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DYNAMIC INTERACTION BETWEEN LIQUIDITY AND SOVEREIGN CREDIT RISK: EVIDENCE FROM TURKEY

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A Master's Thesis

by
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Ankara
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To my lovely wife, daughter and to my entire beloved family; without them I couldn't survive

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Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

MUSTAFA AHÇI

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I certify that I have read this thesis and have found it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science in Finance.

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ABSTRACT

DYNAMIC INTERACTION BETWEEN LIQUIDITY AND SOVEREIGN CREDIT RISK: EVIDENCE FROM TURKEY

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In this thesis, the dynamic interaction between liquidity and credit risk for Turkey, which highly needs capital inflow to finance its current account deficit, is examined. A firm/country defaults when it is unable to pay the lender (buyer of its bond) expected cash flows it committed to pay. Bond holders expect to be compensated by a premium in exchange for bearing default risk. Liquidity, on the other hand, is basically defined as the ease of trading a security, especially in large quantities quickly, at low cost and without moving the price. The investors require a premium for a possible difficulty in selling the securities in question. Although, there is a vast literature on the question of how to measure liquidity and default (credit) risk and the pricing impact of these two risk factors on financial assets, the dynamic interaction between these two has received very little attention, especially for sovereign (government) securities. If it turns out that credit (liquidity) risk affects liquidity (credit) risk, then any (precautionary) measures to improve one of these risks may alleviate the severe implication of the other. To this end, we used a model proposed in the literature to observe the dynamic interaction between liquidity and credit risk for Turkey. Using sovereign bond market data of Turkey, we build three different measures for liquidity and exploit sovereign Credit Default Swap (CDS) spreads to proxy credit risk in order to observe lead-lag relation between these two risk factors in a Vector Auto Regressive (VAR) setting. We find significant evidence of Granger-causality in both daily and monthly terms.

Keywords: Credit Risk, Granger-Causality, Liquidity, Time-Series Econometrics, Yield Curve Fitting

ÖZET

LİKİDİTE VE ÜLKE KREDİ RİSKİ ARASINDAKİ DİNAMİK ETKİLEŞİM: TÜRKİYE ÖRNEĞİ

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Haziran 2017

Bu tezde, cari işlem açığını finanse etmek için yüksek derecede sermaye akışına ihtiyaç duyan Türkiye'nin likidite ve kredi riskinin birbiri üzerindeki dinamik etkileşimi incelenmiştir. Bir firma/ülke borç verenine (tahvil sahibine) taahhüt ettiği nakit akışını sağlayamadığı zaman temerrüte düşer. Tahvil sahipleri, bu temerrüt riskini yüklenmeleri karşılığında bir ücret talep ederler. Diğer yandan likidite, temel olarak bir teminatın, özellikle yüksek miktarları, düşük maliyetle ve fiyatında fazlaca bir oynama gerektirmeksizin, kolaylıkla alınıp satılması olarak tarif edilir. Yatırımcılar sözkonusu teminatların satışında karşılaşabilecekleri muhtemel zorluklara ilişkin bir ücret talep ederler. Her ne kadar, likidite ve kredi riskinin nasıl ölçülebileceği ile bu faktörlerin finansal varlık fiyatlaması üzerine etkisi üzerine literatürde bir çok çalışma mevcutsa da, bu iki risk faktörü arasındaki dinamik etkileşim, özellikle ülke bağlamında, çok az dikkate alınmıştır. Eğer kredi (likidite) riskinin likidite (kredi) riski üzerindeki etkisi kanıtlanabilirse, bu iki risk faktöründen birisi için alınacak tedbirlerin diğer risk faktörünün yıkıcı etkisini azaltmada etkin olacağı beklenebilir. Bu kapsamda, Türkiye'nin likidite ve kredi riskinin birbiri üzerindeki dinamik etkileşimini gözlemlemek amacıyla literatürde yer alan bir model kullandık. Türkiye'nin devlet tahvil piyasa verilerini kullanarak üç ayrı likidite ölçütü inşa ettik ve kredi riski için ülke kredi temerrüt swap fiyatlarını kullanarak bu iki risk faktörü arasındaki etkileşimi VAR düzeninde gözlemledik. Bu kapsamda, hem günlük hem de aylık bağlamda Granger-nedenselliğine ilişkin ciddi kanıtlar bulduk.

Anahtar Kelimeler: Getiri Eğrisi Tahmini, Granger-nedenselliği, Kredi Riski, Likidite, Zaman-Serileri Ekonometrisi

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

We know from traditional asset pricing theory that, given the same discount factor, if two securities have identical cash flows in all states of the world, then these two securities should have the same value. Otherwise, that would pose a challenge to the theory of asset pricing (Longstaff, 2004). However, one can observe different prices in real world for different assets having identical features.

Let us think about a US treasury security and its identical high-grade corporate counterpart (in terms of coupons, maturity etc.) that should have the same value according to their expected cash flows. But one can observe that US treasury security, which is known as risk-free security, has a higher price than its corporate counterpart. Then, where does this deviation come from while their fundamental value should be the same? Intuitively, it can easily be inferred that this difference in the prices comes from the probability that the firm which issued the bond in question may default and fail to pay its obligations. So, this probability urges investors to require a default premium for holding a corporate bond.

On the other hand, let us consider the US treasury security and the bond of Refcorp[1] which is a US government agency in which its bonds are guaranteed by the US treasury. Thus, one can say that Refcorp bonds literally have the same credit (default) risk

[1] Resolution Funding Corporation

as its treasury counterparts. But again, a difference can be observed in their prices (yields) while they have the same default risk. Longstaff (2004) explained this difference as a flight-to-liquidity premia in Treasury bond prices. In other words, since treasury securities are more popular among investors and thus more liquid, investors require a liquidity premium for holding RefCorp bonds instead of US treasury bonds. Then, as a general implication, we can easily say that default and liquidity risks are somehow priced in financial assets.

The credit (default) risk is strongly related with the probability of a firms/country's default that will cause the expected cash flows cease to exist. Liquidity, on the other hand, is generally defined as the cost of immediacy to liquidate the assets in hand. Most recent financial crisis of 2008 has illustrated that liquidity risk, along with credit risk, matters and should not be underestimated (Brunnermeier, 2009). The question of how these two risk factors are priced in financial assets has too much attention in the literature. Especially, the literature on liquidity and its effect on asset pricing have grown dramatically after 2008 financial crisis. Some literature (Chordia et al. (2000); and others) also touches upon the commonality and systemic nature of the liquidity that can affect all financial assets in the market.

The decomposition of default and liquidity risk from widely used government bond yields or yield spreads is a good way to extract useful information and act upon, especially for policy makers. This forward looking approach is instantly observable. For example, for policy makers, if it is known that widening sovereign yield spreads is mainly ascribed to liquidity matters, measures to improve secondary market liquidity could be considered, through Quantitative Easing (QE) programs and Treasury buy-back auctions etc. Else, if it is ascribed to credit risk, corrective fiscal policy measures can be taken to mitigate insolvency risk.

Although pricing of these two factors have considerable attention in the literature, the dynamic interaction between credit risk and liquidity has been barely investigated. In the theoretical framework by Pelizzon, Subrahmanyam, Tomio, and Uno (2016) a market maker, holding an inventory of risky assets and setting optimal bid-ask spread in the presence of margin constraints and borrowing costs, provides liquidity to the market. Bid-ask spread is determined considering mainly three factors: risk of asset as measured by CDS spread, central bank policy which is a driving factor for borrowing costs, and margin requirements which is set by clearing houses and depends on both borrowing rate and risk of the asset. According to this theoretical model, when the credit risk becomes higher, depending also on the policy of central bank, bid-ask spread quoted by market maker becomes higher, resulting illiquidity in the market. Another intuitive explanation may be the case that investors, by looking a country's credit profile, may refrain from investing in that country which will trigger deterioration in liquidity in aggregate manner.

Intuitively, on the other hand, when liquidity dries up in overall financial market, this will reduce the availability of funds, in other words, speculators' capital as described in the literature. In mid- and long-term, the firms would have to cut their investments and even fail to meet their debt/tax obligations that may eventually cause deterioration in banks' balance sheets, tax revenues of the government, deteriorating fiscal consolidation. This, in fact, will negatively affect the overall picture of the country, resulting in deterioration of its credit profile. This effect may be more pronounced for such countries, for instance emerging markets, which have lower savings and which highly need foreign capital to finance their investments.

