LIQUIDITY IN THE EMERGING MARKET LOCAL CURRENCY BOND MARKET: MEASUREMENT, COMMONALITY, AND SUPPLY OF RISK CAPITAL

A Thesis

by

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Submitted to the
The Graduate School Of Business
In Partial Fulfillment of the Requirements for
the Degree of

Doctor of Philosophy

in the
Department of Business Administration

Özyeğin University
June 2016

To My Lodestar, My Mother, Father and Beloved Wife,

And to All People Whom I Call Family...

ABSTRACT

Major emerging markets sovereigns have started financing a significant component of their budget deficits issuing local currency (LC) bond, reaching to the total outstanding size over 5 trillion dollar almost half of the size of the US Treasury markets. The current consensus is that LC bond yields are rather rich with respect to benchmark U.S. Treasury rates and the literature argues that this occurs as a compensation two major types of risk: currency (depreciation) risk and credit (default) risk. I contribute to this literature by investigating the role of liquidity risk in these markets. Moreover, we investigate if liquidity risk is specific to the characteristics of the issuing country (thus diversifiable) or rather affected by global effects related to global asset markets (thus un-diversifiable). To address these questions, I build a unique *bond-specific* data set covering major LC markets until November 2015. I study the role of several liquidity measures in the context of LC bonds to identify potentially different channels of liquidity shock transmission. I find strong evidence that LC bond liquidity i) is a priced-factor, (ii) is state-dependent, and (iii) shows significant commonality across countries. I also document the new evidence that procylical nature of global LC bond funds domiciled in developed countries can destabilize LC bond market liquidity with potential adverse consequences for the LC debt markets. As liquidity provision is an important function in general and crucial in periods of market stress, EM economies that are relying heavily on pro-cyclical investors such as global bond mutual funds should comprehend, how activities of asset managers and their investor base can affect EM economies.

ÖZETÇE

Başlıca gelişmekte olan ülkeler bütçe açıklarının önemli bir bölümünü yerel para cinsinden bono ihraç ederek finanse etmeye başlamıştır. Bu ihraçların boyutları 5 trilyon ABD dolarını bulurken, bu rakam ABD tahvil piyasası büyüklüğünün yarısına ulaşmıştır. Ortak görüşe göre, bu ülkelerin yerel para cinsinden bonoları benzer ABD bonolarından daha pahalıdır. Literatür, bu ekstra risk priminin kaynağı olarak iki türlü risk primini işaret etmektedir: kur(değer kaybı) riski ve kredi (temerrüt) riski. Bu tez, bu piyasalardaki likidite riskini araştırarak literatüre katkıda bulunmayı hedeflemektedir. Ek olarak, likidite riskinin ihraçcı ülkeye özgü (dolayısıyla dağıtılabilir) bir risk çeşidi veya alternatif olarak küresel piyasalardan etkilenen (dolayısıyla dağıtılarak giderilemeyen) bir risk çeşidi olup olmadığı araştırılmaktadır. Bu soruları cevaplamak için, Kasım 2015'e kadar olan zaman dilimini kapsayacak şekilde, başlıca gelişmekte olan ülkelerin yerel para cinsinden bonolarını içeren, özgün, bono-spesifik bir veri seti oluşturulmuştur. Farklı likidite değişkenleri kullanılarak, yerel para cinsinden bonolara farklı kanallardan gelen likidite şoklarının etkileri araştırılmıştır. Bulgular yerel para cinsinden bonoların likiditelerinin i) fiyatlara etki eden ii) durum ve koşullara bağlı ve iii) farklı ülkeler arasında ortak özellikler gösteren bir faktör olduğunu işaret etmektedir. Ek olarak, yerel para cinsinden bonolara yatırım yapan gelişmiş ülke fonlarının döngüsel karakteristiklerinin bu ülkelerin bono piyasalarını daha dengesiz hale getirebileceği yönünde yeni bulgulara ulaşılmıştır. Likidite temininin önemli olduğu, özellikle piyasaların türbülans yaşadığı dönemlerde ise daha kritik olduğu düşünüldüğünde, döngüsel karakteristiklere sahip yatırımcılara yüksek oranda bağımlı olan gelişmekte olan ülkelerin, yatırımcı tabanı ve bu varlık yöneticilerinin aktivitelerini kavramaları gerekmektedir.

ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere gratitude to my advisor Asst. Prof. Emrah Şener for the continuous support of my Ph.D study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and lodestar for my Ph.D study. Besides my advisor, I would like to thank the rest of my thesis committee.

My gratitude also goes to my dearest friends Arden Agopyan, Emrah Ahi, Sait Şatıroğlu and Osman Yılmaz with whom I started this PhD program and shared this journey. And much gratitude goes to Faruk Özbaş, who made valuable comments through my journey and made my day enjoyable with his positive energy, and helpful attitude.

Finally, I would like to thank My family & friends. My dearest wife, Nirva Baronyan, through the hardest moments in this journey, your beatiful smile made me go forward and gave the energy to succeed. My mother, Ani Baronyan who has been a great teacher of faith and My father, Mihran Baronyan who has been a great guru for honesty, I could not even start this journey without you. My mother-in-law Kayane Bağam and father-in-law Halil Şencan, I am very lucky to have all of you and many more wonderful people in my life. Thank you Lord, for giving me these people.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

The word liquidity has so many facets that is often counter-productive to use it without further and closer definition. Charles Goodhart

CHAPTER I

LIQUIDITY IN THE EMERGING LOCAL CURRENCY BOND MARKET

1.1 Introduction

During the last decade, financial markets have witnessed a remarkable development in emerging market (EM) sovereign capital structure. Major emerging markets sovereigns have started financing a significant component of their budget deficits by issuing local currency (LC) bonds. LC bond trading on exchange listed and over-the counter markets now exceeds $800 billion dollar per year, with the total outstanding notional of over $5.3 trillion, which constitutes almost half of the U.S. Treasury market size. The current literature analyzing the yield spread over the benchmark U.S. Treasury argues that it contains two major types of risk: currency (depreciation) risk and credit (default) risk. The primary contribution of this paper is to verify that liquidity risk is a significant priced factor in LC sovereign bond markets. Furthermore, I show that commonality in LC bond market liquidity is strong in times of high market turbulence and demand shocks which stem from correlated trading activity of foreign investors.

Historical episodes of high inflation, currency crises, and deposit freezes have been considered as some of the reasons why emerging markets find it difficult to borrow abroad in their own currency (e.g. [1]) referred to these episodes as the *original sin* of emerging markets). During the 2000-2014 period, however, LC sovereign debt issuance grew dramatically by an average of 14.4% per year, far outpacing the 2.3% average annual growth rate of foreign currency (FC) sovereign debt. As a result, while FC denominated debt doubled (from $510 billion to $1 trillion), LC debt grew more than six-fold (from \$700 billion to \$5.3 trillion), as shown in Figure 1 (a).[1] By 2014, 88% of total emerging market debt was in local currency and the vast majority of new issuance by emerging market governments has been directed to debt denominated in local currencies. Another major fact observed in LC bond markets is the rise of foreign investors as a substantial component of the investor base. As it is shown in Figure 1 (b), due to the significant increase in local currency bond purchases of foreign investors since 2009, participation of the foreign investors in LC bond markets rises over time. In April 2012, foreign holdings of emerging market LC bonds reached a record-high 36% of the total stock. Although foreign participation provides an additional source of financing for emerging markets, it may also play a role in transmitting global financial shocks to local-currency sovereign bond markets ([2]). Indeed, Figure 1(c) suggests that during the 2010-2013 period, when foreign investors increased the supply of risk capital to emerging markets via LC bond markets, the average LC yields dropped dramatically. On the other hand, after 2013, there occurs a significant foreign investors net outflow and a sharp rise in both LC yields and yield volatility at the same time. Another prominent phenomenon observed in LC debt markets is that retail investors gradually became the predominant investor base of global LC bond funds in place of institutional investors over the past decade. As shown in Figure 1(d), heterogeneous reactions of retail- and institutional-oriented LC bond funds to the changes in financial and economic conditions in EM economies, highlight the fact that monitoring the investor base of LC debt markets is key to identify financial vulnerabilities.

How do financial markets value LC debt of emerging markets? How much of LC bond yield is related to liquidity premium? Are the fund flows of foreign investors to emerging market assets systematically linked to liquidity pricing in LC bond markets? Answers to these questions have a profound effect not only on the valuation

[1] Bloomberg and Trade Association for the Emerging Markets.

of emerging markets assets but also on important economic issues, such as the cost of capital, international diversification benefits, and international risk sharing. To examine these questions, I use a new data-set which provides cross-sectional information on major LC sovereign bonds across different geographical areas and maturities. The first data-set provides a detailed coverage of LC bond pricing at the individual bond level that I collect from local exchanges[2]. It includes detailed information on issuer-specific individual LC bond variables (including the price, volume and total amount outstanding) which are useful to distinguish among various credit and liquidity components of LC sovereign yield. The primary contribution of this paper is to use the bond-specific LC bond yield components for each bond rather than a yield curve analysis over a benchmark ([3]). I select those emerging sovereign local currency bond markets which are traded through central exchanges and also listed in the J.P. Morgan GBI-EM (Local Currency Government Bond Index-Emerging Markets) index, an investable index for emerging market LC bonds. The feature of being traded through central exchanges enables me to collect detailed data also on transaction prices, volumes, and several other market variables. Because of the preceding reasons, these bond markets stand as the most frequently traded LC bond markets (according to volume surveys conducted by the Emerging Market Trading Association). They account for more than 30% of the total local currency debt outstanding and 40% of the J.P. Morgan GBI-EM index. A second data set provides detailed emerging market local currency fund flow which is available at the investor level (institutional vs. retail). I use the information extracted from this data-set to explore the roles of the foreign investors on LC bond market liquidity.

This paper stands out as one of the first empirical studies that investigate the impact of *liquidity* and *price of liquidity* on LC bond market and makes a number of

[2]The lack of data on emerging market fixed income markets has posed a challenge for research on liquidity. Both FC and LC bonds mainly trade over-the-counter (OTC), in a broker market which is notoriously noisy. I have the advantage of investigating exchange-traded markets.

contributions to the current literature. First, I build a novel comprehensive data-set of LC bond-specific data, from January 2010 to November 2015. There is a considerable variation in credit quality as well as liquidity during this period, providing the opportunity to examine the dynamics of liquidity. Motivated by reported results of previous literature on larger liquidity effects in down markets, I look at sub-samples, namely; pre-tapering (January 2010-May 2013): a period with plenty of liquidity for emerging markets, and post-tapering (June 2013-November 2015): a period of turbulence triggered by the FED's announcement that it may start to decrease its quantitative easing programme and related asset purchases sooner than expected. To capture different dimensions of liquidity, I search the theoretical and empirical liquidity literature and identify eight liquidity proxies under three categories, namely price impact, transaction cost and other liquidity measures. Then, I propose a parsimonious way to define a single aggregate measure of liquidity ([4]). Secondly, I pay great attention to control for risk factors (e.g; credit and currency risks) other than liquidity in order to investigate several hypotheses about the main drivers of liquidity premium and to properly identify the premium associated with liquidity.

I find a number of novel results. First, I explore the hypothesis that liquidity is priced in the sovereign LC bond markets. I examine the cross-sectional behavior of the LC yield spread using Fama-MacBeth regressions. My findings reveal that the proposed liquidity measures account for about 11% to 15% of the explained cross-sectional variation of the LC yield spread changes during *pre-tapering*. However, a completely different picture emerges during the *post-tapering*. I find strong evidence that the liquidity measures provide the greatest marginal contribution during the post-tapering, explaining on its own up to 31% to 35% of the total variation in LC yield spreads. Overall, cross-sectional regressions show that FED's tapering announcements - it later became known as the taper tantrum- made LC yield spreads more sensitive to liquidity. I also observe that Gibbs, Amihud and High-Low liquidity measures take clear lead over the other measures and exhibit stronger effects in terms of economic impact.

Secondly, I investigate whether the effect of liquidity is stronger in times of market turbulence. Indeed, my results show that the liquidity component of LC bonds yield spread rises in all countries after the Fed tapering announcement. Before the FED tapering announcement, the liquidity premium was small in all countries, ranging from 19 basis point (bps) to 24 bps, consistent with a high liquidity environment for emerging markets. However, the impact of tapering announcements by the FED on emerging markets was so strong that the liquidity component for LC bonds spreads increased, on average, by 3 to 4 times reaching a value between 60 bps to 120 bps, depending on the country. For all countries, liquidity premium peaked one month after the tapering announcement and it has almost never returned to pre-crisis levels. The increase in liquidity premium occurred both because of an increase in the price and quantity of liquidity risk, showing that tapering tantrum represents concerns over liquidity rather than solvency. I also document a strong linkage from LC bond market liquidity to sovereign credit risk which implies that changes in liquidity significantly affect the credit risk, not vice versa.

Finally, I study how the level of commonality in LC bond market liquidity varies over time and what fundamental sources drive it. I find strong evidence of commonality in LC bond market liquidity premia, even for issuers that are geographically far from each other. This suggests that LC bond market liquidity premia are largely driven by shocks that affect the LC bond market as a whole, rather than individual LC bond markets. I also investigate whether the concentration of foreign investors exposed to LC bond markets in portfolio holdings is a source of commonality in LC bond market liquidity. Global asset managers and global banks constitute the main examples of foreign investor group. I find that co-movement in global funds' net fund flow plays a very prominent role in the commonality level of LC bond market liquidity.

My results also document an interesting phenomenon that during volatile times, when global investors' effective risk aversion increases (proxied via Closed End Funds), the level of commonality also increases, indicating this to be a decisive demand side factor in explaining commonality in liquidity.

My findings have also important implications for policymakers and global fund managers. A deeper understanding of the liquidity-versus-credit decomposition will allow policymakers to assess the efficacy of their interventions in financial markets in terms of diminished risk perceptions. If rising LC yield spreads primarily represent the effects of poor market liquidity, then policy makers can take actions to improve LC bond market functioning to dampen LC yield spread widening. For example, LC bond purchases during market distress (such as in the EM central banks securities lending facility) could make securities markets to behave more effectively. Additionally, if the widening of LC yield spread is due to a higher default risk, then regulatory actions to improve the solvency of financial institutions in question will be more likely to succeed. Liquidity-versus-credit decomposition is also important for fund managers' asset allocation decisions. Funds with the longest investment horizons (e.g., pension, endowment and sovereign wealth funds) prefer to hold higher yielding assets like LC bonds if higher yields are related to poor liquidity, but not for a greater risk of default (see Krista Schwarz (2015)). Also, regime dependence of liquidity betas of LC bonds implies that global asset managers should be cautious of using normal-time risk management models for LC bond portfolios. Unconditional model specifications might imply significant misspecification errors and portfolio decisions should explicitly consider the liquidity risk under stressed market conditions (see [5]).

This paper is related to three streams of the asset pricing literature. The first stream studies the impact of *liquidity* and *liquidity risk* in developed markets. In the wake of the financial crisis of 2008-2009, the Eurozone sovereign crises of 2011, and the Fed Taper-tantrum of 2013, the financial industry and regulators have displayed an increasing interest in the role of liquidity risks. The *liquidity* of an asset refers to the ability in execution of large sized trades with minimal price impact and it is often measured as an average per unit of time (see, for instance, the pioneering work of [6]). The *liquidity risk premium* of an asset is related to the expected excess return that is due to its (lack of) liquidity and it is proportional to the covariance between changes in asset prices and changes in aggregate liquidity. Several papers argue that liquidity is indeed a priced risk factor: assets that are more sensitive to liquidity shocks demand larger expected excess returns.[3] Some studies suggest that it can help to explain some well-known asset-pricing anomalies ([9]). However, recent studies show that the significance of liquidity shocks is highly time-varying and higher in bad economic times (e.g, [5] and [10]) and tight monetary conditions (e.g. [11]). Thus, it may be difficult to asses the full extent of liquidity risk using data set on liquid assets during normal times.[4].

A second stream of the literature investigates the impact of *liquidity* in emerging markets. As noted by [14], emerging markets provide a unique opportunity to study liquidity risk. While there exists a vibrant literature studying liquidity risk in equity and bond markets of developing countries (e.g. [15] and [14])[5] and in foreign currency bond markets (e.g. [16] and [17]), little is known about the liquidity premia in LC sovereign bonds. The increasing size of this market, which is recently approaching almost six trillion dollars of notional, underscores the importance of addressing this question.

A third stream of the literature related to my research here is the work on the impact of foreign investors on local asset prices, especially in emerging markets (e.g. [18]

[3]This effect was found in different asset classes (e.g. in equity markets, see [7], in corporate bond market, see [4], in foreign exchange markets, see [8]).

[4]Studies on corporate bonds with newly available daily trading data from TRACE platform in the United States also find evidence that liquidity worsened substantially for corporate bonds from the onset of the sub-prime crisis (e.g. [12], [4], and [13]).

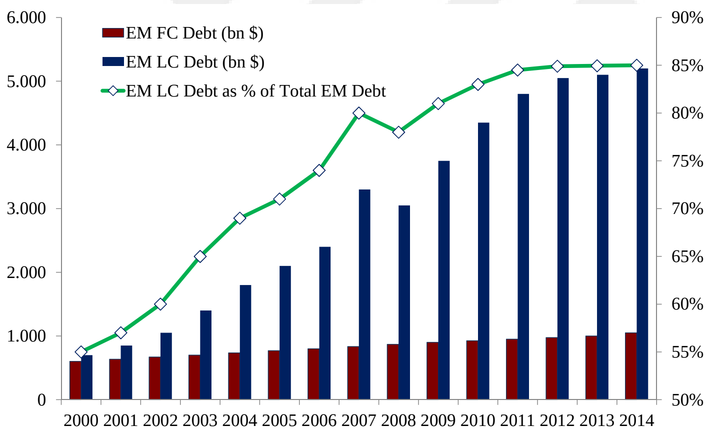
[5] [14] show that the covariance of country-portfolio returns with local market liquidity predicts future returns, but they could not find evidence that global liquidity risk is priced.

and [19])[6]. [22], and [23] document significant effects of portfolio investment flows in aggregate on local market equity returns. In recent years, strong fluctuations in international portfolio flows have raised concerns about amplification effects due to the behavior of asset managers in response to shocks (e.g. [24] and [25]). I contribute to this literature by investigating whether the variation in bond fund flow is systematically linked to liquidity pricing in LC bond market.

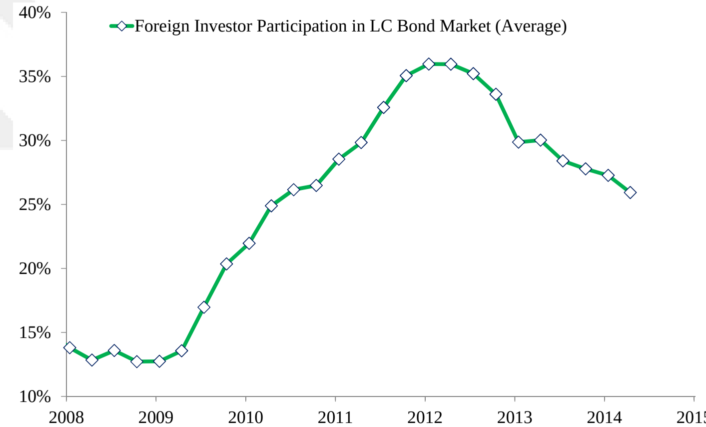
The remainder of this thesis is organized as follows: Section II discusses the hypotheses being tested in this thesis and the economic motivation behind them. In Section III, I explain the composition of my data set. In Section IV, I outline the methodology, theoretical background and the alternative measures of liquidity. Section V explains how I extract market-wide liquidity measure. Chapter II explains the measurement of the size of the liquidity component. Chapter III examine the fundamental sources behind commonality in local currency bond market liquidity. Chapter IV runs various robustness checks. Chapter V concludes.

[6]There is also significant discussion in the literature on the role of liquidity shock channel for transmission of crises across emerging market (e.g. [20] and [21])

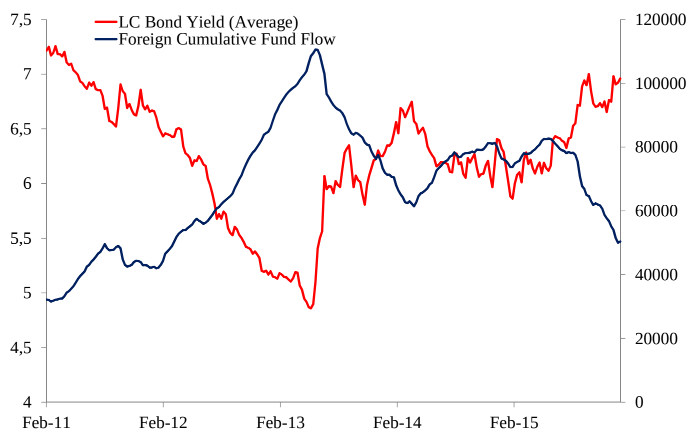
(a) EM LC debt vs. FC debt outstanding (US $ bn)



(b) Foreign Investor Participation in LC Bond Market (Average)



(c) LC Bond Yield (Average) vs Cumulative Foreign Flow



(d) Total Cumulative Institutional Flows vs Retail Flows

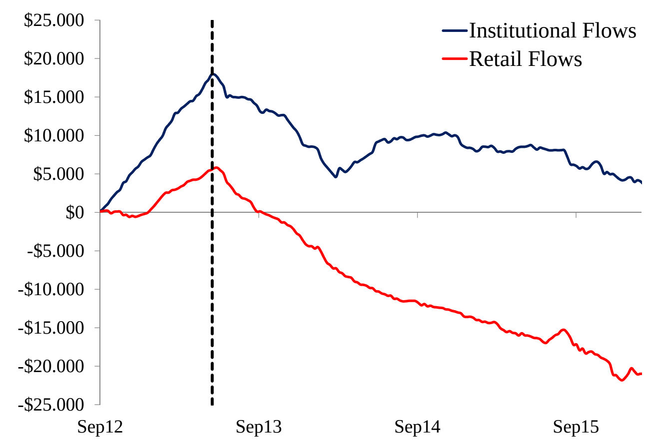


Figure 1: The top left panel (Panel A) display EM LC outstanding debt vs EM FC outstanding debt (in US-billion$) and share of LC EM debt in total em debt (in percentages) . The bottom left panel (Panel C) displays LC Bond Yield (Average) vs Cumulative Foreign Flow. The bottom right panel (Panel D) shows total cumulative institutional flows vs retail flows.

1.2 Hypothesis

In this section, I provide an overview of the research questions I pose and the hypotheses I test in my research. My approach is to examine the validity of specific arguments regarding the effect of liquidity in the EM local currency (LC) sovereign bond market.

Hypothesis 1. *Liquidity is an important priced factor in the local currency bond markets.*

The total return (in US dollar) performance of LC bonds compared to the benchmark U.S. Treasury with the same duration, starting from 2009. If one invests 100$ in LC bonds, one would have made an impressive return of 70% by mid 2013, which is almost triple of the return in U.S. Treasury. However, excess returns over U.S. Treasuries became negative when the U.S. Federal Reserve first announced plans of tapering its monthly asset purchases. Most empirical and theoretical studies of LC sovereign yields argue that currency and credit are the main risk premia channels for driving LC bonds yield spread over benchmark US Treasury bonds. This observation motivates my first question which conjectures that a third risk premium is responsible for the large ex-ante return, namely a liquidity risk premium.

Hypothesis 2. *Impact of liquidity on local currency bond markets is state dependent, being significantly stronger in adverse economic and financial times.*

The relation between liquidity shocks and adverse economic conditions is not only noted by financial economists (e.g. [26] and [27]), but also highlighted by regulators and central bankers (e.g Federal Reserve Chair Janet Yellen noted in testimony in May 2015 that "..many market participants have raised concerns that market liquidity may deteriorate during stressed conditions."). [5] and [4] provide empirical support for the importance of liquidity during the crisis periods. Figure 2(a) shows that the five-year maturity local currency bond prices for major emerging market countries (e.g. Brazil, Indonesia, South Africa and Turkey) drop dramatically right after the Fed tapering announcement. One can ask if the higher interest rate in these bonds is due to illiquidity or credit deterioration? Figure 2(b) suggests why many market practitioners describe taper tantrum as a liquidity crash rather than a credit (default) event. Indeed, credit risk profiles of most EM countries were upgraded by rating agencies before the tapering announcement[7]. Market confidence in EM credit markets was so strong that Brazil's oil company Petrobras achieved the biggest emerging-market debt sale on record worth $11 billion in May 2013. This was the second-largest corporate bond sale in the world after the $17 billion bond that Apple issued in April 2013. Thus, my second research question is related to the time-varying characteristics of liquidity risk premia.

Hypothesis 3. *Commonality in LC bond market liquidity arises from correlated trading among the global asset managers who are investing into EM assets.*

Recent studies have argued that commonality in liquidity should increase during episodes of large market declines (e.g [28] and [29]). Commonality in liquidity may arise from supply-side or demand-side shocks. A part of the literature trying to explain commonality in liquidity is primarily based on the supply side arguments put forward in [30]. Some recent empirical studies have found support for supply-side sources of commonality in liquidity related to the funding constraints of financial intermediaries (e.g. [31], [28] and [32]). Another part of the literature has explored

[7] In fact, the percentage of investment-grade countries in the JP Morgan Emerging Markets Bond Index (EMBI) Global Diversified Index increased from 2% to 63% between 1994 and 2013. This increase in creditworthiness is due largely to focused efforts by many emerging markets governments to drastically cut their debt levels, stockpile foreign currency reserves, and commit to market friendly policies that encourage local savings and investments.

demand-side sources driven by correlated trading activity (e.g. [33] and [34]) and investor sentiment (e.g. [35] and [29]).

Figure 2(c) shows the net-flows of the LC fixed income funds around *announcement of FED tapering.* Net-flows into Brazil, Indonesia, South Africa and Turkey are highly correlated (around 91%), i.e. if one country's LC bond market faces outflows, others face outflows, as well. I believe that the knowledge of how foreign investors' fund flow responds to EM LC bond market behavior and how those responses are shaped during volatile market conditions are critical to my understanding of financial markets in general, and emerging markets fixed-income markets, in particular. Thus, I examine the role of LC fixed income funds primarily domiciled in developed market jurisdictions which can also play an important role in causing commonality in LC bond liquidity.

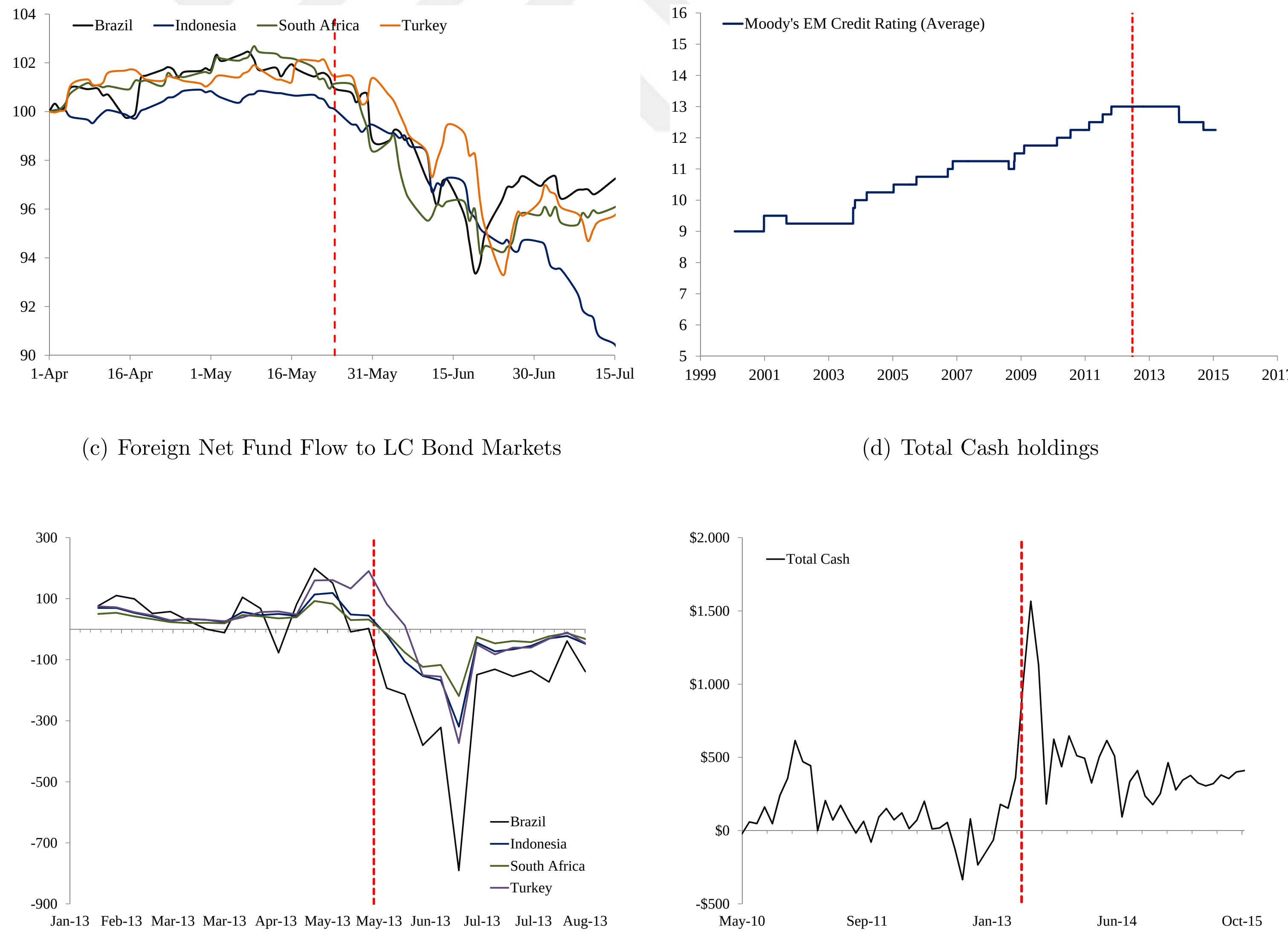
Hypothesis 4. *Global LC bond funds demand liquidity during the market turbulence and exacerbate LC bond market liquidity.*

Recent financial crises prompted debate among policymakers, academics and asset managers about whether *liquidity transformation* by asset managers - the creation of liquid claims that are backed by illiquid assets, can cause financial stability problems (e.g., Financial Stability Oversight Council, 2014; [25]; [36]). As foreign investors have come to rely on open-end global mutual funds as an investment vehicle to invest in LC debt, the role of asset managers in *liquidity management* for reducing the risk that a LC bond fund will be unable to meet its obligations to redeeming shareholders is has become more important than ever.[8] Because redemptions from an open-end mutual fund can lead to sales of illiquid assets, depressing asset prices increases the scope for fire sales to amplify fundamental shocks.

Figure 2(d) shows the evolution of aggregated cash holdings carried across global

[8]These concerns even lead Security Exchange Commission (SEC) to propose new regulations on liquidity risk management of open-ended mutual funds, in September 2015.

