lendable inventory, capturing bond supply at a given day, filtered out from the inactive loans.

Categories	**Determinant**	**Unit**	**Bond Pairs**	**Period**		
				Liquidity Crisis	*Credit Crisis*	*Post-Crisis*
Short-Selling Constraints	*Inventory*	USD millions	Brazil 2010	27.15	21.83	9.42
				6.53	7.23	5.03
			Brazil 2015	416.76	343.24	354.60
				38.69	56.23	43.16
			Brazil Total	3719.14	3441.33	3707.79
				257.76	395.48	277.87
		USD millions	Turkey 2014	218.39	169.56	78.73
				59.97	70.76	15.01
			Turkey 2019	-	176.05	150.99
				-	49.07	17.50
			Turkey Total	3293.57	2670.60	2740.75
				426.31	403.54	211.29
		USD millions	Mexico 2020	276.03	156.95	164.09
				36.46	32.66	28.25
			Mexico Total	2030.21	1251.12	713.25
				183.47	258.79	203.64

Table 4.3:

Panel regressions on liquidity risks, short-selling constraints, and funding costs
Summary fixed-effects panel regressions on net $Basis_{\text{bond}}$ of Brazil 2010, Brazil 2015, Mexico 2020, Turkey 2014, and Turkey 2019 bond pairs. Δ denotes first-difference, $\bar{\Delta}$ denotes percentage difference, and j denotes the specific bond pair. We report the slope coefficients, and the associated t-statistics (immediately below), based on White's standard errors. Sample is the Credit Crisis period. Results for Liquidity Risks (i.e. BidAsk, Liq-FX, Liq-PS), as in Eq. (A), are shown in Column A. Results for the Short-Selling Frictions (i.e. Inventory), as in Eq. (B), are shown in Column B. Results for Funding Costs (i.e. Secured, Unsecured), as in Eq. (C), are shown in Column C. Results for Liquidity Risks, Short-Selling Frictions and Funding Costs together, as in Eq. (D), are shown in Column D. In Eq. (A), dependent variable is the absolute value of gross $Basis_{\text{bond}}$ (without bid-ask adjustment), and in Eq. (B), (C) and (D), dependent variable is net $Basis_{\text{bond}}$. Intercepts are not reported. (**) shows a 95% confidence interval, and (*) shows a 90% confidence interval.

$$
\begin{aligned}
(A)\quad & \Delta\,|\text{Gross } Basis(bond)_{j,t}| = \alpha_j + B_1\,[\Delta BidAsk_{j,t}] + B_2\,[\Delta Liq\ FX_t] + B_3\,[\Delta Liq\ PS_t] + \epsilon_{j,t}.\\
(B)\quad & \Delta\,[\text{Net } Basis(bond)_{j,t}] = \alpha_j + \lambda_1\,[\bar{\Delta} Inventory_{j,t}] + \epsilon_{j,t}.\\
(C)\quad & \Delta\,[\text{Net } Basis(bond)_{j,t}] = \alpha_j + \theta_1\,[\Delta Unsecured_t] + \theta_2\,[\Delta Secured_t] + \epsilon_{j,t}.\\
(D)\quad & \Delta\,[\text{Net } Basis(bond)_{j,t}] = \alpha_j + \gamma_1\,[\Delta Liq\ FX_t] + \gamma_2\,[\Delta Liq\ PS_t] + \gamma_3\,[\bar{\Delta} Inventory_{j,t}]\\
& \qquad + \gamma_4\,[\Delta Unsecured_t] + \gamma_5\,[\Delta Secured_t] + \epsilon_{j,t}.
\end{aligned}
$$

		Credit Crisis			
		(A)	**(B)**	**(C)**	**(D)**
Category	**Variable**	**Coeff./t-stat**	**Coeff./t-stat**	**Coeff./t-stat**	**Coeff./t-stat**
Liquidity Risks	**BidAsk**	1.4477 *1.4598*			
	Liq-FX	0.0169 *0.9989*			0.0164 *0.8407*
	Liq-PS	-0.7671 *-0.6258*			0.2248 *0.1903*
Short-Selling Frictions	**Inventory**		-0.0283 *-2.9924***		-0.0189 *-2.3919***
Funding Costs	**Unsecured**			0.4174 *1.6724**	0.4409 *1.7311**
	Secured			0.0778 *0.5199*	-0.0792 *-0.5189*
	R-Squared	3%	3%	5%	7%

Table 4.4:

Panel regressions on funding costs, short-selling constraints, and other macroeconomic shocks
Summary fixed-effects panel regressions on net $Basis_{\text{bond}}$ of Brazil 2010, Brazil 2015, Mexico 2020, Turkey 2014, and Turkey 2019 bond pairs. Δ denotes first-difference, and j denotes the specific bond pair. We report the slope coefficients, and the associated t-statistics (immediately below), based on White's standard errors. The regression specification is specified below. Samples are the Liquidity, Credit and Post-Crisis periods. Explanatory variables, shown as vectors, are Funding Costs [Unsecured, Secured]; Global Cash-Flow Factors [LN-Macro, TP]; Credit Risk Factor [EM-CDSI]; Risk Aversion Factors [Closed End, VIX]; Global Uncertainty [DiB]; Short-Selling Constraints [Inventory]. Funding Costs are regressed with the weekly lag parameter v = 0 for Unsecured Funding, and v = 1 for Secured Funding. Intercepts are not reported. (**) shows a 95% confidence interval, and (*) shows a 90% confidence interval.

$$\begin{aligned}\Delta\,[\text{Net } Basis(bond)_{j,t}] = \alpha_j &+ \beta_1\,[\Delta Funding\ Costs_{t-v}] + +\beta_2\,[\Delta Short\ Selling\ Constraints_{j,t}]\\ &+ \beta_3\,[\Delta Global\ Cash\ Flow\ Factors_t] + \beta_4\,[\Delta Credit\ Risk\ Factor_t]\\ &+ \beta_5\,[\Delta Risk\ Aversion\ Factors_t] + \beta_6\,[\Delta Global\ Uncertainty_t] + \epsilon_{j,t}.\end{aligned}$$

Categories	Variables	Liquidity Crisis Period	Credit Crisis Period	Post-Crisis Period
		Slope Coef. / t-stat	**Slope Coef. / t-stat**	**Slope Coef. / t-stat**
Funding Costs	**Unsecured**	*-0.0403*	*0.2656*	*0.4168*
		-0.4385	*2.0802***	*0.9020*
	Secured	*0.1600*	*0.2968*	*-0.0654*
		*1.8669**	*2.4662***	*-0.5844*
Short-Selling Constraints	**Inventory**	*0.0019*	*-0.0303*	*-0.0069*
		0.4596	*-3.6616***	*-3.6543***
Global Cash-Flow Factors	**LN-Macro**	*-0.0039*	*-0.0276*	*0.0107*
		-0.3364	*-2.0285***	*1.1546*
	TP	*-0.0569*	*0.1334*	*-0.0520*
		-0.8401	*1.0520*	*-0.5134*
Credit Risk Factor	**EM-CDSI**	*-0.0062*	*-0.0342*	*-0.0046*
		-0.5393	*-3.5113***	*-0.8928*
Risk Aversion Factors	**Closed End**	*0.5100*	*-2.5454*	*-0.1152*
		0.9591	*-4.5498***	*-0.1307*
	VIX	*0.1023*	*-0.4153*	*0.0922*
		*1.7366**	*-1.1869*	*0.9258*
Global Uncertainty	**DiB**	*0.2415*	*0.4360*	-
		1.1770	*0.4718*	-
	R-squared	*7%*	*43%*	*5%*

Table 4.5:

Panel regressions on individual determinants of Basis(bond)
Summary fixed-effects panel regressions on net $Basis_{\text{bond}}$ of Brazil 2010, Brazil 2015, Mexico 2020, Turkey 2014, and Turkey 2019 bond pairs. Explanatory variables are Liquidity Frictions [Liq-FX, Liq-PS]; Short-Selling Constraints [Inventory]; Funding Costs [Unsecured, Secured]; Global Cash-Flow Factors [LN-Macro, TP]; Risk Aversion Factors [Closed End, VIX]; Credit Risk Factor [EM-CDSI]; Uncertainty Factor [DiB]. Each category is regressed individually from Columns (A)-(G). We report the slope coefficients, and the associated White-robust t-statistics (immediately below the slope coefficients). Sample is Credit Crisis. Intercepts are used but not reported. (**) shows a 95% confidence interval, and (*) shows a 90% confidence interval.

	Determinants of Basis(bond)						
Categories	**(A)**	**(B)**	**(C)**	**(D)**	**(E)**	**(F)**	**(G)**
Liquidity Frictions							
Liq-FX	*0.0191*						
	1.1303						
Liq-PS	*-0.7061*						
	-0.5622						
Short-Selling Constraints							
Inventory		*-0.0283*					
		*-2.9924***					
Funding Costs							
Unsecured			*0.4174*				
			*1.6724**				
Secured			*0.0778*				
			0.5199				
Global Cash-Flow Factors							
LN-Macro				*-0.0627*			
				*-5.7212***			
TP				*-0.0738*			
				-0.8540			
Risk-Aversion Factors							
Closed End					*-2.1654*		
					*-3.9424***		
VIX					*0.5137*		
					1.5655		
Credit Risk Factor							
EM-CDSI						*-0.0304*	
						*-2.9451***	
Uncertainty Factor							
DiB							*0.7316*
							0.7813
R-squared	*1%*	*3%*	*5%*	*11%*	*23%*	*7%*	*1%*

Table 4.6:

Price discovery analysis
Summary results of the price discovery regressions between the USD and Euro credit yield spreads of the bond pairs used in our analysis. The tests are based on weekly-frequency VECM specification shown below. We let $S_t = [S_t^a, S_t^b]$ be the vector of bond credit yield spreads in a=USD, b=EUR, and $z_t \equiv [S_t^a - k_1 \times S_t^b]$, where k_1 is the average of $X(t)/F(t,T)$. We denote the corresponding error terms as $u_t = [u_{1t}, u_{2t}]$, so that σ_1, σ_2, σ_{12} are the standard deviations and covariance of u_{1t} and u_{2t}, respectively. The optimal number of lags N=2 are determined by Akaike Information Criteia (AIC). We report the average of A_1 and A_2 coefficients for each region, and the average t-statistics immediately below. H_l and H_u are the Hasbrouck bounds, and H_m is the average of the two. We report the average H_m for each bond pair (i.e. Turkey 2014, Brazil 2015, Mexico 2020), capturing the contribution of S^a to the price discovery process. 1-H_m captures the contribution of S^b to the price discovery process. VECM and Hasbrouck bounds are specified in order as follows:

$$\Delta S_t^a = A_1 z_{t-1} + \sum_{n=1}^{N} \phi_{1n} \Delta S_{t-n}^a + \sum_{n=1}^{N} \gamma_{1n} \Delta S_{t-n}^b + u_{1t}$$
$$\Delta S_{c,t}^b = A_2 z_{t-1} + \sum_{n=1}^{N} \phi_{2n} \Delta S_{t-n}^a + \sum_{n=1}^{N} \gamma_{2n} \Delta S_{t-n}^b + u_{2t}$$

$$H_l = \frac{A_2^2 \left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{A_2^2\sigma_1^2 - 2A_1A_2\sigma_{12} + A_1^2\sigma_2^2}, \qquad H_u = \frac{\left(A_2\sigma_1 - A_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{A_2^2\sigma_1^2 - 2A_1A_2\sigma_{12} + A_1^2\sigma_2^2}$$

Region	**Coeff.**		**Hasbrouck Measure**
	A_1	A_2	H_m
Brazil 2015	0.02	0.16	66%
	0.27	2.30	
Mexico 2020	0.01	0.04	84%
	0.56	2.07	
Turkey 2014	-0.14	-0.09	29%
	-1.73	-1.18	

Table 4.7:

Central bank international reserve distribution
Time evolution of the distribution of foreign asset values to total foreign assets of the Central Bank of Brazil (Banco Central do Brazil) from 2004 to 2010, and that of the Central Bank of Turkey (Turkiye Cumhuriyeti Merkez Bankasi) from 2008 to 2010. The reserve distribution data preceding 2008 is not available for Turkey. The foreign assets include the following currencies: the U.S. dollar (USD), Euro (EUR), and others (e.g. Japanese Yen (JPY), British Pound (BGP), Canadian Dollars (CAD), Australian Dollars (AUD)).