Given the provisions above, if we can demonstrate that market-wide liquidity or credit risks lead/lag the other, then taking some measures to improve liquidity (credit risk) may lead to an improvement in credit (liquidity) risk. To this end, we used the model proposed by Pelizzon et al. (2016) and test the model for Turkish data by using three different liquidity measures which reflect different aspects of liquidity for financial markets. We also apply Granger-causality test whether credit risk have a direct and/or lagged impact on liquidity or vice versa. Pelizzon et al. (2016) investigated the relation between those two by using daily sovereign CDS data and bond market liquidity proxied by daily average of bid-ask spread of bonds traded each day. Although they didn't rule out the possibility that liquidity may have an impact on credit risk, neither they provide a model nor did they find any results supporting this hypothesis in their paper. This thesis differs from the paper above in several aspects. First, we believe that rather than only focusing on bond market liquidity, which is measured by the conventional bid-ask spread, different types of liquidity measures or market-wide liquidity may have more explanatory power to observe the effect of credit risk on liquidity or vice versa. In this regard, we will have a chance to build the liquidity (noise) measure which is proposed by Hu, Pan, and Wang (2013) and derived from the dispersion in daily yield curve and test whether this computationally demanding liquidity measure can, indeed, explain the liquidity effects in Turkish financial markets. Second, while the original paper couldn't find a causality of liquidity on credit risk, the test of the hypotheses is carried out in daily frequency by looking just 4-day-ahead, where the liquidity effects may not be observable in that short period of time. So, as opposed to limited time series data on liquidity (only approximately 2 years of intraday data for calculating daily bid-ask spreads), the mid- and long-term effect of liquidity could well be observed in an extended time frame and/or by using lower-frequency data such as monthly or quarterly time series data. Third, this thesis explores the relation between credit risk and liquidity in an emerging market setting, Turkey, which has a low-saving rate and highly needs foreign capital to finance its investments, where the hypothesized relation may be more pronounced.

In this thesis, we test the causality between liquidity and sovereign credit risk by using proxies which are widely used in the literature. While we use, in line with the literature, sovereign CDS spreads for Turkey as a proxy for credit risk, we used three different liquidity measures which will be more explained in Chapter 2 and 4. Some of our results are in line with the results in the literature which says that CDS Granger-cause liquidity but not vice versa. However, we also show that converse relation is also possible and significant with different measures and time scale.

The results are mixed and changing according to the measures we used as the liquidity variable and to the period. In daily terms, for the whole period covering the years from 2010 to 2016, we find that there is strong evidence that credit risk Granger-causes liquidity. When we divide the sample period into two sub-periods (2010-to-2013 and 2013-to-2016), the daily results are mixed. In the first period and while using noise measure as the liquidity variable, we observed a significant feedback relation between credit risk and liquidity. We also repeated our tests in monthly terms in the sense that liquidity effects (on credit risk) may be better observed in mid- and long-terms. Using whole sample period (2010-to-2016), while we couldn't observe any causality between liquidity and credit risk in monthly terms the tests in sub-periods show significant but again mixed results.

The remainder of this thesis is organized as follows. Chapter 2 reviews the relevant literature and gives the theoretical background on concepts used in this thesis, such as credit risk and liquidity. Chapter 3 explains the theoretical framework of the model and the methodology used to test the hypotheses formed in line with the existing literature. Chapter 4 provides information on the data, data source and the description of variables via thoroughly explaining how to build each measure (if applicable). Descriptive statistics on variables are also given in this chapter. Chapter 5 gives the empirical results and, finally, Chapter 6 concludes.

CHAPTER 2

LITERATURE REVIEW

1. Theoretical Background

1.1. Default (Credit) Risk

A firm defaults when it fails to meet its debt obligations. The vast literature on the pricing of credit (default) risk has two approaches: model-dependent and model-free approach. Some studies, using structural models, relate the default of firm to its value and usually follow Merton (1974). In this class of models, default occurs when the process describing the value of the firm hits a given boundary[2]. On the other hand, another model-dependent approach which is referred as reduced-form or intensity-based models, instead defines hazard rate that determines the pricing and timing of default. Duffie (1999), and Hull and White (2000a, 2000b) applied these reduced-form models to price credit derivatives[3].

The default risk has a potential to affect every financial contract and pricing of securities issued by any firm. Therefore, investigation of pricing default risk has received much attention both by traders and researchers. A bond issued by a firm can be the most basic and straight example. The theoretical price of a bond is the present value of its cash flows discounted by a proper discount rate. Since the default of a firm is stochastic over time, at each instant, there is a probability that the firm in question will be unable to pay

[2] For this line of literature, see Black and Cox (1976), Longstaff and Schwartz (1995) and others.
[3] For a comprehensive survey: Jarrow, Lando, & Yu (2008) and Schonbucher (2000)

the lender (buyer of the bond) cash flows it promised to pay. So, in a given time there is a possibility that cash flows cease to exist that pulls down the value of the bond issued, considering also the recovery rate. So, investors expect to be compensated by a premium. This premium, or a spread over a risk free rate, is an increasing function of the firm's default probability (Vassalou & Xing, 2004).

There are various studies that extract information about default risk through examining corporate bond spreads calculated as the yield on a corporate bond minus the yield on a riskless bond with the identical coupon rate and maturity date. However, as will be explained later, measuring default risk directly from bond spread is not fully accurate as the yield (and price) of a bond is also affected by the bond's liquidity. The lower the liquidity, the lower its price and higher its yield.

Credit Derivatives and Credit Default Swaps (CDS)

Credit derivatives are financial instruments that allow companies/investors to transfer credit risk, in the same way they transfer market risks, without actually transferring the ownership of the underlying assets. By using these instruments, instead of waiting and hoping for the best, investors can actively manage their portfolios and protect themselves from credit risk stemming from their risky investments. Since late 1990s credit derivative markets have been growing. While in 2000, the total notional principal for credit derivatives contracts was approximately $800 billion (Hull, 2015), reached at its peak at the end of 2007 with $58 trillion and has a steady declining thereafter to $15 trillion at end-June 2015 (BIS, Nov 2015 OTC statistical report).

The most popular and liquid credit derivative product is the *Credit Default Swaps (CDS)*. CDS is an insurance-like instrument that the buyer of insurance (protection buyer) wishes to insure itself against a possible default, while seller of the insurance (protection seller) is willing to bear the default risk in return for a fee. In more detail, protection buyer has the right to sell bonds issued by the *reference entity* (issuer of the bond) for their face value and protection seller agrees to buy the bonds for their face value when a *credit event*, which is usually defined as the default of the reference entity, occurs. In this transaction, protection buyer pays a periodic fee to protection seller until maturity of the contract or until a credit event occurs (see Figure 1). This fee is typically quoted in basis points per 100 notional amount of the reference obligation, and is called the default swap premium. If a credit event does not occur during the life of the contract, then the contract expires at its maturity date. The credit event can be defined in the contract and, other than default; it can also include a credit downgrade, or failure to make a scheduled payment. Since CDS contracts are over-the-counter products, the terms of contracts are negotiable, so as the maturity. Although there are, for instance, 1,2 and 5 years of maturity for Turkish sovereigns, 5 year horizon is the most common and liquid one.

While market value of overall CDS market continued to decline to $453 billion at the end of June 2015 in gross terms, sovereign CDS has increased steadily. Before the global financial crisis, the sovereign CDS market largely belonged to emerging markets which is assumed, by investors, to have higher credit risk. However, since end-2009, this view has changed. The revised perception that sovereign debt of advanced economies is no longer purely safe and rising hedging demands have boosted sovereign CDS market for those developed economies (IMF Global Financial Report, 2013). The share of sovereign CDS in overall market rose from 4% at the end of 2008 to 16% at mid-June 2015. The notional amount of sovereign CDS contracts grew from $1.7 trillion at-the-end of 2008 to $3 trillion at-the-end of 2011 then fall back to $2.3 trillion at mid-June 2015 (BIS, Nov 2015 OTC statistical report). In terms of gross notional amount, sovereign CDS contracts of Turkey is consistently ranked within top 10. The rank of Turkey reduced from the 1st in 2008 to 3rd and 6th at the end of 2010 and of 2012, respectively, after Italy, Spain, France, Brazil and Germany (IMF Global Financial Report, 2013).

In over-the-counter-market where CDS contracts are traded, clearing houses are at key position to reduce counterparty risk. For Turkish Sovereign CDS, the inter-continent exchange (ICE) clearing house, one of the biggest clearing houses in the world, launched sovereign CDS clearing for Turkey and Russia starting from 18 November 2013. They claim to be the world's first CDS clearing house in 2009, and clear more than 500 single name and index CDS instruments[4]. So, the margin requirement for Turkish sovereign CDS is launched on 18 November 2013 which is a critical fact that one should be aware

[4] ICE cleared more than $58 trillion in gross notional amount of CDS including both corporate and sovereign debt. See www.theice.com

of since it is one of the channels that CDS prices affect the liquidity given in the theoretical model (see Chapter 3)

Table 1: Rankings of CDS Amounts Outstanding

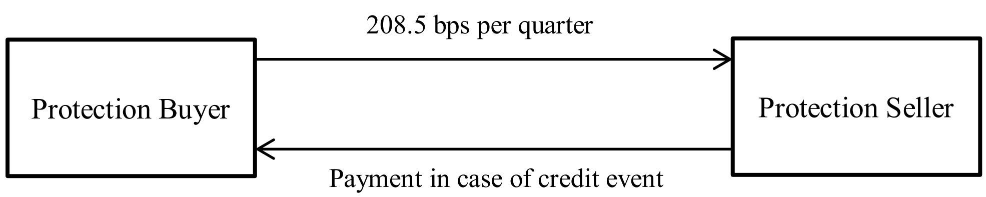
Gross Notional Amounts Outstanding (in billion dollars)								
Top 10		**End-2008**	**Top 10**	**Count**	**End-2010**	**Top 10**	**Count**	**End-2012**
1	**Turkey***[5]	165	1	Italy	267	1	Italy	388
2	Italy	158	2	Brazil*	160	2	Spain	212
3	Brazil*	126	3	**Turkey***	135	3	France	177
4	Russia*	98	4	Spain	132	4	Brazil*	156
5	Morgan Stanley	79	5	Mexico*	111	5	Germany	154
6	Goldman Sachs	76	6	Russia*	96	6	**Turkey***	137
7	Mexico*	74	7	GE Capital	96	7	Mexico*	117
8	GE Capital	74	8	Germany	80	8	Russia*	109
Below Top 4								
262	Ireland	18	24	United Kingdom	61	14	Portugal	71
377	United Kingdom	14	44	Ireland	46	15	United Kingdom	71
592	Japan	7	50	Japan	41	30	Ireland	51
740	United States	5	291	United States	16	124	United States	23

Source: IMF Global Financial Report (2013)

[5] * represents emerging economies

How does CDS work?