LC bond funds. Aggregate cash level across global LC bond funds remained small around 1.5% during the pre-tapering period which is consistent with an environment described as of high liquidity. However, a completely different picture emerges during the tapering period. Aggregated cash holdings of LC bond funds increase by a factor six and reaches to 9.7%, highlighting a more challenging environment for global fund managers after tapering announcement. Since the liquidity provision is an important function for securing the health of financial system in general and substantially crucial in periods of market stress, I investigate whether cash hoarding by asset managers generates fire-sale externalities which exacerbates LC bond market liquidity.



(a) LC Bond Market Prices (May-2013)

(b) EM Countries Credit Rating (Average)

(c) Foreign Net Fund Flow to LC Bond Markets

(d) Total Cash holdings

Figure 2: The top left panel (Panel A) shows LC Bond Market Prices (May-2013), and top right panel (Panel B) shows the time series evolution of EM Countries Credit Rating (Average). The bottom left panel (Panel C) displays Foreign Net Fund Flow to LC Bond Markets. The bottom right

1.3 Data Description

Most emerging markets local and foreign currency bonds are usually traded in over-the-counter (OTC) markets in absence of a centralized clearing house. This makes the research rigorous, especially in terms of liquidity effects and difficult to implement since prices and volumes are not readily available. Important aspects of these markets can only be inferred from indicative dealer quotes, which are not necessarily representative of the market as a whole. My data sample focuses on those sovereign issuers with LC bonds traded on central exchanges. This enables me to collect precise data on bond prices, volumes, and other market variables. This data set includes LC sovereign bonds from four major emerging markets, namely Brazil(USD 780 billion), Indonesia (USD 112 billion) , South Africa (USD 114 billion) and Turkey (USD 390 billion), which account for over 30% of total local currency debt outstanding. From 2000 to 2014, these countries were among the top local currency debt issuers together with India and China. The share of local currency debt in percentage of the total sovereign debt is 94.2% for Brazil, 54.6% for Indonesia, 90.9% for South Africa and 67.7% for Turkey by the end of 2014. My data is drawn from the following sources:

Individual Bond Data: My data set of emerging market LC bonds is composed of 630 bonds issued by these four major emerging markets. I restrict my attention to plain LC bonds to minimize the impact of confounding effects related to special fixed-income features. Specifically, I exclude LC bonds with floating rate coupons inflation- or index-linked LC bonds. I collect the daily bond price (bid, ask, mid, max and min), the daily trading volume, and bond outstanding directly from the country exchanges: for Brazil, Sistema Especial de Liquidacao e Custodia (SELIC), for Indonesia, Bursa Efek Indonesia (BEI), for South Africa, Johannesburg Stock Exchange (JSE) and for Turkey, Borsa Istanbul (BIST). I also obtain tick-by-tick trade data of Turkish local currency bond market so that I can run several robustness tests to compare end of day data results with that of tick-by-tick data. Bond characteristics, and U.S.

Treasury and swap data are available from Bloomberg. Credit ratings are obtained from Standard Poor's, Moody's, and Fitch.

Fund Flow Data: I use Emerging Portfolio Fund Research Global (EPFR) database to track the actions of global funds and asset managers in EM fixed income markets. In examining fund flows to emerging markets, EPFR database is one of the most advanced and largely used resource as it provides high frequency data on several funds. EPFR captures (monthly and weekly) fund flows and monthly country-allocations of global investment managers that invest in emerging markets. More importantly, in addition to aggregate fund flows, EPFR provides disaggregated data on the basis of investor type (institutional vs. retail). I find that EPFR bond flows into EM-dedicated funds are primarily domiciled in developed market jurisdictions: at the end of 2014, for example, 85% of the funds are domiciled in Ireland, Luxembourg, the U.K. (39%) or the U.S. (46%).

Foreign Investor Bond Holding: I collect data on foreign participation in domestic sovereign debt markets from the IMF Sovereign Investor Base Database for Emerging Markets (see [37]). I also collect several macro economic variables directly from each countries's Central Bank.

The key advantages of my data set compared to those used in prior research are: i) the data set provides information in individual bonds as opposed to yield curve analysis over benchmarks, ii) the data set covers two major financial crises (the European sovereign debt crisis and the FED tapering tantrum) providing an unique ground to study credit risk and liquidity's interaction in a framework that has never been used in previous studies of corporate or other sovereign bond markets, and iii) observe the investor type specific breakdown of fund flows into LC bonds, which allows me to analyze the differential role of institutional and retail investors in LC bond market liquidity.

1.4 Methodology

This section describes the methodology used to investigate the importance of liquidity in the LC bond market.

1.4.1 Local Currency Yield Spread

I use *Spread*, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. I exclude LC yield spreads for bonds that have less than one month to maturity. I winsorize the 0.5% highest and lowest spreads, so all LC spreads above the 99.5% percentile are set to the 99.5% percentile and all spreads below the 0.5% percentile are set to the 0.5% percentile.

1.4.2 Liquidity Measures

Liquidity has different facets and the literature has proposed different ways to capture how liquidity risk manifests itself[9]. Among these different measures, I consider eight liquidity proxies, which intend to capture price impact, transaction cost and market liquidity. For price impact, I employ two measures, namely, i-) Amihud [38] measure, which relates absolute daily returns to daily trading volumes and ii-) Pastor-Stambaugh [7] measure, which measures price reversals after trading days with large volumes within a regression framework. For transaction cost, I use bid-ask spread as the direct measure of transaction cost and also consider three more liquidity measures as bid-ask spread estimator, which is derived from high and low prices developed by Roll [39] measure, Gibbs [34] measure and high-low [40] measure. While Roll [39] utilizes the bid-ask bounce which is the negative autocovariance of returns from bond prices, Gibbs measure adds a market factor to Roll measure, which is otherwise similar to Roll [39] measure. Using daily high-low data, High-Low measure filters out

[9]The challenges to measure liquidity is highlighted by Federal Reserve Chair Janet Yellen "... we see this decline in liquidity in some measures, but not others."}

bid-ask spreads. One can think High-Low measure, as a shadow bid-ask spread derived from the information contained in the ratio between daily high and low prices, and it reflects both bond's variance and bid-ask spread. Finally, I calculate the proportion of zero returns directly as a measure of illiquidity and the turnover as a proxy for trading activity. I classify them within other liquidity measures. In the appendix, I describe the measures and their implementation in more detail.

1.4.3 Time-variation and Sub-period Analysis

Several studies claim that most emerging markets were severely affected in terms of price and liquidity when the US Federal Reserve announced tapering plans for its monthly asset purchases. [25] find that during the tapering tantrum of summer 2013, risk premia inherent in market interest rates fluctuated so widely that it even had consequences for consumption and investment decisions. Several EM central banks issued statements warning about the potential feedback effects in their bond markets. Thus, I examine how LC liquidity changed in two sub-periods: i-) the pre-tapering (January 2010-May 2013): a period with plenty of liquidity for emerging markets. Shin (2013) classifies this period as *the Second Phase of Global Liquidity*. Beginning in 2010, this period is characterized as the time when EM debt markets become more integrated to global markets and international investors, and ii-) the post-tapering period (June 2013-November 2015).

1.5 Liquidity Premia in Local Currency Bond Yield Spreads

In this section, first I explore the cross-sectional differences in explaining the LC bond yield spreads considering all liquidity measures. Then, I extract market-wide LC bond liquidity. In the literature, there are two proposed approaches to calculate market-wide liquidity: Principal Component Analysis (PCA) and averaging. For completeness, I implement both methods, but most of the analysis will be based on the latter. Finally, I identify the relative contribution of liquidity premium in LC bond yield spread and investigate the interaction between liquidity and credit risks.

1.5.1 Liquidity Effects in Cross-section

To explore the cross-sectional differences in explaining the LC bond yield spreads considering all liquidity measures, I use the Fama-MacBeth procedure. For each country, the regressions are performed with the following structure:

$$\text{Spread}_{i,t} = \alpha + \beta \text{ Liquidity Variables}_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{it} \tag{1}$$

where i refers to local currency bonds. Liquidity Variables$_{i,t}$ is one of the liquidity measures. Following previous literature, I also control for: bond-specific variables (amount outstanding, coupon, maturity and age), credit risk controls (credit risk via credit default swaps and political risk via ICRG political risk index), currency risk controls (implied exchange rate volatility and and inflation) and several macroeconomic variables (current account, reserves, debt service and fiscal balance)[10]. I run this regression for every country based on weekly averages from the daily data of all variables.

Table 1 summarizes the results of regressions. I recognize that the nature of liquidity evolves during sub-samples (i.e. pre-tapering, and post-tapering). Overall, I find that a large part of the cross-sectional differences in the LC yield spread across bonds can be explained by my specification as the regression results indicate an R^2 ranging between 59% to 65%. Liquidity measure alone can explain 25% to 28%. Also, the results show that Gibbs, Amihud and High-low measures are positive and significant across all countries. These findings highlight the economic importance of liquidity effects for the pricing of LC sovereign bonds.

[10] Bond-specific variables: [41], credit risk controls: [42], currency risk controls: **Blaise Gadanecz, Ken Miyajima, Chang Shu (2014)** and macroeconomic variables: [43]

As shown in Table 1, overall model R^2 values in the *pre-tapering* period range between 42% and 51%. Liquidity measures alone contribute between 11% and 15%. A majority of the liquidity measures, even when significant, has low statistical powers. This is broadly consistent with the findings of [25] that during this period, plenty of liquidity was available for emerging markets. However, a completely different picture emerges during the *post-tapering*. The R^2 values of the model increase substantially, reaching up to 69% to 78%. I find strong evidence that the liquidity measures provide the greatest marginal contribution during the post-tapering, explaining on its own up to 31% to 35% of the total variation in LC yield spreads. This makes liquidity measures the primary source of widening LC yield spread. These findings are consistent with recent studies concluding that the impact of liquidity shocks is highly conditional and significantly stronger in bad economic times (e.g, Acharya et al. (2010)) and tight monetary conditions (e.g. Jensen and Moorman (2010)). In unreported results, I test the robustness of the previous results by using liquidity variables lagged by one week. I find a similar level of explanatory power in comparison to the contemporaneous regressions.

The positive signs of liquidity variables are consistent with economic intuition, implying that the LC yield spread increases when the liquidity conditions deteriorate. When I rank liquidity measures of explanatory variables in terms of their contribution to the overall R^2 values, some important results emerge. I find strong evidence that the transaction cost based liquidity variables (Gibss measure and High-Low measure) are the most significant liquidity measures. This finding is also consistent with [44] that [40] High-Low estimator and Hasbrouck's (2009) Gibbs measure take the lead for measuring the bond market liquidity. These measures have the greatest marginal contribution during the post-tapering period. Within price impact group, I find that while the Pastor-Stambaugh measure has lower statistical significance for some countries, the Amihud measure has positive and very significant factor loadings for all countries. The significance of Turnover and Zeros measures are very low. These results are fairly stable across market regimes.

I also analyze economic effects of my liquidity measures from my Fama-MacBeth regressions. A one standard deviation increase of Gibbs, High-Low, Amihud and Roll measures tends to increase bond spreads by 17 bps to 24 bps during the pre-tapering period. The effects are smaller for other measures like Pastor-Stambaugh, Bid-Ask and Zeros, ranging between 4 bps to 9 bps. The smallest impact is provided by the turnover measure (2 bps to 5 bps), which seems not to be particularly relevant given its low economic significance. As expected, the economic effect of liqudity increases during post-tapering period, and a one standard deviation shock to Gibbs, High-Low, Amihud measures increases LC yield spreads by 28 bps to 36 bps. Considering all liquidity proxies together, a one standard deviation move in the direction of greater illiquidity in all measures would increase the LC yield spreads by about 37 bps to 45 bps in the pre-tapering period, and 84 bps to 98 bps in the post-tapering period. I also examine the time-series behavior of the changes in LC yield spread using panel regressions and confirm that the time-series results are very similar to picture of cross-sectional analysis.

Overall, cross-sectional regressions show that after the taper tantrum, LC yield spreads became more sensitive to liquidity. Another potential reason for the liquidity dry up for EM fixed income markets is the recent regulations such as Dodd-Frank Wall Street Reform and Consumer Protection Act, known as the Volcker Rule, which was finalized on December 10, 2013, aiming to curtail big banks' risks and most fundamentally, the practice of pure proprietary trading. Many investment banks have scaled back their prop trading business since the rule was first introduced. This had significant effects on liquidity of emerging market fixed income securities and swap market where US based financial institutions were among the most active market participants. Also, under new Basel III requirements, banks and financial institutions are required to set aside additional capital for their emerging market investments. It is now widely accepted among trading community that in the absence of proprietary traders, there is less liquidity than before.

Table 1: Fama-Macbeth Regressions.

This table reports the cross-sectional regression models explaining the weekly averages of LC yield spreads based on the Fama-MacBeth procedure, estimated for the three regimes (pre-tapering, post-tapering and all sample period) for each country:

$$\text{Spread}_{i,t} = \alpha + \beta \text{ Liquidity Variables}_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

where i is for bond and t is time measured in weeks. The level of the yield spread is defined by bond-specific variables (amount outstanding, coupon, maturity and age), credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index), several macroeconomic variables (current account, reserves, debt service and inflation)and liquidity variables (L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure and L^{zr} Zeros Measure). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. The pre-tapering period is January 2, 2010 - 24 May, 2013 and the post-tapering period is 24 May, 2013 - November 11,2015. The t-statistics are given in parentheses and are calculated from [45] standard errors. Significance at 10% level is marked *, at 5% marked **, and at 1% marked ***. In addition,the table also reports each model's R^2.

	Pre-Tapering				Post-Tapering				All Periods			
	Brazil	Indonesia	South Africa	Turkey	Brazil	Indonesia	South Africa	Turkey	Brazil	Indonesia	South Africa	Turkey
Amihud	0,283*	0,239*	0,128*	0,337**	0,390***	0,307**	0,190**	0,352***	0,348***	0,276*	0,159**	0,341***
	[1,735]	[1,811]	[1,751]	[2,158]	[2,725]	[2,086]	[2,268]	[2,976]	[2,433]	[1,918]	[1,985]	[2,528]
Roll	0,187*	0,146**	0,137*	0,126*	0,304**	0,386***	0,396**	0,406***	0,242*	0,292**	0,312*	0,338**
	[1,848]	[1,992]	[1,733]	[1,861]	[2,276]	[2,418]	[1,987]	[2,987]	[1,941]	[2,128]	[1,808]	[2,224]
Zero	0,029*	0,066	0,052	0,121*	0,042*	0,087	0,054	0,265**	0,033*	0,072	0,052	0,162**
	[1,735]	[0,528]	[1,116]	[1,809]	[1,784]	[0,988]	[1,368]	[2,297]	[1,751]	[0,707]	[1,236]	[2,018]
Turnover	1,408*	1,207*	0,277	1,017	2,046**	1,701***	0,020	0,005	1,709**	1,493**	0,118	0,306
	[1,748]	[1,673]	[0,674]	[0,283]	[2,262]	[2,490]	[0,764]	[0,513]	[2,033]	[2,104]	[0,706]	[0,350]
High-Low	0,873*	0,828**	2,375*	1,201**	1,931***	1,464***	3,314***	2,514***	1,378***	1,113**	2,742**	1,808***
	[1,935]	[2,055]	[1,821]	[2,177]	[3,946]	[2,464]	[2,429]	[2,853]	[3,089]	[2,236]	[2,134]	[2,530]
Pastor-Stambaugh	0,144	0,166	0,131*	0,207*	0,182*	0,175*	0,249**	0,232*	0,167	0,170	0,191**	0,213*
	[0,785]	[0,695]	[1,698]	[1,760]	[1,758]	[1,826]	[1,986]	[1,774]	[1,177]	[1,366]	[2,254]	[1,768]
Bid-Ask	0,683*	0,311	1,082	0,509*	0,596*	0,164	1,100*	0,174*	0,618*	0,218	1,012*	0,399*
	[1,808]	[0,672]	[1,096]	[1,686]	[1,822]	[1,066]	[1,943]	[1,724]	[1,812]	[0,846]	[1,725]	[1,697]
Gibbs	0,104*	0,212**	0,163*	0,230**	0,330***	0,385***	0,399***	0,471***	0,187***	0,321**	0,281**	0,345***
	[1,935]	[2,084]	[1,745]	[2,077]	[3,968]	[3,333]	[2,936]	[3,307]	[3,146]	[2,300]	[2,112]	[2,842]
Liquidity Partial R	13,9%	12,1%	11,1%	15,1%	34,7%	32,8%	31,2%	35,2%	26,6%	26,1%	25,8%	27,4%
Total R	47,1%	44,5%	42,3%	51,1%	74,1%	76,2%	69,8%	78,1%	63,1%	61,1%	59,2%	65,3%

1.5.2 Market-wide Liquidity Across Measures

I have found that liquidity measures can explain a fair proportion of LC bond yield spreads; in particular, liquidity measures estimating price impact (via Amihud measure) and transaction cost (via Gibbs measure) seem to be particularly important in all countries. To formally observe the commonalities between liquidity measures, I run principal component analysis. I define L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure and L^{zr} Zeros Measure. Since the units across different liquidity measures vary, I de-mean and standardize all liquidity measures.

I do factor decompositions individually for each country across a set of standardized liquidity measures $(\tilde{L}^{(am)}, \tilde{L}^{(gb)}, \tilde{L}^{(hl)}, \tilde{L}^{(rl)}, \tilde{L}^{(bd)}, \tilde{L}^{(ps)}, \tilde{L}^{(tm)}, \tilde{L}^{(zr)})$ [11]. I call these factors *within-country* liquidity factors. I also extract the common systematic components of liquidity across a large sample of LC bonds for four major emerging markets and across a set of eight measures of liquidity. I call these *across-country* liquidity factors. Such decomposition is repeated for each country and across the country to capture the most salient features of liquidity with a few factors. Table 2 shows *within-country* and *across-country* liquidity factors. First factor (F^1) within each country are remarkably similar across all countries and load on to Amihud, Gibbs and High-Low measures. This factor is stable in two periods and explains between 54% to 60% of the variation in LC bond liquidity. Second components (F^2) seem to be country specific and is loaded on Turnover measure for Indonesia and Brazil, Pastor-Stambaugh measure for South Africa and Zeros measure for Turkey. The explanatory power and the loadings of the first two PCs of the *across-country* are stable and have clear interpretations in the two period. The first component, which on average explains 57% of the variation in liquidity measures, loads roughly equally on

[11] I standardize each liquidity measure by μ^j and σ^j which are the the mean and standard deviation of L^j. As a result $\tilde{L}_{i,t}$ is defined as $\tilde{L}_{i,t} = L^j_{i,t} - \mu^j/\sigma^j$

Amihud, Gibbs and High-Low measures. The second principle component is country-specific and accounts for an additional 27% of variation. Third component does not have a clear interpretation.

To formally test for the commonality, the first three principle components are computed for each daily standardized measure of liquidity. Then, for each country and each standardized liquidity measure $\tilde{L}_{i,t}$, liquidity is regressed on these computed first three principle components. Figure 3 reports the cross-country average of the R^2 of these regressions based on different liquidity measures. The first principle component explains between 45%-65% of the variation in daily LC bond market liquidity, depending on which measure is used. Amihud, Gibbs and High-Low measures exhibit the highest level of commonality. While these R^2 statistics are significantly larger than those typically reported for equity markets (e.g. [34] and [46]), they are lower than those found for the foreign exchange market (e.g [8]).

Table 2: Principal Component Analysis of Liquidity Variables - Pre Tapering

This table shows principle component loadings for the first three factors (F^1, F^2 and F^3) together with cumulative variation in liquidity that is explained by each factor. For country j, all eight demeaned and standardized liquidity measures L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure, L^{zr} Zeros Measure are de-meaned, standardized and collected in the $8xT$ matrix $\tilde{L}_j$, where T is the number of weeks in my sample. Each four columns in each panel shows *within-country* factor loadings for Brazil, Indonesia, South Africa and Turkey respectively. The fifth column in each panel shows *across-country* factor loadings. The sample is January 2, 2010 - November 11, 2015. This table covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013.

Panel A. Pre-Taper Tantrum	Brazil	Indonesia	South Africa	Turkey	Across-Country
First principal component loadings (F^1)					
Amihud	0,61	0,56	0,55	0,62	0,63
Roll	0,34	0,43	0,48	0,42	0,44
Bond Zero	0,04	0,06	0,03	0,04	0,05
Turnover	0,02	0,06	0,01	0,03	0,04
High-low	0,62	0,48	0,56	0,46	0,59
Pastor-Stambaugh	0,08	0,03	0,02	0,00	0,03
Bid-Ask	0,02	0,09	0,07	0,09	0,02
Gibbs	0,71	0,64	0,58	0,65	0,67
Cum. % explained	58%	57%	54%	56%	57%
Second principal component loadings (F^2)					
Amihud	0,04	0,06	0,19	0,02	0,01
Roll	0,03	0,02	0,07	0,05	0,07
Bond Zero	0,06	0,05	0,11	0,54	0,07
Turnover	0,55	0,54	0,04	0,06	0,01
High-low	0,02	0,03	0,08	0,05	0,12
Pastor-Stambaugh	0,03	0,12	0,54	0,10	0,02
Bid-Ask	0,18	0,08	0,04	0,22	0,12
Gibbs	0,05	0,07	0,16	0,01	0,04
Cum. % explained	87%	82%	78%	83%	84%
Third principal component loadings (F^3)					
Amihud	0,21	0,03	0,23	0,13	-0,02
Roll	0,04	0,15	0,51	0,07	0,05
Bond Zero	0,22	0,10	0,11	0,28	0,17
Turnover	-0,03	-0,04	0,00	-0,03	-0,01
High-low	0,04	0,06	0,09	0,05	-0,01
Pastor-Stambaugh	-0,07	0,26	0,24	0,06	-0,26
Bid-Ask	0,07	0,06	0,34	-0,22	-0,03
Gibbs	0,23	0,04	0,27	0,11	0,05
Cum. % explained	91%	96%	86%	91%	91%

Table 3: Principal Component Analysis of Liquidity Variables - Post Tapering

This table shows principle component loadings for the first three factors (F^1, F^2 and F^3) together with cumulative variation in liquidity that is explained by each factor. For country j, all eight demeaned and standardized liquidity measures L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure, L^{zr} Zeros Measure are de-meaned, standardized and collected in the $8xT$ matrix $\tilde{L}_j$, where T is the number of weeks in my sample. Each four columns in each panel shows *within-country* factor loadings for Brazil, Indonesia, South Africa and Turkey respectively. The fifth column in each panel shows *across-country* factor loadings. The sample is January 2, 2010 - November 11, 2015. This table covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015.

Panel B. Post-Taper Tantrum	Brazil	Indonesia	South Africa	Turkey	Across-Country
First principal component loadings (F^1)					
Amihud	0,59	0,51	0,51	0,69	0,63
Roll	0,36	0,44	0,47	0,41	0,45
Bond Zero	0,07	0,06	0,01	0,04	0,06
Turnover	0,01	0,01	-0,02	-0,01	0,02
High-low	0,64	0,49	0,55	0,52	0,57
Pastor-Stambaugh	0,03	0,07	0,01	0,00	0,04
Bid-Ask	0,08	0,21	0,08	0,05	0,04
Gibbs	0,72	0,65	0,65	0,61	0,68
Cum. % explained	60%	59%	55%	54%	59%
Second principal component loadings (F^2)					
Amihud	0,06	0,04	0,17	0,05	0,11
Roll	0,09	0,04	0,08	0,08	0,07
Bond Zero	0,05	0,08	0,01	0,57	0,05
Turnover	0,59	0,61	0,05	0,03	0,08
High-low	0,09	0,07	0,10	0,07	0,14
Pastor-Stambaugh	0,04	0,01	0,62	0,06	0,06
Bid-Ask	0,08	0,07	0,02	0,02	0,11
Gibbs	0,06	0,08	0,20	0,03	0,10
Cum. % explained	88%	84%	80%	86%	84%
Third principal component loadings (F^3)					
Amihud	0,18	0,14	0,21	0,11	0,07
Roll	0,02	0,16	0,04	0,00	0,03
Bond Zero	0,19	0,12	0,12	0,22	0,06
Turnover	-0,01	-0,02	-0,05	-0,04	-0,06
High-low	0,03	0,05	0,04	0,08	0,03
Pastor-Stambaugh	-0,08	0,24	0,07	0,08	0,15
Bid-Ask	0,03	0,08	0,12	0,09	0,01
Gibbs	0,16	0,34	0,23	0,10	0,05
Cum. % explained	92%	97%	89%	92%	93%

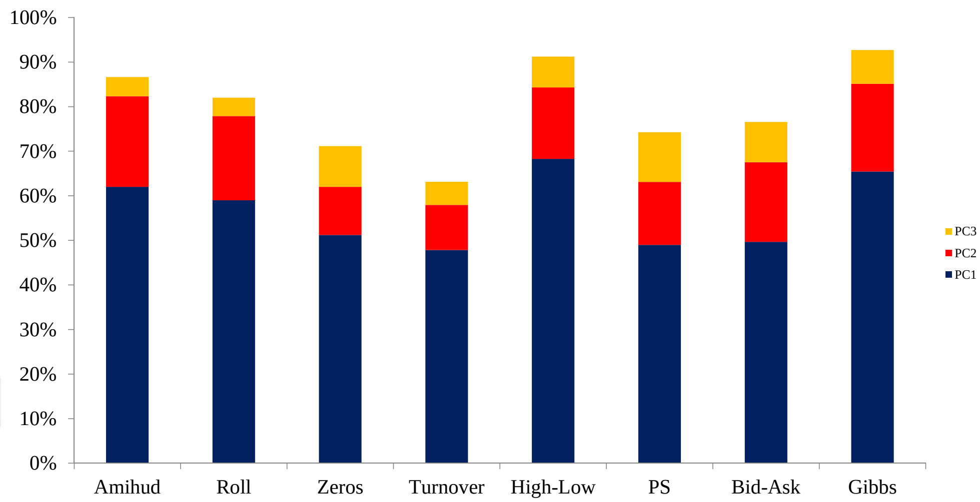


Figure 3: Commonality. For each daily standardized measure of liquidity the first three common factors are computed using PCA. Then, for each country and each standardized liquidity measure, liquidity is regressed on the first three principle components. Each column represents the average adjusted- R squares of these regressions using one, two, and three common factors. The sample is January 2, 2010 - November 11, 2015.

The principal component loadings on the first PC presented at Table 2, Table 3 and Figure 3 lead me to define a factor that loads evenly on Gibbs, High-Low and Amihud liquidity measures, and does not load on the other liquidity measures. For every bond j and at time t, I define bond-specific liquidity variable as follows.

$$\lambda_{i,t} = \sum_{j=1}^{3} \tilde{L}_{i,t}^{j} \tag{2}$$

where I define $\tilde{L}_{i,t}^{1}$ as Gibbs Measure, $\tilde{L}_{i,t}^{2}$ as High-Low measure, and $\tilde{L}_{i,t}^{3}$ as Amihud Measure. $\lambda_{i,t}$ can also be regarded as a close approximation to the first principal component extracted from a large number of potential liquidity proxies.

Finally, to get better understanding whether my proposed liquidity measure $\lambda_{i,t}$ is a more consistent proxy for LC bond market liquidity, I regress LC bond yield spreads on each liquidity variable separately after controlling for control variables. Each individual regression is performed with the following structure:

$$Spread_{it} = \alpha + \beta L_{it} + \text{Control Variables}_{it} + \epsilon_{it} \tag{3}$$

L_{it} is one of the liquidity measures ($\tilde{L}^{(am)}, \tilde{L}^{(gb)}, \tilde{L}^{(hl)}, \tilde{L}^{(rl)}, \tilde{L}^{(bd)}, \tilde{L}^{(ps)}, \tilde{L}^{(tm)}, \tilde{L}^{(zr)}$ and $\lambda_{i,t}$ (equally weighted sum of three liquidity measures all normalized to a common scale)). Table 4 and Table 5 summarize the results of the regressions.

Tables 4 and Table 5 reveal an important element about $\lambda_{i,t}$ compared to other liquidity measures. $\lambda_{i,t}$ is significant at a 1% level for all countries both in pre-tapering period and post-tapering period, showing that $\lambda_{i,t}$ is a more consistent proxy for liquidity of LC bond market. The fact that $\lambda_{i,t}$ is more robust than the other measures allows me to get a more detailed picture of LC bond market liquidity across different emerging markets. There may be a two-way causal relationship between contemporaneous measures of liquidity and credit risk, and failing to account for such a relationship in regressions results in inconsistent estimates. In unreported results, to test for potential endogeneity bias, I use the Durbin-Wu-Hausman test. I do this for every marginal regression in Table 4 and Table 5, that is, test every liquidity variable separately. If the test is not significant, the liquidity variable can be regarded as exogenous. Out of the 36 test statistics, 88% are insignificant, indicating that endogeneity is not a major concern.

Table 4: Liquidity regressions - Pre Tapering

For each country and each liquidity variable L a pooled regression is run with control variables.

$$\text{Spread}_{i,t} = \alpha + \beta L_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

where i is for bond and t is time measured in weeks. In total, 36 regressions are run (nine liquidity variables x four countries). This table shows for each regression the coefficient and t-statistics in brackets for the liquidity variable. The level of the yield spread is defined by credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index), several macroeconomic variables (current account, reserves, debt service and inflation) and $L_{i,t}$ is one of the liquidity variables (L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure and L^{zr} Zeros Measure). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. This table covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013. The t-statistics are given in parentheses and are calculated from Newey and West(1987) standard errors. Significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel A. Pre-Taper Tantrum

	Brazil	Indonesia	SOAF	Turkey
λ	0,015***	0,014***	0,014***	0,012***
	[3,01]	[2,74]	[2,69]	[2,82]
Amihud	0,336***	0,262*	0,124*	0,372**
	[2,85]	[1,71]	[1,86]	[2,07]
Roll	0,183*	0,243**	0,139*	0,123*
	[1,78]	[1,99]	[1,72]	[1,95]
Bond Zero	0,0301*	0,064	0,051	0,147*
	[1,76]	[0,08]	[0,98]	[1,81]
Turnover	1,272*	1,258**	0,315	1,013
	[1,68]	[2,01]	[1,52]	[1,19]
High-low	0,858***	0,951**	2,517*	1,378**
	[2,65]	[2,31]	[1,93]	[2,08]
Pastor-Stambaugh	0,148	0,174	0,142**	0,204
	[1,12]	[1,23]	[1,97]	[0,05]
Bid-Ask	0,691*	0,367	1,034	0,52*
	[1,70]	[0,38]	[1,02]	[1,77]
Gibbs	0,127*	0,238**	0,163*	0,248***
	[1,78]	[2,05]	[1,84]	[2,86]

Table 5: Liquidity regressions - Post Tapering
For each country and each liquidity variable L a pooled regression is run with control variables.

$$\text{Spread}_{i,t} = \alpha + \beta L_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

where i is for bond and t is time measured in weeks. In total, 36 regressions are run (nine liquidity variables x four countries). This table shows for each regression the coefficient and t-statistics in brackets for the liquidity variable. The level of the yield spread is defined by credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index), several macroeconomic variables (current account, reserves, debt service and inflation) and $L_{i,t}$ is one of the liquidity variables (L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure and L^{zr} Zeros Measure). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. This table covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015. The t-statistics are given in parentheses and are calculated from Newey and West(1987) standard errors. Significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel B. Post-Taper Tantrum

	Brazil	Indonesia	SOAF	Turkey
λ	0,164***	0,147***	0,115***	0,113***
	[4,36]	[3,54]	[3,21]	[3,72]
Amihud	0,435***	0,375**	0,237**	0,402***
	[3,07]	[1,99]	[1,99]	[3,26]
Roll	0,267**	0,352***	0,383**	0,401***
	[2,29]	[2,49]	[1,98]	[2,78]
Bond Zero	0,033*	0,106*	0,062	0,155**
	[1,82]	[1,72]	[1,51]	[2,10]
Turnover	2,009**	1,692**	0,021	0,006
	[2,14]	[2,18]	[0,60]	[1,16]
High-low	1,964***	1,525***	3,319**	1,614**
	[3,25]	[3,57]	[2,18]	[2,24]
Pastor-Stambaugh	0,11	0,152	0,271***	0,252*
	[1,09]	[1,05]	[2,65]	[1,68]
Bid-Ask	0,654*	0,216	1,202	0,22*
	[1,74]	[1,49]	[1,09]	[1,91]
Gibbs	0,349**	0,455***	0,477**	0,452***
	[2,19]	[3,19]	[2,18]	[2,95]

CHAPTER II

THE SIZE OF LIQUIDITY COMPONENT

2.1 Methodology

In this section, I first introduce a theoretical background on the existence of the currency, credit and liquidity premiums and then give a detailed explanation on the calculation of the liquidity component.