Year	**Brazil**			**Turkey**		
	EUR	*USD*	*Other*	*EUR*	*USD*	*Other*
2004	35.1%	54.6%	10.3%	-	-	-
2005	21.3%	73.2%	5.5%	-	-	-
2006	10.3%	88.3%	1.4%	-	-	-
2007	9.5%	90.0%	0.5%	-	-	-
2008	9.4%	89.1%	1.5%	46.0%	51.0%	3.0%
2009	7.0%	81.9%	11.1%	44.6%	52.6%	2.8%
2010	4.5%	81.8%	13.7%	46.5%	51.3%	2.2%

Table 4.8:

Regressions on commercial paper rates and deposit rates
Summary regressions on net $Basis_{\text{bond}}$ of Brazil 2010, Brazil 2015, Mexico 2020, Turkey 2014, and Turkey 2019 bond pairs. Δ denotes first-difference, $\bar{\Delta}$ denotes percentage difference. Bond pairs of Turkey are denoted by TR, and those of Brazil and Mexico by j= [BR, MX], respectively. We report the slope coefficients, and the t-statistics (below), based on White's standard errors. Sample is the Credit Crisis. The variable *Euribor* and *Libor* stand for 3-month Euribor and Libor rates, respectively; and the variables CP stand for 3-months commercial paper rate, and *Depo* stand for 3-months deposit rate in their corresponding currencies, USD and EUR. The variable L_{t-1} denotes the one-week lag of the dependent variable of each given regression. Panel regression results of each specification (A)-(C) are displayed in their respective columns. Intercepts are used but not reported. (**) shows a 95% confidence interval, and (*) shows a 90% confidence interval.

$$(A) \quad \Delta\left[\text{Net } Basis(bond)_{TR,t}\right] = \alpha + \beta_{1,1}\left[\Delta(USD\ CP - EUR\ Depo)_t\right] + \beta_{1,2}\ \Delta Euribor_t + \beta_{1,3}\ \Delta Libor_{t-1} + \beta_{1,4}\ \Delta L_{t-1} + \epsilon_{TR,t}$$

$$(B) \quad \Delta\left[\text{Net } Basis(bond)_{j,t}\right] = \alpha_j + \beta_{2,1}\left[\bar{\Delta}(EUR\ CP - USD\ Depo)_t\right] + \beta_{2,2}\ \Delta Euribor_t + \beta_{2,3}\ \Delta Libor_{t-1} + \beta_{2,4}\ \Delta L_{t-1} + \epsilon_{j,t}$$

$$(C) \quad \Delta\left[\frac{\left[\text{Net } Basis(bond)_{j,t}\right]}{\left[\text{Net} Basis(bond)_{TR,t}\right]}\right] = \alpha_j + \beta_{3,1}\ \Delta\left[\frac{(EUR\ CP - USD\ Depo)_t}{(USDCP\ - EUR\ Depo)_t}\right] + \beta_{3,2}\ \Delta L_{t-1} + \epsilon_{j,t}\ \ j = MX, BR$$

Variables	**Credit-Crisis Period**		
	Column A	**Column B**	**Column C**
	Coef. / t-stat	**Coef. / t-stat**	**Coef. / t-stat**
USD CP - EUR Depo	*0.5706* *2.3434***		
EUR CP - USD Depo		*0.0470* *10.8556***	
Ratio CP Depo			*0.0288* *6.4546***
Euribor	*-1.3149* *-3.0005***	*2.3640* *5.8598***	
Libor	*0.0390* *0.2145*	*-0.3821* *-1.9014**	
L(-1)	*-0.2761* *-1.8715**	*-0.4933* *-4.0571***	*0.2500* *2.7415***
R-squared	*21%*	*47%*	*18%*

Table 4.9:

Policy events and announcements summary

This table summarizes the classification and sample characteristics of the policy events and news that occurred during the sample period. The event categories are: (1) “Funding Relief Policy” variables, divided into three subsets (a) Policy announcements of the Fed (PAF), (b) Policy announcements of the US Treasury (PAT), (c) USD Swap Lines to developed and emerging markets (SWAP); (2) “Uncertainty Relief Policy” variable, which consists of the announcements of stress tests on U.S. financial institutions (STRESS); (3) “News Controls” variables: (a) Positive News and (b) Negative News. The control group includes financial news originating from the U.S., Europe and the rest of the world (e.g. China), as well as announcements on write-downs and subprime losses for U.S. financial institutions, and the announcements on the U.S. housing market. An example event is reported for each category. Sample is the Liquidity, Credit and Post-Crisis periods. The entries are left undefined (-) for the events that had no occurrence in the given subsample periods.

Category	**Event**	**Definition**	**Example**	**Date**	**Number of Events**		
					Liquidity	**Credit**	**Post**
Funding Relief Policies	PAF	Policy announcements on Federal Reserve’s balance sheet	The Fed announced the creation of the Commercial Paper Funding Facility (CPFF) to provide liquidity backstop to U.S. issuers of commercial paper	07.10.2008	9	8	4
	PAT	Policy announcements on the US Treasury’s balance sheet	U.S. Treasury announces Troubled Asset Relief Program (TARP) to purchase capital in fin. institutions under Emergency Economic Stabilization Act 2008.	14.10.2008	-	27	18
	SWAP	The Fed Swap Lines to developed and emerging markets	$330 billion of swap lines to nine central banks of developed markets $120 billion of swap lines to four central banks of emerging markets	29.09.2008 29.10.2008	4	9	3
Uncertainty Relief Policy	STRESS	Stress Tests on US financial institutions	For U.S. bank holding companies with assets over $100 billion, the Fed announces that it will make stress tests or economic assessments	25.02.2009	-	1	2
News Controls	Positive News	News on U.S. finance	3 Billion dollars of stock is sold by Citigroup to boost capital	29.04.2008	13	5	-
		News on European finance	205 Billion dollar loans are guaranteed by Sweden	20.10.2008	16	7	-
		News on UK finance	4.5 Billion pounds Quatari investment plan is launched by Barclays	25.06.2008	3	7	-
		News on Rest of the World finance	586 Billion dollars stimulus plan over 2 years is announced by China	10.11.2008	-	3	-
		News on US Housing market	Housing and Economic Recovery Act of 2008 signed into law by President Bush	30.07.2008	3	3	1
	Negative News	News on U.S. finance	MBIA and Ambac, 1 Trillion dollars of Debt, lose S&P AAA Rating	05.06.2008	8	-	-
		News on European finance	Soc Gen announces 84% slump in profits of 3Q	03.11.2008	5	5	-
		News on UK finance	Biggest fall in UK house prices since 1991	31.07.2008	13	5	-
		News on Rest of the World finance	Market disruption in Canada	14.08.2007	1	-	-
		News on US Housing market	Fannie MaeÂ announces 25.2 Billion dollars loss in fourth quarter 2008	26.02.2009	2	4	6
		News on Writedowns	18 Billion dollars write-down of Citi	24.10.2007	16	-	-

Table 4.10:

Event analysis regressions
Event analysis regressions on Brazil, Turkey and Mexico. The dependent variable consists of $3WBasis_{bond}$ of Turkey 2014, Brazil 2015 and Mexico 2020 bond pairs, where $3W$ denotes the three-week forward-looking rolling average of net $Basis_{bond}$ of each bond pair. The dispersion variable for Turkey vs. Brazil is denoted by Disp(TRBR)=$[|3WBasis(bond)_{TR}| - |3WBasis(bond)_{BR}|]$, whereas the dispersion variable for Turkey vs. Mexico is denoted by Disp(TRMX)=$[|3WBasis(bond)_{TR}| - |3WBasis(bond)_{MX}|]$. Explanatory variables are the policy and news events, each treated as a dummy variable on the dates of the announcements. The event categories are: (1) the "Funding Relief Policy" variables: (a) Policy announcements by the Fed (PAF), (b) Policy announcements of the US Treasury (PAT), (c) USD Swap Lines to developed and emerging markets (SWAP); (2) the "Uncertainty Relief Policy" variable, which consists of the announcements of stress tests on U.S. financial institutions (STRESS); (3) "News Controls" variables: (a) Positive News and (b) Negative News. The control group includes financial news originating from the U.S., Europe and the rest of the world (e.g. China), as well as announcements on write-downs and subprime losses for U.S. financial institutions, and the announcements on the U.S. housing market. Sample is from July 1, 2005 to April 30, 2010. Results for Eq. (A) are shown under Column A; Results for Eq. (B) are shown under Column B. Columns (C)-(F) give the corresponding results after dropping PAT and PAF interchangeably. We report the parameter estimates, and the associated t-statistics are displayed immediately below. Intercepts are not reported. (*) shows a 90% confidence interval, and (**) shows a 95% confidence intervals.

$$(A) \quad \Delta\text{Disp(TRBR)}_{t+1} = \rho + \pi_1 PAF_t + \pi_2 PAT_t + \pi_3 SWAP_t + \pi_4 STRESS_t + \pi_5[\text{Positive News}]_t + \pi_6[\text{Negative News}]_t + \pi_7 \Delta\text{Disp(TRBR)}_t + \epsilon_t$$

$$(B) \quad \Delta\text{Disp(TRMX)}_{t+1} = \rho + \pi_1 PAF_t + \pi_2 PAT_t + \pi_3 SWAP_t + \pi_4 STRESS_t + \pi_5[\text{Positive News}]_t + \pi_6[\text{Negative News}]_t + \pi_7 \Delta\text{Disp(TRMX)}_t + \epsilon_t$$

Categories	**News**	**Turkey-Brazil**	**Turkey-Mexico**	**Turkey-Brazil**		**Turkey-Mexico**	
		Column A	**Column B**	**Column C**	**Column D**	**Column E**	**Column F**
Funding Relief Policy Variables	**PAF**	0.0050	0.0055	0.0055		0.0056	
		*1.735**	*1.9897***	*1.8974**		*2.0194***	
	PAT	0.0043	0.0006		0.0045		0.0009
		*2.1429***	*0.3226*		*2.283***		*0.4718*
	SWAP	0.0111	0.0108	0.0118	0.0109	0.0113	0.0110
		*3.3802***	*3.4117***	*3.5843***	*3.4584***	*3.4428***	*3.4865***
Uncertainty Relief Policy Variable	**STRESS**	-0.0269	-0.0263	-0.0257	-0.0261	-0.0271	-0.0264
		*-3.5686***	*-3.6301***	*-3.4043***	*-3.6173***	*-3.5856***	*-3.6543***
News Control Variables	**Positive News**	-0.0049	-0.0043	-0.0050	-0.0043	-0.0046	-0.0040
		*-2.7478***	*-2.5054***	*-2.8097***	*-2.5183***	*-2.5979***	*-2.3385***
	Negative News	0.0043	0.0025	0.0044	0.0026	0.0044	0.0026
		*2.5213***	*1.5528*	*2.5642***	*1.5597*	*2.5525***	*1.5820*
	Disp(t)	0.8145	0.8124	0.8150	0.8122	0.8141	0.8111
		*50.3203***	*50.3782***	*50.2854***	*50.4079***	*50.2958***	*50.3126***
	R-squared	68%	68%	67%	68%	67%	68%

Chapter 5

Supply of Risk Capital: Role of Arbitrageurs and Cross-Market Interactions

This chapter empirically studies the impact of hedge funds' supply of risk capital and banks' collateral restrictions on the anomalous growth of a set of LOP deviations across credit and swap markets, during 2007-2008 crisis. We investigate the extent to which LOP condition and hedge fund capital structure are related. An important component of our study is the combination of three unique datasets that provide detailed information on hedge fund assets under management, hedge fund leverage ratios, and survey results of Euro area collateral requirements for credit line extensions.

As a continuation of Chapter 3 and 4, which investigate the financial constraints that impede the exploitation of sovereign bond basis strategies in emerging markets, this chapter focuses on the *role of arbitrageurs* as specialized institutions in ensuring the LOP equilibrium. Modern finance theory suggests that arbitrageurs (e.g. hedge funds) target positive returns from any mispricing of assets with similar cash flows, and take long/short positions, thus providing the required liquidity to inefficient markets, helping to move the dislocated prices back to equilibrium. As discussed in Shleifer and Vishny (1997), Fleckenstein, Longstaff, and Lustig (2010), and Mitchell and Pulvino (2012), the main hypothesis states that any hedge fund capital dry-up would eventually lead the associated hedge fund to reduce or liquidate its positions and shy away from markets with mispriced assets. This would eventually leave the so-called arbitrage opportunities unexploited, adversely affecting relative prices from converging to equilibrium. In this context, therefore, the role of hedge funds and other arbitrageurs becomes a crucial one for market efficiency and the attainment of the

LOP condition. This chapter mainly tests this hypothesis. We proceed as follows.

1. We identify two main categories of LOP deviation, namely Credit Market LOP, and Swap Market LOP, which displayed changing characteristics from Pre-Crisis to Post-Crisis periods, and experienced substantial violations during the Lehman collapse in particular.

   (a) In Credit Market LOP, we work with two major proxies, (i) Emerging Market Eurobond yield mispricing, as derived and discussed in Chapter 3 and 4; and (ii) Developed Market CDS-Bond Basis, as discussed in Giglio (2011). While the former proxy, $Basis_{bond}$, is concerned with the relative yield mispricing of two bonds issued by the same sovereign across two foreign currencies; the latter proxy, $Basis_{cds}$, refers to the differential between the CDS rates and the credit yield spreads of the corporate bonds of the same issuer taken from a set of U.S. and European financial institutions.

   (b) In Swap Market LOP, we work with the covered interest rate parity (CIRP) violations across two different currencies. While the proxy called $Basis_{scirp}$ is generated using two-year risk-free rates in USD and Euro, the proxy called $Basis_{lcirp}$ is generated using five-year risk-free rates in USD and Euro.

   We define a vector $B\vec{a}sis$ as:

$$B\vec{a}sis = [Basis_{bond(br)}, Basis_{bond(mx)}, Basis_{bond(tr)}, Basis_{cds}, Basis_{scirp}, Basis_{lcirp}]$$

   where br, mx and tr represent Brazil, Mexico and Turkey, respectively. If LOP holds, each component of $B\vec{a}sis$ must be zero.

2. We conduct commonality tests among each component of $B\vec{a}sis$ via principal component analysis (PCA) and vector autoregressive (VAR) models. This allows us to see whether there was an underlying systemic risk factor driving them simultaneously.

3. We test whether the AuM reduction of hedge funds and the debt deleveraging component contribute to the anomalous growth of $B\vec{a}sis$ during Credit Crisis. We also quantify the impact of the tightening of loan collateral requirements on both $B\vec{a}sis$ and hedge fund leverage ratios.

In these analyses, we utilize four different data sources (described in Section I): (i) Bloomberg data for generating each component of the vector $B\vec{a}sis$, (ii) Barclay Hedge database for studying hedge fund assets under management, (iii) Ang, Gorovyy, and Inwegen (2011) fund-of-funds database for studying the hedge fund leverage ratios, (iv) Euro Area Bank Lending Survey for studying collateral restrictions. We find a number of novel results:

1. There is evidence for a strong level of cross-market linkage among the components of $\vec{Basis}$. These components are shown to be driven by an underlying systemic risk factor during Crisis period.

2. There is significant real-life impact of the hedge fund capital structure (through both AuM reduction and debt deleveraging) on the anomalous growth of $\vec{Basis}$ during Credit Crisis. The sign of regression coefficients are found to be in line with the theoretical arguments. A decrease of AuM in hedge funds, coupled with a decrease in leverage ratios, can be associated with an increase in the $\vec{Basis}$ deviations. This shows that, as arbitrageurs shy away from markets with seemingly attractive (but increasingly risky and costly) arbitrage opportunities, prices tend to keep diverging further away from equilibrium.

3. There is strong evidence that an increase in loan collateral requirements can be associated with a decrease in the hedge fund leverage ratios, and an increase in the $\vec{Basis}$ in the market. This supports the hypothesis that the deterioration in hedge fund debt-financing, through tighter collateral restrictions, could subsequently lead to increasing LOP deviations.

The chapter is organized as follows: Section I details the data description. Section II gives the generation of the components of $\vec{Basis}$ across credit and risk-free markets, and discusses the commonality and cross-market linkages in $\vec{Basis}$. Section III discusses the empirical results of the impact of hedge fund capital and collateral restrictions on $\vec{Basis}$. Section IV concludes.