In order to understand more clearly, let us give an example on how CDS works in practice. Suppose that on April 28, 2017, Investor A, the protection buyer, wishes to buy 5 years of protection against the default of the Firm B (reference entity)'s bond maturing June 1, 2022. The protection buyer owns 1,000 of these bonds, each having a face value of 100 TL. Thus, the notional principal value is 100,000 TL. The buyer enters a contract to obtain a full protection for the face value of total debt via CDS with, let's suppose, a 208.50 basis point premium. The Figure 1 explains the relation between protection buyer and seller. Here, let's suppose, each quarter the buyer pays a premium to protection seller of D/360 × 208.50, or approximately 52.125 basis points per quarter, where D denotes the actual number of days during a quarter. This is approximately a quarterly payment of



Source: Hull (2015)

Figure 1: Credit Default Swap

100,000 TL× D/360 × 0.020850 ≈ 521.25 TL. In case of a default, the buyer delivers the 1,000 Firm B's bonds to the protection seller and receives a payment of 100,000 TL. Moreover, if the credit event (default) occurs between quarterly payments, then the protection buyer must also pay to the protection seller the relevant portion of swap premium that has accrued since the most recent default swap premium payment.

Credit derivatives are claimed to be one of the most successful financial innovations of the past decade. This financial instrument is widely used by researchers as a model-free approach to directly measure the size of the default component in yield spreads (Longstaff, Mithal, & Neis, 2005). Blanco, Brennan, and Marsh (2005) showed that the CDS market leads the bond market in determining the price of credit risk due to the fact that price discovery will occur in the market in which informed traders transact most. The CDS market benefits from being the easiest place in which to trade credit risk.

Instead of pricing credit risk, the question why CDS is appropriate proxy of credit risk for corporate bonds is explained by loose arbitrage relation that exists between CDS prices and credit spreads for a given reference entity, as discussed in Duffie (1999) and Hull and White (2000a). Suppose an investor buys a T-year par bond issued by reference entity with a yield to maturity of Y%, and enters also a CDS contract for credit protection for T-years that costs P_{CDS}. Here, the investor is assumed to eliminate the default risk associated with the bond. Suppose P_{CDS} is expressed annually as a percentage of the notional principal. Thus, the investor's net annual return is calculated as $(Y- P_{CDS})$ percent. Assuming no arbitrage, this net return should be equal to T-year risk-free annual return, denoted by X%. Otherwise, if $(Y- P_{CDS})$ is less than X, then an arbitrage portfolio formed by shorting the risky bond, writing the CDS contract, and buying the risk-free asset would yield a positive return and vice versa. So, with no arbitrage opportunity, it can be said that the price of CDS contract, P_{CDS}, should equal to $(Y-X)$ % which is the corporate yield spread.

Any Disadvantages?

In case a credit event occurred, there are options clearly set out in CDS contracts how to execute the settlement payment. The payment can be made in two ways: cash and physical settlement. Cash settlement, as the usual case now in the market, is made by delivering the notional amount minus post-default market value of the reference obligation. Suppose, the bonds which had $100 million face value is worth now, after credit event, $35 million. Then, in this setting, $65 million is the cash payoff. Whereas, the physical delivery is repayment at par against physical delivery of a reference asset: that is $100 million payment for bonds having $100 million face value. The key problem is that owner of the CDS has the cheapest-to-deliver (CTD) option, which is specified in the contract to deliver a number of different bonds (having the same seniority), in case any credit event occur. It is conceivable that some deliverable obligations will be cheaper than others. Then, it is discussed in the literature that physically settled CDS price with CTD option may not be a pure measure of credit risk (Blanco, Brennan, & Marsh, 2005).

1.2. Liquidity and Liquidity Risk

Standard asset pricing is based on the assumption of frictionless (or, perfectly liquid) markets, where every security can be traded at no cost all of the time (Amihud, Mendelson, & Pedersen, 2005). However, in practice there are frictions in financial markets. One of the most known is the transaction costs such as fees, order-processing costs, and taxes.

Liquidity is basically defined as the ease of trading a security. It is also defined as "the ability to trade large quantities quickly, at low cost and without moving the price" (Pástor & Stambaugh, 2003). The investors require a premium for the assets for a possible difficulty, especially in case of distressed market conditions, that may be faced in selling those assets before its redemption (Monfort & Renne, 2013). Their asset will be priced at a discount to fundamental values to compensate investors for liquidity costs (Amihud & Mendelson, 1986, 1987). Liquidity is considered, on the other hand, an elusive concept in that it is not observed directly but measured relatively and there are number of aspects including tightness, depth, and resiliency[6] (Kyle, 1985) that cannot be captured in a single measure. (Amihud, 2002).

Widely used measures to quantify liquidity are trading based liquidity measures such as: the quoted and effective bid-ask spread, bid-ask spreads percentage or market depth. Amihud measure (Amihud, 1986) which is the daily stock price reaction to a dollar of trading volume, is one of popular proxy frequently used in the literature. Atilgan, Demirtas, and Gunaydin (2016), by using this measure and several of its derivatives, found evidence in Borsa Istanbul Stock Exchange (BIST) that there is a significant positive relationship between illiquidity and one- to six-month ahead stock returns. They found that "stocks that are in the highest liquidity quintile earn 7.2%-19.2% higher risk-adjusted annual returns than those in the lowest illiquidity quintile." (Atilgan et al., 2016).

On the other hand, one popular measure of liquidity for the Treasury market is the premium enjoyed by on-the-run bonds over their off-the-run counterparts that are

[6] *Tightness* is defined as the cost of a reversal position (e.g. bid-ask spread as transaction cost), where *Depth* is the size required to affect prices, *Immediacy* is the speed of order execution, and *Resiliency* is the ease with which prices to return normal after a shock.

previously issued. Another important measure of liquidity is studied by Longstaff (2004) that US treasury bonds enjoys a considerable price premium, named as flight-to-liquidity premium, compared to RefCorp bonds which are also guaranteed by the US government, thus have identical default risk. Using German T-bills and its government guaranteed counterparts, KfW bonds, Schwarz (2017) also employed this methodology and named it 'K-measure' which is claimed to be market-wide liquidity measure in Euro-area. One of other popular measures worth to mention is the one proposed by P´astor and Stambaugh (2003) and claimed to be a market-wide liquidity priced in U.S. equity market. This monthly liquidity measure is an aggregate of the cross-sectional average of individual-stock liquidity measures, using the idea that order flow induces greater return reversals when liquidity is lower.

Some studies also investigate and study on empirical evidence whether there is a systemic nature of liquidity that is priced in financial markets. For instance, Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Eckbo and Norli (2002) show the commonality in liquidity measures. Acharya and Pedersen (2005) gives a theoretical framework for the liquidity as a risk factor in their liquidity adjusted CAPM and mentions three channels through which liquidity affect asset prices. They find that commonality of liquidity, as one of these three channels, has a return premium on stock returns. Moreover, Sadka (2006) provides evidence that the stocks whose returns are more sensitive to aggregate liquidity in market earn higher returns. Given various liquidity measures in the literature, Korajczyk and Sadka (2008) discuss whether these liquidity measures are just noisy estimate of a common liquidity factor rather than representing different aspects of liquidity. They find that, across assets, there is commonality for each measure of liquidity and that aggregate systematic liquidity is a priced factor.