Consider the case in which a US investor buys Brazil LC bonds at time t and sells at time $t+1$. Local currency gross return of the bond at $t+1$ is given by $r^{C,gross}_{LC,t+1}$. To calculate the dollar return, the US investor needs to make two adjustments. The first one would be the currency adjustment which is equal to the local currency return substracted by the exchange rate change in local currency in that period. Secondly, the investor needs to subtract the transaction costs. I postulate that the log of the transaction cost measure is proportional to the liquidity measure L, that is,

$$ln(TC_{t+1}) = v_i L_{i,t+1}(v < 0) \tag{4}$$

Using these two adjustments in the pricing equation and assuming log-normality, the expected excess return of a US investor can be decomposed into three subcomponents, namely, liquidity, credit and currency risk premiums:

$$
\begin{aligned}
logE_tR^{i,US}_{t+1} - r^{f,US}_t &= \underbrace{-cov_t(m_{t+1}, r^{LC,gross}_{i,t+1})}_{\text{Country Risk Premium}} \\
&+ \underbrace{-cov_t(m_{t+1}, -\Delta q)}_{\text{Currency Risk Premium}} \\
&+ \underbrace{-cov_t(m_{t+1}, -v_iL_{i,t+1})}_{\text{Liquidity Risk Premium}}
\end{aligned}
$$

where $R^{i,US}_{t+1}$ is the US dollar return of LC bond, $r^{f,US}_t$ is the risk-free return in US dollar terms, m is the stochastic discount function, Δq is the log change in exchange rate and $v_iL_{i,t+1}$ is the transaction cost. The proof can be found in the appendix.

After explaining the theoretical background for the liquidity premium, I now explain the methodology behind calculating liquidity premium. I use quantile methodology (see [4]) to measure liquidity component. This methodology assigns a liquidity score to each individual LC bond and calculates the impact of bond market liquidity on yield spreads. For each country, I run the following pooled regression in both regimes:

$$
Spread_{i,t} = \alpha + \beta\lambda_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t} \tag{5}
$$

where i refers to local currency bonds and λ_{it} is my liquidity measure. To calculate the liquidity component, I first sort observations according to their liquidity score ($\beta\lambda_{it}$), within each country and maturity bucket (0 - 2y, 2 - 5y, and 5 - 10y) and then define liquidity component as $\beta^C(\lambda_{50} - \lambda_5)$ where λ_{50} and λ_5 are the %50 and 5% quantile of the liquidity measure, respectively[1]. Calculating how and to what extent λ contributes to local currency bond spreads gives the opportunity to analyze

[1] In unreported results, I also define liquidity component as the 75% quantile minus 5% quantile which can be interpreted as that of an illiquid bond relative to a very liquid bond. Main results of the paper are unchanged: the liquidity premium is higher post-tapering compared to pre-tapering.

liquidity as a separate premium. Table 6 and Table 7 report not only the absolute size of liquidity, credit and currency premiums and the fraction of each risk component in the LC yield spread for both regimes.

Table 6 and Table 7 show that on average Brazil pays the highest and South Africa pays the lowest LC yield spreads over corresponding U.S. Treasuries across all maturities during both periods. Table 6 and Table 7 also reveal that during the post-tapering period, all countries paid higher yield spreads on their local currency debts. The liquidity component is small during pre-tapering with an average of 29.9 bps for Brazil, 20.1 bps for Indonesia, 18.8 bps for South Africa, and 22.4 bps for Turkey. The contribution of liquidity premium to LC yield spread remained small around 2.9% to 4.5% across the countries -consistent with a high liquidity environment. During this period, a broad pattern with around one forth of the LC spread being composed of credit risk while the remaining part being composed of currency risk, validating the results reported at [3]. However, the picture dramatically changed in the post-taper period. During the post-tapering period, a persistent and steadily increasing liquidity premium is observed as demonstrated in Table 7. Figure 4 shows the evolution of liquidity premium for each country. The liquidity premium for all of the countries peaks in the third quarter of 2013 (163 bps for Brazil, 142 bps for Turkey, 101 bps for Indonesia and 87 bps for South Africa) and shows less persistence. The average liquidity component for each country increases by a factor of 3 to 4, showing that LC bond market liquidity has dried out after tapering announcement and LC bond yield spread-widening was mainly due to a higher liquidity premium. Liquidity spread was, on average, around 8% to 10% of total LC yield spread and has never returned to its pre-tapering levels. As I am also endowed with intraday transaction based data of Turkish LC bond market, I try to find out whether my liquidity measure based on daily data actually measures the intraday nature of the transaction based data. Panel D in Figure 4 compares the end of day liquidity measure with tick-by-tick liquidity measure (plotted with dashed black line) for Turkish LC bond market. Panel D in Figure 4 clearly illustrates that my liquidity measure is insensitive to the choice of data frequency, validating the findings of Schestag (2016) that liquidity proxies constructed from low-frequency (daily) data are generally strongly correlated with intraday based liquidity proxies.

To shed further insights into joint dynamics of different risk premiums, Figure 5 and Figure 6 demonstrate the evolution of credit and currency risk premiums for all countries across different maturities over time. These figures reveal the three important elements of these risk premiums. First, LC bond investors care about currency, credit and liquidity risk premiums, but they do so at different times and for different reasons. While LC yield spreads were largely explained by differences in credit risk premium during the Eurozone sovereign crises, the bulk of sovereign LC yield spreads were explained by the liquidity premium in the taper tantrum. Second, while there is a high level of commonality in EM credit spreads of countries across all maturities, the currency risk premium of each country displays various levels of segmentation. In Table 5 and Table 6, I also apply factor analysis to determine the extent of fluctuations in credit and currency spreads which are driven by common components or by idiosyncratic country shocks. In particular, the first principal component account for the 77% of the variation in sovereign credit spreads. Furthermore, this value increases up to 90% in times of market turbulence. These results show that an overwhelming amount of the variation in sovereign credit spreads is highly related with the first principal component. For the same countries, the first principal component of currency returns explains only about 49% of the variation in currency returns for the entire sample period, and 58% in times of market turbulence. These findings point the country-specific idiosyncratic components as important drivers of currency risk premium, in contrast to the credit risk premium where global factors are by far the most important drivers[2]. Third, as one moves along the yield curve of each individual local currency bond, market expectations reflect a decreasing currency risk premium and an increasing credit risk premium over time.

Overall, my findings verify that wide and volatile LC bond yield spread during tapering tantrum represents concerns about liquidity rather than solvency. These results are in line with findings of [12], and [13] that the effect of liquidity is more influential during financial market turbulence and these effects are more powerful on bonds with low credit quality. Turning to the term structure of liquidity, the general pattern across each individual country is that the liquidity component decreases as maturity increases. This finding is in line with Ericsson and Renault (2006) which states that the liquidity premium is downward sloping due to the fact that selling pressure faced by liquidity-shocked investors leads to sales at discounted prices.

[2]Longstaff, Pan, Pedersen, and Singleton (2011) and Du and Shrenger (2015) find that first PC of credit spreads has very high correlations (around 90%) with VIX.

Table 6: Liquidity, Credit and Currency components in basis points - Pre Tapering. For each country and λ a pooled regression is run with control variables.

$$Spread_{i,t} = \alpha + \beta\lambda_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

To calculate the liquidity component, I first sort observations according to their liquidity score ($\beta\lambda_{it}$), within each country and maturity bucket (0 - 2y, 2 - 5y, and 5 - 10y) and then define liquidity component as $\beta(\lambda_{50} - \lambda_5)$ where λ_{50} and λ_5 are the %50 and 5% quantile of the liquidity measure respectively. Control Variables are credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index) and several macroeconomic variables (current account, reserves, debt service and inflation). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. I use maturity specific credit default swaps for credit risk premium. The remainder of the spread is defined as the currency risk premium. The percentage of risk premiums in terms of yield spreads are given in parentheses. This table covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013.

Panel A. Pre-Taper Tantrum

	Liquidity				Credit				Currency				Yield Spread			
	Average	0-2 year	2-5 year	5-10 year	Average	0-2 year	2-5 year	5-10 year	Average	0-2 year	2-5 year	5-10 year	Average	0-2 year	2-5 year	5-10 year
Brazil	29,9	31,8	31,3	26,6	135,3	88,3	128,1	189,5	787,8	941,2	737,0	685,2	953,0	1061,3	896,4	901,3
	(2,9)	(2,8)	(3,0)	(2,9)	(14,8)	(8,5)	(14,7)	(21,3)	(82,3)	(88,7)	(82,3)	(75,8)				
Indonesia	20,1	24,2	16,0	20,1	157,7	83,5	169,3	220,4	294,6	444,4	215,3	224,0	472,4	552,1	400,6	464,5
	(4,5)	(4,7)	(4,3)	(4,6)	(36,0)	(15,7)	(43,6)	(48,8)	(59,5)	(79,6)	(52,1)	(46,6)				
South Africa	18,8	21,3	16,8	18,3	131,5	80,4	152,8	161,4	435,3	541,2	362,1	402,7	585,7	642,9	531,7	582,4
	(3,3)	(3,4)	(3,2)	(3,4)	(23,3)	(12,9)	(29,5)	(27,5)	(73,4)	(83,7)	(67,3)	(69,1)				
Turkey	22,4	28,3	19,8	19,2	174,6	119,7	184,4	219,7	497,7	665,4	428,5	399,3	694,8	813,4	632,6	638,2
	(3,4)	(3,3)	(3,3)	(3,6)	(26,6)	(15,1)	(29,8)	(34,9)	(70,0)	(81,6)	(66,9)	(61,5)				

Table 7: Liquidity, Credit and Currency components in basis points Post Tapering. For each country and λ a pooled regression is run with control variables.

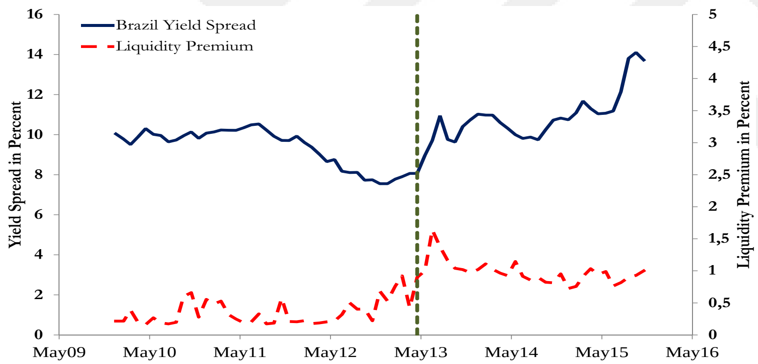
$$Spread_{i,t} = \alpha + \beta\lambda_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

To calculate the liquidity component, I first sort observations according to their liquidity score ($\beta\lambda_{it}$), within each country and maturity bucket (0 - 2y, 2 - 5y, and 5 - 10y) and then define liquidity component as $\beta(\lambda_{50} - \lambda_5)$ where λ_{50} and λ_5 are the %50 and 5% quantile of the liquidity measure respectively. Control Variables are credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index) and several macroeconomic variables (current account, reserves, debt service and inflation). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. I use maturity specific credit default swaps for credit risk premium. The remainder of the spread is defined as the currency risk premium. The percentage of risk premiums in terms of yield spreads are given in parentheses. This table covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015.

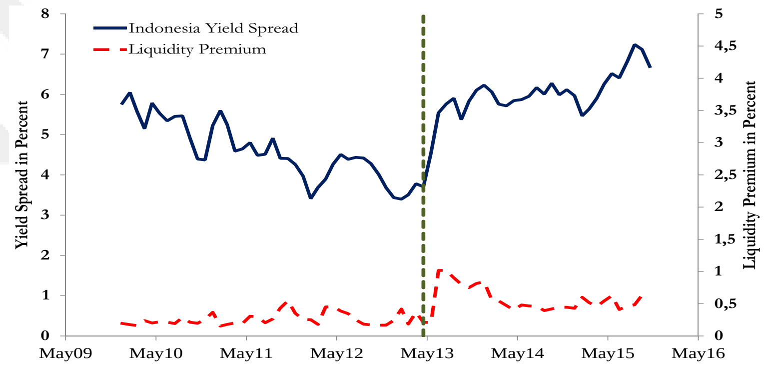
Panel B. Post-Taper Tantrum

	Liquidity				Credit				Currency				Yield Spread			
	Average	0-2 year	2-5 year	5-10 year	Average	0-2 year	2-5 year	5-10 year	Average	0-2 year	2-5 year	5-10 year	Average	0-2 year	2-5 year	5-10 year
Brazil	111,9	123,8	108,5	103,4	194,8	114,3	208,1	262,0	807,3	963,6	688,5	769,7	1114,0	1201,7	1005,1	1135,1
	(10,4)	(10,3)	(10,8)	(10,2)	(18,7)	(9,5)	(20,7)	(25,9)	(70,9)	(80,2)	(68,5)	(63,9)				
Indonesia	55,1	60,8	50,1	54,4	176,7	80,3	190,8	259,0	387,2	554,4	295,0	312,4	619,0	695,5	535,8	625,8
	(9,2)	(8,7)	(9,3)	(9,6)	(30,9)	(11,5)	(35,6)	(45,7)	(59,8)	(79,7)	(55,0)	(44,7)				
South Africa	50,5	51,8	45,8	54,0	201,0	132,2	205,3	265,4	353,9	466,3	288,1	307,2	605,4	650,4	539,2	626,7
	(8,8)	(8,2)	(8,8)	(9,3)	(35,4)	(20,9)	(39,5)	(45,7)	(55,9)	(70,9)	(51,7)	(45,0)				
Turkey	70,3	78,2	63,5	69,3	198,9	128,6	209,9	258,2	483,0	658,9	393,3	396,6	752,2	865,7	666,7	724,2
	(9,6)	(9,0)	(9,5)	(10,3)	(28,3)	(14,9)	(31,5)	(38,5)	(62,1)	(76,1)	(59,0)	(51,2)				

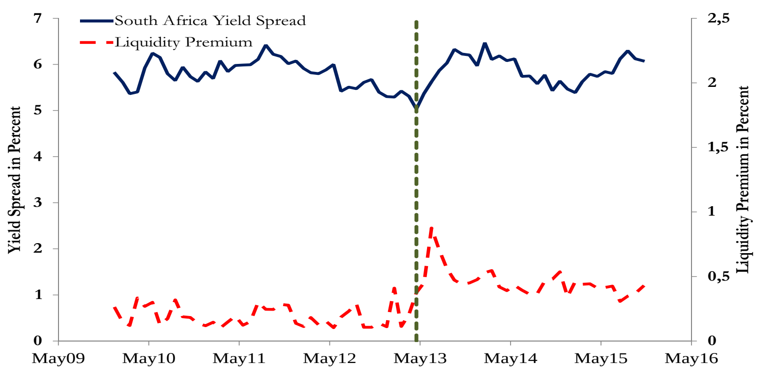
(a) Brazil



(b) Indonesia



(c) South Africa



(d) Turkey

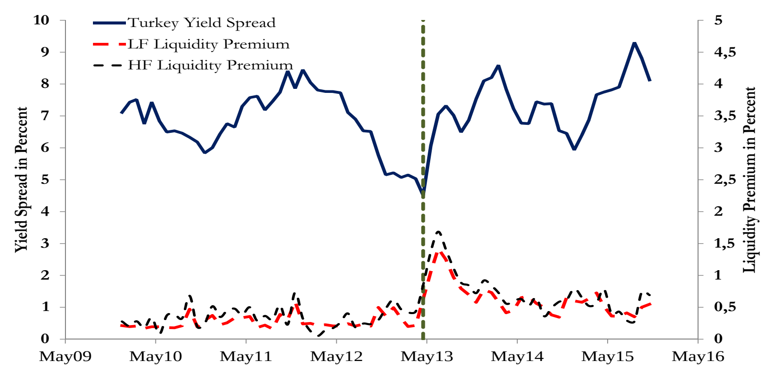


Figure 4: Local Currency Yield Spreads vs Liquidity Premiums for Brazil, Indonesia, South Africa and Turkey. For each country and λ a pooled regression is run with control variables.

$$Spread_{i,t} = \alpha + \beta\lambda_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

To calculate the liquidity component, I first sort observations according to their liquidity score ($\beta\lambda_{it}$), within each country and maturity bucket (0 - 2y, 2 - 5y, and 5 - 10y) and then define liquidity component as $\beta(\lambda_{50} - \lambda_5)$ where λ_{50} and λ_5 are the %50 and 5% quantile of the liquidity measure respectively. Control Variables are credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index) and several macroeconomic variables (current account, reserves, debt service and inflation). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate.

Credit Risk Premium

(a) 2 Year (b) 5 Year (c) 10 Year

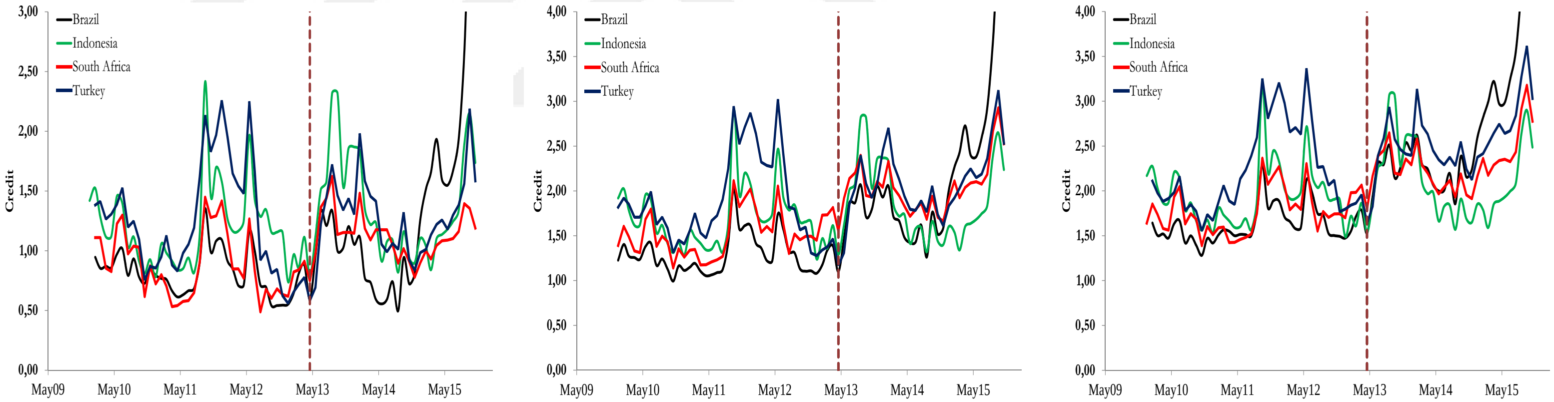


Figure 5: Credit Risk Premiums for Brazil, Indonesia, South Africa and Turkey. For each country and λ a pooled regression is run with control variables.

$$Spread_{i,t} = \alpha + \beta\lambda_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

To calculate the liquidity component, I first sort observations according to their liquidity score ($\beta\lambda_{it}$), within each country and maturity bucket (0 - 2y, 2 - 5y, and 5 - 10y) and then define liquidity component as $\beta(\lambda_{50} - \lambda_5)$ where λ_{50} and λ_5 are the %50 and 5% quantile of the liquidity measure respectively. Control Variables are credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index) and several macroeconomic variables (current account, reserves, debt service and inflation). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. I use maturity specific credit default swaps for credit risk premium. The remainder of the spread is defined as the currency risk premium.

Currency Risk Premium

(a) 2 Year (b) 5 Year (c) 10 Year

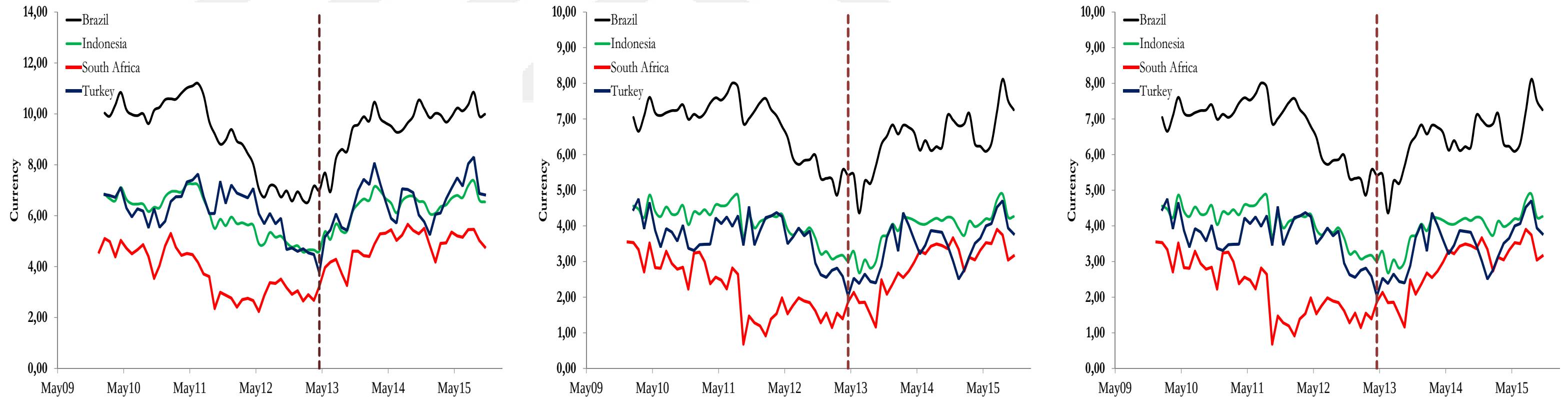


Figure 6: Currency Risk Premiums for Brazil, Indonesia, South Africa and Turkey. For each country and λ a pooled regression is run with control variables.

$$Spread_{i,t} = \alpha + \beta\lambda_{i,t} + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

To calculate the liquidity component, I first sort observations according to their liquidity score ($\beta\lambda_{it}$), within each country and maturity bucket (0 - 2y, 2 - 5y, and 5 - 10y) and then define liquidity component as $\beta(\lambda_{50} - \lambda_5)$ where λ_{50} and λ_5 are the %50 and 5% quantile of the liquidity measure respectively. Control Variables are credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index) and several macroeconomic variables (current account, reserves, debt service and inflation). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. I use maturity specific credit default swaps for credit risk premium. The remainder of the spread is defined as the currency risk premium.

Table 8: Principal Component Analysis of Credit Risk Premiums. The table below presents the results for static Principal Components Analysis (PCA) of credit risk premiums. In the spirit of Avellaneda and Scherer (2000), I run a time-dependent PCA. The sample is divided into pre-tapering and post-tapering periods. I show the percentage of variation explained by each component and the cumulative explanatory power in percentages by the extracted components. The dataset includes Brazil, Indonesia, South Africa and Turkey with three maturities ranging from 2 years to 10 years. For all maturities and time periods, single and cumulative explanatory powers are reported respectively.

Panel A. Pre-Tapering

	0-2 Year		2-5 Year		5-10 Year	
	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)
PC1	71,82	71,82	78,45	78,45	77,30	77,30
PC2	14,46	86,28	13,33	91,78	13,07	90,36
PC3	9,78	96,06	5,82	97,60	7,72	98,08

Panel B. Post-Tapering

	0-2 Year		2-5 Year		5-10 Year	
	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)
PC1	84,40	84,40	89,16	89,16	88,31	88,31
PC2	11,33	95,73	7,29	96,45	7,78	96,09
PC3	2,95	98,68	2,12	98,57	2,36	98,45

Panel C. All-Period

	0-2 Year		2-5 Year		5-10 Year	
	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)
PC1	76,22	76,22	83,06	83,06	82,58	82,58
PC2	11,80	88,02	9,08	92,14	9,77	92,35
PC3	8,72	96,74	5,40	97,54	5,35	97,70

Table 9: Principal Component Analysis of Currency Risk Premiums. The table below presents the results for static Principal Components Analysis (PCA) of the currency risk premiums. In the spirit of Avellaneda and Scherer (2000), I run a time-dependent PCA. The sample is divided into pre-tapering and post-tapering periods. I show the percentage of variation explained by each component and the cumulative percentage of variation explained by the extracted components. The dataset includes Brazil, Indonesia, South Africa and Turkey with three maturities ranging from 2 years to 10 years. For all maturities and time periods, single and cumulative explanatory powers are reported respectively.

Panel A. Pre-Tapering

	0-2 Year		2-5 Year		5-10 Year	
	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)
PC1	48,78	48,78	49,69	49,69	51,61	51,61
PC2	24,94	73,73	19,31	69,01	17,43	69,03
PC3	17,44	91,17	14,02	83,03	12,92	81,95

Panel B. Post-Tapering

	0-2 Year		2-5 Year		5-10 Year	
	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)
PC1	58,12	58,12	55,70	55,70	49,57	49,57
PC2	16,42	74,53	19,95	75,65	23,85	73,42
PC3	14,79	89,32	14,69	90,34	19,02	92,44

Panel C. All-Period

	0-2 Year		2-5 Year		5-10 Year	
	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)	Exp.(%)	Cum.(%)
PC1	56,07	56,07	54,15	54,15	50,92	50,92
PC2	19,49	75,56	20,35	74,50	19,10	70,02
PC3	15,14	90,70	16,79	91,30	18,56	88,58

2.2 Interaction Effects between Liquidity and Credit

Recent literature also argues that liquidity premium should amplify credit risk rather than affecting asset prices independently (e.g, Morris and Shin (2009) and He and Milbradt (2014)), implying that liquidity and default might be endogenously linked so that there can be an economically significant interaction between these two risk premiums. Hence, I also investigate the interaction between credit, currency risks and liquidity, i.e., how credit and currency risks affect illiquidity and vice versa.

In order to determine the nature of the relationship between (changes in the) each component -namely the liquidity (ΔLiq), credit (ΔCr) and currency (ΔCry) components, I investigate first whether there exists a lead-lag relationship between them, using a Granger-causality test, a statistical notion of causality based on the relative forecasting power of two time-series for each other: Time-series i 'Granger-cause's time-series j if previous lagged values of i can be used - and hence, embodies crucial information - to forecast j, compared to using only the information embedded in j alone. I can represent their linear inter-relationships with the following vector autoregression (VAR) model:

$$\begin{bmatrix} \Delta Liq_t \\ \Delta Cr_t \\ \Delta Cry_t \end{bmatrix} = \begin{bmatrix} c_{Liq} \\ c_{Cr} \\ c_{Cry} \end{bmatrix} + \begin{bmatrix} \alpha_{11}^1 & \alpha_{12}^1 & \alpha_{13}^1 \\ \alpha_{21}^1 & \alpha_{22}^1 & \alpha_{23}^1 \\ \alpha_{31}^1 & \alpha_{32}^1 & \alpha_{33}^1 \end{bmatrix} \begin{bmatrix} \Delta Liq_{t-1} \\ \Delta Cr_{t-1} \\ \Delta Cry_{t-1} \end{bmatrix} + \begin{bmatrix} \alpha_{11}^2 & \alpha_{12}^2 & \alpha_{13}^2 \\ \alpha_{21}^2 & \alpha_{22}^2 & \alpha_{23}^2 \\ \alpha_{31}^2 & \alpha_{32}^2 & \alpha_{33}^2 \end{bmatrix} \begin{bmatrix} \Delta Liq_{t-2} \\ \Delta Cr_{t-2} \\ \Delta Cry_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{Liqt} \\ \epsilon_{Crt} \\ \epsilon_{Cryt} \end{bmatrix} \quad (6)$$

where $\epsilon_t \sim \mathcal{N}(0; \Omega)$ and α_{ij}^p is the coefficient of a pth lag. If α_{21}^1 and α_{21}^2 are both different from zero at the same time, then I can conclude that liquidity premium Granger-causes credit risk premium. On the contrary, if α_{12}^1 and α_{12}^2 are different from zero jointly, credit risk would be Granger-causing liquidity premium. Similar hypotheses would be tested for other coefficients to investigate the relationships between credit and currency risk premiums and between liquidity and currency risk premiums. The results of the Granger-causality test, with two lags, for the relationship between the changes in the liquidity, credit and currency components for each country, are reported in Table 10, where I report Wald test statistics for the contemporaneous significance of the cross-variable terms for each equation[3].

As Table 10 shows, the liquidity Granger-causes credit risk premium in each LC bond market at 5% significance level, while the opposite directionality is not significant at any of the usual confidence levels. I find that a change in liquidity significantly affects credit risk. This result is in line with He and Milbradt (2014) which suggests that illiquidity of the bond market can feedback to the credit risk. Further, I also find that the coefficients of both contemporaneous and lagged changes of the LC bond market liquidity premium are statistically and economically significant in explaining the credit risk premium for each country, after controlling for the lagged variables of liquidity and currency risks. Not only are the results statistically and economically significant, but they also validate the outcomes of the Granger-causality. The opposite of this relationship is posited in Pelizzon, Subrahmanyam, Tomio and Uno (2014) for Italian sovereign government bond market. One possible explanation for this result may be that the arguments used by them in the context of Eurozone sovereign bonds which only bear the credit and liquidity risk premiums, do not apply for EM local currency sovereign bonds.

In order to interpret the dynamics of the system, I also calculate the impulse response functions (IRF) for the relationships between these risk premiums. IRF are generated using a VAR(2) setting explained in Eq. 6 using rescaled variables with mean 0 and standard deviation 1 to ease interpretation. Figure 7, Figure 8, Figure 9 and Figure 10 shows the results, where the 5% confidence bands were bootstrapped based on 10,000 repetitions. As shown in Panel (a) in corresponding figures, a one-standard-deviation shock to the liquidity premium at time 0 corresponds to a change

[3] The Akaike criterion suggests a lag-length of 2.

of 0.2% to 0.4% in credit spread components across countries and is absorbed in four to six weeks. The results are both statistically and economically significant and confirm the results of the Granger-causality. The IRF in Panel (b-c) of corresponding figures show that a shock at time 0 to credit only affects currency premium and has very limited impact on liquidity, indicating that the reaction of the credit spread to a shock in market liquidity is never different from zero, in line with the findings of the Granger-causality tests. In unreported results, I also check these dynamics for pre- and post-tapering periods. My main findings imply that, after the tapering announcement, the relationship between credit risk and liquidity strengthened and this relationship depends not simply on the dynamics of liquidity risk but also on the level of liquidity premium.