I. Data Description and Exploratory Analysis

A. *Market Data*

The time series of the underlying USD and Euro risk-free rates, Emerging Market USD and Euro sovereign bond yields,[1], EUR/USD spot and forward exchange rates are retrieved from Bloomberg as the end-of-day bid, ask and mid prices on an annualized basis at daily frequency. These are used to generate the LOP proxies across credit and swap markets, to be discussed below under the subsection "Types of LOP Anomalies". The Bloomberg Generic (BGN) prices, which are updated intra-day by accounting for market trading hours, are based on the weighted average of the quotes submitted by a minimum of five brokers and dealers, and the weighting is based on the updating frequency of each contributor. This allows to minimize the impact of measurement error from a specific broker dealer, and to make prices more reflective of market conditions. Refer to Blanco,

[1] To be more specific, we use the USD and Euro yields of the Turkish bond pair with maturity 2014, Brazilian bond pair with maturity 2015, and Mexican bond pair with maturity 2020, as discussed in Chapter 3.

Brennan, and Marsh (2005), Chen, Lesmond, and Wei (2007), Landschoot (2008), Fleckenstein, Longstaff, and Lustig (2010), and Bao, Pan, and Wang (2011) for the use of BGN prices for similar works.

B. *Hedge Fund Data*

Assets Under Management (valued in terms of current market prices, and hereafter denoted by AuM) of hedge funds represent equity capital that corresponds to the net asset value (NAV) of the assets being managed.[2] One can write:

$$\text{Total Capital} = \text{Equity} + \text{Debt} = \text{AuM} + \text{Debt} \tag{5.1}$$

where Debt is mostly comprised of short positions and short-term borrowing. Eq. (5.1) describes the relationship between the two components of the hedge fund capital.[3]

We have access to two unique datasets that capture (1) AuM of hedge funds, and (2) leverage ratios of hedge funds, each to be detailed below. While the former represents the dynamics of equity funding, the latter captures the dynamics of debt funding.

1. **Assets Under Management**

   A monthly cross-sectional time series of hedge fund AuMs are retrieved from Barclay Hedge database for July 2005 - April 2010. The Barclay Hedge database has the largest number of funds available (compared to TASS, HFR, Eurekahedge and Morningstar), the highest percentage of dead/defunct funds (as to minimize survivorship bias), and the highest AuM coverage with the least number of missing observations (see Joenvaara, Kosowski, and Tolonen (2012); Buraschi, Kosowski, and Sritrakul (2012)). We study 2,406 hedge funds that operate under six different investment strategies: Arbitrage, Equity, Options, Distressed Securities, Global Macro and Commodity. The number of hedge funds included is 444 for Arbitrage, 979 for Equity, 33 for Options, 76 for Distressed Securities, 120 for Global Macro, and 754 for Commodity. The main focus of this work is given to hedge funds that operate under Arbitrage strategies.

   Summary Statistics

   Figure 5.1 presents the time-evolution of total AuM decomposed into six investment strategies, and reveals important patterns about the dynamics of AuM for each investment strategy across

[2] On March 31, 2012, SEC announced the creation of a new metric called Regulatory Assets Under Management (RAUM), which represents gross assets under management involving long/short positions (on gross basis) and leverage.

[3] An important distinction is that while bank equity is non-redeemable, hedge fund equity is redeemable (following lock-up periods), rendering hedge funds relatively more vulnerable to direct investor behavior.

the four time periods being studied. It should be noted that AuMs of all six investment strategies tend to increase from Pre-Crisis to Liquidity Crisis, and experience a serious fall thereafter, experiencing the most serious drop during Credit Crisis. The monotonic increase in AuM between Pre-Crisis and Liquidity Crisis is indicative of the fact that hedge funds generate high returns, and have easy access to equity capital. The sharp fall between Liquidity Crisis and Credit Crisis, on the other hand, suggests that hedge funds lose significant portfolio value, and have restricted access to equity capital.

Studying Figure 5.1 more closely, and referring to Table 5.1 that presents the corresponding summary statistics, we find that the average value of AuM during Pre-Crisis is 69.9 billion USD for Arbitrage hedge funds, 151.2 billion USD for Commodity, 26.1 billion USD for Distressed Securities, 158.4 billion USD for Equity, 24.5 billion USD for Global Macro, and 1.7 billion USD for Options. In this period, it is noted that hedge funds focused on Equity-based strategies enjoy the greatest AuM, followed by Commodity and Arbitrage, while Options have the smallest AuM. In the periods that follow, the same order holds, with the notable exception of Commodity-based hedge funds, which become the number one in terms of AuM.

From Pre-Crisis to Liquidity Crisis, AuM on average rises by 14% (up to 79.5 billion USD) for Arbitrage, 48% (up to 223.8 billion USD) for Commodity, 70% (up to 44.2 billion USD) for Distressed Securities, 25% (up to 198.6 billion USD) for Equity, 18% (up to 29.0 billion USD) for Global Macro, and 65% (up to 2.8 billion USD) for Options. This indicates that hedge funds on average still acted as fairly profitable investment vehicles during the Liquidity phase, even though this phase is generally characterized by increasing liquidity risks and deteriorating funding constraints. As of the last months of Liquidity Crisis, however, it is noted that AuM shows the first signs of disruption, and begins to fall.

From Liquidity Crisis to Credit Crisis the situation takes a turn for the worst. AuM on average drops by 35% (down to 52.0 billion USD) for Arbitrage, 2% (down to 219.6 billion USD) for Commodity, 29% (down to 31.4 billion USD) for Distressed Securities, 37% (down to 125.4 billion USD) for Equity, 29% (down to 20.5 billion USD) for Global Macro, and 19% (down to 2.3 billion USD) for Options. Compared to others, Equity- and Arbitrage-based strategies experience the largest fall in their AuMs, which are both substantially lower than their Pre-Crisis levels. As a noteworthy fact, the AuM of Commodity-based funds is almost unaffected, in line with the relatively less downbeat investment outlook that prevailed for commodities all along this and the following periods.

Except for Commodity-based funds, the situation keeps deteriorating (though at a slower rate) during Post-Crisis. From Credit Crisis to Post-Crisis, AuM on average drops further by 19% (down to 42.0 billion USD) for Arbitrage, 33% (down to 21.1 billion USD) for Distressed

Securities, 4% (down to 120.0 billion USD) for Equity, 6% (down to 19.3 billion USD) for Global Macro, and 26% (down to 1.7 billion USD) for Options. Compared to others, Distressed Securities- and Options-based strategies experience the largest fall in their asset values. On the other hand, it is noteworthy that Commodity-based funds maintain their contrary stand, and their AuM on average increases by 2% (up to 224.1 billion USD).

To give an idea of the overall picture in the hedge fund industry, Figure 5.2 presents the time-evolution of aggregate AuM across all six investment strategies. The average of the aggregate AuM during the Pre-Crisis is 432 billion USD, and increases by 35% (up to 578 billion USD) during Liquidity Crisis. However, it falls by 22% (down to 451 billion USD) during Credit Crisis, and falls further down by 5% (down to 428 billion USD) during Post-Crisis. Note that the speed at which the net asset value increases and later decreases is important. For instance, as of the first month of Pre-Crisis until the last month of Liquidity Crisis, the total AuM increases by more than 242 billion USD (from 325 billion USD to 567 billion USD). This takes over three years. However, during Credit Crisis, 68% of this total gain in value (242 billion USD) is rapidly lost in only half a year, the aggregate AuM dropping from 567 billion USD to 403 billion USD. This frightening velocity at which the size of this industry falls points to a serious disruption in the total profitability of hedge funds, and to a severe reduction of capital made available to them.

Correlation of AuMs

The second interesting fact is concerned with the cross-correlation of hedge fund AuMs across different investment strategies during different periods. Hedge funds operating under different investment strategies are normally known to be weakly correlated with the market, and with each other, granted that they aim to outperform the market, and each other, by specializing in unique, undiscovered opportunities. As shown in Table 5.2, AuM correlations between investment strategies change from one period to the next, and do not always confirm the weak-correlation conjecture. During Pre-Crisis, for instance, the correlation is highly positive, and ranges between 84% and 98%. The uncharacteristically close correlation experienced during Pre-Crisis could be explained by arguing that the extended period of easy money in those times systemically drove all AuMs to move up regardless of the strategy followed. During Liquidity Crisis, we have evidence for a notable "de-coupling" effect, the correlation ranging between -96% and 97%. As for Credit Crisis, however, we observe a strong "re-coupling" shift towards a very high degree of co-movement, the correlation ranging between 87% and 100%. During this period, Arbitrage-focused hedge funds are most correlated with Equity-focused (100%) funds, and least with Distressed Securities-focused funds (88%). The very high degree of co-movement determined during Credit Crisis can be regarded as an evidence for the sweeping propagation of a systemic financial shock across the normally self-contained categories of hedge funds, creating a contagious, self-exacerbating mechanism. Finally, during Post-Crisis period, we have yet another evidence for a "de-coupling" effect, and the correlation ranges between -81% to 93%.

2. **Leverage Ratios**

   A monthly cross-sectional time series of hedge fund gross leverage ratios are obtained from Ang, Gorovyy, and Inwegen (2011) for July 2005 - September 2009.[4] This is a unique, high-quality dataset that uses actual time-variant leverage ratios (reported directly by hedge funds), as opposed to those used in prior works that rely either on static ratios or estimates (see Lo (2008)). Ang, Gorovyy, and Inwegen (2011) retrieve the leverage ratios from a large fund-of-hedge-funds, which they refer to as the Fund. The Fund standardizes the leverage ratios reported at different frequencies, and if necessary, obtains values by directly calling hedge fund managers and making analyst site visits. The Fund database includes the hedge funds in TASS, Barclay Hedge and other databases, but it excludes the implicit leverages in client-based funding options, and focuses only on those that are reported in active strategies. As described by Ang, Gorovyy, and Inwegen (2011), the Fund database uses both *top down* and *bottom up* selection approaches in order to reduce the selection bias.[5] The dataset is of high quality because the Fund investigates the individual hedge funds through due diligence, and frequently monitors their investments. The fact that the risk and performance reports of the included hedge funds' are audited adds to the reliability of the data.

   For our sample of 2005-2009, the dataset has a total of 208 hedge funds, such that 114 follow long-short equity (EQ), 36 follow relative-value arbitrage (RV), 21 follow credit (CR) and 37 follow event-driven (ED) strategies.[6]

   Summary Statistics

   Table 5.3 shows interesting patterns for the sector-based leverage ratios for each subsample period. The time evolution of leverage ratios for each investment strategy is shown in Figure 5.3. During Pre-Crisis, the average leverage ratio is 5.8 for RV, 3.1 for CR, 1.7 for EQ, and 1.4 for ED. This shows that relative-value arbitrage strategies had the largest leverage ratios (3x as large as Equity and 4x as large as Event-Driven strategies). In fact, this is the case for all periods. Nevertheless, starting from the Liquidity Crisis, we observe a continuous trend of deleveraging, though in different magnitudes and severity, in all four categories, until

[4] We thank Andrew Ang for his kind support.

[5] Ang, Gorovyy, and Inwegen (2011) also state that "survival biases are mitigated by the fact that often hedge funds enter the database not when they receive funds from the Fund, but several months prior to the Fund's investment and they often exit the database several months after disinvestment. [The] database also includes hedge funds which terminate due to poor performance."

[6] Investment strategies are categorized under different names for Barclay Hedge (as above) and the Fund.

the end of Post-Crisis period. The leverage ratios from Pre-Crisis to Liquidity Crisis, for instance, drop by 19% (down to 4.7) for RV, 24% (down to 2.3) for CR, 2% (down to 1.7) for EQ, and 1% (down to 1.4) for ED. As deleveraging continues from Liquidity Crisis to Credit Crisis, the leverage ratios drop by 29% (down to 3.3) for RV, 32% (down to 1.6) for CR, 28% (down to 1.2) for EQ, and 34% (down to 0.9) for ED. Compared with the levels of Pre-Crisis, the largest deleveraging is observed for CR, the leverage ratio of which is almost halved (with -48%). Considering the deteriorating credit-related nature of the market turmoil, this is hardly surprising. RV also suffers one of the biggest deleveraging in terms of percentages (-42%) compared to Pre-Crisis levels. The leverage ratios in Post-Crisis continue to decrease for CR and RV, though they tend to increase very slightly for ED and EQ, when compared to Credit Crisis. From Credit Crisis to Post-Crisis, while the leverage ratios drop by 27% (down to 2.5) for RV, and 18% (down to 1.3) for CR, they increase by 3.3% (up to 1.3) for EQ, and 22% (up to 1.1) for ED. On average, the leverage ratio drops by 41% from Pre-Crisis to Post-Crisis periods, given that the ratios of CR and RV are more than halved compared to Pre-Crisis. When all hedge funds are included (denoted as All HF), the average leverage ratio is 2.36 during Pre-Crisis, 2.07 during Liquidity, 1.47 during Credit, and 1.46 during Post-Crisis periods.

As an interesting note, we observe that leverage ratios during the entire time spanned considered reach a maximum of 6.8 for RV, and 3.9 for CR, whereas for EQ and ED, they never exceed 2.2 and 2.6 for EQ and ED, respectively. First, this highlights the heterogeneity in the magnitudes of hedge fund leveraging, which directly depends on the type of the investment strategy undertaken. Second, it shows that hedge fund leverage ratios have been "fairly modest" compared to those of investment banks during 2005-2010 period (see Ang, Gorovyy, and Inwegen (2011)). This is worth noting, as one would suspect that hedge funds, operating with little regulatory oversight, would tend to take on leverages higher than those set by Reserve Board's Regulation T.

Correlation of Leverage Ratios

As discussed for the case of AuM correlations, hedge funds operating under different investment strategies are known to be weakly correlated with the market, and with each other. As shown in Table 5.4, leverage ratio correlations between investment strategies change from one period to the next, and do not always confirm the weak-correlation conjecture. The sign of correlations is interesting. RV is negatively and weakly correlated with all remaining strategies during Pre-Crisis, while the others are positively and strongly correlated among each other. The same pattern is observed during Liquidity Crisis. During Credit Crisis, however, all strategies, including RV, are strongly and positively correlated with each other. As in the case of AuMs, it could be argued that the contagion of a systemic financial shock causes massive deleveraging across all strategies. During Post-Crisis, RV becomes negatively and strongly correlated with other strategies, except CR.[7]

C. *Collateral Requirement Data*

Our work retrieves from Datastream the results of The Euro Area Bank Lending Survey on collateral requirements for loans and credit lines extended to enterprises, covering a period of May 2006 to May 2010, provided quarterly by the European Central Bank. By directly targeting the senior loan officers at a representative group of 112 banks in the Euro area (including all Euro area countries), the survey determines the number of banks tightening their collateral requirements vs. the number of banks easing their collateral requirements. Using the survey results, we define the following (based on The Euro Area Bank Lending Survey):

$$Col(req) = \%\text{ of Banks with Tightened Credit} - \%\text{ of Banks with Eased Credit} \tag{5.2}$$

such that a positive $Col(req)$ shows that a larger proportion of banks have tightened credit standards (*net tightening*), and a negative $Col(req)$ shows that a larger proportion of banks have eased credit standards (*net easing*).[8] We use this variable as a proxy for collateral restrictions in the financial markets during Credit Crisis.