Another group of literature links arbitrage capital to liquidity and asset prices. In this line of study, Brunnermeier and Pedersen (2008) introduce the funding liquidity as the ease with which traders obtain funding. Trading can't happen without capital even in the case of short-selling that requires a capital margin. They link traders' ability to provide liquidity to the market with their availability of funding. They also state that the liquidity providers such as speculators, hedge funds, and trading desks in investment banks are subject to margin constraints. So, any negative shocks to the capital of these agents cause liquidity to decline and risk premia to increase. This concept is especially important for the model used in this thesis that margin requirements affect funding liquidity of traders that, in consequence, affect traders' ability to provide market liquidity (please see Chapter 3 Model Description). Furthermore, one of the liquidity measures, namely the noise measure, used in this thesis also relies on this concept in that, lack of arbitrage capital or unwillingness to deploy it causes dispersion between assets' fundamental values and observed prices. So, the difference between fundamental values and observed prices (noise) is an indication of decreasing arbitrage capital, so liquidity, in financial markets (Hu, Pan, &Wang, 2013).

Since the market microstructure and models are beyond the scope of this thesis, we will just provide some essential information about market makers and market making in order to understand basics of theoretical model and intuition to be presented in Chapter 3. As known, market makers quote two prices at which the bid-price represents the price they are willing to buy and the ask-price they are willing to sell the security they hold in their inventory. While primary function of market maker is being a supplier of immediacy, they also play important role in setting prices. Volume, risk, price and firm size, together with inventory risk is discussed to be the determinants of the variability of bid-ask spread[7]. By adjusting these prices, the market makers provide liquidity to financial markets. For instance, the spread between bid and ask prices is wider for riskier securities (Madhavan, 2000), which signals a decrease in liquidity.

The Turkish exchange market (BIST) is purely order-driven, where no designated market maker with an obligation to quote prices, exists. In these markets, actually, liquidity is provided by market participants (traders) who submit orders to the exchange. Although most of the market microstructure literature is mostly on quote-driven markets, there exist studies examining the market microstructure of order-driven markets. Hamao and Hasbrouck (1995) (as cited in Ahn et al., 2002) find evidence in Tokyo Stock Exchange (TSE) that is consistent with effects of asymmetric information. The other study on Tokyo Stock Exchange by H.J Ahn, Cai, Hamao, and Ho (2002) finds different

[7] For a detailed survey on market microstructure please see Madhavan (2000).

aspects on how information is incorporated into stock prices from what is reported for ordinary quote-driven or hybrid (order+quote) systems. While Marshall and Young (2003) find no significant evidence that liquidity is priced in stock returns in purely order driven Australian stock market, they state that it may be due to the fact that order-driven markets are more liquid than purely quote-driven markets. Investigating price formation in an order-driven market, ParisBourse CAC40 index, Handa, Schwartz and Tiwari (2003) find that the size of the spread is due to differences in valuation of stocks among investors and adverse selection. In summary, there are aspects that the order-driven and quote-driven markets conform and not conform to each other.

Although BIST stock market has no traditional market-maker system, market-making is provided by public orders. In addition, the bond market is somewhat different. There are actually market-maker banks (piyasa yapici bankalar), called 'primary dealers'[8], which have some privileges and obligations in the bond market. According to the 'primary dealership contract'[9] between these primary dealers and Turkish Treasury, in exchange for the right to submit non-competitive bids before the auctions and being exempt from collateral requirement for participation in auctions, primary dealers are obliged to enhance liquidity in secondary bond market. They provide liquidity by quoting prices (for coupon bonds) or yields (for discount bonds), with a minimum size of 5 million TL in nominal terms, for 6 of 9 pre-determined benchmark bonds set out in the contract which are negotiable. However, quoted spreads are, again, pre-determined by Turkish Tresury (max. 50 Kurus for coupon bonds and changing yield spreads for discount bonds), not by these primary dealers. Although they provide liquidity and have influence to affect the bond spreads in overall market, they do so not by considering specific properties of securities, such as risk of those bonds. Moreover, minimum size they are obliged to quote is very small compared to daily nominal trade size which is 686 Million TL for 2013-2016 period (Please also see Chapter 4 for Descriptive Statistics). However, different from the stock market where bid-ask spread sticks to the tick size which is 'minimum allowable price change', we observe difference in bid-ask spreads of

[8] Turkish Treasury announced on 21 December 2016 that 13 banks are accepted as primary dealers for January-December 2017 period.

[9] For more information see https://www.treasury.gov.tr/en-US/Pages/Primary-Dealership-System. For the year 2017, Turkish Treasury announced 13 banks as primary dealers

bonds especially when the risk in the bond market changes. In this sense, in our view, spread measures for Turkish markets may not well quantify liquidity. Rather, we think that the noise measure which is closely linked to the available arbitrage capital (speculators' capital) may perform better to see the dynamic relations between credit risk and liquidity. That is one of the reasons why we used three different liquidity measures in this study.

Liquidity measures used in the literature are formed either by intra-day (high-frequency) data or daily (low-frequency) data. Although high-frequency (intra-day) measures are claimed to be more accurate, they require calculations of microstructure data on transactions and quotes. They are costly, mostly not available in markets all over the world for especially long horizons and require time-consuming data handling and filtering techniques. Because of mentioned disadvantages, it is very frequent to use daily available measures, as does this thesis. For instance, one of the reasons why Amihud measure is very popular is that it does not require high frequency data and it is easily calculated by using daily return and volume which is readily available for almost any market.

In their paper which investigates the performance of various liquidity measures in bond markets, including variety of high- and low-frequency measures, Schestag et al. (2016) find that most of daily proxies are "able to capture variations in transaction costs on both time-series and cross-sectional level" and comparable to those high-frequency measures. Given low-frequency measures' performance in its 'horse race', the paper recommends to use Roll's, Gibbs and High-Low measures[10] for researchers to proxy transaction cost. However, in their recent paper, Guloglu and Ekinci (2016) calculate five daily low-frequency effective spread proxies most popularly used in the literature and compare their performance with high-frequency bid-ask spread for futures market in Borsa Istanbul Futures and Options Market (VIOP). They find that while Effective Tick proxy appears to perform better than others, most low-frequency spread proxies perform poorly in the futures market. For the sake of computational efficiency, in this thesis, we also preferred the measures calculated from daily observable data.

[10] For Roll's measure see Roll (1984), for Gibbs measure see Hasbrouck (2009), and for High-Low measure see Corwin & Schultz (2012).

2. Empirical Studies on Bond Yield (Spread), Credit Risk and Liquidity

Early researches have studied the determinants of US corporate yield spreads. For instance, using both model-dependent approach and CDS data to investigate the default risk and other components of the spread, Longstaff et al. (2005) found that the default component accounts for the majority of the corporate spread across all credit ratings. They found that while substantial part of the spread may be attributable to the default risk, there is also a considerable component of the spreads that can't be explained by default risk.

Using CDS premiums to estimate the default and non-default component of 21 emerging market (EM) sovereign bond yields, Küçük (2010) concluded that a considerable part of sovereign yields can be attributable to the factors other than default risk such as liquidity. Similarly, using data from 16 EM countries, Hund and Lesmond (2008) developed some methods for assessing the liquidity component of the emerging market debts for both sovereign and corporate bonds. By using different measures of liquidity in their paper, they find that liquidity is highly significant in explaining variation of yields and changes across rated and unrated categories, for both corporate and sovereign issuers. They show that liquidity dominates credit risk in explaining yield spreads for both corporate and sovereign bonds across all of the emerging markets examined.

In their study, Beber, Brandt, and Kavajecz (2008) emphasize that in times of economic distress, it is often observed that investors rebalance their portfolios and run to less risky and more liquid securities, especially in fixed-income markets. These phenomena are commonly referred to as flight-to-quality and flight-to-liquidity effects, respectively. Using Euro-area government bond market to disentangle the credit and liquidity part of the sovereign bond spreads, they find that investors care about both credit quality and liquidity, but they do so at different times and for different reasons. They find that while most part of sovereign yield spreads is explained by the credit quality, liquidity has considerable role for explaining the yields especially for low credit countries and during rising market uncertainty. Furthermore, they also find that during periods of large flows into or out of the bond market, liquidity explains a substantially greater part of sovereign yield spreads. That means; while credit quality substantially explains the bond valuation, investors prefer liquidity rather than credit quality during times of financial distress.

Schwarz (2017) decomposes the yield spreads of the 11 European countries into market liquidity and sovereign credit components and argue that traditional measures of liquidity, such as bid-ask spreads, do not capture all liquidity effects and tend to understate the contribution of liquidity especially in times of market stress when liquidity risk premium plays an important role. So, similar to one proposed by Longstaff (2004), she constructed her 'market-wide' liquidity measure by calculating the difference in yields between German federal government bond and the yields of their less-liquid German development bank, KfW[11] agency counterparts which have an explicit guarantee from the government for its all debt obligations. She contends that this liquidity measure, namely K-measure of euro area market liquidity, is entirely free from credit influences and that it captures all effects of market liquidity across Euro-area. This measure is frequently used by researchers who investigate the liquidity effects across Euro-area[12]. She finds that while both liquidity and credit show a significant effect on most country yield spreads, contrary to what is claimed by Beber et al. (2008), liquidity explains more: on average, liquidity explains around 1.5 times as much as credit in government debt spreads. Liquidity risk premia is a major driver of yield spread which widens over the crisis sample period that is also claimed by Beber et al. (2008).