Given the strong linkage between LC bond market liquidity and sovereign credit risk, my results will be of interest to EM regulators and central bankers, helping them to improve their tools for monitoring both credit and liquidity risks. Market liquidity is largely affected by investors' behavior, their risk attitudes and perceptions. Thus, increasing foreign participation in LC bond markets indicates that dramatic changes in liquidity conditions (e.g, FED tapering announcement) can change foreign investors' risk attitudes which could lead to a solid impact on market sovereign credit risk. A close coordination between regulators and central banks is fundamental to avoid strong negative externalities.

Table 10: Vector Autoregression.
This table presents the results for the regressions of the weekly changes in credit (ΔCr), currency (ΔCry) and liquidity premiums (ΔLiq) on the lagged terms of both variables in a VAR(2) setting. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

$$\begin{bmatrix} \Delta Liq_t \\ \Delta Cr_t \\ \Delta Cry_t \end{bmatrix} = \begin{bmatrix} c_{Liq} \\ c_{Cr} \\ c_{Cry} \end{bmatrix} + \begin{bmatrix} \alpha_{11}^1 & \alpha_{12}^1 & \alpha_{13}^1 \\ \alpha_{21}^1 & \alpha_{22}^1 & \alpha_{23}^1 \\ \alpha_{31}^1 & \alpha_{32}^1 & \alpha_{33}^1 \end{bmatrix} \begin{bmatrix} \Delta Liq_{t-1} \\ \Delta Cr_{t-1} \\ \Delta Cry_{t-1} \end{bmatrix} + \begin{bmatrix} \alpha_{11}^2 & \alpha_{12}^2 & \alpha_{13}^2 \\ \alpha_{21}^2 & \alpha_{22}^2 & \alpha_{23}^2 \\ \alpha_{31}^2 & \alpha_{32}^2 & \alpha_{33}^2 \end{bmatrix} \begin{bmatrix} \Delta Liq_{t-2} \\ \Delta Cr_{t-2} \\ \Delta Cry_{t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{Liqt} \\ \epsilon_{Crt} \\ \epsilon_{Cryt} \end{bmatrix}$$

	Brazil			Indonesia			South Africa			Turkey		
	ΔLiq	ΔCr	ΔCry	ΔLiq	ΔCr	ΔCry	ΔLiq	ΔCr	ΔCry	ΔLiq	ΔCr	ΔCry
ΔLiq_{-1}	-0,057*	0,488**	0,284**	-0,002**	0,556**	0,298*	-0,025**	0,471**	0,026*	-0,082*	0,523***	0,221*
	-[1,841]	[2,286]	[2,024]	-[2,016]	[2,258]	[1,957]	[2,082]	[2,042]	[1,862]	-[1,699]	[3,209]	[1,760]
ΔLiq_{-2}	-0,315***	0,173	0,103*	-0,253*	0,217*	0,553	-0,291**	0,291*	0,194	-0,250**	0,239*	0,304
	-[2,331]	[1,237]	[1,752]	-[1,854]	[1,737]	[1,032]	-[2,178]	[1,681]	[0,472]	-[1,993]	[1,747]	[1,166]
ΔCr_{-1}	0,050	0,168*	0,028**	0,129	0,052*	0,008*	0,023	0,045**	0,399**	0,052	0,110**	0,030**
	[0,505]	[1,834]	[2,129]	[1,288]	[1,737]	[1,932]	[0,362]	[2,004]	[2,076]	[0,447]	[2,066]	[2,124]
ΔCr_{-2}	0,064	0,028*	0,025*	-0,054	0,177	0,048	0,028	0,117*	0,040*	-0,182	0,237*	0,254*
	[0,665]	[1,810]	[1,720]	-[1,100]	[1,318]	[1,224]	[0,453]	[1,798]	[1,808]	-[1,078]	[1,701]	[1,827]
ΔCry_{-1}	-0,001	0,381	0,020	0,073	0,486	-0,297*	-0,010	0,316	-0,483***	-0,023	0,286	-0,153
	-[0,014]	[1,231]	[0,142]	[1,099]	[1,558]	-[1,860]	-[0,179]	[1,528]	-[2,957]	-[0,361]	[1,124]	-[1,159]
ΔCry_{-2}	-0,013	-0,005	-0,058	-0,040	0,009	-0,191	-0,027	0,087	-0,004	-0,144	0,003	0,082
	-[0,173]	-[0,053]	-[0,364]	-[0,925]	[0,076]	-[1,022]	-[0,501]	[0,689]	-[0,026]	-[1,020]	[0,038]	[0,557]
Intercept	-0,002	0,032	0,013	0,004	0,003	0,010	0,001	0,023	-0,007	0,011	0,011	-0,014
	-[0,078]	[1,091]	[0,280]	[0,377]	[0,092]	[0,189]	[0,080]	[0,914]	-[0,202]	[0,385]	[0,358]	-[0,253]
Granger Causality												
$Liq \rightarrow Cr$		3,0785***			2,1523**			2,1829**			3,7509***	
$Cr \rightarrow Liq$	0,0152			0,7015			0,9019			0,6628		
$Liq \rightarrow Cry$		1,6822*			1,8753*			1,8072**			3,4925***	
$Cry \rightarrow Liq$	0,2312			0,6580			0,9342			1,1299		
$Cr \rightarrow Cry$			1,7421*			2,1086**			1,8563**			1,7584*
$Cry \rightarrow Cr$		0,3212			0,7971			1,8656*			0,9314	

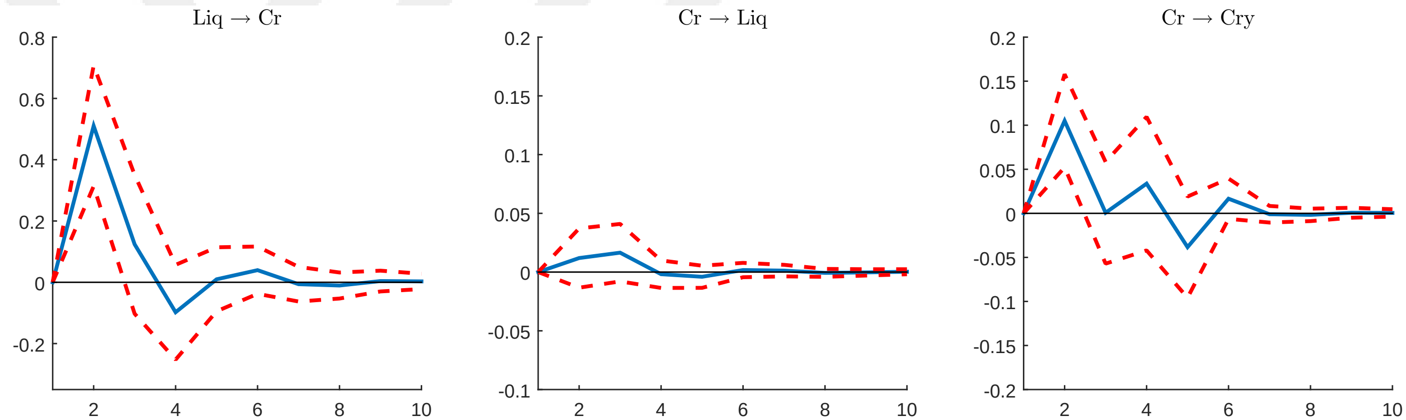


Figure 7: Brazil Impulse Response Functions.
This graph shows the evolution of the impulse response functions (a) of credit risk premium to a shock in the liquidity premium, (b) of liquidity risk premium to a shock in the credit risk premium, (c) of currency risk premium to a shock in the liquidity risk premium where the confidence bands were bootstrapped based on 5,000 repetitions. Impulse response functions are generated using a VAR(2) setting explained in Eq.(5). The response functions (blue lines) from the VAR(2) is shown in each chart with a one standard deviation bandwidth (red lines).

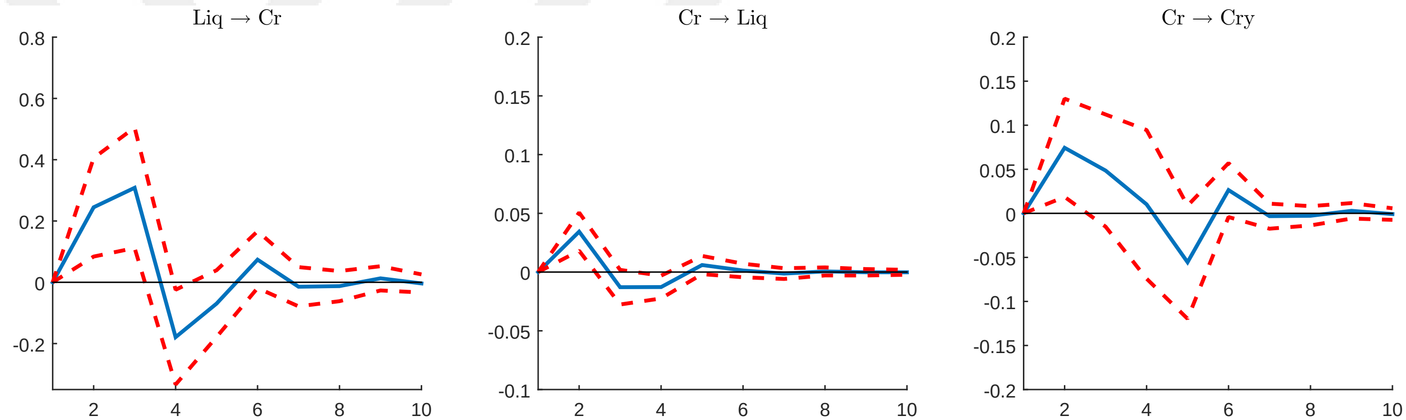


Figure 8: Indonesia Impulse Response Functions.
This graph shows the evolution of the impulse response functions (a) of credit risk premium to a shock in the liquidity premium, (b) of liquidity risk premium to a shock in the credit risk premium, (c) of currency risk premium to a shock in the liquidity risk premium where the confidence bands were bootstrapped based on 5,000 repetitions. Impulse response functions are generated using a VAR(2) setting explained in Eq.(5). The response functions (blue lines) from the VAR(2) is shown in each chart with a one standard deviation bandwidth (red lines).

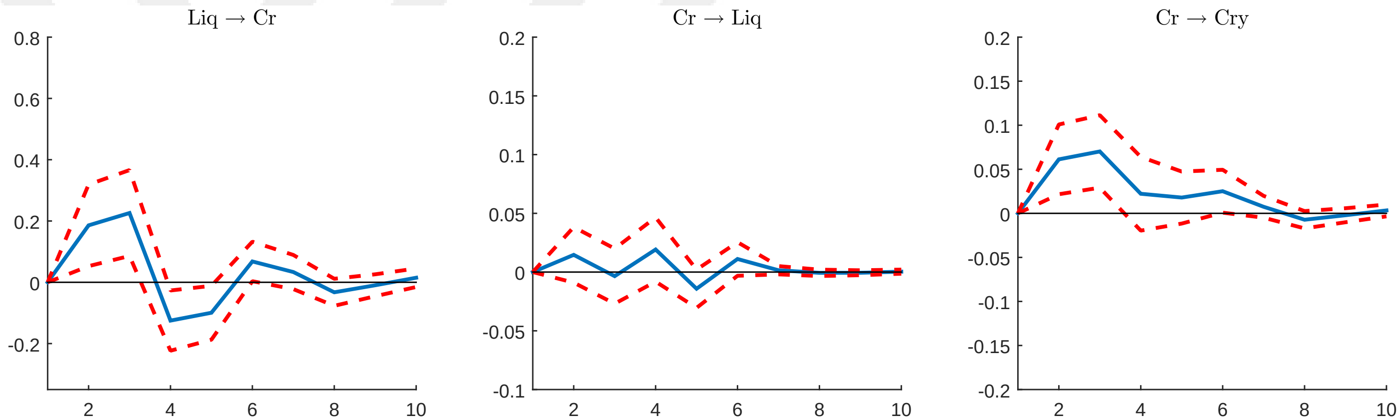


Figure 9: South Africa Impulse Response Functions.
This graph shows the evolution of the impulse response functions (a) of credit risk premium to a shock in the liquidity premium, (b) of liquidity risk premium to a shock in the credit risk premium, (c) of currency risk premium to a shock in the liquidity risk premium where the confidence bands were bootstrapped based on 5,000 repetitions. Impulse response functions are generated using a VAR(2) setting explained in Eq.(5). The response functions (blue lines) from the VAR(2) is shown in each chart with a one standard deviation bandwidth (red lines).

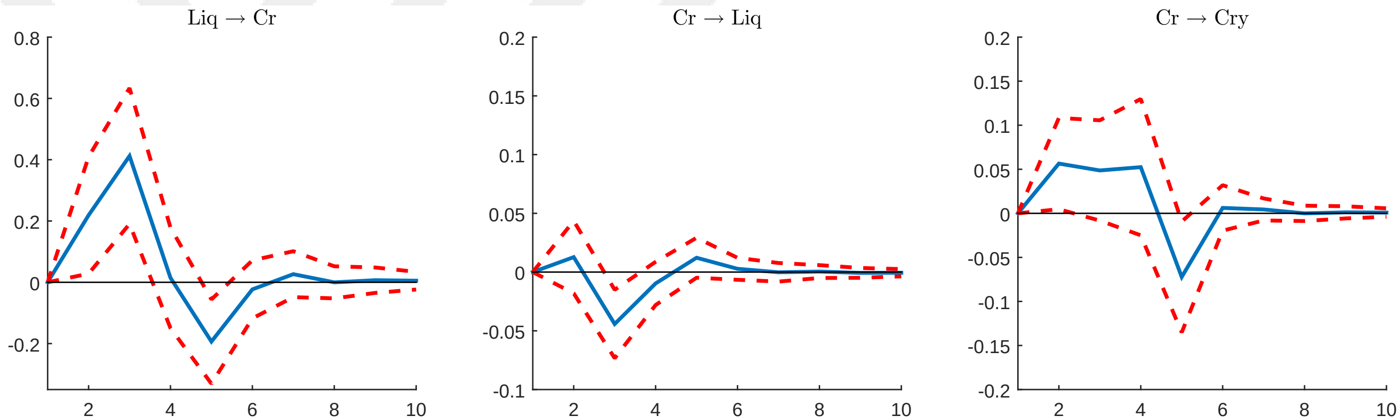


Figure 10: Turkey Impulse Response Functions.
This graph shows the evolution of the impulse response functions (a) of credit risk premium to a shock in the liquidity premium, (b) of liquidity risk premium to a shock in the credit risk premium, (c) of currency risk premium to a shock in the liquidity risk premium where the confidence bands were bootstrapped based on 5,000 repetitions. Impulse response functions are generated using a VAR(2) setting explained in Eq.(5). The response functions (blue lines) from the VAR(2) is shown in each chart with a one standard deviation bandwidth (red lines).

2.3 Price Discovery Analysis

A common practice in the empirical literature is to decompose LC bond spreads over US treasury into a currency and a credit (default) component, which naturally leads to the interpretation that these components are independent of each other (see [3]). However, recent literature also argues that liquidity premium should amplify credit risk rather than affecting asset prices independently (e.g, He and Xiong (2009) and Morris and Shin (2009)), implying that liquidity and default might be endogenously linked so that there can be an economically significant interaction between these risk premiums.

Traditional price discovery analysis would show which risk premium has better information content for price discovery of LC bond yield spread. Given my objective, I conduct the analysis for the entire period without subdividing the sample. There are two traditional ways to conduct price discovery analysis which are information share measure (IS) (Hasbrouck (1995)) and component share (CS) measure (Gonzalo Granger (1995)). Both of these two measures can be estimated by a vector error-correction model (VECM) for market prices, but besides assuming that price volatility reflects new information, IS considers the correlation among different markets. Following Blanco,Brennan & Marsh (2005), I calculate the IS measure to find the contribution of risk premiums to each other. Let $S_t = [S_t^1, S_t^2]$ be the vector of a selected pair of credit, currency or liquidity risk premiums. The three risk premiums must satisfy an arbitrage restriction dictated by Eq(7). It is natural to specify and estimate the system S_t in a Vector Error Correction form (i.e. VECM) as follows:

$$\Delta S_t = A z_t + \Phi(L)\Delta S_{t-1} + u_t \tag{7}$$

with $A = [A_1, A_2]'$. I determine the lags (L) by using Akaike Information Criteria(AIC). I use Johansen cointegration test and find that the risk premiums are highly cointegrated during the sample period. I am interested in exploring two properties of this dynamic system: (a) the existence of an asymmetric structure in the vector A; (b) the Hasbrouck information-share coefficient.

Hasbrouck(1995) measure of "information share" is based on the Stock & Watson(1988) decomposition. It assumes that the price volatility reflects new information. Let σ_1 and σ_2 be the volatility of the estimated residuals u_1 and u_2, and let σ_{12} be the covariance. The market that contributes the most to the variance of the innovations to the common factor is presumed to be the one that contributes most to the price discovery. When $\sigma_{12} = 0$, the Hasbrouck's measure is defined uniquely; when the $\sigma_{12} \neq 0$, this measure provides two bounds, H_l and H_u, expressed as follows:

$$H_l = \frac{A_2^2\left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{A_2^2\sigma_1^2 - 2A_1A_2\sigma_{12} + A_1^2\sigma_2^2}, \quad H_u = \frac{\left(A_2\sigma_1 - A_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{A_2^2\sigma_1^2 - 2A_1A_2\sigma_{12} + A_1^2\sigma_2^2} \tag{8}$$

In the latter case, Baillie, Booth, Tse, & Zabotina(2002) suggest to use the average of H_l and H_u, namely H_m. Based on Eq. (8), H_m estimates how much S^1 contributes to the price discovery process. If $H_m > 50\%$, then S^a is the main contributor. Therefore, $1 - H_m$ shows how much S^b contributes to price discovery process. I report H_m for simplicity. Table 11 summarizes the results, indicating a clear pattern. Across all pairs, A2 coefficient in Eq. (8) is positive and statistically significant, implying that the liqudity risk premium tends to lead credit risk premium in terms of price discovery. I find that the contribution of liquidity premium to credit risk is 75% on average. This price discovery process structure is remarkably similar across all countries.

Table 11: Price discovery analysis. Summary results of the price discovery regressions between Liquidity, Credit and Currency risk premium used in my analysis. The tests are based on VECM specification shown below. I analyze three possible price discovery processes betweeen: (a) Liquidity-Credit, (b) Liquidity-Currency and (c) Currency-Credit. For each pair I let $S_t = [S_t^1, S_t^2]$ be the vector of selected risk premiums. I, denote $A = [A_1, A_2]'$, and the corresponding error terms as $u_t = [u_{1t}, u_{2t}]$, such 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 (L) are determined by AIC. I 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. I report the average H_m for each region, capturing the contribution of S^1 to the price discovery process. 1-H_m captures the contribution of S^2 to the price discovery process. The VECM and the Hasbrouck bounds are specified in order as follows:

$$\Delta S_t = Az_t + \Phi(L)\Delta S_{t-1} + u_t$$

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

	Country	A1	A2	1-HASM
	Brazil	-0,35 -[3,15]	-0,04 -[0,20]	**78%**
	Indonesia	-0,07 -[0,55]	1,08 [3,08]	**82%**
(a) Liquidity- Credit	**South Africa**	-0,45 -[3,62]	0,06 [0,19]	**71%**
	Turkey	-0,32 -[3,10]	0,05 [0,41]	**69%**
	Brazil	-0,34 -[2,96]	0,75 [3,01]	**48%**
	Indonesia	-0,23 -[2,64]	0,57 [1,51]	**55%**
(b) Liquidity- Currency	**South Africa**	-0,60 -[4,11]	0,46 [0,88]	**51%**
	Turkey	-0,41 -[3,44]	0,15 [0,57]	**46%**
	Brazil	-0,09 -[1,76]	0,03 [0,74]	**89%**
	Indonesia	0,01 [1,15]	-0,01 -[2,78]	**74%**
(c) Credit-Currency	**South Africa**	-0,14 -[1,32]	-0,09 -[0,98]	**83%**
	Turkey	-0,32 -[3,21]	0,10 [1,82]	**88%**

CHAPTER III

UNDERSTANDING THE LC BOND MARKET LIQUIDITY

What are the reasons for the sudden evaporation of LC bond market liquidity after the FED tapering announcement? Are foreign investors' fund flow, liquidity, and the credit quality of LC bonds related regardless of the adversity of economic conditions periods and market turbulence? Can global fund managers diversify liquidity risk by holding a diversified portfolio constructed from emerging market LC bonds? To answer these questions, first I investigate whether pricing of liquidity risk in the LC bond market is conditional on the state of the economy, and whether in liquidity risk become more crucial in distressed market conditions. Then, I examine how the LC bond market liquidity varies over time and what fundamental sources drive it.

3.1 Unconditional versus Conditional Liquidity Risk

Financial theory asserts that expected asset returns are related to systematic risk associated with common factors. Under the ceteris paribus, investors should require higher returns on assets which are more sensitive to market-wide liquidity. To examine whether the pricing of liquidity risk in LC bond market is conditional on the state of the economy, I first define a measure of systematic liquidity β_i as the covariation between an individual LC bond's liquidity $\lambda_{i,t}$ and market-wide liquidity $\lambda_{M,t}$ in the spirit of [5] and [4]. I calculate market-wide liquidity as a weighted average of the λ_{it} as $\lambda_{M,t}$ as follows,

$$\lambda_{M,t} = \sum_{i=1}^{N} w_i \lambda_{i,t} \tag{9}$$

where w_i is the size-weight of an individual LC bond in the cross-section of all LC bonds through all countries in the sample, N is the number of bonds in the data-set and λ_{it} is the bond specific liquidity measure as described at Eq.(2). I estimate bond-specific liquidity betas through the slope coefficient in the regression of bond-specific $\lambda_{i,t}$ on market-wide $\lambda_{M,t}$. For each country, I run pooled regressions where LC yield spreads are regressed on each bond β_i and $\lambda_{i,t}$, with control variables:

$$Spread_{i,t} = \alpha + \gamma_1 \lambda_{i,t} + \gamma_2 \beta_i + \text{Control Variables}_{i,t} + \epsilon_{i,t} \tag{10}$$

The results of the regression are reported in Table 12. I run two types of regressions; one with the liquidity beta as the only regressor in addition to bond specific controls, and another one with my liquidity measure $\lambda_{i,t}$ included as an additional regressor.

Both types of regressions, the one with the liquidity beta as the only regressor and the other one with $\lambda_{i,t}$ included, conclude that there is no significance for any of the countries during pre-tapering period. However, the picture changes dramatically after the Fed tapering announcement and LC yield spread for all countries becomes dependent on the liquidity betas. This shows that the my systematic liquidity risk measure did not contribute significantly to LC bond spread before the FED tapering announcement, but after tapering is announced, it started to contribute LC yield spread significantly. This finding is consistent with the regime-dependent importance of liquidity betas reported in [5] and [4] and further substantiates that liquidity risk of LC bond market is conditional on the economy's current state. Regime dependent nature of liquidity betas of LC bonds also implies that global asset managers should be cautious of using normal-time (unconditional) risk management models for the LC bond portfolios as they might entail significant errors. They should also consider not only LC bond market liquidity risk but also a probable change in the liquidity risk under stressed market conditions.

In conclusion, during the times of market turbulence, each individual LC bond's liquidity beta increases across different geographical areas and maturities, proving that liquidity risk is systematic rather than a country specific phenomenon. This is generally consistent with the predictions of [31] and [10] that the typical starting point of liquidity spirals is an increase of uncertainty in the economy and expanding risk aversion of investors. In the next sections, I investigate in detail the role of the global fund managers' risk aversion and funding liquidity in generating a preference for time-varying liquidity risk premium.

Table 12: For each Country and each λ a pooled regression is run with control variables.

$$Spread_{i,t} = \alpha + \gamma_1 \lambda_{i,t} + \gamma_2 \beta_i + \text{Control Variables}_{i,t} + \epsilon_{i,t}$$

where i is for bond and t is time measured in weeks. Each bond's β_i is calculated as the covariance between this bond's monthly λ_{it} and a size-weighted monthly market $\lambda_{M,t}$. Two regressions for each rating pre- and post-tapering are run; one with only β included and one with both β and λ included. Control Variables are credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index) and several macroeconomic variables (current account, reserves, debt service and inflation). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. Panel A covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013 and panel B covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015. The t-statistics are given in parentheses and are calculated from Newey and West(1987) standard errors. Significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

	Pre-Tapering		Post-Tapering	
	β	λ	β	λ
Brazil	0,0130693		0,320782***	
	[1,52]		[2,98]	
	0,0098849	0,0471158**	0,36591***	0,300072***
	[1,58]	[2,22]	[2,90]	[7,06]
Indonesia	0,00814		0,15098**	
	[1,45]		[2,23]	
	0,009281	0,09871**	0,212133**	0,286458***
	[1,50]	[2,06]	[2,37]	[3,37]
South Africa	0,010648		0,160167**	
	[1,23]		[2,04]	
	0,0088592	0,067278*	0,1703982*	0,162136**
	[1,18]	[1,77]	[1,87]	[2,24]
Turkey	0,011997		0,39361**	
	[0,52]		[2,50]	
	0,00987	0,0203718**	0,38408**	0,436258**
	[1,47]	[1,97]	[2,39]	[4,35]

3.2 *Determinants of Commonality in LC Bond Market Liquidity*

The sudden evaporation of LC bond market liquidity across different geographical areas may arise from both supply-side (funding liquidity) and demand-side sources (correlated trading activity of foreign investors). I argue that the demand for liquidity of global institutional investors investing into LC bond markets which are holding similar assets and trading in similar patterns is associated with commonality in LC bond market liquidity. Similar to [47], my intuition is as follows: global asset managers investing into LC bond markets are long only and typically hold large, well-diversified portfolios while regularly facing with liquidity shocks in the form of positive or negative net-flows. The trades of these certain groups of investors may exhibit similarity in both direction and timing. If a group of investors is subject to similar liquidity shocks or changes in their information set (such as *announcement of FED QE tapering*) the trades of these global asset managers will likely be in the same direction and occur with the similar timing[1]. Thus, I specifically examine the role of LC fixed income funds primarily domiciled in developed market jurisdictions as an investor group that can be a source of commonality in LC bond liquidity. My experimental setting is designed to investigate a number of determinants related to supply and demand-side explanations for commonality in liquidity. Specific details about the construction of each determinant are summarized in the appendix.

Supply side: Supply side theoretical models predict that large market declines or high volatility adversely affect the supply of the funding liquidity, which results in a decrease in market liquidity and an increase in commonality in liquidity. In particular, the supply- side hypothesis predicts that commonality in liquidity is positively related to the level of global and local short-term interest rates. Thus, I use the TED spread

[1] In a micro study of mutual fund flows, [48] find that mutual fund flows follow a factor framework, and one of the factors is the US monetary policy stance.

as a proxy for the global level of funding liquidity in the interbank market (e.g [49]), an average of local short-term interest rates of countries under investigation for the proxy of local funding conditions (e.g [29]). Following [28], I also consider EM-CDSI Index as a proxy for perceived default risk for emerging markets as they reflect more constrained credit conditions. Figure 11 summarizes the dynamic behavior of market-wide liquidity with supply-side determinants around tapering tantrum.

Demand side: Demand-side hypothesis predicts that commonality in liquidity is higher where share of institutional investors is greater and also there is greater correlated trading activity (e.g [50] and [29]. My intuition is that growing foreign ownership of LC bond market via global asset managers may give rise to correlated trading across LC bonds across different countries, which, in turn, creates common buying or selling pressure, so higher levels of common variation in LC bond market liquidity. Similar to Feroli, Kashyap, Schoenholtz, and Shin (2014), I extract the first principal component of net fund flows of global funds investing into LC bond markets as my proxy for correlated trading behavior of foreign investors[2]. I call this factor F-Flow. In addition to aggregate fund flows, EPFR provides disaggregated data on the basis of investor type (institutional vs. retail). In Table 14, I show that, similar to developed markets bond funds, LC EM bond funds consist almost exclusively of open-end and actively managed bond funds. There is no leverage embedded in these investment funds. Distinctive feature of the LC bond funds is that retail investors constitute the main investor base of LC EM bond funds (around 60%) and the rest is institutional investors.[3]

Various studies focusing on the demand-side explanation also suggest that investor sentiment might be an important source of commonality in liquidity (e.g. [35]).

[2]Feroli, Kashyap, Schoenholtz, and Shin (2014) extract first factor from fund flows and call it 'bond market sentiment indicator'.

[3]According to EPFR, solely institutional investor targeted funds or funds accepting minimum $100,000 per account are categorized as institutional funds.

Although [28] support supply-side explanations for commonality in liquidity, they evidence that panic selling by investors is a potential sentiment-based cause of commonality in liquidity. To test the sentiment channel, I include Chicago Board Options Exchange Volatility Index (VIX) which is often used as an investor fear index in financial markets (e.g. [8]) and closed end discounts of emerging market debt funds (e.g. [51]) as proxies for variation in investor sentiment. Figure 12 summarizes the dynamic behavior of market-wide liquidity with demand-side determinants around, revealing an important element: institutional fund flow and closed end fund decrease monotonically from the pre-tapering to the market turbulence period, displaying a 84% correlation with LC bond market liquidity.

I regress LC bond market liquidity $\lambda_{M,t}$ on supply and demand side determinants for all sample period as well as sub-periods. The result of the regressions is reported in Table 13. I find evidence that variables within the demand-side (correlated trading and investor sentiment) are highly significant. First, my proxy for the correlated trading activity of foreign investors (F-Flow), is highly significant with a negative slope coefficient, suggesting that a decrease in the net fund flow increases the LC bond market illiquidity, above and beyond the role played by supply side determinants. This result accords well with the demand-side explanation for commonality in liquidity proposed by [50] and [29], who link commonality in liquidity into trading behavior of mutual fund investors. Second, the closed-end discount factor is also highly and statistically significant with a negative slope coefficient sign, suggesting that a larger discount correlates with a decrease in LC bond market liquidity. This finding is in line with theoretical prediction of Kondor and Vayanos (2016) that the risk aversion of global fund managers increases during volatile times and they become less willing to hold illiquid assets due to potential withdrawals from their funds. This generates a natural link between increasing risk aversion and preference for liquidity. Third, supply-side determinants EM-CDSI (the proxy of EM default risk), is also significant and has a positive slope coefficient sign, indicating that an increase in the EM- CDS index (an increase in EM default risk) correlates with deteriorating LC bond market liquidity. Perhaps the most surprising result is that both TED spread (proxy for global funding liquidity) and local short-term interest rate (proxy for local funding liquidity) are found statistically insignificant. This comes as a surprise, given the extensive debate on the conjectured importance of the funding liquidity (e.g. [31] and [52]). Other factors, such as VIX are found statistically insignificant. As [53] noted, the VIX has remarkable predictive power for many other financial and non-financial macroeconomic variables. However, my results suggest that commonality in LC bond market liquidity can be captured by something more than just the volatility of equity markets.