Figure 5.4 indicates that $Col(req)$ is -1% in Quarter 3, 2006, 0% in Quarter 4, 2006, -1% in Quarter 1, 2007 and -4% in Quarter 2, 2007. The negative values all indicate a period of net easing in the collateral standards of loans during Pre-Crisis, confirming the arguments made about the availability of easy money during this period. Starting from Quarter 3, 2007, however, we observe the beginning of tighter collateral requirements. The average $Col(req)$ between Quarter 3, 2007 to Quarter 2, 2008, jumps up to 25.3%. The largest restriction on collateral is observed following the Lehman collapse, during the 3^{rd} Quarter of 2008, when $Col(req)$ increases to its maximum of 46%. According to Euro Bank Lending Survey October 2008 report: "The results [...] indicate a significant increase in the net tightening of credit standards for loans to enterprises in the third quarter of 2008. The most important factors in net tightening remained the expectations regarding future economic activity and the industry or firm-specific outlook." The same pattern continues during the last quarter of 2008, and the first quarter of 2009, when $Col(req)$ is 41%, and 36%, respectively. As of Quarter 2, 2009, $Col(req)$ gives signals of converging back to its Pre-Crisis levels, even though net tightening affects persists.

[7] For the first time, CR becomes negatively correlated with ED and EQ.

[8] Refer to http://www.ecb.int/stats/money/surveys/lend/html/index.en.html for the related reports and descriptions.

II. LOP Anomalies In Different Markets

Exploratory analysis of AuM and leverage ratio data in Section I has uncovered instances of close correlation across normally impermeable hedge fund strategies during Credit Crisis, where AuMs and leverage ratios of all hedge fund strategies experienced a sharp decline, and Pre-Crisis, which coincided with a long stretch of rising AuMs and leverage ratios. Such occurrences of co-movement are indications of contagious interactions between different markets during times of financial distress (Credit Crisis) or undeserved optimism (Pre-Crisis). In the present section, we start from these findings and expand our coverage of cross-market interactions to credit and swap markets.

A. *Construction of LOP Proxies*

We empirically generate a set of LOP proxies that displayed a substantial anomaly during the recent Credit Crisis. The main point is to keep the nature of the strategies diverse, so that they would represent different segments of financial markets, and potentially different types of arbitrageurs. Using the Market Data unless otherwise noted, we analyze credit and swap markets, and use the empirical proxies as outlined below. For each proxy, there is a specific LOP condition that must hold in equilibrium. While this condition was satisfied to a large extent during the Pre-Crisis period, it was considerably violated following the Lehman collapse. An interesting aspect of this violation was its persistence, since most trades were left unexploited for a time that seems inconsistent with the existing theoretical models. We divide LOP proxies into two main categories: (i) Credit Market LOP, and (ii) Swap Market LOP. The details are given below.

Credit Market LOP

1. *Emerging Market Eurobond Basis:* This is the proxy defined, constructed and used in Chapters 3 and 4:

$$Basis_{bond,t} = Y_t^{a^*} - Y_t^a \tag{5.3}$$

   where Y_t^a and $Y_t^{a^*}$ are the yields, respectively, of the original and the synthetic USD-denominated bonds committed at time t, referencing to the same issuer. For this analysis, we consider 2014-maturity Turkish bond pair ($Basis_{bond(tr)}$), 2015-maturity Brazilian bond pair ($Basis_{bond(br)}$), and 2020-maturity Mexican bond pair ($Basis_{bond(mx)}$), discussed in Chapters 3 and 4. Recall from Figure 3.1 in Chapter 3 that net $Basis_{bond}$ deviations exceed 209 bps in Brazil, 136 bps in Mexico and -169 bps in Turkey in Credit Crisis.

2. *Developed Market CDS Basis:* The credit yield spread of a corporate bond and the Credit Default Swap (CDS) spread of the same reference entity, having the same maturity, are bound by an LOP condition. In theory, the credit yield spread of a bond must be equal to the CDS spread of the same underlying bond. Any divergence from this equality (called CDS-Bond Basis in literature) would approximate an LOP violation, and would allow an investor to transact a corporate bond by insuring it against default with positive return. As Hull, Predescu, and White (2004) state, if CDS spread is greater than the reference bond's credit yield spread, "[...] arbitrageur will find it profitable to buy a riskless bond, short a corporate bond and sell the credit default swap"; and if CDS spread is smaller than the reference bond's credit yield spread, "[...] arbitrageur will find it profitable to buy a corporate bond, buy the credit default swap and short a riskless bond". This LOP condition has been documented and studied extensively in the literature (see Blanco, Brennan, and Marsh (2005); De Wit (2006); Garleanu and Pedersen (2011); Nashikkar, Subrahmanyam, and Mahanti (2011); Bai and Collin-Dufresne (2011); Mitchell and Pulvino (2012); Giglio (2011)). The empirical proxy follows as:

$$Basis_{cds,t} = CDS^{corp}_{t,m+t} - S^{corp}_{t,m+t} \tag{5.4}$$

where the CDS spread, and the underlying bond's credit yield spread issued by the reference entity *corp* (composed mainly of investment banks), are represented by CDS^{corp} and S^{corp}, respectively, and m is the number of years to maturity. Any deviation from the zero bound approximates an LOP violation.

In this chapter, we use the results of Eq. (5.4) for m=5 years, calculated by Giglio (2011). Their calculations are based on a reference bond constructed by averaging the data for 15 largest American and European investment banks, commercial banks and dealers and brokers that also have the highest gross exposures to the CDS market, covering about 90% of the total CDS transaction volume.[9] Figure 5.5 shows the time evolution of $Basis_{cds}$, which is often large and negative during Credit Crisis (exceeding -311 bps), suggesting that investors could make positive returns by longing both the bond and the CDS protection, and shorting the riskless bond. The results suggest the extent to which $Basis_{cds}$, being close to zero during Pre-Crisis, could be so severely violated even for the so-called "too-big-to-fail" financial institutions, during Credit Crisis.[10]

[9] The institutions involved are Bank of America, JP Morgan, Merrill Lynch, Goldman Sachs, Morgan Stanley, Lehman Brothers, Wachovia, Citigroup, Deutsche Bank, HSBC, Abn Amro, Credit Suisse, UBS, Bnp Paribas and Barclays.

[10] Ironically, all of these "too-big-to-fail" financial institutions involved in the sample faced severe problems during Credit Crisis. In September 15, 2008, for instance, Lehman Brothers files Chapter 11 bankruptcy, and Bank of America announces the purchase of Merrill Lynch.

Swap Market LOP

Covered Interest Rate Parity: The covered interest rate parity states that the money market investments in two different risk-free rates must generate equal returns across two corresponding currencies, as long as the investments are hedged in the FX forward market. Otherwise, an arbitrageur would be able to lock in a riskless profit by borrowing at the cheaper side, and lending at the more expensive one for the same maturity. Let us construct an idealized example of this arbitrage strategy in FX swap markets. Suppose an arbitrageur borrows USD at a risk-free rate for two years (e.g. by shorting a two-year zero coupon USD government bond), converts the proceeds into EUR at the spot exchange rate, and then invest in EUR again at a risk-free rate rate for two years (e.g. by longing a two-year zero coupon EUR government bond). Simultaneously, the arbitrageur enters into a two-year forward contract to sell the future value of the two-year EUR investment to receive USD in return for EUR. CIRP violation occurs if the future dollar value of the EUR investment exceeds the future dollar cost of USD debt.

CIRP violations have been documented and studied extensively in the literature (see Peel and Taylor (2002); Akram, Rime, and Sarno (2008), Akram, Rime, and Sarno (2009); Coffey, Hrung, and Sarkar (2009); Fong, Valente, and Fung (2010); Griffoli and Ranaldo (2011)). We test the CIRP condition by borrowing USD and investing in EUR (the same direction of $Basis_{bond}$) at risk-free rates. The empirical proxy follows:

$$Basis_{cirp,t} = \sqrt[m]{\frac{X_t}{F_{t,m+t}}}(1 + R^b_{t,m+t}) - (1 + R^a_{t,m+t}) \tag{5.5}$$

where m is the number of years to maturity. Any deviation from zero implies LOP violation. Following the same notation in the previous chapters, R^a and R^b are the U.S. and Euro Government risk-free rates, respectively, such that a=USD and b=Euro. The spot and forward exchange rates (Euro per USD) are denoted as X and F, respectively. We calculate Eq. (5.5) for two maturity buckets. The calculation based on m=2 years is called $Basis_{scirp,t}$, and the calculation based on m=5 years is called $Basis_{lcirp,t}$.[11] The $Basis_{scirp}$ exceeds 145 bps, and $Basis_{lcirp}$ exceeds 106 bps during Credit Crisis. See Figure 5.5 for their time evolution.

B. *Commonality in LOP Proxies*

One motivation of this study is to evaluate whether there exists any commonality in the variation of the LOP proxies described above. The recent Credit Crisis offers a unique opportunity to test this

[11] All rates with the given two fixed maturity points (i.e. m=2 years and m=5 years) are retrieved from Bloomberg as BGN.

across credit and swap markets, and see whether there exists any cross market linkages in a period of financial distress. This draws links with the literature of contagion transmission as discussed in Longstaff (2010).

In order to carry out this analysis, it is required to have two main conditions: (1) one must have a period of severe market distress that differs substantially from the preceding periods, and (2) one must have a vector of LOP deviations directly associated with that period. Our analysis satisfies both conditions. The LOP proxies described above display substantial differences from one period to the next. The fact that they are diverse in nature not only reduces the possibility of finding a common systemic component that may simultaneously drive them, but it also makes the issue of potential cross-market linkage more relevant for our purposes.[12] We define a vector $\vec{Basis}$ as:

$$\vec{Basis} = [Basis_{bond(br)}, Basis_{bond(mx)}, Basis_{bond(tr)}, Basis_{cds}, Basis_{scirp}, Basis_{lcirp}] \tag{5.6}$$

where each component represents the net deviation from zero (based on absolute values), and br, mx and tr represent Brazil, Mexico and Turkey, respectively. The usage of absolute values is to allow for a consistent economic interpretation (see Section II, Chapter 4). Since each component of $\vec{Basis}$ is represented in absolute value terms, any rise in this component would directly indicate a rise in the pricing anomaly. This way, a significantly positive/negative slope coefficient of an explanatory variable, when regressed against the component of $\vec{Basis}$, could be unambiguously interpreted as increasing (or decreasing) the size of the anomaly, regardless of whether the actual LOP deviation is positive or negative. IF LOP holds, each component of $\vec{Basis}$ should be equal to zero.

We apply two procedures to study the nature and extent of commonality among the components of $\vec{Basis}$. (i) The first procedure aims to identify whether there are any common factors that jointly explain the variations in $\vec{Basis}$. We use principal component analysis (PCA) for this purpose. (ii) The second procedure aims to study the nature and the extent of any cross-market linkages between the components of $\vec{Basis}$. We run vector autoregressions (VAR) on each component of $\vec{Basis}$ (see Fleckenstein, Longstaff, and Lustig (2010) for a similar analysis). The details of the analyses follow.

Common Factors Among Basis Components

Supposing that N is the total number of variables in the dataset, PCA is a method to find a small number of orthogonal principal components (generated from the eigenvectors of the NxN covariance matrix) that would best represent the total variability of the dataset. In literature, the

[12] Initially, we observe that during Pre-Crisis, Credit and Swap Market LOPs are jointly violated only 11% of the time. During Liquidity Crisis, however, they are jointly violated 38% of the time, which still indicates to a higher level of commonality compared to Pre-Crisis period. Nevertheless, this statistic increases substantially during the Credit Crisis (more than two times), when they are jointly violated 81% of the time. This suggests that if LOP is violated in one market, it is very likely to be violated simultaneously in the other five markets as well. During Post-Crisis, the co-movement tends to diminish, such that they are jointly violated only 16% of the time.

first principal component (corresponding to the largest eigenvalue) often refers to a systemic shock, whereas the second and third principal components (corresponding to the second and the third largest eigenvalues) are often associated with more regional factors.

Using the covariance matrix of the six components of $\vec{Basis}$, we calculate the associated six eigenvalues and six principal components, where λ_n for n (from 1 to 6) denotes the n^{th} eigenvalue corresponding to the n^{th} principal component (from largest to smallest). The contribution of each principal component to the total variance of $\vec{Basis}$ is captured by calculating the "coupling coefficient" (see Scherer and Avellaneda (2002)), which is obtained by dividing the n^{th} eigenvalue to the sum of all eigenvalues. Scherer and Avellaneda (2002) state that "[...] coupling coefficient represents the frequency with which the market moves as a single block under a typical shock". The calculation follows:

$$\text{Coupling Coefficient} = \frac{\lambda_n}{\sum_{n=1}^{N} \lambda_n} \tag{5.7}$$

Table 5.5 reports the cumulative coupling coefficients generated for Pre-Crisis, Crisis and Post-Crisis periods.

Our calculations reveal that, while the coupling coefficient of the first principal component (associated with systemic risk) explains 28% of the total $\vec{Basis}$ variability during Pre-Crisis, it explains 50% during Crisis period. This gives strong evidence for the presence of an underlying common risk factor that tends to have an increasing influence over LOP deviations from Pre-Crisis to Crisis, explaining half of the total variance of $\vec{Basis}$ components during the latter period. The influence of this factor tends to persist, though to a slightly smaller degree, during Post-Crisis, having 44% marginal contribution. Our findings suggest that the cumulative coupling coefficients of the first three principal components rise up to 88% during Credit Crisis, indicating that almost the entire dataset can be explained by three underlying common factors, and that regional shocks are also strong drivers of $\vec{Basis}$ components during the market turmoil.