3. Dynamic Interaction Between Credit Risk and Liquidity

Although early researchers have different conclusion on the role of liquidity or credit component of sovereign yields in explaining the yields, they have the common idea that liquidity and default risks are priced in sovereign bond market. While some of the researchers used model-dependent approach to explain and decompose these components of the sovereign yields, some others explained them by using proxies which is referred as model-free approach. For these proxies, early studies indicate that CDS is a good proxy for credit risk while market-wide liquidity measures capture the information on liquidity

[11] Kreditanstalt für Wiederaufbau
[12] See also Ejsing et al. (2012), Monfort & Renne (2013).

more accurately compared to their trade-volume based counterparts. Several researchers find that the proportion of liquidity and credit premium changes according to market conditions; investors prefer liquidity rather than credit quality especially in times of financial distress. Some also claimed that liquidity is more of an issue for especially low-credit sovereigns.

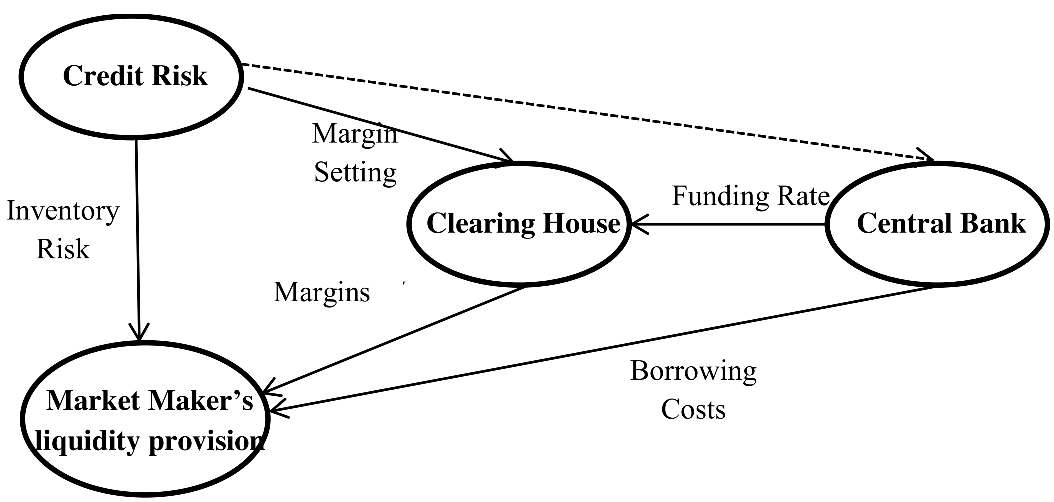
While there is wide literature on pricing effect of liquidity and credit risk on asset prices, dynamic interaction of liquidity and credit risk has received very little attention. Although, as early studies, Ericsson and Renault (2006) show theoretically that corporate bond liquidity is positively correlated with the likelihood of default, and He and Milbradt (2014) (as cited in Pelizzon et al., 2016) show that decreasing market liquidity affects the shareholders' default decision, they are not applicable to, as a theoretical framework, to sovereigns because of the difference on nature of credit events. There are, actually, no bankruptcy and strategic default choices in sovereigns other than debt renegotiation (Pelizzon et al., 2016). The most relevant paper in this field is the paper by Pelizzon et al. (2016) who investigate the dynamic interaction between sovereign bond market liquidity and sovereign credit risk and the effects of the intervention by European Central Bank (ECB)'s on this interaction. In this paper, they introduce a theoretical framework inspired from Stoll (1978) and extend it by including additional determinants of market liquidity and show both theoretically and empirically that there is a significant relationship between credit risk and liquidity in the bond market. They show that credit risk is one of driving forces in determining the liquidity of the Italian sovereign bond market. Focusing on the sample period covering Eurozone sovereign debt crisis, they show that credit risk significantly Granger-cause liquidity while there is no significant evidence that the reverse relation is also valid. Furthermore, they also show that ECB intervention on margin settings and, especially, on providing funding liquidity available to the banks has been successful to mitigate the severe effects of credit risk on liquidity and weakens the dynamic relation between them.

CHAPTER 3

MODEL AND METHODOLOGY

1. Model Description

In this thesis, the theoretical model proposed by Pelizzon et al. (2016) has been used. This section presents the theoretical model with the hypotheses and the basic intuition behind the theoretical framework. The model has been originally proposed by Stoll (1978) and extended by Pelizzon et al. (2016) through including some liquidity factors. In this model, key players are market maker, the traders, clearing house, and the central bank (Please see Figure 2).



Source: Pelizzon et al. (2016), p. 90

Figure 2: Dynamics of the Theoretical Model

In literature review section (Chapter 2) of this thesis, we mentioned about different aspects of liquidity such as speculators' capital and funding liquidity. As introduced in Brunnermeier and Pedersen (2008) the funding liquidity is defined as the ease with which traders obtain funding. So, the ability of market makers to provide liquidity is closely linked with the ease they obtain funding. Since, capital is required for any size of trading including short-selling, margin requirements is also an important factor that affects the market makers ability to obtain and provide funding. When margin requirement increases, the availability of funds to provide liquidity to the market decreases. So, market makers also consider margin requirements (consequently availability of funds) and adjust their quotes accordingly to provide liquidity to market.

In order to gain some intuition on what bid-ask spread the market maker of the bond market will quote, let us assume that liquidity of the market is provided by market maker which stands ready to quote prices. While doing that, she extracts information about riskiness of bonds from sovereign CDS market. The margin requirement that she will probably be facing is also determined by her inventory risk that rises with the riskiness of the assets she holds in her inventory. There are actually two channels that affect the choice of liquidity provision by the market maker: risk of the security itself and dealer's cost of financing a bond in repo market, including margin requirement settings by clearinghouses. In the second (indirect) channel, the clearing house determines the margins by looking at several factors such as CDS prices, the yield spread of the bond over German government bonds for Euro-area bonds etc. So, the higher the CDS prices or bond yield spreads, higher the margin required. The margin setting decision is also affected by Central Bank policies through volume traded in repo market which affects the risk-bearing capacity of the clearing house. Similar inference can be made from the model proposed by Brunnermeier and Pedersen (2008) which states that availability of funding liquidity loose grip on market makers' borrowing constraints. Central Bank policy (funding rate) is also a key factor that affects the market makers' borrowing costs.

In the model proposed by Pelizzon et al. (2016), market maker is assumed to make the market continuously. At a point in time, it is assumed that she has bonds in her inventory and she has an investment on optimal portfolio including both market portfolio and risk free asset. Let us assume that she has an initial wealth of W_0 and an inventory value, I, that is made up of the bond. She invests a fraction (k) of W_0 to market portfolio and the remainder of her wealth ($(1-k)W_0 - I$) on risk free asset, r_f , if it is positive (surplus), i.e . $(1-k)W_0 - I > 0$. However, if it is negative, she will borrow the remainder from central bank at a rate $r_b = r_f + b$. On the other hand, if the inventory, I, is negative, she borrows the bond from repo market where there is margin requirement, $m(CDS, b)$, which incur an additional cost for borrowing a *specific* bond instead of any bond in a collateral agreement. In the model, it is assumed that the dealer has a constant absolute risk aversion utility function, $U_x = e^{-\mu x}$, and she quotes the prices so as to keep her expected utility the same before and after trading quantity, Q:

$$E[U(W_I)] = E\left[U\left(W_{I+Q}\right)\right] \quad (1)$$

It is shown in the paper (Pelizzon et al., 2016) that the forward looking, CDS price implied volatility, $\sigma(CDS)$ is calculated as:

$$\sigma(CDS) = (1 + r_f)\frac{CDS}{p_0 n(0)} \quad (2)$$

where $n(0)$ is the probability density function of the standard normal distribution evaluated at 0.

Finally, with some adjustments the bid-ask spread that the market maker quote can be written as follows[13]:

$$BA(b, CDS) = \delta CDS^2 + m(b, CDS)p_0 + bn \quad (3)$$

where $\delta = \frac{\mu(1+r_f)}{n(0)^2} > 0$ and $n = \frac{p_0 - W_0(1-k)}{(1+r_f)} > 0$. Here, the bid-ask spread depends on the risk of the bond itself (first term) plus margin requirement (second term) and borrowing cost (third term). In addition, margin requirement also depends on both CDS prices and borrowing rate. According to the equation, it is easy to see that the higher the CDS prices or margin requirement or borrowing cost, the higher the bid-ask spread. As explained before, equation shows that CDS prices affect the bid-ask spread via two channel: the first term (δCDS^2) representing the riskiness of the bond and an indirect channel via margin requirement, $m(b, CDS)$, which is also changing with CDS prices.

[13] For detailed explanation for the calculation of bid-ask spread see the Appendix A of Pelizzon et al. (2016)

The second determinant of the bid-ask spread is the borrowing rate which is determined by the central bank. One should also keep in mind that changing borrowing costs will again affect bid-ask spreads in two ways: directly (third term) and through margins (second term).