The results also reveal that, during the pre-tapering period, the size of market-wide liquidity premium was small and no variables (except proxies correlated with trading activity of foreign investors and average local interest rate) were statistically significant. In this period, the model produces an R^2 of 24%. During the post tapering, the two main demand factors (except proxies correlated trading activity and investor sentiment) and the EM-CDS index are highly significant and the model produces an R^2 of 63%. These findings suggest that concentration of portfolio holdings and correlated trading of global asset managers domiciled in developed markets may constitute an important transmission channel for financial shocks from developed to emerging markets (see Jotikasthira, Lundblad, and Ramadorai (2012)) and play a role to explain commonality in LC EM bond markets of seemingly uncorrelated economic areas.[4]

In addition to aggregate fund flows, EPFR Global also provides disaggregated data on the basis of investor type (institutional vs. retail). To better understand

[4]For related work in other markets, see [50] and [29], who find correlation between commonality in liquidity and trading behavior of mutual fund investors.

the interaction between the behavior of ultimate investors flow and LC bond market liquidity, next I specifically investigate whether the composition of the investor base plays an important role in LC EM bond market liquidity. Table 14 introduces statistics on strategies, fund and investor types of the global bond funds. Similar to developed markets bond funds, LC EM bond funds consist almost exclusively of open-end and actively managed bond funds.[5]

I calculate the share of funds having inflows or outflows from January 2013 to September 2014 separately for both institutional and retail investors using weekly data. Figure 13 shows that institutional and retail investors react heterogeneously to changes in financial and economic conditions. Retail investors give coordinated decisions during both buying (blue shaded area) or selling (yellow shaded area). Before taper tantrum in May 2013, retail investors had a common propensity to buy. However after May 2013, there has been a strong bias towards getting out of bond funds between retail investors. This high commonality in redemptions continued until the first quarter of 2014. In contrast, institutional investors seemed to be more heterogeneous in their movements. There was a huge redemption during May 2013, but after a short while, the number of funds with outflows vs inflows by institutional investor remained balanced. This finding is in line with Chen, Goldstein, Jiang (2015) that funds with a higher percentage of retail investors exhibit more redemptions than funds having a higher percentage of institutional investors.

Figure 14 and Figure 15 show the marginal contributions of different factors for the total R^2 reported in Table 13, after controlling for lagged values of $\lambda_{M,t}$. I replace net fund flows in/out global funds (F-Flow) factor with net fund flows in/out global

[5]There are mainly two fund structures: open-end and closed-end funds. While closed-end funds, issue a fixed number of shares that are traded on secondary market, open-end funds allow its shareholders to add or substract capital freely. Exchange-traded funds (ETFs) are similar to open-end funds except that they are traded on regular exchanges. Global asset managers are also divided into two camps by their investment strategy. Actively managed funds are funds which are not directly linked to a benchmark index. On the contrary, passively managed funds are closely tied to a specific benchmark index.

retail and institutional bond funds separately and I call them R-Flow and I-Flow respectively. Overall, I interpret my evidence as retail fund flows being more influential than institutional fund flows in explaining variation in LC bond market liquidity. My results clearly indicate that the composition of the investor base plays an important role in LC EM bond market liquidity. Therefore, it is crucial for EM policymakers to become aware of the relationship between market stability, asset managers and investor base.

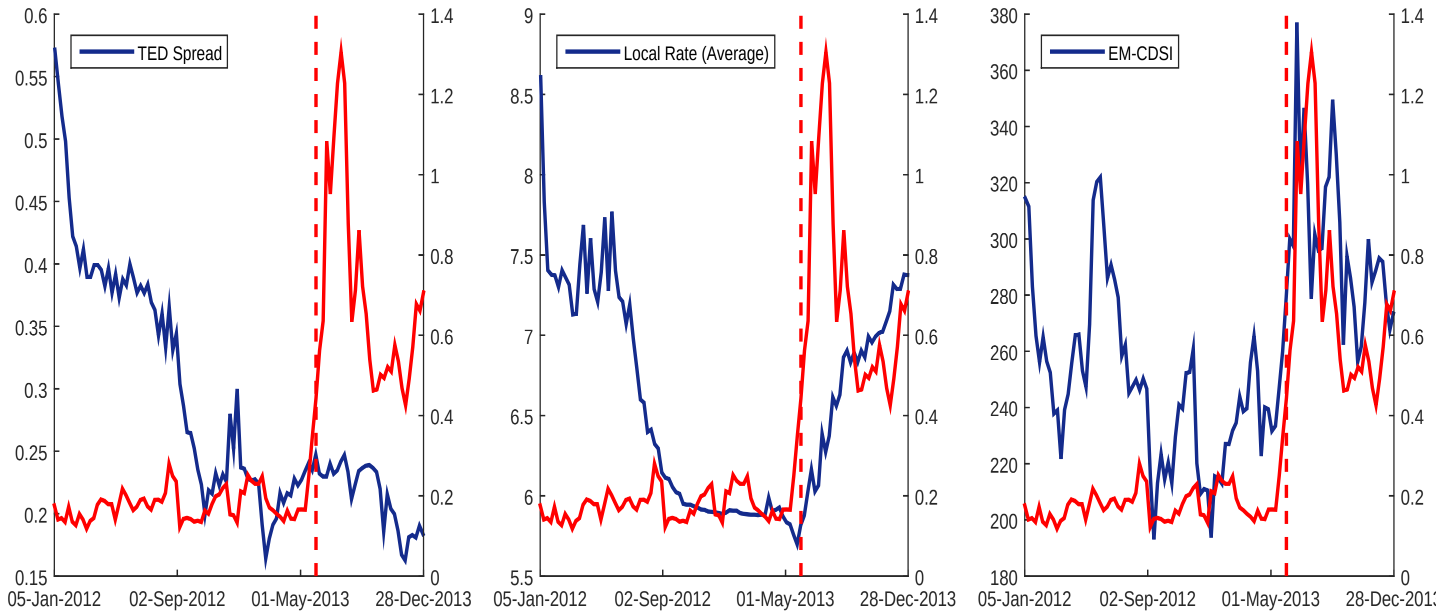


Figure 11: Liquidity Risk Premium vs Supply Factors. This graph shows liquidity risk vs Supply factors: TED Spread, Average Local Rates and EM CDS. The dotted green lines shows FED QE Tapering on 24 May, 2013. Liquidity risk are shown in right hand side vertical axis other variables are shown on the left hand side vertical axis. The sample is January 2, 2010 - November 11, 2015.

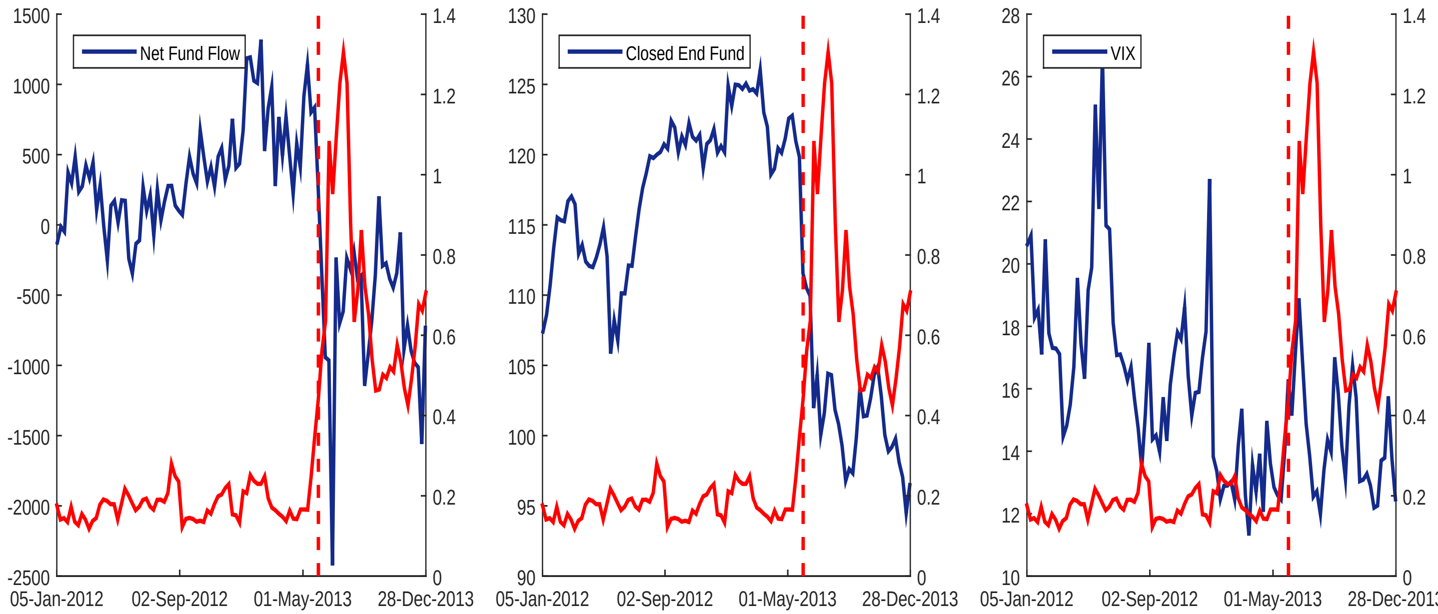


Figure 12: Liquidity Risk Premium vs Demand Factors. This graph shows liquidity risk vs Demand factors: Institutional Fund Flows, Closed End Fund and VIX. The dotted green lines shows FED QE Tapering on 24 May, 2013. Liquidity risk are shown in right hand side vertical axis other variables are shown on the left hand side vertical axis. The sample is January 2, 2010 - November 11, 2015.

Table 13: Regression of Liquidity Risk Premium on Supply and Demand Factors with the control variables. I report the slope coefficients, and the associated White-robust t-statistics (below). The general regression specification is given in the equation below. Explanatory variables, shown as vectors, are Supply Side Factors [TED Spread, Average Local Short Rates, Markit EM-CDS Index]; Demand Side Factors [EPFR Net Fund Flows, Closed End Fund, CBOE VIX Index]; Control Variables [W-Equity, DM-FX Vol, EM-FX Vol]. The sample is January 2, 2010 - November 11, 2015. First column covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013 and second column covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015. Third column covers the whole period. Intercepts are used but not reported. (***) shows a 99% confidence interval, (**) shows a 95% confidence interval, and (*) shows a 90% confidence interval.

		Pre-Tapering	Post-Tapering	All Period
	$L_{M,t-1}$	-0,5792**	-0,6799*	-0,8473**
		-[1,84]	-[1,72]	-[1,77]
	TED Spread	0,0895	0,013	0,1628
		[1,21]	[0,07]	[1,36]
Supply Side	Local Short Rate	0,1455*	0,9907	0,9938
		[1,69]	[0,94]	[1,19]
	EM-CDS	0,0138	0,1791**	0,1723**
		[0,88]	[2,37]	[2,49]
	F-Flows	0,0115*	-0,0817***	-0,1302***
		[1,84]	-[5,88]	-[3,82]
Demand Side	Closed End Fund	-0,0651	-0,4996***	-0,463**
		-[0,82]	-[3,43]	-[2,46]
	VIX	0,0016	0,0087	0,00571
		[1,19]	[1,48]	[1,35]
	W-Equity	-0,0002	-0,0009*	-0,0007*
		-[1,46]	-[1,72]	-[1,67]
Control Variables	DM-FX Vol	0,0082	0,0256	0,0017
		[0,58]	[1,49]	[0,26]
	EM-FX Vol	0,0029	0,0229*	0,0069
		[0,48]	[1,80]	[1,19]
	R-square	24,4%	63,8%	42,1%
	Adj. R-square	23,7%	61,3%	41,9%

Table 14: Types of collective investment vehicles investing in bonds
The share of net total assets as of April 2016, in percentages. According to EPFR, solely institutional investor targeted funds or funds accepting minimum $100,000 per account are categorized as institutional funds.

		Bond Funds Investing in:	
	Advanced Economies	Emerging Market Hard Currency	Emerging Market Local Currency
Fund Structure			
Open-end mutual funds	82%	84%	86%
Closed-end mutual funds	3%	0%	1%
Exchange-traded funds	15%	16%	13%
Investor			
Institutional	61%	60%	33%
Retail	39%	40%	67%
Strategy			
Actively managed	82%	84%	87%
Passively managed	18%	16%	13%

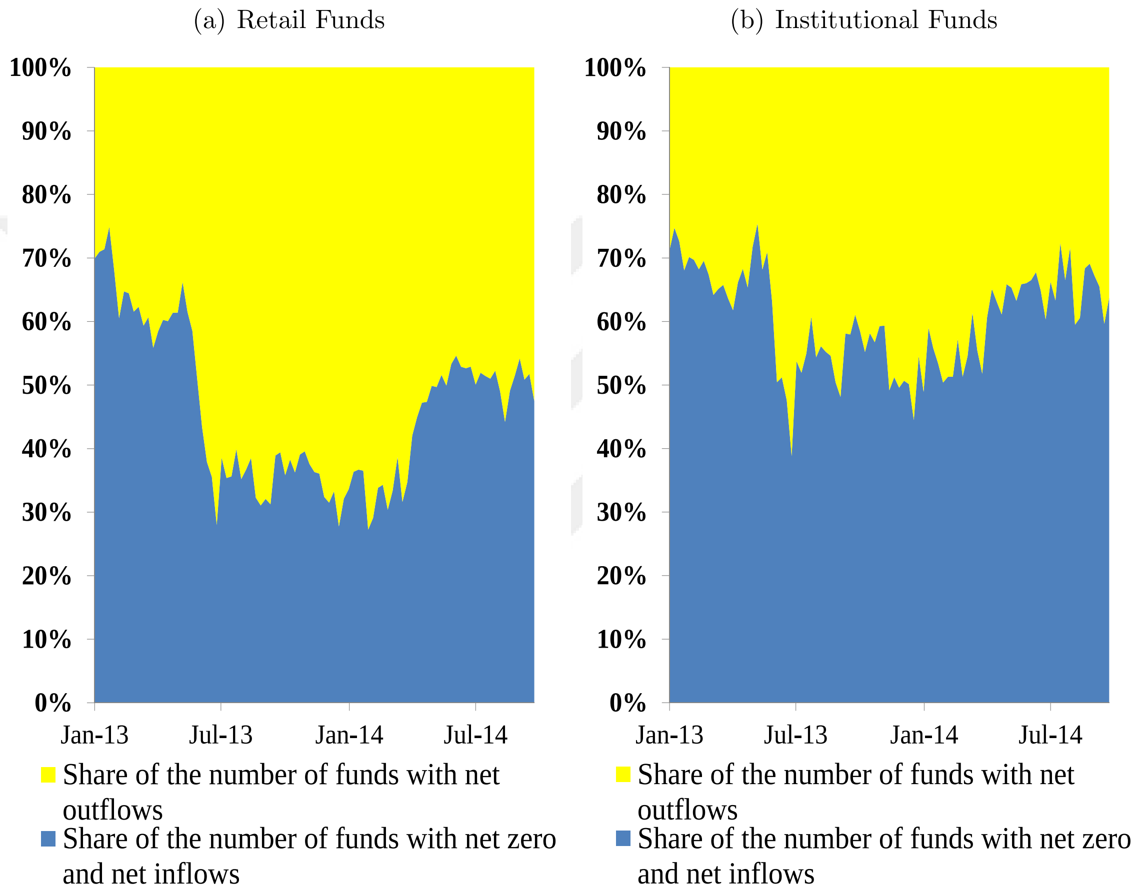
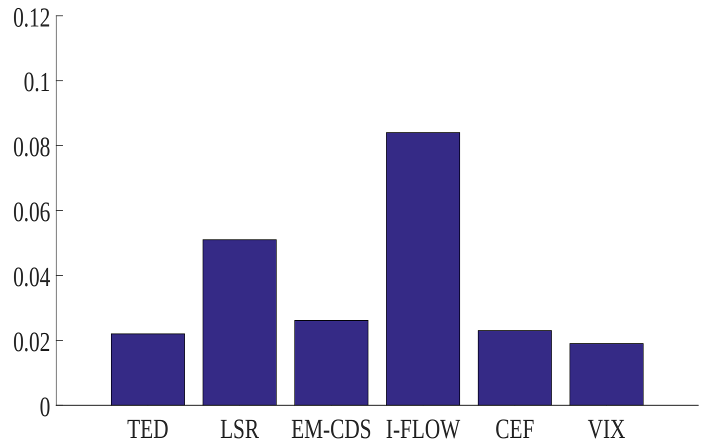


Figure 13: Share of Outflows vs Inflows . Panel (a) and Panel (b) show share of funds with outflows vs inflows using weekly data, as a percentage of the total number of funds in each category. According to EPFR, solely institutional investor targeted funds or funds accepting minimum $100,000 per account are categorized as institutional funds.

(a) Panel A: Institutional Flows - Pre Tapering



(b) Panel B: Institutional Flows - Post Tapering

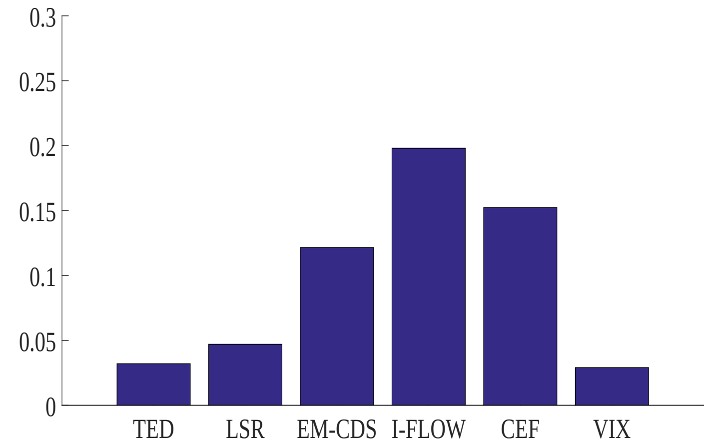


Figure 14: The marginal contribution in percentages of each factor to the total R^2. Explanatory factors, shown as vectors, are Supply Side Factors [TED Spread (TED), Average Local Short Rates (LSR), Markit EM-CDS Index(EM-CDS)]; Demand Side Factors [EPFR Net Retail Fund Flows(R-FLOW),EPFR Net Institutional Fund Flows(I-FLOW), Closed End Fund (CEF), CBOE VIX Index (VIX)]. The marginal contributions of each factor are calculated by excluding one of them each time from regressions. EPFR Net Retail Fund Flows(R-FLOW) and EPFR Net Institutional Fund Flows(I-FLOW) variables are excluded separately. ReG_1 is the R^2 of the regression using whole set of factors, and ReG_2 is the R^2 of the regressions leaving out the factor F, I calculate the MC_f (marginal contribution) as follows:

$$MC_f = ReG_1 - ReG_2$$

The sample is January 2, 2010 - November 11, 2015. The pre-tapering period which is January 2, 2010 - 24 May, 2013 and the post-tapering period is 24 May, 2013 - November 11,2015.

(a) Panel A: Retail Flows - Pre Tapering

(b) Panel B: Retail Flows - Post Tapering

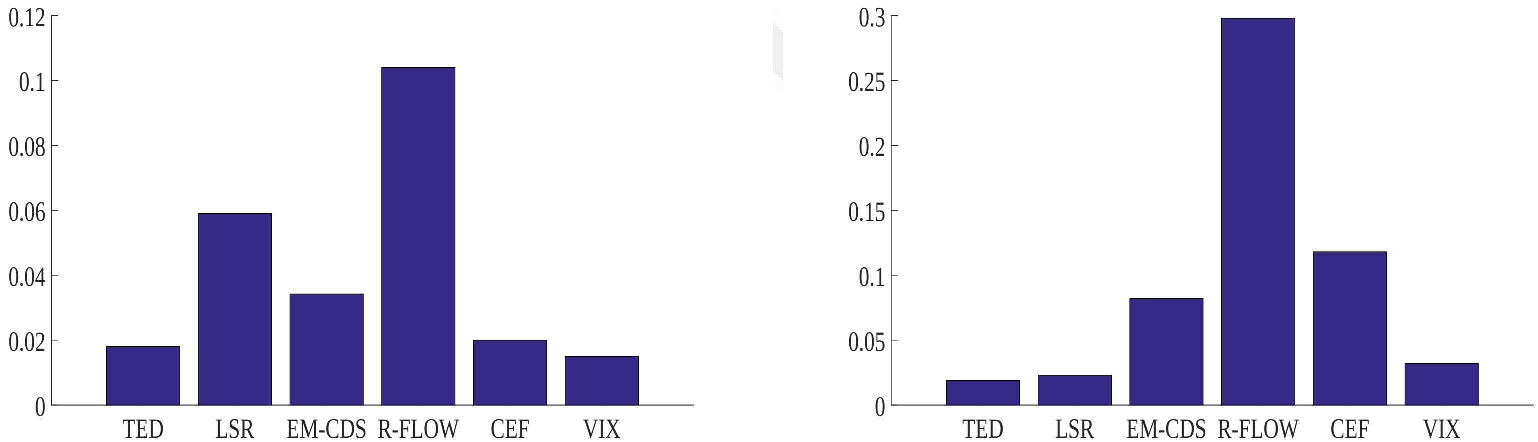


Figure 15: The marginal contribution in percentages of each factor to the total R^2. Explanatory variables, shown as vectors, are Supply Side Factors [TED Spread (TED), Average Local Short Rates (LSR), Markit EM-CDS Index(EM-CDS)]; Demand Side Factors [EPFR Net Retail Fund Flows(R-FLOW),EPFR Net Institutional Fund Flows(I-FLOW), Closed End Fund (CEF), CBOE VIX Index (VIX)]. The marginal contributions of each factor are calculated by excluding one of them each time from regressions. EPFR Net Retail Fund Flows(R-FLOW) and EPFR Net Institutional Fund Flows(I-FLOW) variables are excluded separately. ReG_1 is the R^2 of the regression using whole set of factors, and ReG_2 is the R^2 of the regressions leaving out the factor F, I calculate the MC_f (marginal contribution) as follows:

$$MC_f = ReG_1 - ReG_2$$

The sample is January 2, 2010 - November 11, 2015. The pre-tapering period which is January 2, 2010 - 24 May, 2013 and the post-tapering period is 24 May, 2013 - November 11,2015.

3.3 *Do Global LC Bond Funds Supply or Demand Liquidity?*

While my findings document that supply of risk capital by global LC bond funds play an important role in the sudden evaporation of LC bond market liquidity after the FED tapering announcement, micro aspects of the inner-workings of global LC bond funds are essential to understand how the actions of asset managers and ultimate investor base exacerbate aggregate LC bond market liquidity. In this section, I use micro-level data set on international LC bond funds that are domiciled in foreign jurisdictions to shed new light on how asset managers and investors impact EM bond market liquidity. I use cash holdings and asset allocations, as well as investor flows of 17 global LC bond mutual funds tracked by EPFR Global. These LC bond funds are mostly managed by European and US global asset management companies and among the largest EM bond funds (see Appendix for full list of LC bond funds). This data-set is especially useful as they enable to analyze separately: i-) the redemption (or injection) by the ultimate investor base ii-) the actual portfolio re-balancing by asset managers and iii-) the relative contribution of asset managers and ultimate investors to LC bond fund flows.

At first glance, global LC bond funds can be seen as benign with regarding the financial stability of EM economies as LC bond funds' investors provide equity capital. However, open-ended mutual funds play a similar role to bank in liquidity transformation - the creation of liquid claims that are backed by illiquid assets (see Chernenko and Sunderam (2016)). While bankers create illiquid loans backed by very highly liquid deposits, mutual funds managers invest in relatively illiquid assets such as emerging markets asset and corporate bonds. Similarly, global LC bond funds allow their ultimate investor base to redeem any number of shares at the LC fund's end-of-day net asset value (NAV), which changes the assets under management of the LC bond fund. Once investors start redeeming assets, a feedback loop between redemptions by investors and sales of asset managers can emerge (see [54] and [55]). LC bond fund managers' fire sales can drive down prices further, affecting both the EM economies and LC bond fund investors' balance sheets adversely. Accordingly, this may trigger more redemption of investors. LC bond fund managers then would be a fragile decision point, between having forced sales into an illiquid market (and decreasing net asset value), and not having sufficient cash to cover redemptions (see [36]).

Figure 16 shows the evolution of aggregated cash holdings carried across 17 global EM local currency bond funds and the movement of aggregate LC bond liquidity premium. Aggregate cash level across global LC bond funds remained small during the pre-tapering period which is consistent with an environment described as of high liquidity. However, completely different picture emerges during the tapering period. Aggregated cash holdings of LC bond funds increases dramatically, highlighting a more challenging environment for global fund managers after tapering announcement. As discussed by Chernenko and Sunderam (2016), two arguments might emerge regarding the cash management of global LC bond funds' asset managers. First argument is asset managers acting as a pass-through, simply buying and selling the LC bonds on behalf of their ultimate investors. Thus, asset managers have little need for cash holdings to manage their liquidity. Second one is asset manager playing more active role as they are well aware of the potential fire sale risk of the LC bonds. Hence, they take necessary steps to mitigate liquidation costs associated with investor redemtions and fire sale of underlying assets. To examine whether cash holdings play an important role in the way that global LC bond funds manage inflows and outflows, following Chernenko and Sunderam (2016), I estimate regressions of the change in a global LC fund's cash holdings over the last six months on the net flows it received during those months:

$$\frac{\Delta Cash_{i,t-6\rightarrow t}}{Assets_{i,t-6}} = \alpha + \beta_0 \frac{Flows_{i,t}}{Assets_{i,t-6}} + ... + \beta_5 \frac{Flows_{i,t-5}}{Assets_{i,t-6}} \tag{11}$$

Table 17 reports the results for both regimes. The dependent variable is the change in cash holdings over t as a fraction of net assets of the LC fund. For robustness, I also use the change in the fund's cash-to-assets ratio as the dependent variable. In Table 18, I also add fixed effects to my panel regression and show that the results are robust.

Positive (negative) β_0 indicates that outflows (inflows) during month t decreases (increase) cash holdings. The coefficient β_0 is significant in both periods, showing that an economically significant portion of flows is accommodated through cash holdings. This is consistent with the findings of Chernenko and Sunderam (2016), that global LC bond funds utilize their cash to settle their inflows and outflows rather than just transacting in LC bond markets on behalf of their ultimate investors. According to other coefficients on the table, fund flow effects on cash holdings declines over time. During the pre-tapering period β_0 is positive, showing that on average LC funds increase their cash during inflows and decrease their cash during outflows. However, a completely different picture emerges during post-tapering period and β_0 becomes negative, representing cash hoarding by global LC bond funds. When I use the change in fund's cash-to-assets ratio as the dependent variable, regressions show that global LC bond funds are not simply responding to flows by scaling their investment portfolios up and down in response to the regime. My results hold robust when I add time fixed effects (the last four columns of Table 17), indicating that I am not just picking up a correlation between flows and cash holdings.

My findings document that cash hoarding by LC bond fund managers during post-tapering period represents that LC bond fund ultimate investors demand net outflows, but cash holding actually increases. In other words, the LC fund manager sells more bonds than the amount that is necessary to meet redemptions which I define as the discretionary sales. To investigate whether discretionary sales by asset managers generate fire-sale externalities that exacerbate LC bond market liquidity conditions, I decompose changes in the net asset value (NAV) for each global LC bond fund into investor flow-driven sales/purchases and discretionary sales/purchases. Following [56], I apply the following procedure: First, I calculate the difference between the current and previous month's NAV. Second, I subtract flows from the previously calculated change in NAV. Flows are then decomposed into investor flow-driven purchases and increase in cash holdings due to flows after controlling for currency valuation and bond price valuation effects.[6] Figure 17 is a time series chart for the three components of monthly changes in NAV, aggregated across 17 global EM local currency bond funds. Overall, investor flow-driven sales seems to be the most important factor in explaining changes in the value of LC bond funds during the tapering tantrum, followed by discretionary sales, and change in cash holdings. Figure 16 and Figure 17 clearly show that, even global LC bond mutual funds employ no leverage; investor redemption or cash hoarding by asset managers may generate fire-sale externalities that exacerbate aggregate LC bond market liquidity.

It is still an open question whether investment funds (e.g., hedge funds or mutual funds) managed by asset managers supply (e.g., [57]) or demand liquidity (e.g., [31]). Mutual funds and hedge funds differ because of their contractual relationships with investors and their trading strategies. Hedge funds can utilize leverage and invest more patiently than mutual funds by imposing tight lockups and redemption restrictions on their investors. If global LC bond funds act strategically, I expect to see them demanding less liquidity when the overall level of liquidity in LC bond markets is low. I use a regression analysis with conditional variables to analyze the interaction between discretionary purchases/sales, fund flow induced purchases/sales and the LC

[6]One practical complication arises when implementing this methodology adopted by [56] is that variables are observed only at the end of each time interval. However, real life investor flows can happen continuously throughout the time. To overcome these data limitations, I consider where all purchases and sales of bonds happen at the end of the month in frictionless competitive markets at prices reported at the end of the month.

bond market liquidity $\lambda_{M,t}$.[7] The regression is defined in the following form:

$$\Delta\lambda_{M,t} = \alpha + \beta\ \text{Cond} * \big[I_{\text{Cond}<-2\sigma} \quad I_{-2\sigma<\text{Cond}<-\sigma} \quad I_{-\sigma<\text{Cond}<\sigma} \quad I_{\sigma<\text{Cond}<2\sigma} \quad I_{\text{Cond}>2\sigma} \quad I_{Date=2013M05-M07} \big]$$

where $\Delta\lambda_{M,t}$ is the change in LC bond market liquidity and Cond is one of the explanatory variables (discretionary or fund flow induced purchases and sales variables), I represents a dummy variable based on the defined condition and β is a vector of coefficients. By definition, the coefficients in vector β measure the size of the effect of purchases and sales variables on market liquidity $\lambda_{M,t}$. The size of these coefficient needs a careful categorization for interpretation. If $\beta > 0$, sales made by the fund would improve liquidity conditions (decrease $\lambda_{M,t}$) and purchases would worsen liquidity conditions (increase $\lambda_{M,t}$). In this case, funds would *supply liquidity* in the market. If $\beta < 0$, sales made by the fund would worsen liquidity conditions (increase $\lambda_{M,t}$) and purchases would improve liquidity conditions (decrease $\lambda_{M,t}$). In this case, funds would *demand liquidity* from the market.

The results of these regressions are given in Table 15. In column (1) and (2), the coefficients of the condition Cond $< 2\sigma$ are negative and statistically significant. These coefficients show that during turbulent times (defined by extreme outflows), global LC bond funds *demand* liquidity from the LC bond markets both by flow induced and discretionary sales. My findings are in line with growing literature that examines the procyclical investment behavior of global asset managers (see [19] and [58]) that neither asset managers nor ultimate investors are contrarian during the crises, and

[7] To capture the dynamics of the flow (discretionary and fund flow-induced) and liquidity relationship, I run Granger-causality test. The results clearly indicate the direction of the Granger-causality from fund flow to liquidity. Thus, I regress changes in the LC bond market liquidity $\Delta\lambda_{M,t}$ on the contemporaneous changes in the discretionary purchases/sales and fund flow induced purchases/sales.

that their behavior seems to amplify crises and transmit shocks. In normal times and better market conditions, global LC bond funds supply liquidity as the coefficients are greater than zero, however not significant in all conditions. Additionally, as I want to analyze particularly the tapering period, I use a dummy for the months between 2015-May and 2015-August which are likely to capture the most sizable outflows from these funds. The results are given in Column (3) and Column(4). Again, the coefficients of tapering dummy variable are negative and statistically significant, suggesting that pro-cyclical investors *demanded* liquidity and exacerbated aggregate LC bond market liquidity. In unreported results, I test the robustness of the previous results by using conditional variable lagged by one week. The results are broadly consistent with those from contemporaneous regressions.