Cross-Market Linkages Among Basis Components

The topic of cross-market spillover is gaining significant attention from both academics and practitioners following the recent subprime crisis. Longstaff (2010) defines *contagion* as "an episode in which there is a significant increase in cross-market linkages after a shock occurs in one market".[13] Three main channels of contagion have been identified by Longstaff: (i) correlated-information channel (see King and Wadhwani (1990); Kiyotaki and Moore (2002)), (ii) liquidity channel (see

[13] Refer also to Dornbusch, Park, and Claessens (2000); Kaminsky, Reinhardt, and Vegh (2003); and Bae, Karolyi, and Stulz (2003).

Allen and Gale (2000); Kodres and Pritsker (2002); Brunnermeier and Pedersen (2009)), (iii) risk premium channel (see Vayanos (2004); Acharya and Pedersen (2005)). Each channel is argued to have different implications for the asset prices across different markets. Longstaff (2010) finds strong evidence of contagion during the subprime crisis, triggered primarily by liquidity and risk-premium channels. In the framework of LOP deviations, Baba (2009) finds strong evidence of dynamic spillover between the short- and long-term covered interest rate parity violations. Similarly, Fleckenstein, Longstaff, and Lustig (2010) find significant correlation and commonality among different fixed-income arbitrage opportunities (CDS/corporate bond market vs. TIPS-Treasury market), and conclude that different LOP deviations can be interrelated in a contagious environment where they are driven by a small number of common factors.

In the spirit of Longstaff (2010), and Fleckenstein, Longstaff, and Lustig (2010), we investigate the extent of the cross-market linkages among the components of $B\vec{asis}$ by estimating the following VAR system:

$$\Delta B\vec{asis}_{j,t} = a_j + \sum_{k=1}^{2}\sum_{l=1}^{6} V_{j,k,l}\Delta B\vec{asis}_{j,l,t-k} + e_{j,t} \tag{5.8}$$

where notations are as defined above. Idiosyncratic errors are captured by e_t at time t, and the optimal lag structure two weeks is determined by the the Akaike Information Criterion (AIC). Table 5.6 displays the V coefficients, t-statistics, and R-squared values for the Crisis period (9 August 2007 - 31 March 2009).

Our results reveal a significant level of cross-market spillover in Crisis period. To be more specific, we observe a significant information transmission from the weekly-lagged $Basis_{bond(mx)}$ and $Basis_{cds}$ to $Basis_{bond(br)}$; and from the weekly-lagged $Basis_{bond(tr)}$ and $Basis_{bond(br)}$ to $Basis_{bond(mx)}$. The same effect takes place from the two-week lagged $Basis_{bond(br)}$, $Basis_{bond(mx)}$ and $Basis_{cds}$ to $Basis_{scirp}$; and from two-week lagged $Basis_{bond(br)}$, $Basis_{bond(mx)}$, and $Basis_{cds}$ to $Basis_{lcirp}$. Furthermore, both $Basis_{bond(tr)}$ and $Basis_{cds}$ experience a significant information transmission from the two-week lagged $Basis_{bond(br)}$ and $Basis_{scirp}$. R-squared ranges between 24% to 49%.

It is interesting to see a strong spillover effect among trades that belong to different market segments. Our findings support the hypothesis that the financial contagion was primarily diffused through both FX swap and credit markets mutually, giving evidence for a bi-directional transmission rather than a single-directional transmission. Our results are also in line with the interpretations of Fleckenstein, Longstaff, and Lustig (2010) that arbitrageurs who participate in these different markets were limited by similar constraints.

III. Supply of Risk Capital

A. Impact of Hedge Fund Capital on Basis

In this section, we study the impact of the changes in AuM, and the changes in leverage ratio on $\vec{Basis}$. We run the following panel regressions:

$$\Delta \vec{Basis}_{j,t+1} = \alpha_1 + \beta_1 \bar{\Delta}\text{HFAuM}_t + \gamma_{1,j} \Delta \vec{Basis}_{j,t} + \epsilon_{1,t} \tag{5.9}$$

$$\Delta \vec{Basis}_{j,t+1} = \alpha_2 + \beta_2 \bar{\Delta}\text{HFLev}_t + \gamma_{2,j} \Delta \vec{Basis}_{j,t} + \epsilon_{2,t} \tag{5.10}$$

where $HFAuM$ denotes the AuM of hedge funds that specialize on arbitrage-focused strategies, and $HFLev$ denotes the leverage ratio of all hedge funds including arbitrage-focused strategies.[14] First-difference is represented by Δ, and percentage difference is represented by $\bar{\Delta}$. Idiosyncratic errors are captured by ϵ_t at time t. Table 5.7 reports the slope coefficients, White robust t-statistics and R-squared values on each regression.

1. *Impact of AuM:* Our results suggest that $HFAuM$ has no significant impact on $\vec{Basis}$ during Pre-Crisis, Liquidity and Post-Crisis periods. Nevertheless, it becomes highly and statistically significant during Credit Crisis with a negative slope coefficient β_1 and a t-stat of -3.22. R-squared increases to 17% (almost twice as much as that in Pre-Crisis or Liquidity Crisis). The negativity of β_1 suggests that, in distressed periods, an increase in $\vec{Basis}$ deviations can be linked to depletions in AuM. This result suggests that a sizable capital dry-up could indeed lead hedge funds to "de-participate" from dislocated markets, keeping them from providing the required liquidity to arbitrage trades, which in turn would be associated with further relative price divergence in the underlying assets. This conclusion is in direct harmony with the arguments of the related literature (see Shleifer and Vishny (1997), Fleckenstein, Longstaff, and Lustig (2010), Liu and Mello (2011), Mitchell and Pulvino (2012)).[15]

2. *Impact of Leverage Ratio:* Our results suggest that $HFLev$ has no significant impact on $\vec{Basis}$ during Pre-Crisis, Liquidity and Post-Crisis periods. Nevertheless, it becomes highly and statistically significant during Credit Crisis with a negative slope coefficient β_1 and a t-stat of -2.94. R-squared increases to 20% (almost three times higher than that in Pre-Crisis or Liquidity Crisis). Once again, negative slope coefficients indicate that, in distressed periods,

[14] The variables $HFAuM$ and $HFLev$ are interpolated to match the weekly frequency of the components of $\vec{Basis}$. AuM series are standardized.

[15] When we make the same regressions by using the AuMs of Equity, Commodity, Distressed Securities and Global Macro strategies, during Credit Crisis, we find significant impact of Equity (with a t-stat of -2.66) and Global Macro (with a t-stat of -3.30). This shows that capital reduction in hedge funds that specialize on equity markets and broad macroeconomic trends tend to contribute adversely to the pricing anomaly in credit and swap markets, possibly due to an underlying contagion effect.

an increase in $\vec{Basis}$ deviations can be linked to hedge fund deleveraging. Similar to our results discussed above, this finding suggests that hedge funds, exposed to a severe dry-up of debt financing, would be unable to raise sufficient capital that would help move prices back to equilibrium. These conclusions are also in strong agreement with the related literature.[16]

B. *Association of Hedge Fund Capital with Systemic Factor*

PCA conducted in Section II reveals that components of $\vec{Basis}$ are driven simultaneously by an underlying systemic risk factor. Following this analysis, we test whether this underlying systemic risk factor (captured by the first principal component of $\vec{Basis}$) can be associated with the hedge fund capital structure. In order to do this, we run the following regressions:

$$\Delta PC1^{Basis}_{t+1} = \alpha_1 + \beta_1 \bar{\Delta}\text{HFAuM}_t + \epsilon_{1,t} \tag{5.11}$$

$$\Delta PC1^{Basis}_{t+1} = \alpha_2 + \beta_2 \bar{\Delta}\text{HFLev}_t + \epsilon_{2,t} \tag{5.12}$$

where $PC1^{Basis}$ denotes the first principal component of $\vec{Basis}$, and other notations are as defined above. Table 5.8 reports the slope coefficients, White robust t-statistics and R-squared values on each regression. Our results suggest that $HFLev$ is highly and statistically significant on $PC1^{Basis}$ with a t-stat of -2.48, and an R-squared of 12%. The negative slope coefficient suggests that lower hedge fund debt leveraging can be associated with a larger systemic risk that simultaneously drives LOP proxies. This suggests that the variations in the underlying systemic factor may be linked to hedge fund debt constraints that become increasingly binding during Credit Crisis period.

C. *Impact of Collateral Restrictions on Basis*

Our second interest lies in the impact of loan collateral restrictions on $\vec{Basis}$ and hedge fund capital structure. This analysis draws its logic from the literature on the impact of collateral constraints on LOP deviations. Tuckman and Vila (1992) state that the optimal investment of a risk-averse arbitrageur, constrained by holding costs, would lead to limited arbitrage positions. Similarly, Gromb and Vayanos (2002) introduce a multi-period model where collateral directly limits the positions of arbitrageurs. Liu and Longstaff (2004) show that the introduction of collateral constraints would force investors to optimally underinvest in risky arbitrage positions, which may

[16] When we make the same regressions by using the leverage ratios of Arbitrage (RV), Credit (CV), Equity (EQ) and Event-Driven (ED) strategies, individually, during Credit Crisis, we find significant impact of RV (with a t-stat of -2.87), and EQ (with a t-stat of -1.94), and ED (with a t-stat of -2.00). Not only does this analysis show that the deleveraging affect of the arbitrage-focused hedge funds have the highest marginal contribution on LOP growth, it also reveals that deleveraging of hedge funds that specialize on equity markets and corporate events (such as mergers, acquisitions or bankruptcies) also contribute adversely to the pricing anomaly in credit and swap markets, possibly due to an underlying contagion effect.

lead to persistent and widening LOP deviation. The idea is related additionally to the hedge fund literature, as discussed in Mitchell and Pulvino (2012).

Here, we study the impact of the changes in collateral requirements on $\vec{Basis}$ and $HFLev$. We run the following panel regressions:

$$\Delta \vec{Basis}_{j,t+1} = \alpha_3 + \beta_3 \Delta \text{Coll(req)}_t + \gamma_3 \Delta \vec{Basis}_{j,t} + \epsilon_{3,t} \tag{5.13}$$

$$\bar{\Delta}\text{HFLev}_{t+1} = \alpha_5 + \beta_5 \Delta \text{Coll(req)}_t + \gamma_5 \bar{\Delta}\text{HFLev}_t + \epsilon_{5,t} \tag{5.14}$$

where $Coll(req)$ is defined in Section I.[17] Table 5.9 reports the slope coefficients, White robust t-statistics and R-squared values on each regression.

Results suggest that $Coll(req)$ has no significant impact on $\vec{Basis}$ during Pre-Crisis, Liquidity and Post-Crisis periods. Nevertheless, it becomes highly and statistically significant during Credit Crisis with a positive slope coefficient and a t-stat of 2.09. R-squared is 9%. The positivity of the slope coefficient indicates that, in distressed periods, an increase in $\vec{Basis}$ deviations can be linked to an increase in loan collateral requirements in the market. When funding costs through tightened collateral exceed the expected arbitrage returns, traders would withdraw from the implied opportunity. This result directly confirms the arguments of the related literature. Results also suggest that $Coll(req)$ has a statistically significant impact on $HFLev$ during both Liquidity Crisis and Credit Crisis with negative slope coefficients and t-stats of -1.91 and -2.04, respectively. While R-squared is 50% during Liquidity Crisis, it is 70% during Credit Crisis. The increasing R-squared, coupled with negative slope coefficients, suggest that, in distressed periods, a decrease in leverage ratios (and thus debt funding) can indeed be linked to an increase in loan collateral requirements in disrupted markets.

IV. Concluding Remarks

As a continuation to Chapter 3 and 4, and based on the literature stream 5 (in Chapter 2), this chapter investigates the role of arbitrageurs as specialized institutions in ensuring price convergence in mispriced securities. Modern finance theory suggests that, by targeting mispriced securities, hedge funds channel the required liquidity (and the demand/supply dynamics) into arbitrage trades until prices meet at relative equilibrium. Therefore, hedge funds, if allowed to participate in markets during periods of non-binding constraints, tend to contribute positively to the LOP condition. The main hypothesis states that hedge funds, if exposed to severe capital dry-up, would no longer provide liquidity to markets, and consequently force similar assets to trade at similar prices, which in turn

[17]The variable $Coll(req)$ is interpolated to match the weekly frequency of the components of $\vec{Basis}$.

would lead LOP deviations to diverge further away from the zero equilibrium. To the best of our knowledge, the work presented in this chapter is the first in literature to quantify the impact of hedge fund capital withdrawal on LOP deviations from both the equity and the debt sides.

Equity capital and debt capital are the two main funding sources that hedge funds rely on. Debt financing in particular is obtained with substantial leverage to maximize expected returns. The main idea is that, if only AuM falls, the hedge fund can compensate this fall by raising additional leveraged-debt; and similarly, if only debt capital falls, the hedge fund can compensate this fall by raising additional equity. On the whole, the total capital may still remain unaltered, such that the hedge fund would continue to operate with the same capital that it has initially required. Therefore, if only one of the two capital components drops, this does not necessarily mean that the hedge fund would be forced away from the mispriced markets. The real problem, however, arises when hedge fund shrinks simultaneously from both the equity and the debt sides. In this circumstance, the hedge fund would find it increasingly difficult to fund itself through all possible means. An intriguing example is observed during 2008 Credit Crisis, for instance, when hedge funds were indeed unable to replace large AuM reductions with leveraged debt, and vice versa. The significant fall in leverage ratios directly coincided with large AuM reductions.

In this study, we empirically test the proposition of the related literature, and investigate the impact of the massive hedge fund capital dry-up on LOP deviations during 2008-2009 market turmoil. The results validate the main hypothesis of the related literature, and indicate the occurrence of a troubling chain reaction from credit suppliers to hedge funds, and from hedge funds to dislocated markets with the inducement of persistent LOP deviations. Following the severe net tightening of funding facilities through higher funding costs and restricted collateral requirements, hedge funds find it increasingly difficult to raise leveraged debt – a phenomenon that erupts during bad states of the economy when market constraints become strictly binding on traders. When the depletion in the hedge fund debt capital is further coupled with sudden AuM reduction, hedge funds "de-participate" from dislocated markets that offer risky arbitrages. This would further exacerbate the relative pricing anomaly, and can be associated with larger and persistent LOP deviations. Our analysis shows that an increase in LOP deviations can indeed be linked to depletions in AuM and debt capital, and to hikes in loan collateral requirements. Therefore, hedge fund participation in financial markets tends to contribute significantly to the restoration of correct valuation for mispriced assets. This might potentially induce future research.