In summary, according to the model described above, the market maker extracts information about the riskiness of the bond from CDS prices that will make her adjust the quotes accordingly. In addition, she will also reckon her borrowing and margin costs, depending on her net position from inventory and her total investment, and update her quote of the bond simultaneously. Here, one can suspect the informative nature of bid-ask spreads in Turkish bond market since there is no traditional market maker system in Turkey. Still, we need to keep in mind that bid-ask spread is just a proxy to extract information about liquidity. As explained before, bid-ask spreads are determined by the public orders for Turkish bond market. Even though we can't say that the dynamics of the bid-ask spread formation are the same with quote-driven market, we can infer that they are affected by the factors that determine the spread, in a similar fashion.

2. Methodology

In order to test our hypotheses and see the dynamic interaction between our credit risk of Turkish sovereign bonds, proxied by CDS spreads, and liquidity, proxied by different liquidity measures, we will first investigate whether any lead-lag relationship exists. To this end, we construct a VAR structure and apply Granger-causality test.

If two series are non-stationary (unit root) then the regression of these two variables are spurious. That means it has a high R^2 and significant t-statistics while there is no economic meaning. In this case, it is often recommended that the regression equation be estimated in first differences. On the other hand, if a linear combination of two non-stationary series (unit root) having the same order of integration (e.g. $I(1)$) is stationary, then the series are co-integrated in which there is an error correction term that needs to be included to VAR structure to obtain stationarity. So, pre-testing the variables in a regression for non-stationarity is very important. As seen from 'descriptive statistics' section of this thesis, the order of integration of the endogenous variables (Liquidity and CDS) are different, and there can't be a co-integration relation among them. If it were so, we would need to add an error correction term to make the system stationary. Because of this, we choose to apply a VAR structure with differences of endogenous variables series, which are stationary and, in this case, immune to spurious regression.

Although, as in the paper by (Pelizzon et al., 2016), the theoretical framework given in this thesis only show how CDS prices affect the liquidity, we will not rule out the inverse relationship. We will set up a VAR model that allows us to observe this feedback relation simultaneously and test the causality between variables. As proposed by (Pelizzon et al., 2016), we will also include the model some exogenous control variables to filter out some global effects that can contaminate the relationship between our two main variables. We include USVIX, US-Turkish 3-month Bill yield spread and cross currency swap basis as our exogenous variables. This model is called as VAR with eXogenous variables (VARX) model in the literature.

We, simultaneously, regress change in our liquidity measures (each) and change in CDS spreads on their *p* lags and on some exogenous variables given that $\Delta \mathrm{Liq_t}$ and $\Delta \mathrm{CDS_t}$ are two stationary variables and $\Delta \mathrm{X}_t$ is vector of stationary exogenous variables. The model is given below:

$$\begin{pmatrix} \Delta \mathrm{Liq_t} \\ \Delta \mathrm{CDS_t} \end{pmatrix} = \begin{pmatrix} A_{Liq} \\ B_{CDS} \end{pmatrix} + \sum_{\mathrm{i}=1}^{\mathrm{p}} \begin{pmatrix} \varphi_{11}^{\mathrm{i}} & \varphi_{12}^{\mathrm{i}} \\ \varphi_{21}^{\mathrm{i}} & \varphi_{22}^{\mathrm{i}} \end{pmatrix} . \begin{pmatrix} \Delta \mathrm{Liq_{t-i}} \\ \Delta \mathrm{CDS_{t-i}} \end{pmatrix} + \sum_{\mathrm{j}=0}^{\mathrm{q}} (\theta_j) . \begin{pmatrix} \Delta \mathrm{X1_{t-j}} \\ \Delta \mathrm{X2_{t-j}} \\ \cdot \\ \cdot \\ \Delta \mathrm{Xm_{t-j}} \end{pmatrix} + \begin{pmatrix} \epsilon_{Liq_t} \\ \epsilon_{CDS_t} \end{pmatrix}$$

(4)

where $\epsilon_t \sim \mathrm{N}(0, \Omega)$ and $\varphi_{\mathrm{kl}}^{\mathrm{i}}$'s are coefficients of *p*-lag of the VARX model. This model allows *m* exogenous variables to control the dynamics between endogenous variables. In order to test causality with Granger-causality test we should test the null hypothesis of $H_0\colon \varphi_{jk}^i = 0$ for all *i*, where *j≠k*. We can conclude that $\Delta \mathrm{CDS_t}$ Granger-cause $\Delta \mathrm{Liq_t}$ ($\Delta \mathrm{CDS} \overset{\mathrm{GC}}{\Rightarrow} \Delta \mathrm{Liq}$) when φ_{12}^i 's are contemporaneously different from zero. Likewise, if φ_{21}^i's are contemporaneously different from zero then we can conclude that $\Delta \mathrm{Liq_t}$ Granger-cause $\Delta \mathrm{CDS_t}$ ($\Delta \mathrm{Liq} \overset{GC}{\Rightarrow} \Delta \mathrm{CDS}$). If both statements are true at the same time then we can conclude that there is a feedback relation between these two variables.

In order to determine the lag length, we both checked the Akaike information criteria and conducted residual analysis to see whether any serial correlation and/or heteroscedasticity exist. Although Akaike information criteria gives p=5 for noise measure and p=8 for bid-ask spread, in daily terms we choose the lag length of endogenous variables as p=9 and p=12, respectively, in order to remove serial correlation among residuals. Similarly, while Akaike information criteria gives lag length of p=2 or sometimes p=1 for monthly variables, we choose different lag lengths so as to avoid serial correlation and heteroscedasticity effect within residuals. We specify no length for exogenous variables (q=0), which is in line with the original paper (Pelizzon et al., 2016). We use maximum likelihood estimation (MLE) for model parameters and test the significance of the parameters with t-statistics. We also conducted residual analysis to see whether any autocorrelation and/or heteroscedasticity exist between residual series and adjust the lags of parameters, accordingly.

CHAPTER 4

DATA AND DESCRIPTION OF VARIABLES

In this section, the characteristics of the data used in this thesis and description of variables will be given. In addition, construction of liquidity measures will be described.

1. Liquidity Measures

We will use several liquidity measures in this thesis. Our main liquidity measure, which is proposed by Hu et al. (2013), is computed as the average dispersion of the observed yields around the yield curve. We also used other liquidity (spread) measures to be able to capture effects of different liquidity measures on credit risk and for robustness check whether the main liquidity (noise) measure is, in fact, able to capture the liquidity effects in overall financial markets.

1.1. Noise as a Measure of Liquidity

The level of liquidity in an overall financial market is closely interconnected with the available arbitrage capital. When arbitrage capital is abundant in financial markets, the value of securities are close to their fundamental values by arbitrage rule which forces any arbitrage opportunities to diminish, consequently any discrepancies between fundamental values and observed values to be eliminated. When this arbitrage capital is scarce, liquidity dries up in financial markets and the lack of sufficient arbitrage capital cause assets to be traded significantly different from their fundamental values. In line with this philosophy, the noise measure proposed by Hu et al. (2013) is constructed by calculating average dispersion of observed treasury yields from their fundamental values (yields on yield curve) through all maturities. During liquidity crises, lack of arbitrage capital or unwillingness to deploy it (e.g. hedge funds limiting their value trades), leave the yields to move more freely in their own environment, causing more noise (dispersion) on yield curve. In their paper, Hu et al. (2013) argue that abnormal noise in treasury yield curve is a symptom of liquidity shortage in overall financial markets. They claim that, this noise measure of illiquidity captures the information on liquidity not only for bond markets but also for the overall financial market. It is shown that the noise measure has significance on explaining hedge fund returns and returns of currency trade portfolios while other liquidity measures which is used in the original paper don't. The higher the noise, the higher the illiquidity, meaning low liquidity in the market.

In above section, we summarized that there are various liquidity measures in the literature some of which are applicable to all kinds of settings and some are not. For instance, the measure by Schwarz (2017) calculated as the difference between KfW bonds and German government bonds is a good proxy for liquidity, however, it is not applicable to all countries, for instance Turkey, since it is not easy to find an agency issuing bonds which are also guaranteed by the government. However, the noise measure extracted from treasury yields can be applicable to almost any country given that the treasury in question issues bonds covering different segments of the term structure. In following subsections, the basics of term structure and yield curve fitting will be given and construction of noise measure will be explained.

Yield Curve Fitting

Treasury yield curve is a very important tool for both economists and finance executives. Ignoring the default probability, only unknown data to price any fixed-income asset is the proper discount rate. The rates that should be used to discount cash flows of any security are determined by looking at this benchmark curve. By this curve, one can also observe the market expectations on interest rates for a given (short or long) term. The term structure of interest rates, in other words, is the relationship between interest rates (bond yields) and various terms (bond maturities). The curve contains information on bond yields on vertical axis and the time to maturity on the horizontal axis.

The main problem while constructing this term structure is that treasuries issue only limited number of bonds with different type of coupons and maturities, that do not span all maturities. So, in order to find the proper discount rate, we usually have to infer (interpolate) the yields across all of maturities from the prices of existing securities in the market in order to obtain full spectrum of yield curve. This is the conventional exercise on yield curve estimation in the literature[14], which will be more explained below.