Overall, my results reveal that emerging market economies that are relying heavily on pro-cyclical investors such as global investment bond funds should become aware of the relationship between financial market stability, asset managers and investor base.

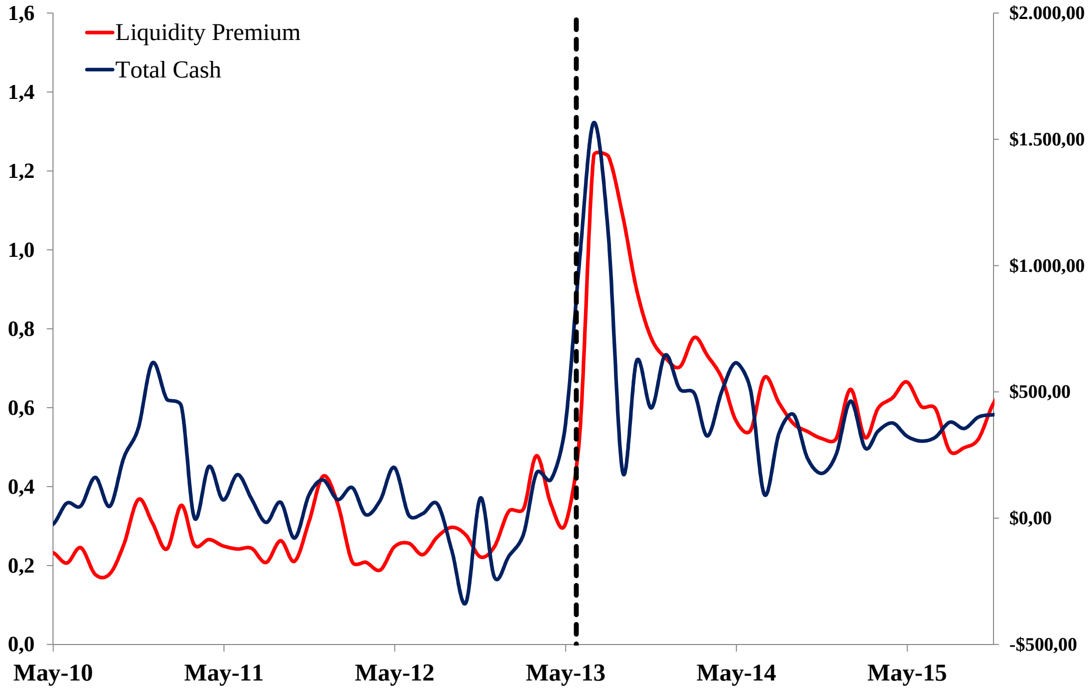


Figure 16: Total Cash vs LC Bond Market Liquidity. This graph shows the total share of cash holdings of 17 selected Emerging Market Local Currency Bond Funds. The data is from EPFR database. EPFR provides monthly data on cash holdings, asset allocations as well as investor flows allowing me to identify discretionary sales and investor-driven sales. Following methodology adopted by Shek, Shim and Shin (2014), for each month and for each fund, I decompose changes in the net asset value (NAV) of the 17 local currency funds.

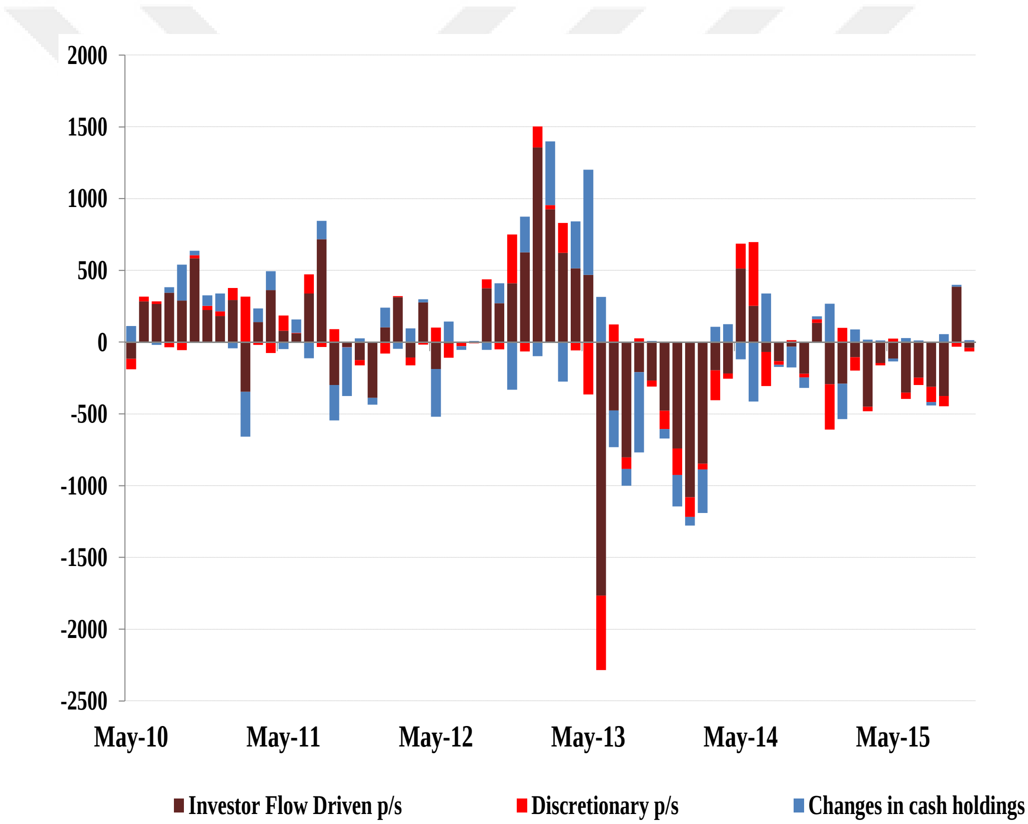


Figure 17: Investor Flow Driven Purchases/Sales, Discretionary Purchases/Sales & Change in Cash Holdings. The data is from EPFR database. EPFR provides monthly data on cash holdings, asset allocations as well as investor flows allowing me to identify discretionary sales and investor-driven sales. Following methodology adopted by Shek, Shim and Shin (2014), for each month and for each fund, I decompose changes in the net asset value (NAV) of the 17 local currency funds.

Table 15: Regressions of Sub-components of flows vs Market Liquidity.Coefficients on the subcomponents of fund flows. Differences of Market Liquidity (ΔLiq) is regressed on condition variables namely, Discretionary purchases/sales and Flows-induced purchases/sales. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***. The regressions are run for each condition variable in the following form.

$$\Delta\lambda_{M,t} = \alpha + \beta \text{ Cond} * \left[I_{\text{Cond}<-2\sigma} \quad I_{-2\sigma<\text{Cond}<-\sigma} \quad I_{-\sigma<\text{Cond}<\sigma} \quad I_{\sigma<\text{Cond}<2\sigma} \quad I_{\text{Cond}>2\sigma} \quad I_{Date=2013M05-M07}\right]$$

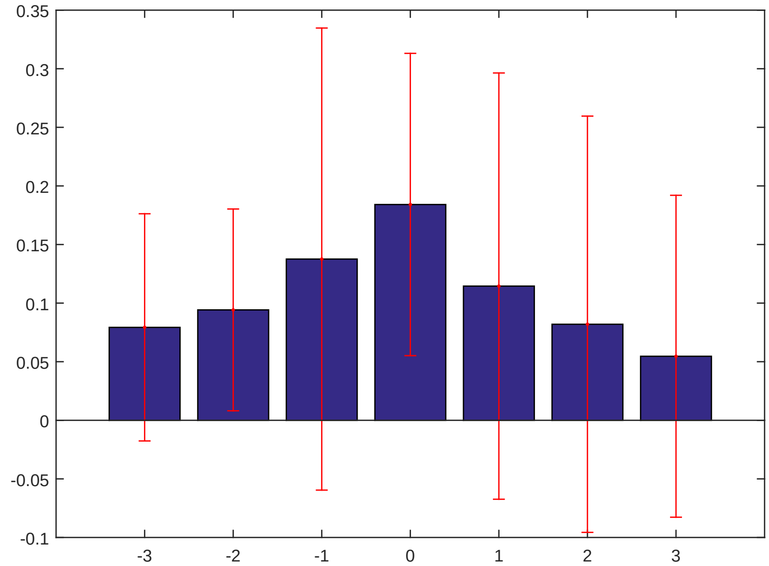
where Cond is one of the explanatory variables (discretionary and fund flow induces purchases and sales variables), I represents a dummy variable based on the defined condition and β is a vector of coefficients.

	Dep: Market Liquidity Cond : Flow Induced Purchases/Sales	Dep: Market Liquidity Cond : Discretionary Purchases	Dep: Market Liquidity Cond : Flow Induced Purchases/Sales	Dep: Market Liquidity Cond : Discretionary Purchases
Cond <-2 σ	-0,292***	-0,061***	-0,170***	-0,057***
	-[6,72]	-[2,60]	-[2,46]	-[2,90]
-2 σ <Cond <* σ	-0,204*	-0,102	0,415	-0,113
	-[1,91]	-[0,63]	[0,67]	-[0,48]
- σ <Cond <σ	-0,002	0,168	0,022	0,050
	-[0,08]	[1,07]	[0,66]	[0,37]
σ <Cond <2 σ	0,145	0,060	0,140	0,049
	[1,35]	[0,02]	[1,36]	[0,16]
Cond >2 σ	0,079	0,191*	0,077	0,151*
	[1,14]	[1,88]	[1,11]	[1,69]
Dummy - Tapering (2013M05-M07)			-0,417***	-0,097***
			-[2,53]	-[2,75]
R Squares	16,1%	8,7%	17,2%	10,8%

Table 16: Vector Auto-Regressions between Fund-Flow Driven, Discretionary Sales and Change in cash flows. Coefficients on the explanatory variables are from panel regressions with fund fixed effect. Dependent and explanatory variables are normalised by the NAV of each fund at the beginning of the month, except the VIX. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

	Flows Induced Purchases	Discretionary Purchases	Change in Cash Holdings
Change in Cash Holdings (-1)	0,544	0,080	-0,031
	[1,35]	[0,55]	-[0,16]
Discretionary Purchases (-1)	1,546	0,122	0,162
	[1,23]	[0,53]	[0,52]
Flows Induced Purchases (-1)	0,272*	0,114***	0,125***
	[1,83]	[3,23]	[2,85]
Constant	38,96	-11,02	-3,611
	[0,74]	-[0,63]	-[0,15]
R-squared	30,6%	17,7%	13,8%

(a) Cash Holdings vs Flow-driven purchases



(b) Discretionary Purchases vs Flow-driven purchases

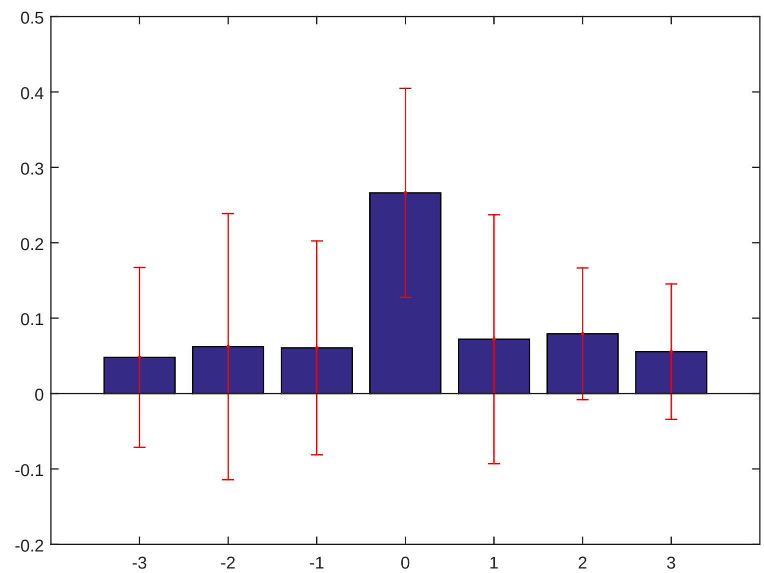


Figure 18: Cross-correlograms between Flow-driven purchases vs Cash Holdings and Flow-driven purchases vs Discretionary Purchases

Table 17: Flow Management through Cash Holdings. This table reports the regression results of changes in cash holdings on fund flows. In the first two columns, the dependent variable is the change in cash over a six-month period, scaled by assets six months ago. In column 3 and 4 the dependent and independent variables are the change in the cash-to-assets ratio over the six-month period and monthly net fund flows, scaled by net assets six months ago, respectively. Standard errors are adjusted for clustering by time.

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$		$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$	
	Pre-Tapering	Post-Tapering	Pre-Tapering	Post-Tapering
$Flows$	0,104***	-0,078***	0,052***	-0,045***
	[3,429]	-[4,370]	[2,774]	-[2,848]
$Flows_{t-1}$	0,082***	-0,061***	0,037*	-0,030**
	[2,765]	-[3,732]	[1,788]	-[2,296]
$Flows_{t-2}$	0,057**	-0,039***	0,042	-0,028*
	[2,314]	-[2,412]	[1,112]	-[1,828]
$Flows_{t-3}$	0,052**	0,011*	0,022	0,017
	[2,117]	[1,717]	[0,813]	[1,220]
$Flows_{t-4}$	0,029	-0,012	0,025	-0,001
	[1,206]	-[1,602]	[1,345]	-[1,166]
$Flows_{t-5}$	-0,094	-0,001	0,033	-0,002
	-[0,804]	-[1,548]	[0,982]	-[1,023]
R-Squares	14,9%	18,7%	1,6%	2,9%

Table 18: Flow Management through Cash Holdings - Fixed Effects. This table reports the regression results of changes in cash holdings on fund flows. In the first two columns, the dependent variable is the change in cash over a six-month period, scaled by assets six months ago. In column 3 and 4 the dependent and independent variables are the change in the cash-to-assets ratio over the six-month period and monthly net fund flows, scaled by net assets six months ago, respectively. Standard errors are adjusted for clustering by time.

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$		$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$	
	Pre-Tapering	Post-Tapering	Pre-Tapering	Post-Tapering
$Flows$	0,107***	-0,077***	0,052***	-0,046***
	[3,498]	-[4,283]	[2,774]	-[2,763]
$Flows_{t-1}$	0,081***	-0,060***	0,038*	-0,029***
	[2,654]	-[3,918]	[1,824]	-[2,365]
$Flows_{t-2}$	0,057**	-0,038***	0,042	-0,027*
	[2,222]	-[2,388]	[1,134]	-[1,865]
$Flows_{t-3}$	0,050**	0,011*	0,023	0,017
	[2,160]	[1,682]	[0,813]	[1,171]
$Flows_{t-4}$	0,030	-0,012*	0,026	-0,001
	[1,242]	-[1,682]	[1,318]	-[1,166]
$Flows_{t-5}$	-0,091	-0,001	0,033	-0,002
	-[0,820]	-[1,548]	[0,972]	-[1,043]
R-Squares	15,6%	17,8%	1,6%	3,0%

CHAPTER IV

ROBUSTNESS

4.1 Benchmark risk-free rate and credit risk

In my analysis, I focus on the yield spread of an LC bond, defined as its yield differential relative to that of a benchmark U.S. swap of similar duration. The benchmark could be either the Treasury bond or the swap rate curve. Similarly, the benchmark credit risk could be either the credit default swap (CDS) or asset swap spread (ASW) derived from Eurobonds. When the Treasury rate is used as the risk free rate instead of the swap rate and ASW is used instead of CDS, the estimated LC liquidity component does not change much. The change in estimated liquidity is less than 2 bps to 5 bps across the countries. Therefore, my findings on the size of the liquidity premium are insensitive to the choice of benchmark risk free rate and choice of benchmark credit risk. I also repeat this analysis by controlling for local currency sovereign credit ratings and find almost identical results.

4.2 Sub-period analysis

To formally examine whether taper tantrum emerges as a structural break and to investigate the null hypothesis that the regression slope coefficients in each sub-sample are equal, I run classical Chow break point tests. As a result of the tests, I strongly reject this null hypothesis. Hence, I conclude that the independent variables have indeed a different effect in each sub-sample[1]. Figure 20 shows the results.

[1] [59] analyze in detail the effects of tapering announcements by FED on emerging economies and find substantial drops in emerging market stock market indices and large exchange rate depreciation.

4.3 Dynamics of LC Bond Yield Spread

In order to analyze the dynamics of LC bond yield spread, I consider a specification in first differences with one autoregressive variable which would help me to control for the potential persistence in LC yield spread changes:

$$\begin{aligned} \Delta \text{Spread}_{i,t} = \alpha + \Delta \text{Spread}_{i,t-1} + \beta_{i,L} \Delta \text{Liquidity Variables}_{i,t} \\ + \Delta \text{Control Variables}_{i,t} + \epsilon_{i,t} \end{aligned} \tag{12}$$

Thus, my panel of the pooled time-series includes the first differences of LC bond yield spreads as the dependent variable and the first differences of liquidity measures as the explanatory variables. In this difference specification, the static bond characteristic variables are dropped out from control variables.

Table 19 summarizes the results. In general, the results are consistent with those from spread levels. Overall, I find that liquidity effects account for approximately 8% to 11% of explained time-series variation in LC yield spread changes over time for individual LC bonds. During the post-tapering period, I find that nearly all the liquidity proxies have a statistically significantly higher impact on the changes in LC bond yield spreads, pointing the fact that liquidity is far more important in times of market turbulence. In particular, Gibbs measure and Amihud's price impact measure show the strongest effects. All variables have the expected signs except the turnover measure in some countries.

Table 19: Panel Regressions - Yield Spread vs Liquidity Variables. This table reports the panel data regression model explaining the yield spread changes based on weekly averages of all variables:

$$\Delta\text{Spread}_{i,t} = \alpha + \Delta\text{Spread}_{i,t-1} + \beta_{i,L}\Delta\text{Liquidity Variables}_{i,t} + \Delta\text{Control Variables}_{i,t} + \epsilon_{i,t}$$

where i is for bond and t is time measured in weeks. The change of the yield spread is defined by the change in credit risk controls (credit risk via credit default swap and political risk via ICRG political risk index), several macroeconomic variables (current account, reserves, debt service and inflation)and liquidity variables (L^{am} Amihud Measure, L^{gb} Gibbs Measure, L^{hl} High-low Measure, L^{rl} Roll Measure , L^{bd} Bid-ask Measure, L^{ps} Pastor-Stambaugh Measure, L^{tm} Turnover Measure and L^{zr} Zeros Measure). I define LC yield spreads for bond i, as the difference between the LC bond yield and the interpolated maturity-matched U.S. swap rate. The pre-tapering period is January 2, 2010 - 24 May, 2013 and the post-tapering period is 24 May, 2013 - November 11,2015. The t-statistics are given in parentheses and are calculated from [45] standard errors. Significance at 10% level is marked *, at 5% marked **, and at 1% marked ***. In addition,the table also reports each model's R^2.

	Pre-Tapering				Post-Tapering				All Period			
	Brazil	Indonesia	South Africa	Turkey	Brazil	Indonesia	South Africa	Turkey	Brazil	Indonesia	South Africa	Turkey
Amihud	0,011*	0,033**	0,003*	0,014**	0,035**	0,042***	0,013**	0,030***	0,028**	0,039***	0,006*	0,021**
	[1,758]	[1,977]	[1,694]	[1,988]	[2,254]	[2,516]	[1,996]	[2,437]	[1,994]	[2,405]	[1,774]	[2,245]
Roll	0,029*	0,028*	0,019**	0,036**	0,035**	0,042**	0,041***	0,054**	0,031**	0,037*	0,033***	0,048**
	[1,800]	[1,752]	[1,994]	[2,018]	[2,137]	[1,984]	[2,860]	[2,302]	[2,060]	[1,804]	[2,370]	[2,114]
Bond Zero	0,009	0,009	0,008	0,002*	0,013	0,005	0,014	0,003**	0,011	0,007	0,001	0,003*
	[1,069]	[0,350]	[0,602]	[1,889]	[1,039]	[0,892]	[0,663]	[1,976]	[1,044]	[0,484]	[0,636]	[1,905]
Turnover	0,021*	0,079*	0,036	0,045	0,030**	0,094**	-0,022	-0,016	0,019*	0,001**	-0,015	-0,003
	[1,850]	[1,756]	[1,277]	[1,162]	[2,050]	[2,248]	-[0,441]	-[0,430]	[1,910]	[2,058]	-[1,022]	[0,013]
High-low	0,205***	0,064**	0,096**	0,285***	0,297***	0,118***	0,174***	0,360***	0,248***	0,085***	0,135***	0,314***
	[2,863]	[2,264]	[2,256]	[2,916]	[3,149]	[2,491]	[2,652]	[3,417]	[2,540]	[2,346]	[2,440]	[3,136]
Pastor-Stambaugh	0,040*	0,017	0,023*	0,017*	0,053*	0,035	0,029**	0,019*	0,048*	0,029	0,025**	0,018
	[1,739]	[1,033]	[1,789]	[1,683]	[1,748]	[1,309]	[2,118]	[1,902]	[1,743]	[1,146]	[2,006]	[1,574]
Bid-Ask	0,031	0,028*	0,033	0,028*	0,048	0,065**	0,195*	0,036**	0,057	0,043*	0,078	0,029*
	[0,756]	[1,736]	[0,948]	[1,830]	[1,431]	[2,046]	[1,699]	[1,972]	[1,226]	[1,856]	[1,397]	[1,927]
Gibbs	0,009***	0,032***	0,001***	0,015***	0,022***	0,063***	0,003***	0,042***	0,015***	0,045***	0,002***	0,029***
	[3,134]	[2,967]	[2,831]	[2,961]	[3,655]	[3,740]	[3,254]	[3,519]	[3,394]	[3,440]	[3,059]	[3,347]
Liquidity Partial R^2	11,1%	10,3%	8,4%	9,3%	14,1%	11,7%	10,5%	12,6%	12,1%	11,2%	9,0%	10,6%
Total R^2	24,1%	23,3%	21,3%	22,5%	28,1%	26,8%	25,4%	27,6%	26,1%	24,6%	23,1%	25,4%

4.4 Descriptive Statistics and Correlations among liquidity variables

In Table 20, Panel A briefly summarizes the specifications of my dataset. In total, my dataset captures almost 1.5$ trillion of issue in four emerging countries I choose. In Panel B, I report quantiles for my liquidity variables. In Panel C, I determine time-series correlations between countries based on the weekly means. My correlation figures are in line with the principal component analysis that I run between liquidity variables. As expected, λ and Amihud, High-low and Gibbs measures are highly correlated. Additionally, Roll and Gibbs measures are correlated around 70%, due to the fact that they are similar in construction. Turnover and Zeros measure have smaller correlation compared to the other proxies. I also provide intra-country correlations between liquidity variables in Table 21. The results are similar to the aggregate correlations that I have calculated previously. Additionally, all correlations behave similarly between countries.

Table 20: Descriptive Statistics & Correlations of Liquidity Proxies. This table shows statistics for LC bond liquidity proxies. The period is January 2, 2010 - November 11,2015. Panel A shows quantiles for the proxies. Panel B shows correlations among the proxies.

Panel A. Summary statistics for LC Bonds Database

	Brazil	Indonesia	South Africa	Turkey
Number of Bonds	56	153	61	128
Number of Datapoints	35042	101980	30749	51075
Amount Outstanding (USD)	787.2B	111.7B	112,11B	389,3B
Avg. Maturity at Issuance	3,31	7,66	17,62	3,91
Average Yield Spread	9,998	5,193	5,821	7,052
Average Credit Spread	1,653	1,765	1,750	1,967

Panel B. Summary statistics for liquidity proxies

	λ	Amihud (10^{-6})	Roll (%)	Bond Zero (%)	Turnover(%)	High-low (%)	Pastor-Stambaugh (10^{-6})	Bid-Ask (%)	Gibbs (%)
99th	13,2120	1,8264	1,98	45,60	0,97	1,93	0,0173	2,49	2,03
95th	4,3974	0,8297	0,96	36,40	0,23	1,06	0,0096	1,32	1,09
75th	0,8848	0,3098	0,37	24,40	0,03	0,48	0,0038	0,51	0,48
50th	-0,4747	0,1415	0,23	10,41	0,01	0,15	0,0017	0,23	0,22
25th	-1,4629	0,0724	0,05	5,12	0,00	0,07	0,0008	0,09	0,04
5th	-2,1784	0,0406	0,01	1,11	0,00	0,03	0,0002	0,02	0,02
1st	-2,4556	0,0013	0,00	0,65	0,00	0,01	0,0000	0,01	0,00

Panel C. Correlations of liquidity proxies

	λ	Amihud	Roll	Bond Zero	Turnover	High-low	Pastor-Stambaugh	Bid-Ask	Gibbs
λ	1,00								
Amihud	0,78	1,00							
Roll	0,30	0,25	1,00						
Bond Zero	0,07	0,03	0,03	1,00					
Turnover	0,08	0,06	0,06	0,05	1,00				
High-low	0,79	0,64	0,67	0,07	0,16	1,00			
Pastor-Stambaugh	0,08	0,14	0,15	0,04	0,13	0,14	1,00		
Bid-Ask	0,05	0,12	0,14	0,06	0,13	0,13	0,19	1,00	
Gibbs	0,75	0,77	0,72	0,06	0,14	0,46	0,74	0,72	1,00

Table 21: Correlations of Liquidity Proxies. This table shows statistics for LC bond liquidity proxies. The period is January 2, 2010 - November 11,2015.

Brazil/Indonesia South Africa / Turkey	Amihud		Roll		Bond Zero		Turnover		High-low		P-Stambaugh		Bid-Ask		Gibbs	
Amihud	100%	100%														
	100%	100%														
Roll	28%	22%	100%	100%												
	24%	26%	100%	100%												
Bond Zero	4%	3%	3%	1%	100%	100%										
	2%	2%	4%	2%	100%	100%										
Turnover	1%	9%	8%	6%	1%	4%	100%	100%								
	5%	8%	9%	2%	5%	8%	100%	100%								
High-low	64%	61%	65%	69%	4%	8%	19%	17%	100%	100%						
	63%	66%	67%	65%	6%	9%	15%	11%	100%	100%						
Pastor-Stambaugh	17%	12%	14%	16%	1%	4%	12%	18%	16%	14%	100%	100%				
	14%	11%	18%	11%	7%	3%	11%	11%	15%	11%	100%	100%				
Bid-Ask	8%	11%	11%	15%	7%	1%	11%	13%	11%	13%	19%	21%	100%	100%		
	15%	13%	13%	16%	9%	7%	19%	10%	14%	12%	20%	17%	100%	100%		
Gibbs	77%	79%	72%	70%	4%	7%	11%	16%	43%	47%	76%	75%	69%	70%	100%	100%
	76%	76%	71%	73%	3%	8%	18%	11%	45%	49%	72%	74%	74%	73%	100%	100%

4.5 Higher-order principal components

I base my definition of liquidity $\lambda_{i,t}$ on the first principal component of eight liquidity measures. My main argument in the paper is that $\lambda_{i,t}$ (equally weighted sum of three liquidity measures all normalized to a common scale) is a more consistent measure for liquidity compared to the individual measures. It might be the case that some of the other principal components also contain important information about LC bond market liquidity. Thus, I also test the remaining seven principal components have predictive power on LC bonds spreads. Table 22 and Table 23 provide the results. As it is seen in the results, I find that only the first principal component consistently predicts LC bond yield spreads with the right sign while the remaining seven principal components are mostly insignificant and often with unexpected signs.

4.6 Comparison of daily liquidity measures to high-frequency benchmarks

As I am also endowed with intraday transaction based data of Turkish LC bond market, I try to find out whether my liquidity measure based on daily data actually measure intraday nature of the transaction based data. My results document that liquidity measure based on end of day data do indeed capture intraday transaction based data, validating the findings of Schestag (2016) that low-frequency liquidity proxies which only need daily data are generally strongly correlated with intraday based liquidity proxies. Figure 19 plots liquidity calculated using high frequency data and low frequency data, these two liquidity premiums are similar and highly correlated.

4.7 Endogeneity Tests

To test for potential endogeneity bias, I use the Durbin-Wu-Hausman test. I do this for every marginal regression in Table 4 and Table 5, that is to test every liquidity variable separately. If the test is not significant, the liquidity variable can be regarded as exogenous. The results are given in Table 24 and Table 25. Out of the 36 test statistics, 88% are insignificant, indicating that endogeneity is not a major concern.

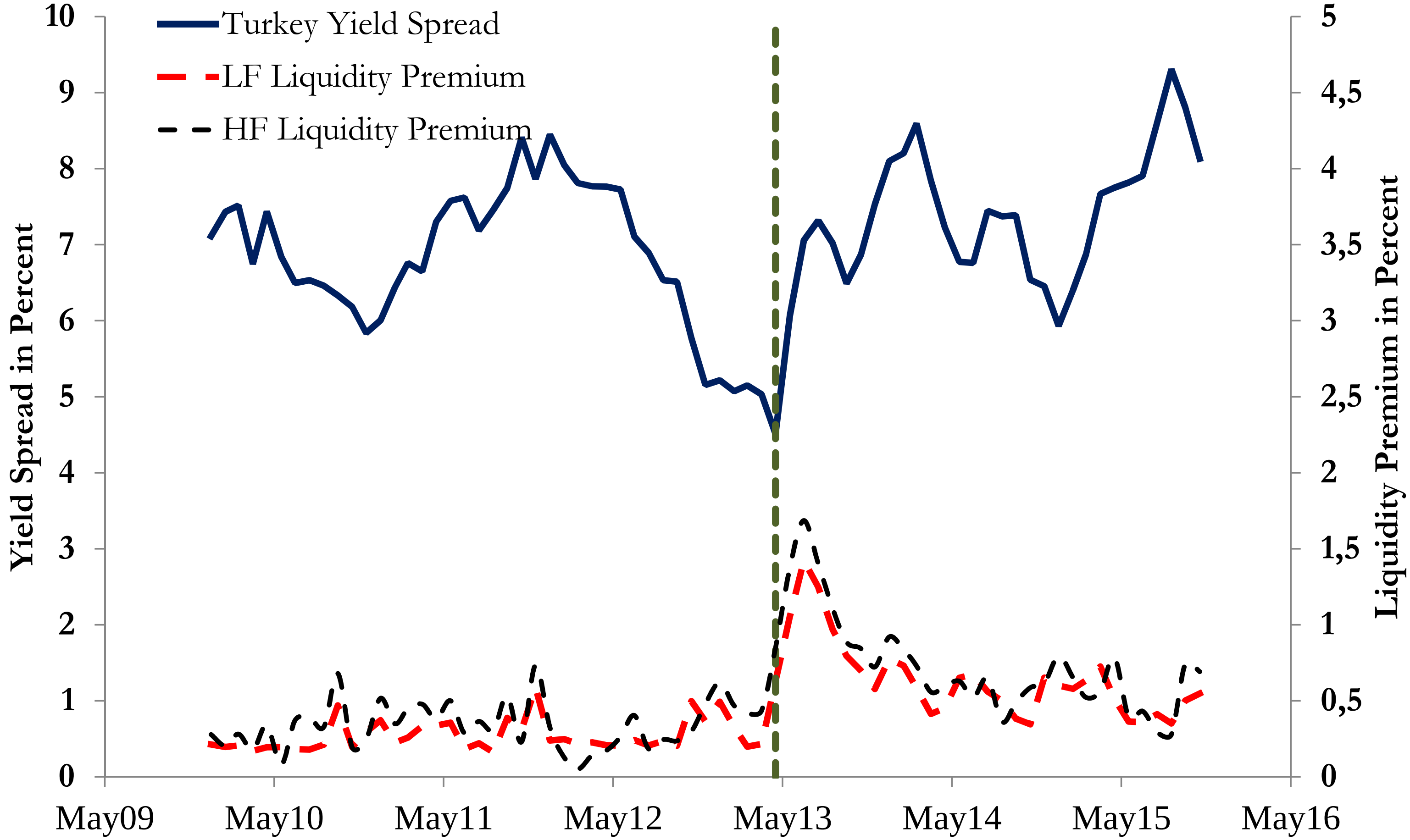


Figure 19: Comparison of daily liquidity measures to high-frequency benchmarks. This graph shows the comparison of the low frequency liquidity measure with its high-frequency counterpart for Turkey.