Figure 5.1:

Hedge fund AuM across individual investment strategies

The figure displays the time evolution (in million USD) of Assets Under Management (AuM) of the hedge funds that specialize on six different investment strategies (i.e. Arbitrage, Options, Commodity, Equity, Distressed Securities and Global Macro). The sample is July 2005 - April 2010, divided into the corresponding subsample periods by dashed vertical lines.

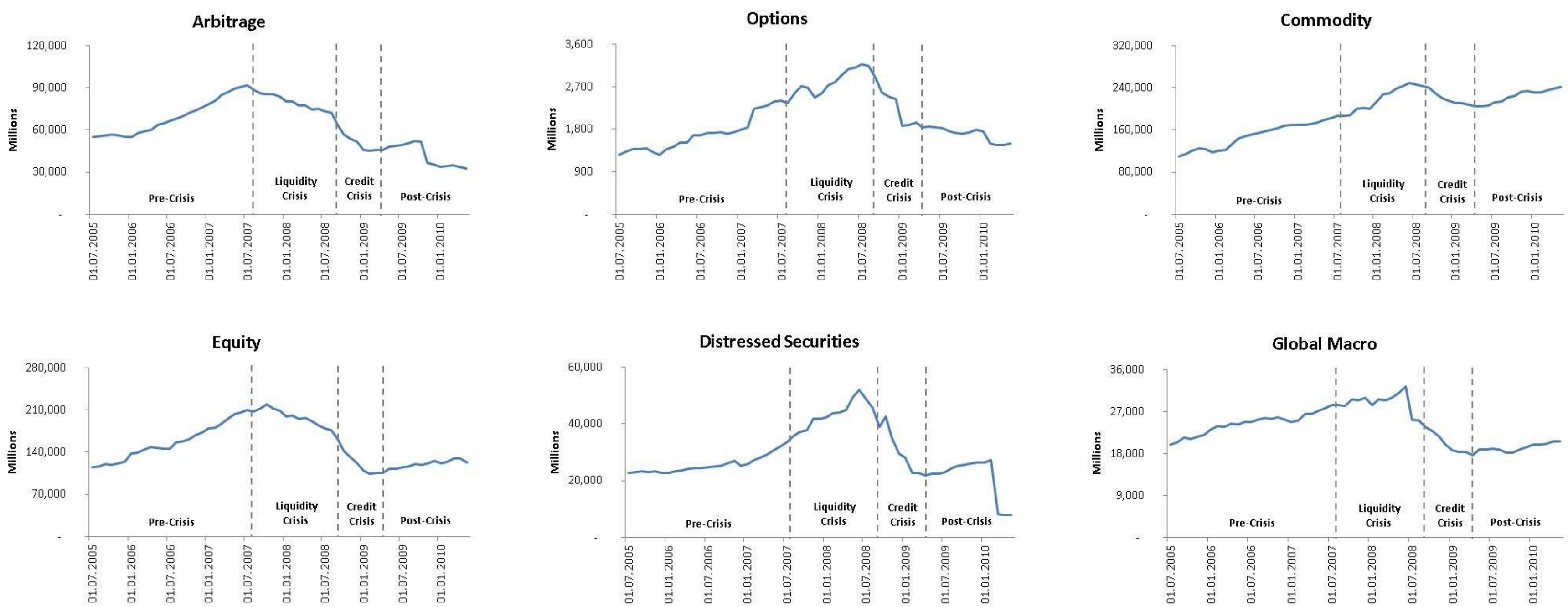

Figure 5.2:

Hedge fund aggregate AuM across six investment strategies
The figure displays the time evolution (in millions USD) of Assets Under Management (AuM) of all hedge funds together under six different investment strategies (i.e. Arbitrage, Options, Commodity, Equity, Distressed Securities and Global Macro). The sample is July 2005 - April 2010, divided into the corresponding subsample periods by dashed vertical lines.

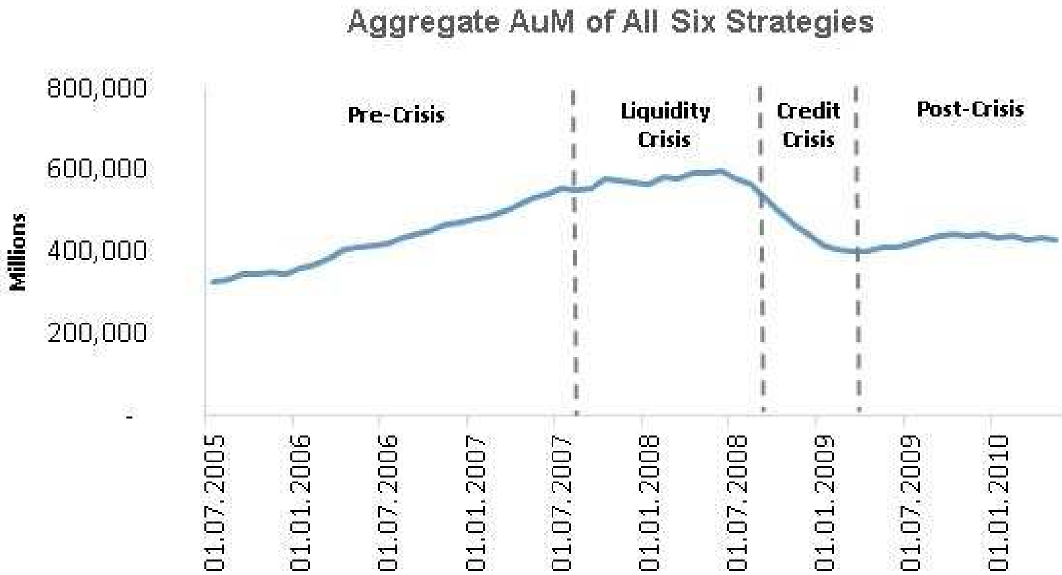

Figure 5.3:

Hedge fund leverage ratios
The figure displays the time evolution of the leverage ratios of hedge funds that specialize on Relative Value, Credit, Equity and Event-Driven strategies. The figure also includes the average leverage ratio generated from all hedge funds, shown as All HF. The sample is from July 2005 - September 2009, divided into the corresponding subsample periods by dashed vertical lines.

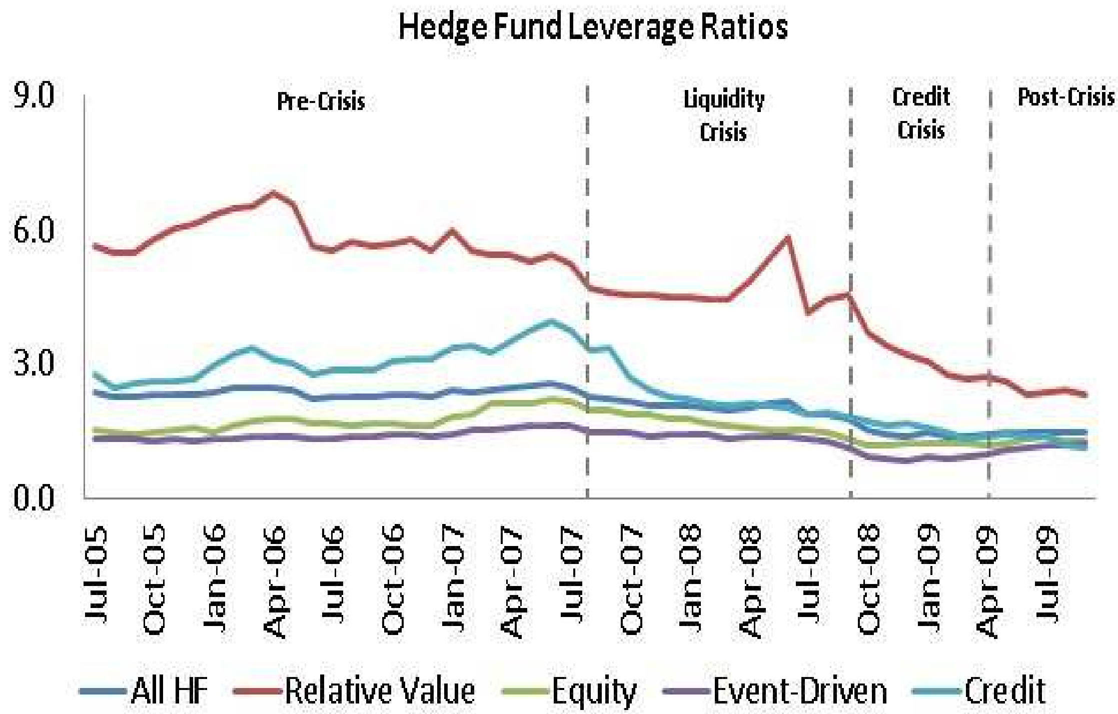

Figure 5.4:

Euro area loan collateral requirements survey results
The figure displays the quarterly results of The Euro Area Bank Lending Survey regarding the collateral requirements for loans and credit lines (extended to enterprises), covering the period May 2006 to May 2010. The survey seeks an answer to the following question: over the last quarter, how have your bank's loan and credit lines to enterprises changed? The graph shows the collateral-specific results in terms of the net percentage, which is defined as the difference between the proportion of banks that report tightened credit standards and the proportion of banks that report eased credit standards. The variable is called $Coll(req)$ which captures the net effect of collateral demands on credit to firms. The sample includes Liquidity, Credit and Post-Crisis periods.

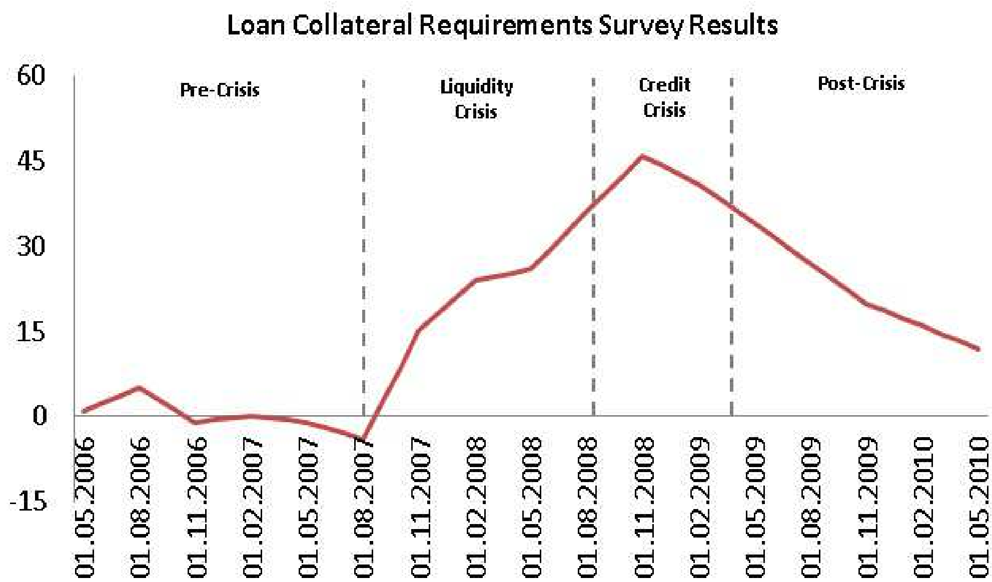

Figure 5.5:

Basis(cds), Basis(scirp) and Basis(lcirp) dynamics

The plots show the evolution of $Basis_{\text{cds}}$ (shown in blue, in percentages); $Basis_{\text{scirp}}$ (shown in orange, in percentages) and $Basis_{\text{lcirp}}$ (shown in green, in percentages). $Basis_{\text{scirp}}$ and $Basis_{\text{lcirp}}$ are constructed by shorting the USD riskless bond and longing the EUR riskless bond, and are positive when the USD riskless bond is trading rich, and negative when EUR riskless bond is trading rich. All figures cover between July 2005 - April 2010, divided into the corresponding subsample periods by dashed vertical lines.

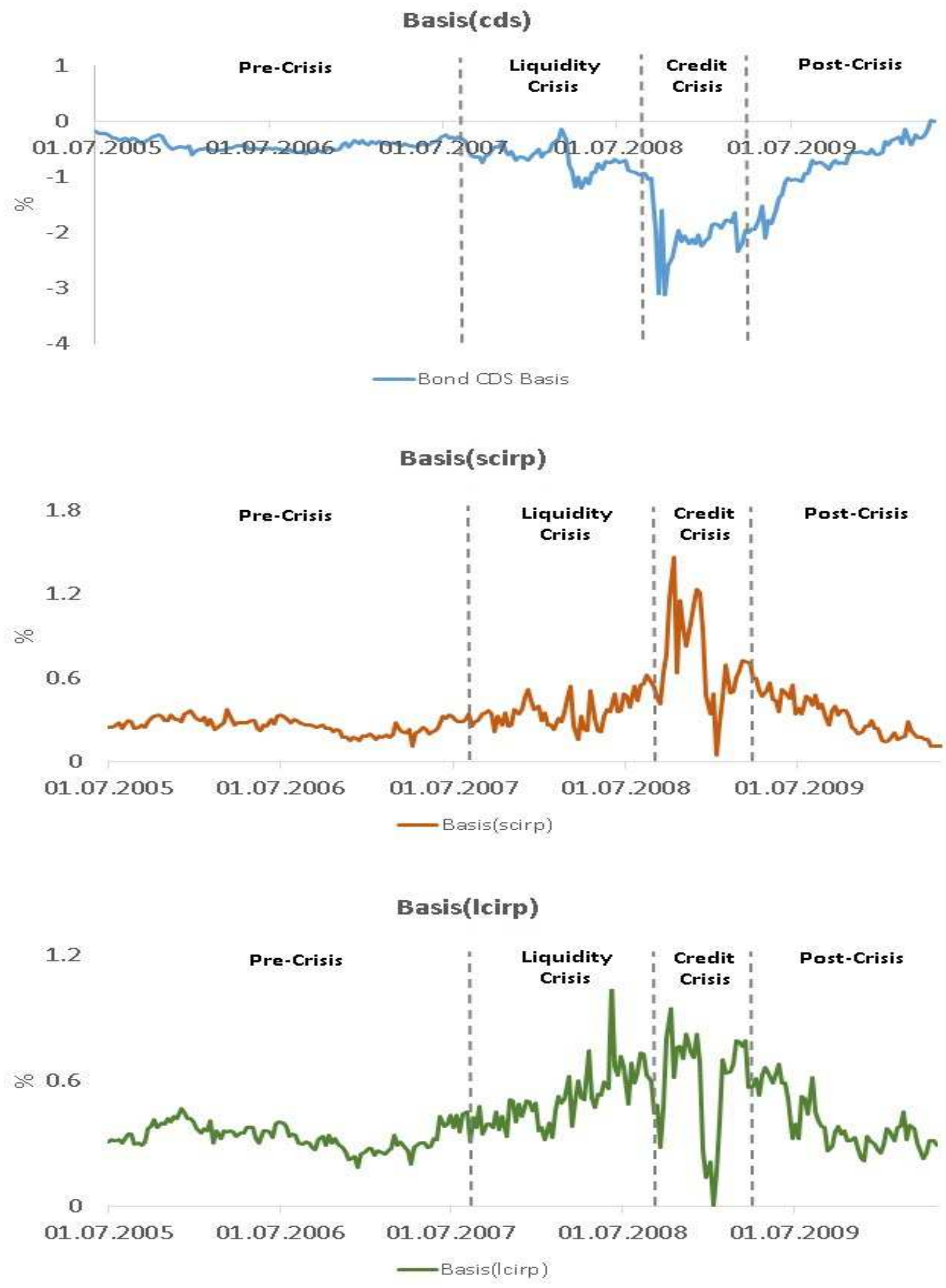

Table 5.1:

Statistics for hedge fund AuMs

This table summarizes the sample-specific average AuMs (in million USD) of hedge funds that operate under six different investment strategies: Arbitrage, Commodity, Distressed Securities, Equity, Global Macro and Options. The percentage change of AuM from the previous period is presented. The entire sample is from July 2005 to April 2010. The data set is divided into Pre-Crisis (1 July 2005 - 8 August 2007), Liquidity Crisis (9 August 2007 - 29 August 2008), Credit Crisis (1 September 2008 - 31 March 2009) and Post-Crisis (1 April 2009 - 30 April 2010) periods.