Fixed income securities consist of *discount* or *zero-coupon* bonds and *fixed-coupon* bonds (floating bonds are not used for curve fitting). While first type of bonds has only one payment at maturity, others have periodic payments until maturity. The price of a coupon-bearing bond, at time *t*, that pays regular coupons *C* and face value of 100 is calculated as the sum of discounted cash flows:

$$P_t(T_n) = \sum_{i=1}^{n} C.\delta_t(T_i) + 100.(T_n) \qquad (5)$$

where $\delta_t(T_i)$[15], $i = 1 \dots n$, are discount functions (factors) with maturities $T_{1,}T_2, \dots\dots, T_n$. A zero coupon bond, on the other hand, is the bond that has only one payment of its face value at its maturity, i.e when *C=0* in above equation. So, yields on zero-coupon bonds can be considered as the discount rate for that maturity date.

Yield to maturity, on the other hand, is the internal rate of return of a bond which makes the price of the bond equal to present value of expected cash flows discounted by this rate and which is denoted below:

$$P_t(T_n) = \sum_{i=1}^{n} \frac{C}{(1+y_t)^{T_i}} + \frac{100}{(1+y_t)^{T_n}} \qquad (6)$$

Yield to maturity is the implied average interest rate of the bond, if it is held until its maturity. Yield to maturity is often thought as the T_n-period interest rate. However, this

[14] For detailed information on yield curve fitting, see Gurkaynak, Sack and Wright (2007).

[15] There may be different discount factors. Continuous discount function is expressed as: $\delta_t(T_i) = e^{(-r_t(T_i).T_i)}$, where $r_t(T_i)$ is the discount rate (yield) and T_i is the time to redemption of each cash flow. Another way to express yields, as widely used convention, can be 'coupon-equivalent' or 'bond-equivalent' basis which is denoted as: $\delta_t(T_i) = \frac{1}{(1+r_t(T_i)/f)^{f.T_i}}$, where f is the compounding frequency. In this thesis, we used 'coupon-equivalent' yield convention to back out zero coupon yield curve, where compounding frequency is 2.

approach is not accurate. While yield to maturity of a zero-coupon bond is equal to spot rate for that maturity, this is not true for coupon bearing bonds because holder of the bond receives some of cash flows earlier than the maturity date. If we had zero-coupon securities at all maturities over the yield curve spectrum, then it would be very easy to calculate discount rates, hence drawing spot (zero) curve, by just interpolating the rates observed on these bonds. However, zero-coupon bonds are generally at the short end of the maturity spectrum and are not many.

Here, the duration[16] of a bond comes to the play. Duration of a bond is defined as the average time (weighted by the PV of each cash payment) in years that a bond holder must wait to receive his cash flows. While the maturity of a zero coupon bond is equal to its duration, coupon bearing bond has a duration less than its time to maturity. For instance, for a given term structure, two bonds with different coupon rates would have different durations and yield to maturities. So, fitting yield to maturities of coupon bearing bonds is not a proper way to find the term structure. Instead, one needs to strip coupon payments and discount them with different discount rates: i.e. to think coupon-bearing bonds as baskets of zero-coupon securities (each cash flow as a face payment).

There are various ways on how to interpolate the terms between observed yields of bonds having different time to maturities. The most popular approaches are spline-based and function-based models. While spline based methods allows more flexible curves, which entails more variability in forward rates, it comes with additional computational costs. Moreover, function-based models are shown to perform favorably (Bliss, 1996). The most well-known and frequently used model for function-based methods is the Svensson model (Svensson, 1994) which is extended from Nelson-Siegel model (Nelson & Siegel, 1987) and also used for the construction of our noise measure. Although it is claimed that the main results are not specific to particular choice of yield curve fitting method, we will stick with the model used in the original paper for noise construction (Hu et al., 2013) and, in this thesis, use popular function-based Svensson method to fit Turkish term structure.

[16] Duration of a coupon-bond is calculated as: $D = \frac{1}{P_t(T_n)}\left(\sum_{i=1}^{n} \frac{T_i.C}{(1+y_t)^{T_i}} + \frac{T_n.100}{(1+y_t)^{T_n}}\right)$

The Svensson model assumes the following functional form for the instantaneous forward rate f:

$$f(m,b) = \beta_0 + \beta_1 \exp\left(-\frac{m}{\tau_1}\right) + \beta_2 \frac{m}{\tau_1} \exp\left(-\frac{m}{\tau_1}\right) + \ \beta_3 \frac{m}{\tau_2} \exp\left(-\frac{m}{\tau_2}\right) \qquad (7)$$

Where m denotes the time to maturity (in years) of cash flow, and $b = (\beta_0 \beta_1 \beta_2 \beta_3 \tau_1 \tau_2)$ is the vector of parameters to be estimated for each day the yield curve is estimated. Moreover, parameters must satisfy the conditions: $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, $\tau_1 > 0$, and , $\tau_2 > 0$. From forward rate equation the corresponding spot rate, $s_t(m,b)$[17] is derived as:

$$s_t(m,b) = \beta_0 + \beta_1 \frac{1-\exp\left(-\frac{m}{\tau_1}\right)}{\frac{m}{\tau_1}} + \beta_2 \left[\frac{1-\exp\left(-\frac{m}{\tau_1}\right)}{\frac{m}{\tau_1}} + \ \exp\left(-\frac{m}{\tau_1}\right)\right] + \beta_3 \left[\frac{1-\exp\left(-\frac{m}{\tau_2}\right)}{\frac{m}{\tau_2}} + \exp\left(-\frac{m}{\tau_2}\right)\right] \quad (8)$$

Actually, fitting the yield curve is, in practice, to find the parameter vector *b* by using observed market prices. It is, indeed, an optimization problem. On each day, *t*, the inputs of our yield curve is the closing prices (weighted average price in BIST daily bulletin) of all Treasury bills and bonds traded on exchange (BIST) on that day with maturity between 1 month up to 10 years. We exclude strips (coupon and principal), floating-coupon bonds, and sukuks from our input pool. Let N_t is the number of bills and bonds traded on day *t*, and P_t^i is the market observed prices for each bond $i = 1, \dots, N_t$. The model parameters is chosen so as to minimize duration weighted sum of squared deviations between the actual and the model-implied prices:

$$b_t = \text{argmin}_b \sum_{i=1}^{N_t} \left[\left(P^i(b) - P_t^i\right) x \frac{1}{D_i}\right]^2 \ ^{18} \qquad (9)$$

In essence, the algorithm we built tries to minimize the distance between observed prices and theoretical prices in each day (as a whole) calculated by sum of present values of each cash flow discounted by the spot rate, $s_t(M,b)$, given above. Theoretical price, $P^i(b)$, is calculated as follows:

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[17] For a bond that has several cash flows, *m* becomes a vector of dates corresponding to each cash flow.
[18] We used *lsqnonlin* optimization tool of MATLAB to minimize sum of squared deviations.

$$\begin{bmatrix} P^i(b) \\ . \\ . \\ . \\ P^{Nt}(b) \end{bmatrix} = \mathbf{1}^{\boldsymbol{T}} \begin{bmatrix} C^i \\ . \\ . \\ . \\ C^{Nt} \end{bmatrix} . \begin{bmatrix} S^i(M^i, b) \\ . \\ . \\ . \\ S^{Nt}(M^{Nt}, b) \end{bmatrix} \qquad (10)$$

Where **C** denotes the cash flow portfolio matrix consisting of cash flow vector of each of the bonds traded on day t and $S^i(M^i, b)$ denotes the discount matrix for bond i with maturity matrix M^i corresponding to each cash flow. Here, cash flow matrix, discount matrix and maturity matrix has the same size ($N_t x C_{max}$), where C_{max} denotes the maximum number of cash flow that usually belongs to the bond having the longest time to maturity and *(.)* denotes point-wise multiplication.

We also employ a filter to avoid any fitting error stemming from obvious pricing errors in bonds that cause distortion in fitted yield curve. We could visually observe whether the curve fits the observed yields and eliminate obvious pricing errors that distort our fit. However, since there is a yield curve for each day in our sample (would be in thousands) that make it nearly impossible to manually do this exercise. So, first we exclude the bonds having obvious pricing errors: for instance we pre-eliminate bonds having annual market observed yield to maturity below a threshold level which is below Turkey's historical low since we thought that these bonds are obvious errors having no information about our liquidity measure. For instance, on 10 May 2016, the yield curve is flat and most of bonds' simple yields are priced around 9% (APR). On this day, however, we observe that out-of 29 bonds traded, just 5 low-coupon bonds (with coupons varying from 2% to 4%) are priced to have 2% and 3% yields that distort our fit. Although it is not proper to assume that the observed yields on coupon-bonds represent the interest rate on the corresponding maturity dates, we shouldn't have observed such big differences considering that we have almost flat yield curve. BIST has an 'Off-Exchange Trades Registration' system that allows institutions to register in BIST of their bond trades in Over-the-Counter (OTC) market within 1 week after the trade occurs. So, in our opinion, these discrepancies may stem from the OTC bond trade (later registered in BIST) between financial institutions possibly in order to adjust their balance sheets. In addition to threshold filter, we also employ a Hampel filter[19] to detect and remove outliers that other filter failed to remove.