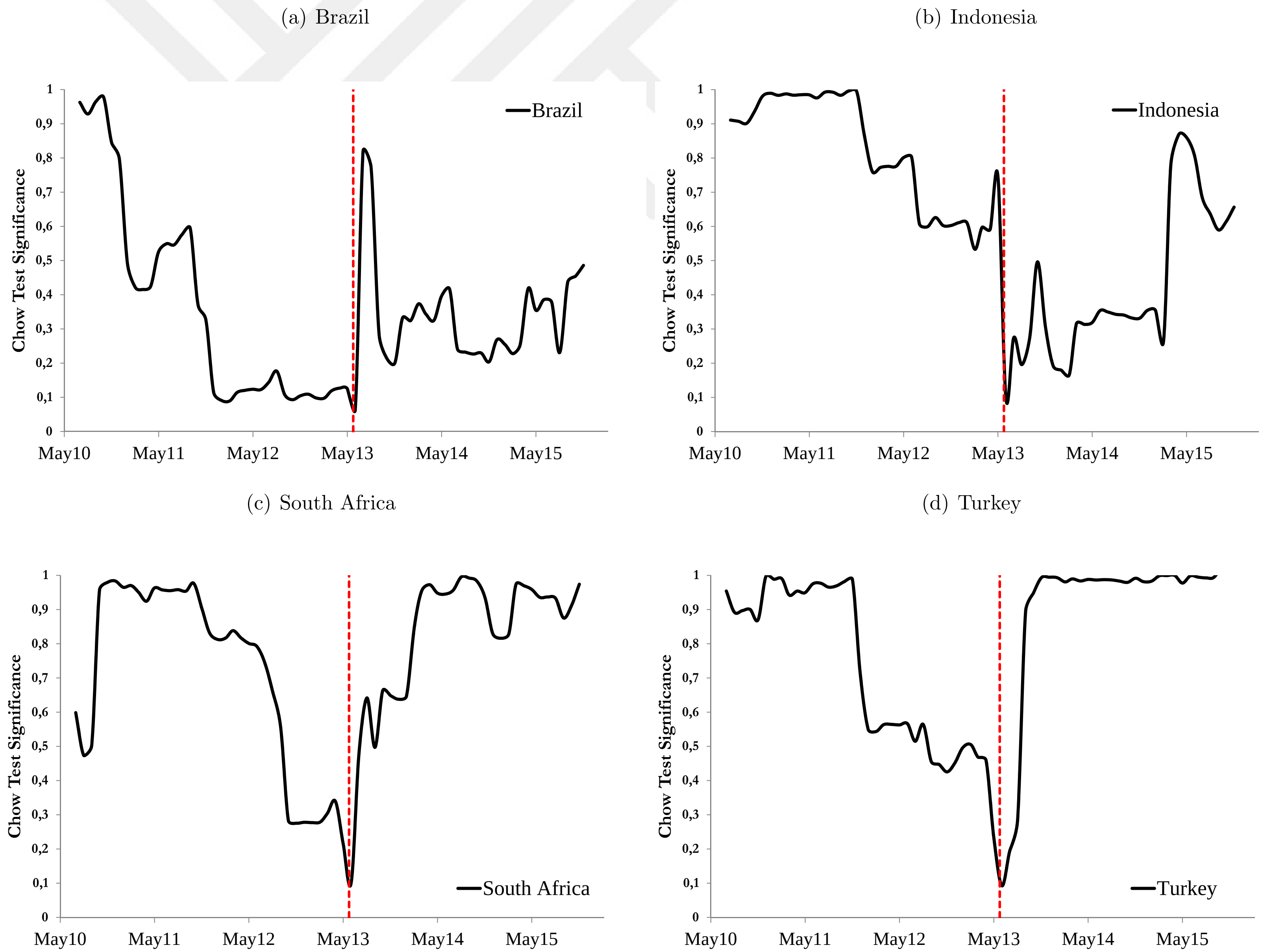


Figure 20: Chow Test Significance for Different Dates. This figure shows the significance of the Chow test calculated by testing each month in my sample as a structural break point for the specification $\Delta Liq_t = \alpha + \Delta Cr_t + \Delta Cry_t$ for each country.

Table 22: Liquidity regressions with eight liquidity PCs - Pre Tapering. For each of the four countries, a pooled regression with monthly observations is run with variables measuring both liquidity and credit risk. The regression coefficients and t-statistics in parentheses are reported. This table covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel A. Pre-Taper Tantrum

	Brazil	Indonesia	South Africa	Turkey
PC 1	0,213***	0,194***	0,116**	0,230***
	[2,62]	[2,43]	[2,02]	[2,86]
PC 2	-0,128	-0,184	-0,152	-0,170
	-[1,02]	-[1,18]	-[1,21]	-[1,26]
PC 3	-0,012	-0,017	-0,012	-0,015
	-[0,98]	-[1,23]	-[1,28]	-[1,15]
PC 4	0,057**	0,070	-0,162	0,159***
	[2,02]	[0,36]	-[1,04]	[2,38]
PC 5	-0,054	0,076*	-0,069	-0,070
	-[0,78]	[1,93]	-[0,92]	-[0,87]
PC 6	0,043	0,052	0,055	0,249*
	[0,53]	[0,54]	[0,55]	[1,65]
PC 7	-0,02	-0,129*	0,142	-0,029
	-[0,76]	-[1,83]	[0,76]	-[0,78]
PC 8	-0,12**	-0,142	0,158	-0,148**
	-[1,99]	-[1,01]	[0,57]	-[2,11]

Table 23: Liquidity regressions with eight liquidity PCs - Post Tapering. For each of the four countries, a pooled regression with monthly observations is run with variables measuring both liquidity and credit risk. The regression coefficients and t-statistics in parentheses are reported. This table covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel B. Post-Taper Tantrum

	Brazil	Indonesia	South Africa	Turkey
PC 1	0,272***	0,356***	0,264***	0,331***
	[3,02]	[4,05]	[3,11]	[3,87]
PC 2	-0,01	-0,015	-0,013	-0,014
	-[0,26]	-[0,33]	-[0,32]	-[0,33]
PC 3	0,389*	0,509	0,482***	0,416***
	[1,86]	[0,27]	[2,46]	[2,47]
PC 4	0,214*	0,306	0,231**	0,216*
	[1,75]	[0,77]	[2,00]	[1,89]
PC 5	-0,476	-0,628*	-0,671	-0,485
	-[1,45]	-[1,65]	-[1,62]	-[1,48]
PC 6	-0,34*	-0,375**	-0,382*	-0,438**
	-[1,69]	-[2,11]	-[1,71]	-[2,13]
PC 7	-0,442	-0,574	-0,587	-0,468
	-[0,87]	-[1,00]	-[0,95]	-[1,04]
PC 8	1,049**	1,248**	1,321**	1,395**
	[2,02]	[2,20]	[2,06]	[2,06]

Table 24: Endogeneity tests - Pre Tapering. For each country and each liquidity variable L, I test for potential endogeneity bias by using a Durbin-Wu-Hausman test. In total, 36 tests are run (nine liquidity variablesfour countries) pre- and post-tapering. This table shows for each test the t-statistics and R^2 for the first-stage regression in parentheses. This table covers the results for the pre-tapering period which is January 2, 2010 - 24 May, 2013. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel A. Pre-Taper Tantrum

	Brazil	Indonesia	South Africa	Turkey
λ	1,1132	1,260142	1,320255	1,169973
	(37%)	(31%)	(31%)	(40%)
Amihud	0,7342	0,820101	0,758429	0,754023
	(42%)	(35%)	(38%)	(47%)
Roll	1,1712	1,37616	1,26841	1,26841
	(31%)	(29%)	(27%)	(31%)
Bond Zero	0,8175	0,883718	0,968738	0,911513
	(14%)	(13%)	(11%)	(16%)
Turnover	-1,1976	-1,209576	-1,362869	-1,354486
	(8%)	(7%)	(7%)	(9%)
High-low	0,4445	0,454279	0,497396	0,454724
	(41%)	(30%)	(32%)	(47%)
Pastor-Stambaugh	-0,6824	-0,741769	-0,712426	-0,697413
	(25%)	(25%)	(25%)	(28%)
Bid-Ask	0,7196	0,846969	0,731114	0,777168
	(18%)	(18%)	(17%)	(21%)
Gibbs	0,9868	0,98976	1,166398	1,083506
	(34%)	(33%)	(27%)	(37%)

Table 25: Endogeneity tests - Post Tapering. For each country and each liquidity variable L, I test for potential endogeneity bias by using a Durbin-Wu-Hausman test. In total, 36 tests are run (nine liquidity variablesfour countries) pre- and post-tapering. This table shows for each test the t-statistics and R^2 for the first-stage regression in parentheses. This table covers the results for the post-tapering period which is 24 May, 2013 - November 11,2015. Standard errors are corrected for time-series effects and heteroskedasticity, and significance at 10% level is marked *, at 5% marked **, and at 1% marked ***.

Panel B. Post-Taper Tantrum

	Brazil	Indonesia	South Africa	Turkey
λ	1,151049	1,509651	1,472085	1,263571
	(47%)	(41%)	(40%)	(52%)
Amihud	0,746681	0,977561	0,793316	0,757794
	(55%)	(45%)	(42%)	(53%)
Roll	1,397242	1,417445	1,471355	1,38764
	(42%)	(36%)	(34%)	(39%)
Bond Zero	-0,979365	-1,025996	-1,065611	-1,05462
	(19%)	(17%)	(12%)	(18%)
Turnover	-1,326941	-1,331743	-1,578202	-1,374803
	(10%)	(8%)	(8%)	(13%)
High-low	0,516509	0,484261	0,574492	0,490192
	(46%)	(33%)	(43%)	(57%)
Pastor-Stambaugh	0,745181	0,794434	0,81359	0,772733
	(34%)	(30%)	(28%)	(33%)
Bid-Ask	0,798036	0,867296	0,754509	0,88364
	(25%)	(22%)	(20%)	(30%)
Gibbs	1,128899	1,038259	1,293535	1,270953
	(40%)	(42%)	(38%)	(50%)

4.8 Alternative Calculation of the Size and Contribution of the Liquidity Component

As a further test showing that my calculation of liquidity premium size and contributions is robust, I employ a different methodology. Both liquidity and credit are relative concepts. An economic agent who is trying to reallocate her capital from one LC Bond to another should account the relative liquidity of the two LC bonds. Thus, the difference between the liquidity (or credit) of a specific bond and the average market liquidity measures the bond specific liquidity (or credit) risk component. I use this methodology following Beber, Brandt and Kavajecz (2008), which also emphasize that credit and liquidity are relative concepts, particularly in the context of flight-to-quality and flight-to-liquidity which is similar to my case, as my dataset captures the period of tapering in 2013.

I regress the difference between the local currency bond yield in bond i and the US-swap rate (*Spread*) onto differences in bond i's credit and liquidity measures from their respective cross-sectional averages, pooling all the countries together. Below is the equation of my regression model:

$$\text{Spread}_{i,t} = \alpha + \beta_i(\lambda_{i,t} - \lambda_{m,t}) + \gamma_i(Cr_{i,t} - Cr_{m,t}) + \epsilon_{i,t} \tag{13}$$

where $Cr_{i,t}$ is the credit default swap spread in bond i during period t. $\lambda_{i,t}$ is my liquidity variable for bond i over period t, and $Cr_{m,t}$ and $\lambda_{m,t}$ are the cross-sectional averages of the $Cr_{i,t}$ and $\lambda_{i,t}$ variables, respectively during period t. This specification also allows me to investigate the country specific econometric identities properly by cancelling out common factors. One way to see this is that the contemporaneous correlation of credit and liquidity for different countries are relatively high in levels (on average 0.81 and 0.42, respectively), but they are basically zero for credit and liquidity differences from the cross-sectional average.

After estimating Eq.(13), I compute for each bond i and country c, the contribution of credit and liquidity risks to the yield spread as follows. Liquidity Contribution$_{i,c}$ = $\sum_{i=1}^{n(c)} \beta_i \overline{(\lambda_{i,t} - \lambda_{m,t})}$, Credit Contribution$_i$ = $\sum_{i=1}^{n(c)} \gamma_i \overline{(Cr_{i,t} - Cr_{m,t})}$. The total of the spread is calculated as Total Spread$_i$ = $\overline{(\text{Spread})_{i,t}}$ where n(c) is the number of bonds in my dataset for country c. And the proportion of credit, currency, and liquidity risks in total spread for each bond i and country c is calculated as below:

$$
\begin{aligned}
\text{Liquidity Proportion}_c &= \frac{\text{Liquidity Contribution}_{i,c}}{\text{Total Spread}_i} \\
\text{Credit Proportion}_c &= \frac{\text{Credit Contribution}_{i,c}}{\text{Total Spread}_i} \\
\text{Currency Proportion}_c &= 1 - \text{Liquidity Proportion}_{i,c} - \text{Credit Proportion}_{i,c}
\end{aligned}
$$

The regression in Eq.(13) allows me to investigate the cross-sectional differences of risk premiums between bonds. Subtracting the average from these risk premiums sets an ideal framework to analyze the time evolution of bond specific effects while canceling out common factors effecting these premiums. The proportion and contribution values give me an idea about the interaction between credit, currency and liquidity risk premiums. The proportions inform about the relative contributions of these risk premiums to the whole yield spread while contributions let me to analyze total magnitude of these risks. My findings show that, in pre-tapering period, LC bond investors need to pay a greater proportion for liquidity premium, even if the credit and currency risks of their investments stay the same. Across all countries, liquidity risk's proportion tends to increase by a factor of 3 in general, while credit and currency risk do not change significantly.

Panel A in Table 26 shows that the contribution of liquidity premium to LC yield spread remained small around 2.9% to 3.4% across the countries-consistent with a high liquidity environment. However, the importance of the liquidity premium increases in the post-tapering period and my analysis shows that liquidity premium has an increased contribution in this period. As it can be seen in Panel B of Table 26, average liquidity contribution increases by a factor of 3 to 4 for all countries, emphasing the less liquid environement after the post tapering period in LC bond market and the increase in LC bond yield spread is largely attributable to increased liquidity premium. Liquidity contributions averaged around 8% to 11% of total LC yield spread.

Table 26: Explanatory power of credit, currency and liquidity risk premiums. This table shows the explanatory power of the credit, currency and liquidity risk premiums on the magnitude of the yield spread. After estimating the following regression, $\text{Spread}_{i,t} = \alpha + \beta_i(\lambda_{i,t} - \lambda_{m,t}) + \gamma_i(Cr_{i,t} - Cr_{m,t})$. I define LC yield spreads for country i, as the difference between the LC bond yield and the U.S. swap rate. The pre-tapering period is January 2, 2010 - 24 May, 2013 and the post-tapering period is 24 May, 2013 - November 11,2015.I compute for each country c and bond i the contribution to, and contribution of credit and liquidity risk to the yield spread and the proportion of these risks in total spread. $\text{Liquidity Contribution}_{i,c} = \sum_{i=1}^{n(c)} \beta_i \overline{(\lambda_{i,t} - \lambda_{m,t})}$, $\text{Credit Contribution}_i = \sum_{i=1}^{n(c)} \gamma_i \overline{(Cr_{i,t} - Cr_{m,t})}$. The total of the spread is calculated as $\text{Total Spread}_i = \overline{(\text{Spread})}_{i,t}$.

	Panel A. Pre-Tapering						**Panel B. Post-Tapering**					
	Contributions			**Proportions**			**Contributions**			**Proportions**		
	Liquidity	**Credit**	**Currency**	**Liquidity**	**Credit**	**Currency**	**Liquidity**	**Credit**	**Currency**	**Liquidity**	**Credit**	**Currency**
Brazil	0,003549	0,012925	0,089294	3,4%	12,2%	84,4%	0,01026	0,018263	0,080956	9,4%	16,7%	73,9%
Indonesia	0,001408	0,012848	0,034337	2,9%	26,4%	70,7%	0,003716	0,011016	0,02959	8,4%	24,9%	66,8%
South Africa	0,001884	0,015085	0,049393	2,8%	22,7%	74,4%	0,006056	0,020955	0,038299	9,3%	32,1%	58,6%
Turkey	0,002514	0,019601	0,054207	3,3%	25,7%	71,0%	0,009058	0,020949	0,050738	11,2%	25,9%	62,8%

CHAPTER V

CONCLUSION

Sovereign local currency debt markets have evolved and expanded over the last 15 years, challenging the traditional original sin, which advocated the inability of emerging economies to borrow in their own currency. This paper contributes to the growing debate over risk factors that influence emerging market local currency sovereign bond pricing (see [3]), by providing implications for both portfolio managers and policy makers. I show that the bulk of emerging market sovereign LC yield spreads is explained by currency and credit risk premiums, though liquidity plays a nontrivial role, especially during the times of heightened market uncertainty. When valuing sovereign LC bonds, portfolio managers should be cautious of normal time (unconditional) risk management and hedging models since they can understate the risk of LC bonds because of the liquidity risk's time-varying nature. Furthermore, my evidence for the strong linkage between liquidity and sovereign credit risk and also the role played by foreign investors' fund flows on commonality in LC bond market liquidity may shed light on excessive fluctuations in LC interest rates and its consequences on real economic decisions, such as consumption and investment. Close coordination between emerging market regulators and central bankers can help reduce the cost of capital and avoid the unintended consequences of funding crisis by devising rules and procedures that increase the liquidity of LC bond markets.

CHAPTER VI

APPENDIX

6.1 Implementation details

6.1.1 Amihud measure

Conceptually related to [60], Amihud measure relates the price impact of a trade to the trade volume. The Amihud's measure at week t for a certain bond with Nxt observed returns is defined as the average ratio of the absolute value of these returns r_j and its trading volumes v_j,

$$L^{(am)} = \frac{1}{N} \sum_{j=1}^{N_t} \frac{|r_j|}{v_j} \tag{14}$$

A larger Amihud measure implies that trading a bond causes its price to move more in response to a given volume of trading, in turn, reflecting lower liquidity. See Figure 21 for quarterly graphical representation of Amihud measure for all countries.

6.1.2 Pastor-Stambaugh Measure

Pastor and Stambaugh (2003) proposes a liquidity measure for the U.S. stock market, based on price reversals. The following regression is used to estimate γ,

$$r^e_{t+1} = \theta + \phi r_t \gamma + \text{sign}(r^e_t) Q_t + \epsilon_t \tag{15}$$

To calculate the excess r^e_t return, I use JP Morgan GBI-EM Emerging Markets Local Currency Bonds Total Return Index as the market index. Q_t is the traded volume on day t. γ measure is negative and assigns greater absolute values to more illiquid bonds. Hence, I take the negative value of this measure and construct my liquidity proxy as,

$$L^{(ps)} = -\gamma \tag{16}$$

See Figure 22 for quarterly graphical representation of Pastor-Stambaugh measure for all countries.

6.1.3 Bid-Ask Measure

A market can be regarded as liquid if the proportional quoted bid-ask spread, $L^{(bd)}$, is low

$$L^{(bd)} = \frac{p_a - p_b}{p_m} \tag{17}$$

where the subscripts a, b and m indicate the ask, bid and mid quotes, respectively. See Figure 23 for quarterly graphical representation of Bid-Ask measure for all countries.

6.1.4 Roll Measure

The [39]) measure provides a simple and intuitive liquidity measure assuming that the subsequent prices arise from the bid-ask bounce. Thus, the bid-ask spread can be extracted from the covariance between consecutive returns as:

$$L^{(rl)} = 2\sqrt{-cov(\Delta p_t, \Delta p_{t-1})} \tag{18}$$

where Δp_t is the change in prices from t to $t-1$. Serially negatively correlated price movements and the strength of this covariation can be regarded as a proxy for the round-trip costs for a particular bond, and hence, as a measure of liquidity. See Figure 24 for quarterly graphical representation of Roll measure for all countries.

6.1.5 High-Low Measure

Corwin and Schultz (2012) construct an estimate of the bid-ask spread using daily high and low prices. They propose that because high prices generally represent buying activity and low prices generally represent selling activity, daily high-low ratio reflects information on selected assets' both variance and bid-ask spreads. Moreover, variance is a function of time, while bid-ask spread is not. Hence, authors use information on two consecutive trading days to calculate their liquidity proxy as follows,

$$L_t^{(hl)} = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{19}$$

where,

$$\begin{aligned}
\alpha &= \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} && (20)\\
\beta &= \sum_{j=0}^{1} (log(\frac{H_{t+j}}{L_{t+j}}))^2 && (21)\\
\gamma &= (log(\frac{H_{t,t+1}}{L_{t,t+1}}))^2 && (22)
\end{aligned}$$

H_t and L_t are the highest and lowest prices on day t, and $H_{t,t+j}$ ($L_{t,t+j}$)are the highest (lowest) price between days t and j. See Figure 25 for quarterly graphical representation of High-Low measure for all countries.

6.1.6 Gibbs Measure

Hasbrouck (2009) proposes to calculate the effective cost of trading using a Bayesian Gibbs estimate that is based only on daily closing prices of the selected assets. They use the following model to estimate c, the half effective cost and D_t, the sell side indicator.

$$r_t = c\Delta D_t + \beta_m r_{m,t} + \epsilon_t \tag{23}$$

where D_t=1 for a buy and D_t=-1 for a sell. r_t^m is the market factor on day t which in my case is JP Morgan GBI-EM Emerging Markets Local Currency Bonds Total

Return Index. After estimating the model for each month, I calculate Gibbs measure as follows,

$$L_t^{(gb)} = 2 * c \tag{24}$$

See Figure 26 for quarterly graphical representation of Gibbs measure for all countries.

6.1.7 Zero-return measure

Zero-return measure is based on the assumption which bond prices that stay constant over long time periods are likely to be less liquid. Thus, the percentage of days during a month in which a bond does not trade is constructed as follows:

$$\text{Zeros}_t = \frac{\text{No of zero return days}_t}{\text{Total Trading days}} \tag{25}$$

Using this measure, [61] propose a new liquidity proxy. Authors define that, S the symmetric transaction cost is related to unobserved true return R^* as,

$$R = \begin{array}{c} R^* + S/2 \text{ if } R^* < -S/2 \\ 0 \text{ if } -S/2 < R^* < S/2 \\ R^* - S/2 \text{ if } S/2 < R^* \end{array}$$

Then, they calculate the following, which I also use as my zero return proxy,

$$L_t^{(zr)} = S = 2\sigma\phi^{-1}\left(\frac{1 + \text{Zeros}_t}{2}\right) \tag{26}$$

where σ is the standard deviation of R^* and ϕ^{-1} is the inverse cumulative standard normal distribution. See Figure 27 for quarterly graphical representation of Zero-return measure for all countries.

6.1.8 Turnover measure

I also consider the monthly turnover in percent of total amount outstanding:

$$L_t^{(tm)} = \frac{\text{Total Trading Volume}_t}{\text{Amount Outstanding}} \tag{27}$$

See Figure 28 for quarterly graphical representation of Turnover measure for all countries.

6.2 *Implementation details - High Frequency Measures*

6.2.1 Amihud measure

Using the intraday trades of a certain bond, Amihud's measure at day t for a certain bond with Nxt intraday observed returns is defined as the average ratio of the absolute value of these returns r_j and its trading volumes v_j,

$$L^{(am),H} = \frac{1}{N}\sum_{j=1}^{N_t}\frac{|r_j|}{v_j} \tag{28}$$

6.2.2 Roll Measure

Following Dick-Nielsen, Feldhutter, and Lando (2012) I also measure Roll Measure using intraday data. The intraday covariance is calculated in the following form.

$$L^{(rl),H} = 2\sqrt{-cov(\Delta p_t^i, \Delta p_{tt-1}^i)} \tag{29}$$

where Δp_t^i is the intraday change in prices of the ith trade. If the covariance is greater than zero, the observation is extracted from the sample.

6.2.3 Round-trip transaction costs

These high frequency measure is constructed by Feldhutter (2012) on a motivation that trades occuring (with the same size) in a short-time interval could be an indicator for a bond's round-trip between a buyer, a seller and a dealer. Consider the case when a buyer(seller) approaches to a dealer, the dealer starts to look for a buyer(seller). If he finds a match for his client, two distinct trades occur in a relatively short time interval as a buy(sell) between the buyer(seller) and the dealer and a sell(buy) between the seller(buyer) and the dealer. The price difference between these two trades would be the bid-ask spread earned by the dealer.

To calculate this measure, I find trades with the same volumes, in a short-time interval as 20-minutes. For every cluster of trades, I calculate the following measure as $L^{(rt),H}$,

$$L^{(rt),H} = \frac{p_{max} - p_{min}}{\frac{p_{max}+p_{min}}{2}} \tag{30}$$

6.2.4 Bid-Ask Measure

Following Chakravarty and Sarkar (2003) I calculate the intraday average of bid-ask prices as follows,

$$L^{(bd),H} = \frac{\overline{p_a} - \overline{p_b}}{\overline{p_m}} \tag{31}$$

where $\overline{p_a}$ is the intraday average of ask prices, $\overline{p_b}$ is the intraday average of bid prices and $\overline{p_m}$ is the intraday average of mid prices.

6.2.5 Price Dispersion

In an analogy to low-frequency High-Low measure, I calculate price dispersion following Jankowitsch, Nashikkar, and Subrahmanyam (2011) as,

$$L^{(pd),H} = 2.\sqrt{\frac{1}{\sum_1^N Q_i}\left(\sum_1^N \frac{p_i - c}{c}\right)^2 Q_i} \tag{32}$$

where c is the closing price for day t. Price dispersion is calculated as the sums of normalized dispersion from the closing price of day t scaled by the individual trade volume Q_i. N is the number of trades on an individual day.

6.3 Local Currency Risk Premium Decomposition: Proof

I introduce transaction costs to express the model in terms of gross observed returns and to implement the effects of liquidity risks. In order to add the currency effects, I introduce currency adjustments.

6.3.1 Transaction costs and Liquidity

Poor local liquidity or high transaction costs drives a wedge between the gross returns that I measure in the data and the actually obtained returns (”net returns”), that is:

$$exp(r_{i,t+1}^{C,net}) = \frac{exp(r_{i,t+1}^{C,gross})}{TC_{t+1}} \tag{33}$$

where $TC >= 1$ presents a transaction cost measure (if $TC = 1$, there are no transaction costs) , $r_{i,t+1}^{C,gross}$ is the gross return in currency C, and $r_{i,t+1}^{C,net}$ is the net return in currency C. I postulate that the log of the transaction cost measure is proportional to the liquidity measure L, that is,

$$ln(TC_{t+1}) = v_i L_{i,t+1} (v < 0) \tag{34}$$

This implies that;

$$r_{i,t+1}^{C,net} = r_{i,t+1}^{C,gross} - v_i L_{i,t+1} \tag{35}$$

where $L_{i,t+1}$ is defined as the market-specific liquidity measure.

6.3.2 Local currency adjustments

The dollar return of a US investor is equal to the local currency return substracted by the exchange rate change in local currency in that period. So I define, $r_{i,t+1}^{US,net} = r_{i,t+1}^{LC,net} - \Delta q$. Here, Δq is the exchange rate change between the US and the local currency (LC), $r_{i,t+1}^{LC,net}$ is the net local currency rate of return of country i. Note that the same equation holds for gross returns.

6.3.3 The pricing equation

I describe a pricing equation in terms of a stochastic discount function m_t at time t which is equiavalent to the marginal value of a dollar delivered at time t in a certain state of the world. The existence of a stochastic discount factor is equal to the existence of risk-neutral probabilities, which can be offered in an arbitrage-free world. Hence, I assume that the markets are complete and portfolio returns are conditionally log-normal.

The price of an asset at time t which is given by P_t, can be calculated by discounting the stochastic cash flow of c_{t+1}, by the stochastic discount factor $m_{t+1}t$

$$P_t = E_t[m_{t+1}c_{t+1}] \tag{36}$$

Or, if I define $R_{t+1} = c_{t+1}/P_t$, in the absence of short-sale constraints or other frictions, net returns are priced for the US investor,

$$E_t[m_{t+1}R^{i,US}_{t+1}] = 1 \tag{37}$$

Taking logs of the both sides, I get,

$$log(E_t[m_{t+1}R^{i,US}_{t+1}]) = 0 \tag{38}$$

and using log-normality,

$$log(E_t[m_{t+1}R^{i,US}_{t+1}]) = E_t[log(m_{t+1}) + r^{i,US}_{t+1}] + \frac{1}{2}var_t(log(m_{t+1}) + r^{i,US}_{t+1}) \tag{39}$$

Note that, I define $r^{i,US}_{t+1} = log(R^{i,US}_{t+1})$. This implies that the Euler equation can be restated as,

$$E_t[m_{t+1}] + E_t[r_{t+1}^{i,US}] + \frac{1}{2}[var_t(m_{t+1}) + var_t(r_{t+1}^{i,US})] + cov_t(m_{t+1}, r_{t+1}^{i,US}) = 0 \quad (40)$$

The price of a one period US risk-free bond is $T_t^1 = E_t[m_{t+1}]$ then the risk-free rate $R_t^{f,US}$ between period t and $t+1$, known at t, would be $r_t^{f,US} = -logE_t[m_{t+1}]$. Using log-normality assumption, $logE_t[F_{t+1}] = E_t[F_{t+1}] + \frac{1}{2}var_t(F_{t+1})$, for both m_{t+1} and $R_{t+1}^{i,US}$ I get

$$logE_t R_{t+1}^{i,US} - r_t^{f,US} = -cov_t(m_{t+1}, r_{t+1}^{i,US}) \quad (41)$$

Note that the above equation includes only the net returns. Now, I incorporate liquidity and currency adjustments.