Periods		**Hedge Fund Investment Strategies**					
		Arbitrage	**Commodity**	**Distressed Securities**	**Equity**	**Global Macro**	**Options**
Pre-Crisis	*AuM (millions)*	69,854.14	151,163.90	26,054.93	158,386.71	24,524.38	1,720.07
Liquidity Crisis	*AuM (millions)*	79,455.59	223,795.05	44,198.11	198,594.48	29,042.22	2,831.19
	% Change from previous period	13.74	48.05	69.63	25.39	18.42	64.60
Credit Crisis	*AuM (millions)*	51,982.15	219,601.71	31,382.98	125,436.85	20,515.72	2,303.35
	% Change from previous period	-34.58	-1.87	-28.99	-36.84	-29.36	-18.64
Post-Crisis	*AuM (millions)*	42,040.72	224,128.70	21,065.35	120,006.48	19,250.83	1,700.58
	% Change from previous period	-19.12	2.06	-32.88	-4.33	-6.17	-26.17

Table 5.2:

Correlations of hedge fund AuMs
This table summarizes the period-specific correlations of the AuMs of hedge funds that operate under six different investment strategies: Arbitrage, Commodity, Distressed Securities, Equity, Global Macro and Options. The entire sample is from July 2005 to April 2010, divided into Pre-Crisis (1 July 2005 - 8 August 2007), Liquidity Crisis (9 August 2007 - 29 August 2008), Credit Crisis (1 September 2008 - 31 March 2009) and Post-Crisis (1 April 2009 - 30 April 2010) periods.

	Correlations				
Pre-Crisis	*Arbitrage*	*Commodity*	*Distressed Securities*	*Equity*	*Global Macro*
Commodity	95%				
Distressed Securities	91%	84%			
Equity	98%	95%	92%		
Global Macro	90%	94%	86%	95%	
Options	98%	91%	94%	95%	90%
Liquidity Crisis	*Arbitrage*	*Commodity*	*Distressed Securities*	*Equity*	*Global Macro*
Commodity	-96%				
Distressed Securities	-87%	92%			
Equity	97%	-90%	-84%		
Global Macro	23%	-4%	14%	35%	
Options	-88%	91%	82%	-84%	-19%
Credit Crisis	*Arbitrage*	*Commodity*	*Distressed Securities*	*Equity*	*Global Macro*
Commodity	98%				
Distressed Securities	88%	89%			
Equity	100%	99%	90%		
Global Macro	97%	97%	95%	98%	
Options	98%	93%	87%	96%	95%
Post-Crisis	*Arbitrage*	*Commodity*	*Distressed Securities*	*Equity*	*Global Macro*
Commodity	-81%				
Distressed Securities	43%	-42%			
Equity	-71%	93%	-41%		
Global Macro	-81%	73%	-61%	75%	
Options	64%	-79%	68%	-78%	-73%

Table 5.3:

Statistics for hedge fund leverage ratios

This table summarizes the leverage ratios per month of hedge funds that operate under Credit (CR), Event-Driven (ED), Long-Short Equity (EQ) and Relative Value Arbitrage (RV). It also includes the leverage using all hedge funds together (All HF). The percentage change of AuMs from the previous period is presented. The entire sample is from July 2005 to September 2009. The data set is divided into Pre-Crisis (1 July 2005 - 8 August 2007), Liquidity Crisis (9 August 2007 - 29 August 2008), Credit Crisis (1 September 2008 - 31 March 2009) and Post-Crisis (1 April 2009 - 30 September 2009) periods.

Periods		**Hedge Fund Investment Strategies**				
		All HF	**Credit**	**Event-Driven**	**Equity**	**Relative Value**
Pre-Crisis	*Leverage Ratio*	2.36	3.08	1.41	1.73	5.81
Liquidity Crisis	*Leverage Ratio*	2.07	2.34	1.40	1.70	4.68
	% Change from previous period	-12.45	-23.84	-0.50	-1.60	-19.40
Credit Crisis	*Leverage Ratio*	1.47	1.59	0.92	1.22	3.34
	% Change from previous period	-29.01	-31.93	-34.41	-28.29	-28.74
Post-Crisis	*Leverage Ratio*	1.46	1.31	1.12	1.26	2.45
	% Change from previous period	-0.64	-17.81	22.10	3.39	-26.61

Table 5.4:

Correlations of leverage ratios

This table summarizes the period-specific correlations of the leverage ratios of hedge funds that operate under four different investment strategies: Credit (CR), Event-Driven (ED), Equity (EQ) and Relative-Value Arbitrage (RV). The entire sample is from July 2005 to September 2009, divided into Pre-Crisis (1 July 2005 - 8 August 2007), Liquidity Crisis (9 August 2007 - 29 August 2008), Credit Crisis (1 September 2008 - 31 March 2009) and Post-Crisis (1 April 2009 - 30 September 2009) periods.

Correlations			
Pre-Crisis	*Credit*	*Event-Driven*	*Equity*
Event-Driven	0.90		
Equity	0.89	0.93	
Relative-Value Arbitrage	-0.17	-0.47	-0.34
Liquidity Crisis	*Credit*	*Event-Driven*	*Equity*
Event-Driven	0.81		
Equity	0.88	0.86	
Relative-Value Arbitrage	-0.09	-0.01	-0.28
Credit Crisis	*Credit*	*Event-Driven*	*Equity*
Event-Driven	0.56		
Equity	0.41	0.78	
Relative-Value Arbitrage	0.92	0.78	0.59
Post-Crisis	*Credit*	*Event-Driven*	*Equity*
Event-Driven	0.50		
Equity	0.72	0.91	
Relative-Value Arbitrage	0.94	0.59	0.75

Table 5.5:

Common factor among Basis components

Table displays the cumulative principal component contributions of the first three eigenvalues generated from the covariance matrix of the six components of $\vec{Basis}_j$ for j=[$Basis_{bond(br)}$; $Basis_{bond(mx)}$; $Basis_{bond(tr)}$; $Basis_{cds}$; $Basis_{scirp}$; $Basis_{lcirp}$], each made stationary by taking first-differences (i.e. Δ). λ_n for n (from 1 to 6) denotes the n^{th} eigenvalue corresponding to the n^{th} principal component (from largest to smallest), generated for Pre-Crisis, Crisis (Liquidity and Credit) and Post-Crisis periods. The contribution of each principal component to the total variance of $\vec{Basis}$ is represented by calculating the coupling coefficient, which is obtained by dividing the n^{th} eigenvalue to the sum of all eigenvalues:

$$\text{Coupling Coefficient} = \frac{\lambda_n}{\sum_{n=1}^{6} \lambda_n}$$

Contribution	**Pre-Crisis** *(1 July 2005 - 8 August 2007)*	**Crisis** *(9 August 2007 - 31 March 2009)*	**Post-Crisis** *(1 April 2009 - 30 April 2010)*
$\frac{\lambda_1}{\sum_{n=1}^{6} \lambda_n}$	28%	50%	44%
$\frac{\lambda_1+\lambda_2}{\sum_{n=1}^{6} \lambda_n}$	50%	71%	63%
$\frac{\lambda_1+\lambda_2+\lambda_3}{\sum_{n=1}^{6} \lambda_n}$	68%	88%	77%

Table 5.6:

Cross-market linkage among Basis components

Summary vector autoregressions are shown for vector $\vec{Basis}_j$ for j=[$Basis_{bond(br)}$; $Basis_{bond(mx)}$; $Basis_{bond(tr)}$; $Basis_{cds}$; $Basis_{scirp}$; $Basis_{lcirp}$], each made stationary by taking first-differences (i.e. Δ). A lag structure of two weeks is chosen according to AIC. We report the V coefficients, t-statistics (immediately below) and R-squared values for the Crisis period (9 August 2007 - 31 March 2009). Intercepts are not reported. (**) shows 95% and (*) shows 90% confidence interval. The following VAR is estimated:

$$\Delta\vec{Basis}_{j,t} = a_j + \sum_{k=1}^{2}\sum_{l=1}^{6} V_{j,k,l}\Delta\vec{Basis}_{j,l,t-k} + e_{j,t}$$

	Basis(bond-TR)	**Basis(bond-BR)**	**Basis(bond-MX)**	**Basis(cds)**	**Basis(scirp)**	**Basis(lcirp)**
Basis(bond-TR) (-1)	-0.3823	0.0220	-0.2082	0.1019	0.0049	-0.0704
	*-3.1189***	*0.1913*	*-1.8068**	*0.5957*	*0.0573*	*-0.8452*
Basis(bond-TR) (-2)	-0.1281	0.1140	0.1707	-0.1424	0.0445	0.0899
	-1.0292	*0.9739*	*1.4585*	*-0.8201*	*0.5095*	*1.0620*
Basis(bond-BR) (-1)	-0.0682	0.5165	0.4846	-0.0583	-0.0616	0.0251
	-0.4521	*3.6425***	*3.4169***	*-0.2769*	*-0.5817*	*0.2445*
Basis(bond-BR) (-2)	0.3278	-0.1307	-0.0068	-0.4039	0.2106	0.2412
	*2.1119***	*-0.8957*	*-0.0467*	*-1.8645**	*1.9325**	*2.2862***
Basis(bond-MX) (-1)	-0.1565	-0.5548	-0.5786	0.1202	-0.2168	-0.1738
	-1.0828	*-4.0827***	*-4.2572***	*0.5960*	*-2.1361***	*-1.7687**
Basis(bond-MX) (-2)	-0.1696	-0.1275	-0.0313	0.3494	-0.2906	-0.2378
	-1.1066	*-0.8849*	*-0.2168*	*1.6333*	*-2.6998***	*-2.282***
Basis(cds) (-1)	-0.0611	0.1501	-0.0991	-0.4753	-0.0241	-0.0048
	-0.7135	*1.8652**	*-1.2319*	*-3.98***	*-0.4006*	*-0.0831*
Basis(cds) (-2)	-0.1257	0.1495	0.0260	0.0059	0.2950	0.1172
	-1.4072	*1.7805**	*0.3099*	*0.0470*	*4.7042***	*1.9312**
Basis(scirp) (-1)	0.4131	-0.3043	0.2622	0.7041	-0.0125	0.2375
	*1.9408**	*-1.5203*	*1.3097*	*2.3702***	*-0.0836*	*1.6409*
Basis(scirp) (-2)	0.0940	-0.0948	-0.0247	-0.2542	0.0184	0.2105
	0.4194	*-0.4502*	*-0.1173*	*-0.8131*	*0.1172*	*1.3821*
Basis(lcirp) (-1)	-0.1419	-0.1217	-0.3254	-0.5447	-0.0720	-0.4317
	-0.5748	*-0.5245*	*-1.4018*	*-1.5813*	*-0.4152*	*-2.5724***
Basis(lcirp) (-2)	-0.0239	0.3392	-0.0349	0.3858	-0.1736	-0.2756
	-0.0939	*1.4173*	*-0.1457*	*1.0862*	*-0.9716*	*-1.5928*
R-squared	29%	45%	49%	34%	44%	24%

Table 5.7:

Regressions on LOP deviations and hedge fund AuMs and leverage ratios
Displays two types of regressions as outlined below for vector $\vec{Basis}_j$ for j=[$Basis_{bond(br)}$; $Basis_{bond(mx)}$; $Basis_{bond(tr)}$; $Basis_{cds}$; $Basis_{scirp}$; $Basis_{lcirp}$]. Variable column shows the explanatory variables, such that $HFAuM$ denotes the AuM of hedge funds that operate under Arbitrage strategies; and $HFLev$ denotes the leverage ratio of the hedge funds that operate under Arbitrage strategies. First-difference is represented by Δ, and percentage difference is represented by $\bar{\Delta}$. Sample is divided into Pre-Crisis, Liquidity, Credit and Post-Crisis periods. We report the average parameter estimates. The associated White-robust t-statistics are displayed immediately beneath. Intercepts are not reported. (**) shows 95% and (*) shows 90% confidence interval. The two specifications from (A) to (B) are shown in table, and are estimated as follows:

$$(A) \qquad \Delta \vec{Basis}_{j,t+1} = \alpha_1 + \beta_1 \bar{\Delta}\text{HFAuM}_t + \gamma_{1,j} \Delta \vec{Basis}_{j,t} + \epsilon_{1,t}$$

$$(B) \qquad \Delta \vec{Basis}_{j,t+1} = \alpha_2 + \beta_2 \bar{\Delta}\text{HFLev}_t + \gamma_{2,j} \Delta \vec{Basis}_{j,t} + \epsilon_{2,t}$$