I recall the liquidity adjusment as,

$$r_{i,t+1}^{US,net} = r_{i,t+1}^{US,gross} - v_i L_{i,t+1} \quad (42)$$

And currency adjustment as,

$$r_{i,t+1}^{US,gross} = r_{i,t+1}^{LC,gross} - \Delta q \quad (43)$$

Combining liquidity and currency adjustments gives the net return of a US investor in terms of local currency denominated gross returns;

$$r_{i,t+1}^{US,net} = r_{i,t+1}^{LC,gross} - \Delta q - v_i L_{i,t+1} \quad (44)$$

Hence, the excess return for a US investor can be rewritten as,

$$logE_t R_{t+1}^{i,US} - r_t^{f,US} = -cov_t(m_{t+1}, r_{i,t+1}^{LC,gross} - \Delta q - v_i L_{i,t+1}) \quad (45)$$

I decompose the excess return of a US investor into three parts; country, currrency and liquidity risk premiums as follows:

$$\begin{aligned} logE_tR_{t+1}^{i,US} - r_t^{f,US} &= \underbrace{-cov_t(m_{t+1}, r_{i,t+1}^{LC,gross})}_{\text{Country Risk Premium}} \\ &+ \underbrace{-cov_t(m_{t+1}, -\Delta q)}_{\text{Currency Risk Premium}} \\ &+ \underbrace{-cov_t(m_{t+1}, -v_iL_{i,t+1})}_{\text{Liquidity Risk Premium}} \end{aligned}$$

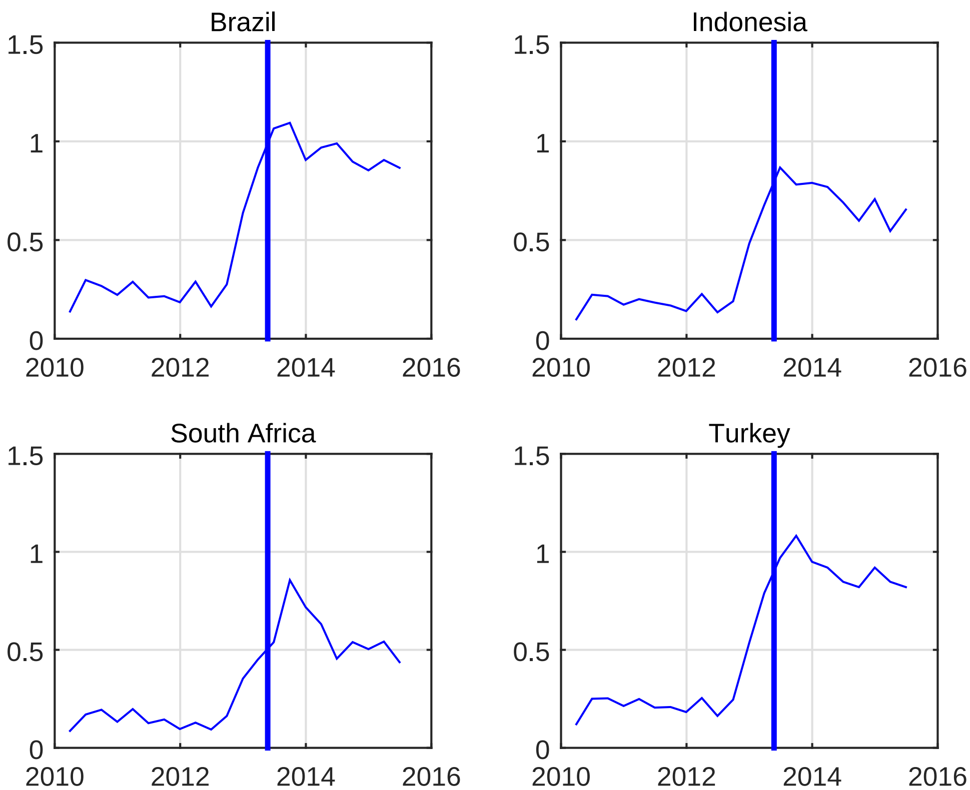


Figure 21: Amihud Measure (10^{-6}). Quarterly averages of Amihud liquidity measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

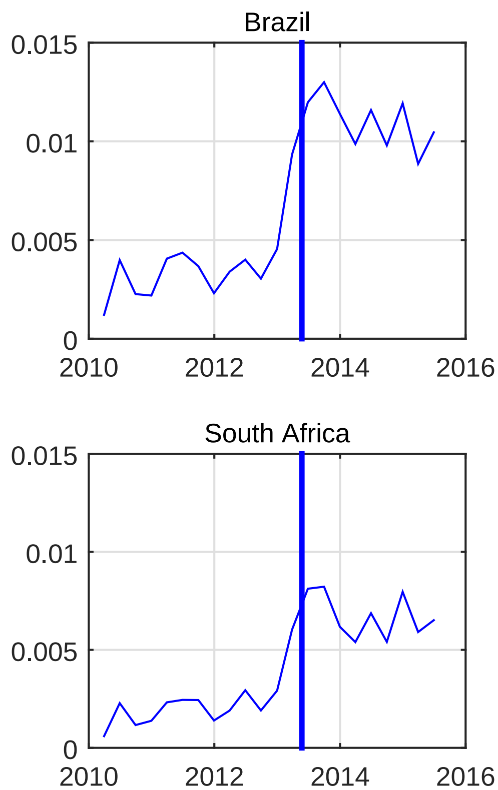


Figure 22: Pastor-Stambaugh Measure (10^{-6}). Quarterly averages of Pastor-Stambaugh measure. The blue lines show FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

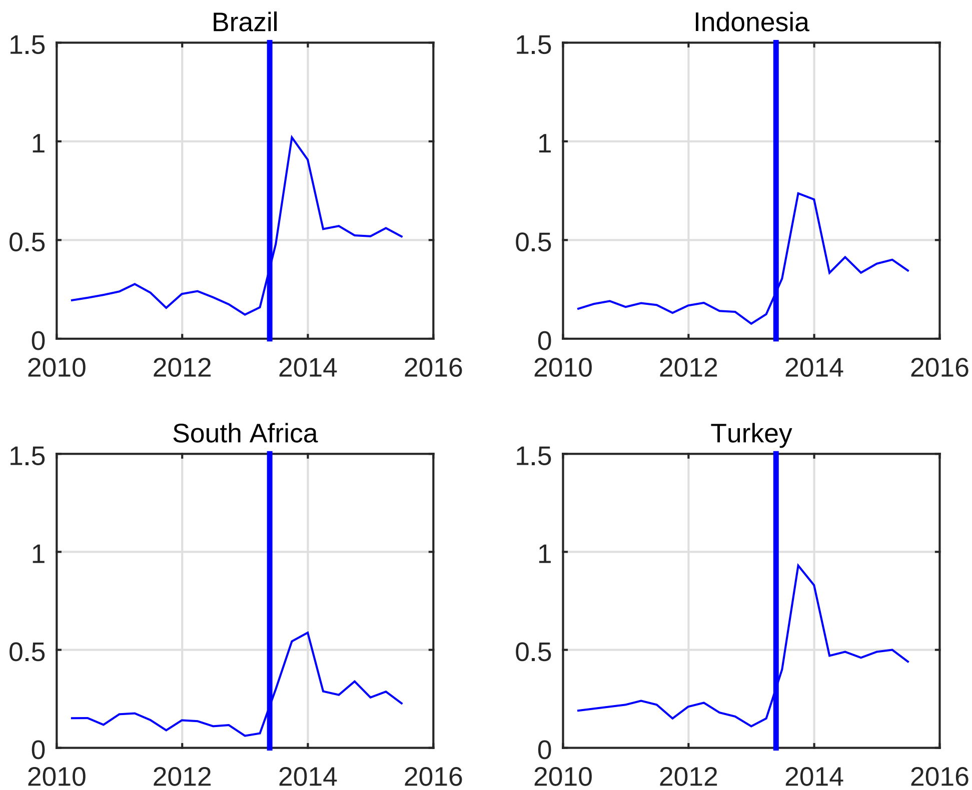


Figure 23: Bid-ask Measure (%). Quarterly averages of Bid-Ask measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

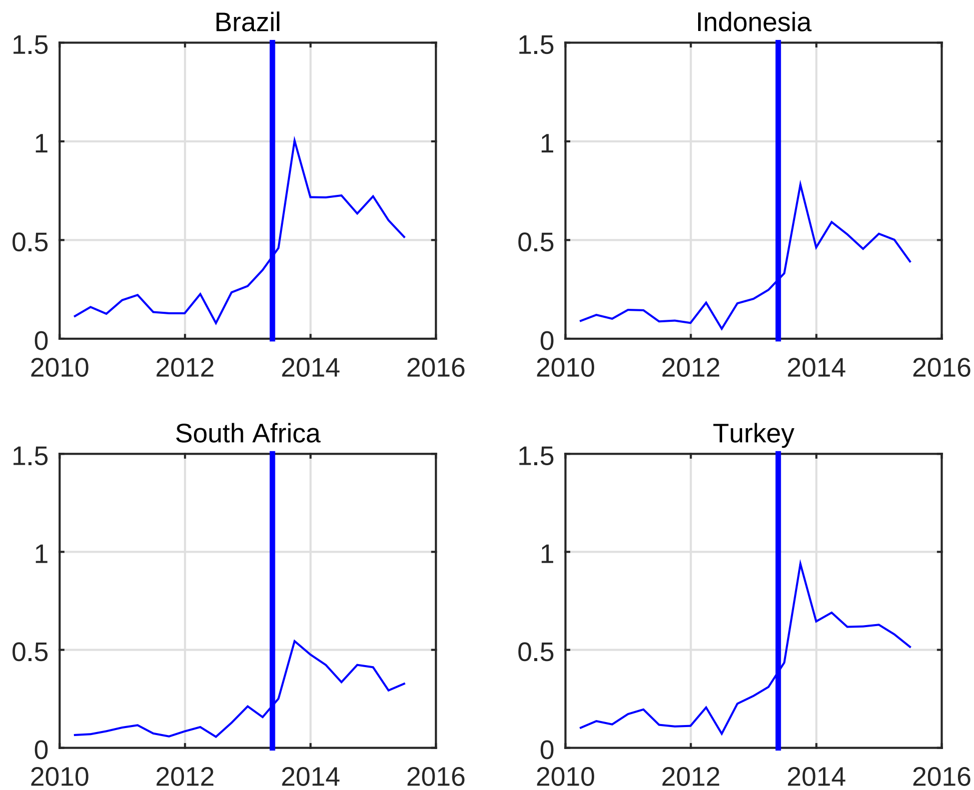


Figure 24: Roll Measure (%). Quarterly averages of Roll measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

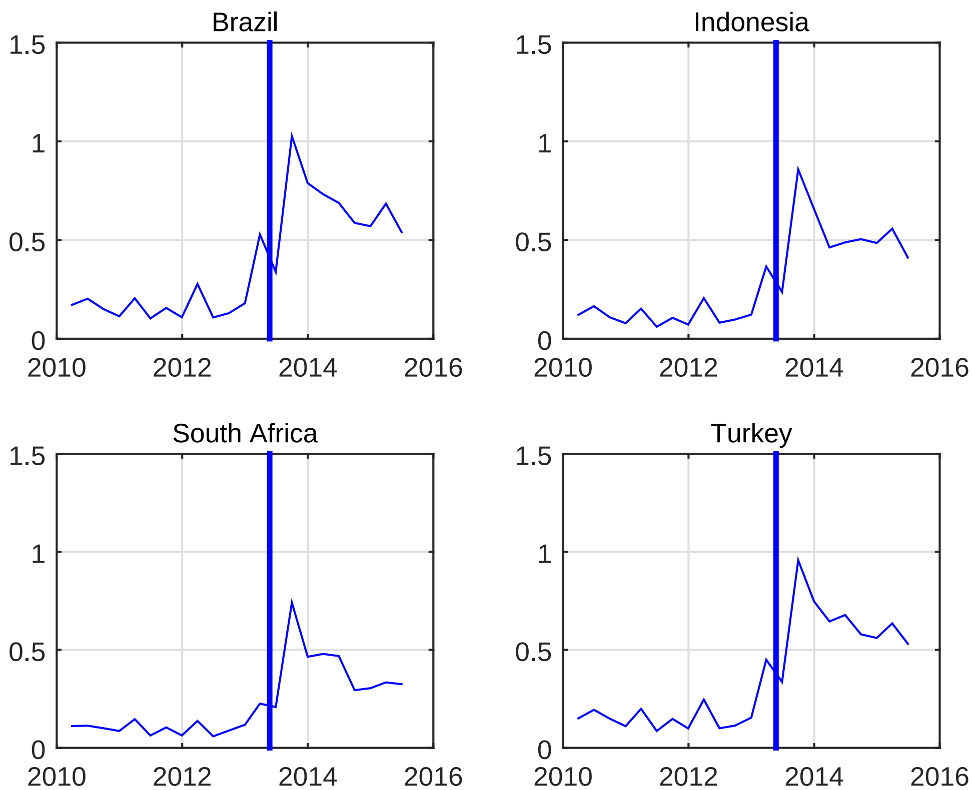


Figure 25: High-Low Measure (%). Quarterly averages of High-Low measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

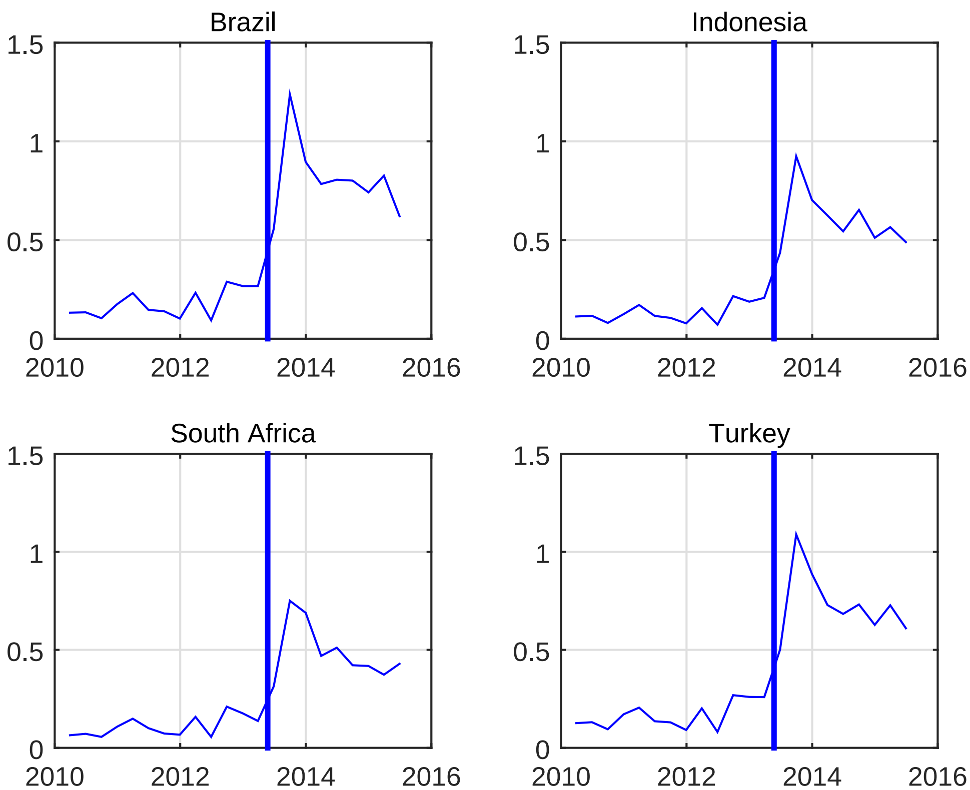


Figure 26: Gibbs Measure (%). Quarterly averages of Gibbs measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

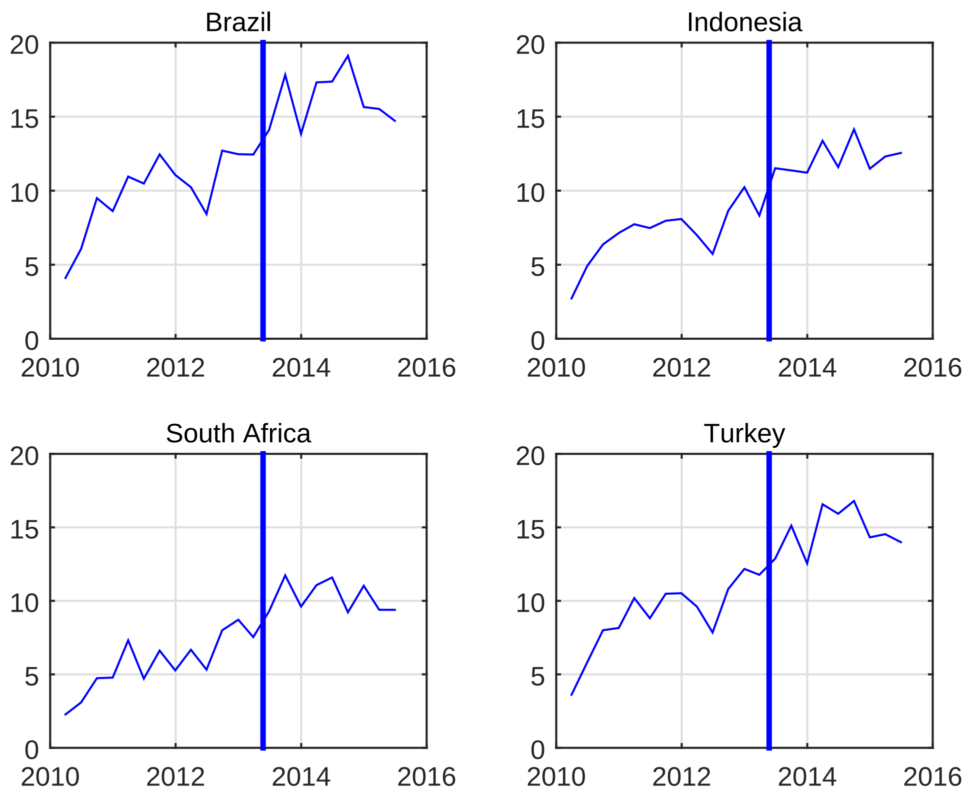


Figure 27: Zero-return Measure (%). Quarterly averages of Zero-return measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

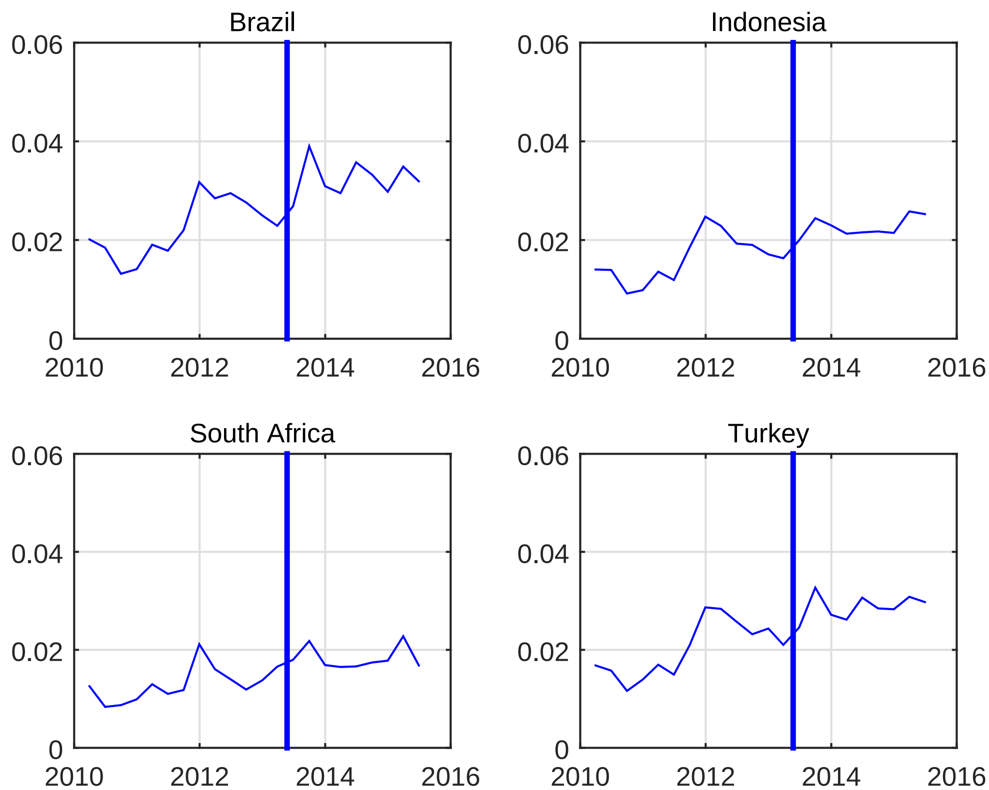


Figure 28: Turnover Measure (%). Quarterly averages of Turnover measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

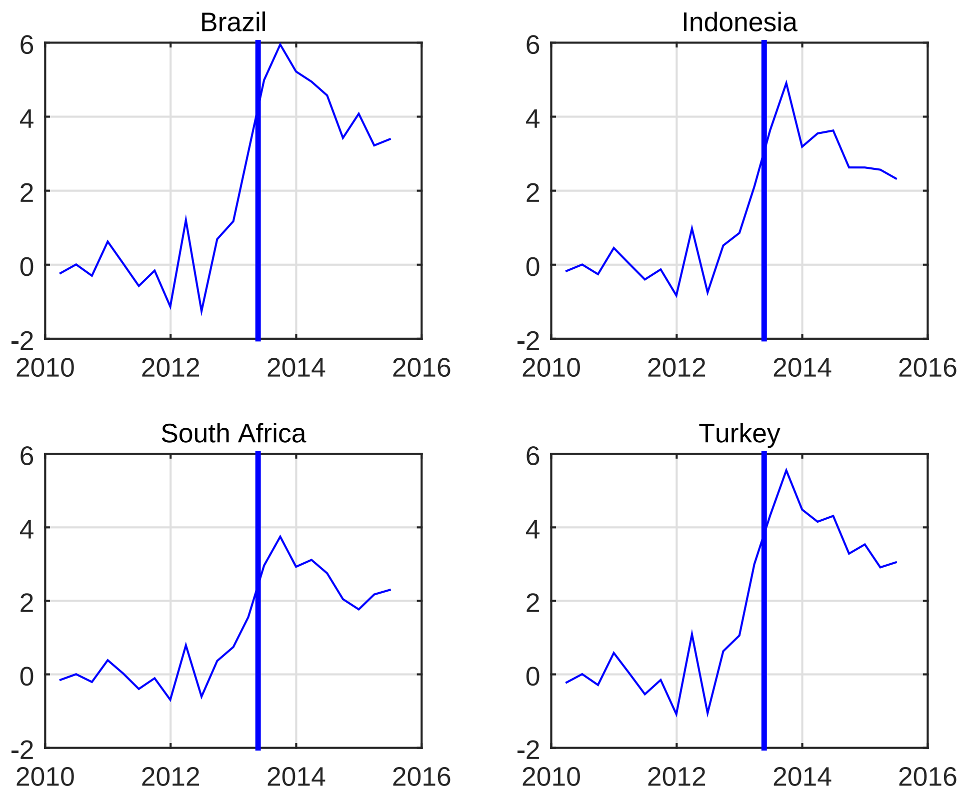


Figure 29: Lambda Measure (%). Quarterly averages of Turnover measure. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

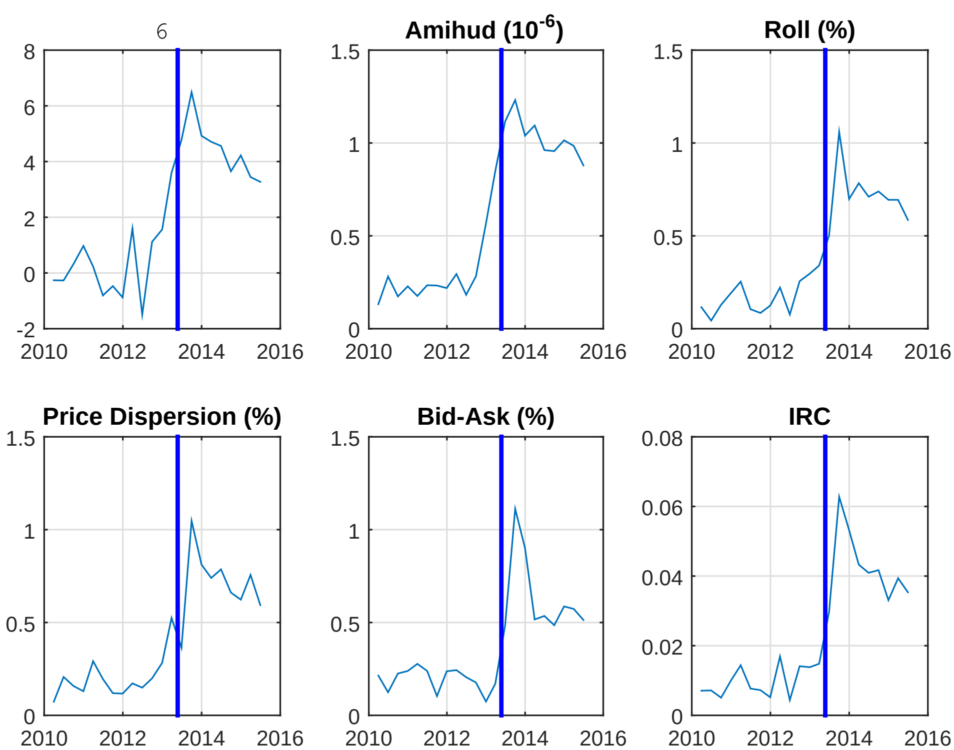


Figure 30: High Frequency Liquidity Measures. Quarterly averages of measures are represented. The blue lines shows FED QE Tapering on 24 May, 2013. The sample is January 2, 2010 - November 11, 2015.

6.4 Summary of determinants

Table 27: The table below summarizes the potential determinants of $L_{M,t}$. Each proxy is assigned to the related category with the corresponding explanations. Explanatory variables, shown as vectors, are Supply Side Factors [TED Spread, Average Local Short Rates, Markit EM-CDS Index]; Demand Side Factors [F-Flow, Closed End Fund, CBOE VIX Index]; Control Variables [W-Equity, DM-FX Vol, EM-FX Vol].

Categories	Determinants	Description
Supply Side	*TED Spread*	LIBOR USD 3 Month minus the US Government 3 Month Yield (Source: Bloomberg)
	Local Short Rate (Average)	Average of the EM local currency short rates. (Source: Bloomberg)
	EM-CDSI	Average of EM Credit Default Swaps. (Source: Markit)
Demand Side	*Net Fund Flows*	First principal component of net fund flows of global funds investing into LC bond markets. (Source: EPFR)
	Closed End Fund	Closed End & Average closed end discounts of emerging market debt funds (EDD, TEI, and MSD)**
	VIX	CBOE VIX option volatility index (Source: Bloomberg)
Control Variables	*W-Equity*	World Equity Index (Source: FTSE, Bloomberg)
	DM-FX Vol	JP Morgan G7 FX Volatility Index (Source: JP Morgan, Bloomberg)
	EM-FX Vol	JP Morgan Emerging Markets FX Volatility Index (Source: JP Morgan, Bloomberg)

* EDD, Morgan Stanley Emerging Markets; TEI, Templeton Emerging Markets Income Fund; MSD, Morgan Stanley Emerging Markets Debt Fund Inc.

Table 28: The table below summarizes the control variables determinants of $L_{M,t}$. Each proxy is assigned to the related category with the corresponding explanations.

Categories	Determinants	Description
Credit Risk Controls	*Credit Risk*	Credit Default Swap Spread (Source: Markit)
	Political Risk	ICRG Political Risk Index (Source: International Country Risk Guide)
Macroeconomic Variables	*Current account*	Current Account Deficit/Surplus (Source: Bloomberg, Local Resources)
	International Reserves	International Gross Reserves (Source: Bloomberg, Local Resources)
	Debt service	Total Public Debt (Source: Bloomberg, Local Resources)
	Inflation	Consumer Prices Index Year-on-year changes (Source: Bloomberg, Local Resources)

Table 29: List of 18 bond funds used in the analysis of flow driven and discretionary sales.

Fund Name	Benchmark
Aberdeen Emerging Markets Debt Local Currency Fund	JPM GBI-EM Global Diversified
Ashmore SICAV Emerging Markets Local Currency Bond Fund	JPM GBI-EM Global Diversified
Aviva Investors - Emerging Markets Local Currency Bond Fund	JPM GBI-EM Global Diversified
Baillie Gifford Emerging Markets Bond Fund	JPM GBI-EM Global Diversified
Baring IF Emerging Markets Debt Local Currency Fund	JPM GBI-EM Global Diversified
BlackRock Global Funds Emerging Markets Local Currency Bond Fund	JPM GBI-EM Global Diversified
BNP Paribas L1 Bond World Emerging Local	JPM GBI-EM Global Diversified
Goldman Sachs Growth & Emerging Markets Debt Local Portfolio	JPM GBI-EM Global Diversified
Invesco Emerging Local Currencies Debt Fund	JPM GBI-EM Global Diversified
Investec GSF Emerging Markets Local Currency Debt Fund	JPM GBI-EM Global Diversified
ISI Emerging Market Local Currency Bonds Fund	JPM GBI-EM Global Diversified
JPMorgan Funds - Emerging Markets Local Currency Debt Fund	JPM GBI-EM Global Diversified
Morgan Stanley Investment Funds - Emerging Markets Domestic Debt	JPM GBI-EM Global Diversified
PIMCO Emerging Local Bond Fund	JPM GBI-EM Global Diversified
Pictet - Emerging Local Currency Debt	JPM GBI-EM Global Diversified
TCW Emerging Markets Local Currency Income Fund	JPM GBI-EM Global Diversified
Threadneedle Emerging Market Local Fund	JPM GBI-EM Global Diversified
WisdomTree Emerging Markets Local Debt Fund	JPM GBI-EM Global Diversified

Table 30: List of 18 Blend currency bond funds used in the robustness analysis of flow driven and discretionary sales.

Fund Name	Benchmark
Aberdeen Emerging Markets Bond Fund	JPM EMBI Global Diversified
Ashmore SICAV Emerging Markets Debt Fund	JPM EMBI Global Diversified
Aviva Investors - Emerging Markets Bond Fund	JPM EMBI Global
Berenberg Emerging Markets Bond Selection	JPM EMBI+
BlackRock Global Funds Emerging Markets Bond Fund	JPM EMBI Global Diversified
BNY Mellon Compass Fund Global Emerging Markets Bond Fund	JPM EMBI Global Diversified
DoubleLine Emerging Markets Fixed Income Fund	JPM EMBI Global Diversified
Federated Emerging Market Debt Fund	JPM EMBI Global
Goldman Sachs Emerging Markets Debt Fund	JPM EMBI Global Diversified
Invesco Emerging Markets Bond Fund	JPM EMBI Global Diversified
ISI Emerging Market Bonds Fund	JPM EMBI Global Diversified
JPMorgan Funds - Emerging Markets Bond Fund	JPM EMBI Global Diversified
Morgan Stanley Emerging Markets Debt Fund, Inc.	JPM EMBI Global
PIMCO Emerging Markets Bond Fund	JPM EMBI Global
Pioneer Funds - Emerging Markets Bond	JPM EMBI Global Diversified
TCW Emerging Markets Income Fund	JPM EMBI Global Diversified
Threadneedle Emerging Market Bond Fund	JPM EMBI Global
Universal Institutional Funds, Inc. - Emerging Markets Debt Portfolio	JPM EMBI Global

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