Variables	**Pre-Crisis**		**Liquidity Crisis**		**Credit Crisis**		**Post-Crisis**	
	(A)	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**
	Basis(+1)	**Basis(+1)**	**Basis(+1)**	**Basis(+1)**	**Basis(+1)**	**Basis(+1)**	**Basis(+1)**	**Basis(+1)**
HFAuM	0.00	-	0.22	-	-0.04	-	-0.01	-
	0.10	-	1.76*	-	-3.22**	-	-0.65	-
HFLev	-	0.00	-	0.01	-	-0.06	-	0.01
	-	-0.17	-	1.31	-	-2.94**	-	0.28
Basis(bond-BR)	-0.24	-0.24	-0.15	-0.17	0.02	0.01	-0.52	-0.52
	-2.03**	-2.04**	-1.46	-1.69*	0.10	0.04	-5.33**	-4.94**
Basis(bond-MX)	-0.26	-0.26	-0.30	-0.30	-0.41	-0.41	-0.37	-0.46
	-3.09**	-3.1**	-2.05**	-2.1**	-3.62**	-3.26**	-2.94**	-2.76**
Basis(bond-TR)	-0.34	-0.34	-0.18	-0.17	-0.40	-0.43	-0.29	-0.43
	-2.99**	-3.**	-1.27	-1.19	-2.1**	-2.5**	-1.81*	-2.16**
Basis(cds)	-0.21	-0.21	-0.09	-0.10	-0.43	-0.50	-0.38	-0.43
	-1.85*	-1.86*	-0.52	-0.57	-1.57	-1.87*	-2.72**	-2.76**
Basis(scirp)	-0.28	-0.28	-0.30	-0.30	-0.28	-0.32	-0.34	-0.44
	-2.55**	-2.54**	-1.87*	-1.77*	-1.37	-1.81*	-2.69**	-2.41**
Basis(lcirp)	-0.41	-0.41	-0.50	-0.51	-0.01	-0.08	-0.24	-0.28
	-4.42**	-4.44**	-3.22**	-3.47**	-0.06	-0.50	-1.99**	-1.68*
R-squared	8%	8%	8%	8%	17%	20%	16%	22%

Table 5.8:

Regressions on first principal component of LOP deviations and hedge fund capital structure
Displays two types of regressions as outlined below for PC^{Basis} denoting the first principal component of $\vec{Basis}_j$ for j=[$Basis_{bond(br)}$; $Basis_{bond(mx)}$; $Basis_{bond(tr)}$; $Basis_{cds}$; $Basis_{scirp}$; $Basis_{lcirp}$]. Variable column shows the explanatory variables, such that $HFAuM$ denotes the AuM of hedge funds that operate under Arbitrage strategies; and $HFLev$ denotes the leverage ratio of the hedge funds that operate under Arbitrage strategies. Percentage difference is represented by $\bar{\Delta}$. Sample is Credit Crisis period. We report the average parameter estimates. The associated White-robust t-statistics are displayed immediately beneath. Intercepts are not reported. (**) shows 95% and (*) shows 90% confidence interval. The two specifications from (A) to (B) are shown in table, and are estimated as follows:

$$(A) \qquad \Delta PC1^{Basis}_{t+1} = \alpha_1 + \beta_1 \bar{\Delta}\text{HFAuM}_t + \epsilon_{1,t}$$
$$(B) \qquad \Delta PC1^{Basis}_{t+1} = \alpha_2 + \beta_2 \bar{\Delta}\text{HFLev}_t + \epsilon_{2,t}$$

Variables	**Credit Crisis**	
	(A)	**(B)**
	$PC1^{Basis}$ **(+1)**	$PC1^{Basis}$ **(+1)**
HFAuM	0.12	-
	1.43	-
HFLev	-	-0.48
	-	*-2.48***
R-squared	0%	12%

Table 5.9:

Regressions on LOP deviations, hedge fund AuMs, leverage ratios and loan collateral tightening
Displays three types of regressions as outlined below for vector $\vec{Basis}_j$ for j=[$Basis_{bond(br)}$; $Basis_{bond(mx)}$; $Basis_{bond(tr)}$; $Basis_{cds}$; $Basis_{scirp}$; $Basis_{lcirp}$]. Variable column shows the explanatory variables, such that $HFLev$ denotes the leverage ratio of the hedge funds that operate under Arbitrage strategies; and $Coll(req)$ denotes the net tightening of collateral requirements for loans and credit lines (extended to enterprises), based on The Euro Area Bank Lending Survey. First-difference is represented by Δ, and percentage difference is represented by $\bar{\Delta}$. Sample is divided into Pre-Crisis, Liquidity, Credit and Post-Crisis periods. We report the average parameter estimates. The associated White-robust t-statistics are displayed immediately beneath. Intercepts are not reported. (**) shows 95% and (*) shows 90% confidence interval. The three specifications from (A) to (B) are shown in table, and are estimated as follows:

$$(A) \qquad \Delta \vec{Basis}_{j,t+1} = \alpha_3 + \beta_3 \Delta \text{Coll(req)}_t + \gamma_3 \Delta \vec{Basis}_{j,t} + \epsilon_{3,t}$$

$$(B) \qquad \bar{\Delta}\text{HFLev}_{t+1} = \alpha_5 + \beta_5 \Delta \text{Coll(req)}_t + \gamma_5 \bar{\Delta}\text{HFLev}_t + \epsilon_{5,t}$$

Variables	**Liquidity Crisis**		**Credit Crisis**		**Post-Crisis**	
	(A)	**(B)**	**(A)**	**(B)**	**(A)**	**(B)**
	Basis(+1)	**HFLev (+1)**	**Basis(+1)**	**HFLev (+1)**	**Basis(+1)**	**HFLev (+1)**
Coll (req)	-0.01	-0.34	0.08	-0.78	0.03	0.73
	-0.40	*-1.91**	*2.09***	*-2.04***	*1.30*	*0.96*
Basis	-0.27	-	-0.27	-	-0.32	-
	*-4.29***	-	*-3.87***	-	*-5.78***	-
HFAuM	-	-	-	-	-	-
	-	-	-	-	-	-
HFLev	-	0.65	-	0.60	-	0.79
	-	*3.49***	-	*3.19***	-	*6.59***
R-squared	8%	50%	9%	70%	11%	56%

Chapter 6

Conclusions

This thesis is dedicated to understanding the state-dependent dynamics of LOP violations in financial markets during different stages (Pre-Crisis, Liquidity Crisis, Credit Crisis and Post-Crisis) related to the recent subprime crisis. To the academic literature, we introduce a new LOP deviation proxy, called $Basis_{\text{bond}}$, which is structured around a sample of emerging market coupon-paying bond pairs issued by the same sovereign (Brazil, Mexico and Turkey) in two different foreign currency denominations (USD and Euro). Our construction is based on shorting the USD-denominated bond and longing the Euro-denominated bond of the same issuer, and converting each future Euro cash-flow of the Euro-denominated bond into dollars using a series of forward FX contracts (see Chapter 3). This way a trader should normally be expected to do no better than meeting the dollar liability cash-flows on the USD bond side using the dollar-converted asset cash-flows on the Euro bond side. Despite some minor structural cash-flow mismatches inherent in the given bond pairs, we show that any sizable deviation of $Basis_{\text{bond}}$ from zero gives a plausible approximation of LOP deviation (i.e. a proxy for near-LOP deviation), and provides a useful insight about a potential pricing anomaly in Eurobond markets.

The conclusions of the thesis can be summarized under the following main points:

1. While $Basis_{\text{bond}}$ moves close to zero (supporting LOP condition) during the good states of the economy (Pre-Crisis), it becomes markedly large, strongly persistent and highly volatile during the bad states of the economy, far outstripping the total transaction cost threshold (Credit Crisis). $Basis_{\text{bond}}$ variation from Pre-Crisis to Credit Crisis not only indicates increasing returns, but also displays increasing volatility (and therefore uncertainty), which could be a factor deterring arbitrageurs from exploiting the implied opportunity (see Chapter 3).

2. Supported by multi-sample hypothesis tests, results give strong evidence that $Basis_{\text{bond}}$ is state-dependent and time-variant, and is a good proxy for testing LOP deviations. Our

findings suggest that the underlying structural limitation of the trade (interest rate risk due to cash-flow mismatches) is far from explaining the high levels of the mispricing encountered (see Chapter 3). This leads us to investigate whether any state-dependent financial constraints are relevant.

3. When trading strategy is constructed by shorting the USD-denominated bond and longing the Euro-denominated bond, $Basis_{\text{bond}}$ deviation in Turkey is generally negative, whereas $Basis_{\text{bond}}$ deviations in Mexico and Brazil are generally positive during Credit Crisis. This indicates that the sign of $Basis_{\text{bond}}$ deviation depends on the geography of the issuing country (see Chapter 3).

4. This interesting sign difference requires investigation. As a result of Turkey paying a higher credit yield spread in USD than Euro ($S^a > S^b$), and forward FX markets being unable to correct this imbalance, $Basis_{\text{bond}}$ deviation in Turkey is negative. On the other hand, as a result of Brazil and Mexico paying a higher credit yield spread in EUR than USD ($S^a < S^b$), and forward FX markets being unable to correct this imbalance, $Basis_{\text{bond}}$ deviations in Brazil and Mexico are negative. The price discovery analysis reveals that S^a contributes more than S^b to the price discovery process in Brazil and Mexico, whereas the opposite is true in Turkey (see Chapter 4).

5. In support of conclusion 4 above, when $Basis_{\text{bond}}$ is decomposed into CIRP and Spread Components, the latter (related to the credit yield spreads) is found to be the dominant factor in explaining the pricing anomaly. Unlike commonly assumed, this implies that investors during times of market turmoil tend to assign different default risks to different foreign-currency securities, even though both securities are issued by the same sovereign. Default risk is not only country-specific, but is also currency-specific in *each* country. Under these circumstances, when investors face discordant default risks across two equivalent securities, $Basis_{\text{bond}}$ trade could indeed be left unexploited, causing prices to diverge further away from each other (see Chapter 4).

6. One clue to the geographic spread difference is obtained by comparing central bank international reserve distributions of Turkey and Brazil. It is observed that Turkey, being a major trade partner with the Euro Zone, tends to hold more Euro than USD in its reserves, while Brazil, being closer to the USD-based trade geography, holds significantly less Euro than USD. Therefore, it could be argued that, during Credit Crisis, markets assigned a relatively lower default risk premium to Euro-based assets in a Euro-strong country like Turkey, while they assigned a relatively lower default risk premium to USD-based assets in a USD-strong country, like Brazil (see Chapter 4).

7. An additional factor that contributes to the sign puzzle arises from differences in arbitrageurs' accessibility to different loan markets. European banks, being major traders of Turkish bonds, have comparative advantage in funding in Euro than USD. Therefore, European traders would tend to short the EUR bonds and long the USD bonds of Turkey. The opposite mechanism is true for Brazil and Mexico. U.S. banks, being major traders of Brazilian and Mexican bonds, have comparative advantage in funding in USD than EUR. Therefore, U.S. traders would tend to short the USD bonds and long the EUR bonds of Brazil and Mexico (see Chapter 4).

8. Our analyses show that the sizable and persistent pricing anomaly encountered during Credit Crisis was the result of a set of macroeconomic and market forces strongly interacting with each other. More specifically, we find that on one side, sharply decreasing supply of funds, due to rising funding costs (captured by Secured and Unsecured), falling bond supply (captured by Inventory), and slowing macroeconomic activity (captured by LN-Macro); and on the other side, sharply decreasing appetite for risky arbitrage, due to deteriorating credit risk perception (captured by EM-CDSI) and increasing risk-aversion (captured by Closed End), jointly acted as binding constraints and/or deterring factors that kept arbitrageurs from exploiting the underlying opportunity, causing prices to diverge further and further away from equilibrium (see Chapter 4).

9. Novel conclusions are obtained regarding the cross-sectional affects of the monetary policy transmission during Credit Crisis. Results show that the U.S. monetary policies, implemented during Liquidity Crisis and Credit Crisis, had significant impact in reducing $Basis_{\text{bond}}$ deviations in the countries that participated in (or indirectly benefited from) them. Following Federal Open Market Committee's policy decision of October 29, 2008 to extend global dollar swap lines to Brazil and Mexico (but not to Turkey), the cross-sectional gap between Turkish $Basis_{\text{bond}}$ and Brazilian/Mexican $Basis_{\text{bond}}$ started to widen. A similar development occurred following the Fed's introduction of the Commercial Paper Funding Facility (October 7, 2008), and the U.S. Treasury's announcement of the Troubled Asset Relief Program (October 14, 2008), both aimed at relieving the funding constraints in the U.S. financial markets. Consequently, Brazil and Mexico, being major trade partners with the U.S., benefited to a greater extent from these policies than Turkey (see Chapter 4).

10. A significant level of linkage exists among the pricing anomalies in credit markets (represented by $Basis_{\text{bond}}$ of Brazil, Mexico and Turkey, and $Basis_{\text{cds}}$) and swap markets (represented by $Basis_{\text{scirp}}$ and $Basis_{\text{lcirp}}$) during market turmoil. This implies that arbitrageurs who participate in these different markets were limited by similar constraints. Based on PCA results, there is strong evidence for the presence of an underlying systemic shock driving different pricing anomalies simultaneously during Crisis period (see Chapter 5).

11. There exists a strong level of correlation across the normally impermeable hedge fund strategies during Credit Crisis, where AuMs and leverage ratios of all hedge fund strategies experienced a sharp decline. Such occurrences of co-movement indicate the presence of a contagious interaction between different markets during Credit Crisis (see Chapter 5).

12. The role of hedge funds as arbitrageurs in ensuring LOP condition is quantified. Analyses confirm the hypothesis that the withdrawal ("de-participation") of hedge funds from the markets, due to reductions of debt financing (captured by changes in leverage ratios) and equity capital (captured by changes in AuM) contributed significantly to relative price divergence across credit and swap markets (see Chapter 5).

13. Collateral constraints (captured by tightened requirements on loans and credit lines) had additional adverse impact on both hedge fund deleveraging and LOP condition, creating a chain reaction from credit suppliers to hedge funds, and from hedge funds to markets with the end result of LOP disequilibrium. The results suggest that the supply of insufficient amount of liquidity to capital markets contributed significantly to the incorrect relative valuation of securities (see Chapter 5).

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