Constructing Noise Measure

After estimating the yield curve for each day, it is an easy task to construct our noise (illiquidity) measure. It is called the noise measure, because it is the average of noise stemming from the difference between observed yields and their fundamental values represented by the yield curve. For each date, t, suppose we have N_t treasury bonds and bills with maturity, this time, between 1 to 10 years. For each of the bond, let y_t^i denotes the market observed yields and $y^i(b_t)$ denotes the model implied yield. So, the noise is calculated as dispersion in yields around the yield curve by calculating the root mean squared error between the market observed yields and model implied yields:

$$Noise_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[y_t^i - y^i(b_t)\right]^2} \quad (11)$$

We stick with the model in the original paper that explains that short maturity bonds/bills (up to 1 year) have limited information explaining the availability of arbitrage capital, the concept where this noise measure originates from. According to the paper, short end of the yield curve is assumed to be noisier due to temporary demand and supply fluctuations in that segment. So, although we use them for curve fitting, we exclude short term bonds while calculating the noise measure. In addition, because of the limited supply of the bonds having maturity more than 10 years, we also exclude them in calculating the noise measure, again, in accordance with the original model.

1.2. Bid-Ask Spread

Using quoted bid-ask spread is a conventional way to proxy for liquidity (the cost of immediacy) in the market. It is the difference between the best ask and best bid prices. While some researchers used intra-day data of bid-ask spread to build their liquidity measure, some others use daily quoted bid-ask spread. In intra-day data as in (Pelizzon et

[19] This filter computes the median of a window composed of the sample and its 6 surrounding samples, three per side. It also estimates the standard deviation of each sample about its window median using the median absolute deviation. If a sample differs from the median by more than four standard deviations, it is replaced with the median. If triggered, this filter affects, in average, 1 or 2 bonds (per day).

al., 2016), bid-ask spread quotes are measured for each bond per 5 minutes, then these spreads are averaged daily for each bond. Averaging, this time, over bonds gives the daily bid-ask measure.

In this thesis we used daily bid-ask prices for the bonds traded at the Borsa Istanbul Debt Instrument market. However, rather than taking high and low prices in BIST daily bulletin, we use bid and ask price quotes from Bloomberg of the bonds traded at exchange. This time, we include all government bonds including fixed, floating, sukuks except for strips and Eurobonds. We eliminate again the bonds having ask or bid price (yield) is missing (not quoted), ask price that is lower than bid price, and bonds having negative yields. Descriptive statistics and time series properties of this measure will be given next section with other variables.

1.3. High-Low Spread

In order to check for robustness for our main liquidity measure and capture liquidity effects on credit risk with a different ‘monthly’ measure, we also build, by using Turkish data, high-low spread measure proposed by Corwin and Schultz (2012). This measure uses high and low prices of securities to calculate bid-ask spread for transition liquidity. It is also claimed that this measure is easy to calculate from daily observable data and generally better perform compared to other daily low-frequency proxies. Furthermore, Schestag et al. (2015) shows that this measure is one of the few successful daily proxies which are able to capture transaction cost variations comparable to high-frequency measures.

Corwin and Schultz (2012) claim that high-low ratio contains information about both stock’s variance and its bid-ask spread. While the variance component of this ratio is proportional to return interval, i.e. volatility increases with time interval, the spread component does not. This is to say that while sum of two consecutive single day price change reflects two days volatility plus twice the spread, two-day price change reflects two days volatility and one spread. So, by using high-low prices in subsequent days and over 2-day periods, it is possible to decompose these two components and derive the spread by filtering variance component. Actually, as a future research, we feel that this measure can be one of the best candidate for liquidity measurement in Turkish stock exchange, where the bid-ask spread for stocks have nearly identical values (equal to minimum tick size) that makes nearly impossible to extract useful information about liquidity from traditional bid-ask spreads for stocks.

Spread proxy, for each bond *i* on day *t,* is calculated as:

$$S_{i,t} = \frac{2.(\mathrm{e}^{\alpha_{i,t}}-1)}{1+\mathrm{e}^{\alpha_{i,t}}} \qquad (12)$$

Where,

$$\alpha_{i,t} = \frac{\sqrt{2.\beta_{i,t}}-\sqrt{\beta_{i,t}}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma_{i,t}}{3-2\sqrt{2}}} \qquad (13)$$

$$\beta_{i,t} = \sum_{j=0}^{1}\left(\log\left(\frac{H_{t+j}^{i}}{L_{t+j}^{i}}\right)\right)^2 \qquad (14)$$

$$\gamma_{i,t} = \left(log\left(\frac{H_{t,t+1}^{i}}{L_{t,t+1}^{i}}\right)\right)^2 \qquad (15)$$

Here, $\mathrm{H}_{\mathrm{t}}^{\mathrm{i}}$ ($\mathrm{L}_{\mathrm{t}}^{\mathrm{i}}$) is the high (low) price of bond i on day t and $\mathrm{H}_{\mathrm{t,t+1}}^{\mathrm{i}}$ ($\mathrm{L}_{\mathrm{t,t+1}}^{\mathrm{i}}$) is the highest (lowest) price on two consecutive days, for bond i on day t. This measure, in nature, is a monthly measure calculated by averaging all $\mathrm{S}_{\mathrm{i,t}}$ in a given month for bond i. Then, for building monthly high-low measure, we average the daily spreads over all bonds for a given month. In our calculations, as proposed in the original paper, we corrected negative values as zero. However, we didn't correct for the overnight returns since we think these are not frequent. We collect the data (high and low prices for each bond) from, again, BIST daily bulletin for bonds. We use the same pool that we use for building our daily bid-ask spread measure.

2. Credit Risk Measure

As seen in our literature survey, although debatable, the researchers widely use sovereign CDS prices to proxy credit risk. In this thesis, we will also use sovereign CDS prices for Turkey to proxy credit risk. However, this proxy should be used with caution since there may be several shortcomings to use this measure. First, credit risk may not be well reflected to CDS prices for developed countries due to counterparty risk (Ejsing et al., 2012). So, the premium would also include the default risk belonging to insurance provider. For example, by the time US government defaults, the counterparty providing insurance, via a CDS contract against US government, should already have been defaulted. In short, if US government fails, everyone fails. However, this risk is mostly eliminated by establishing clearing houses as a central clearing body. Second, although corporate CDS contracts in the US have sufficient liquidity to reflect actual prices, this may not be the case for sovereigns since the nature of default for sovereigns is different from corporations as mentioned before. So, the liquidity of sovereign CDS contracts is also an important factor so that the prices of these contracts reflect the default risk well. Fortunately, CDS for Turkish sovereigns are one of the most liquid products in CDS market (IMF Global Financial Report, 2013).

3. Descriptive Statistics and Time Series Properties of Variables

In this part, we will give descriptive statistics of data we used while constructing our liquidity measures together with other variables. Furthermore, we will present some figures about term structure (yield curve) examples and time series plot of the variables in Turkey.

In bonds characteristic table (Table 2), number of bonds according to maturity (up to 10 year) and number of bonds by their characteristics (zero or coupon-bond etc.) can be observed. Yield curve column includes government bonds used for yield curve estimation (excluding floating bonds and sukuks). On the other hand, liquidity column includes all government bonds including fixed, floating, zero coupon and sukuks (Islamic bonds/kira sertifikasi). As can be seen from the table, while the number of bonds with short term maturity does not significantly change over time, the number of bonds in 5-to-10 year segment significantly increases in the 2^{nd} period. For instance, while the daily average number of bonds having maturity up to 1 year is 8.9 in the first period, it slightly declines to 7.95. Whereas, daily average number of bonds in 5-to-10 year segment significantly increase from 2.7 to 7.8 daily average, which is in line with the strategic target of Turkish Treasury to increase the average maturity of the debt.

Table 2: Bond Characteristics by Maturity and Type

This table shows the characteristics of the bonds in our sample. Panel A shows the bond characteristics by maturity with respect to two sub-periods. Here, while 'Liquidity' column comprises all government bonds including zero-, fixed-, floating-coupon bonds and sukuks in our sample, 'Yield Curve' column includes only bonds used for curve fitting, excluding floating bonds and sukuks. The values represent the total number of bonds traded during that period, while the values in parentheses represent average number of bonds traded each day during that period. Panel B of the table shows the bonds by their type: zero-coupon, fixed coupon, floating, and sukuks (Islamic bonds). Again, the values in parentheses represent average number of daily trades or trade volume. B represents billion and M represents million for trading volume in Turkish Liras.

Panel A: Bond characteristics by maturity

	Jan 2010- Dec 2012		Jan 2013- Dec 2016	
	Yield Curve	Liquidity	Yield Curve	Liquidity
Maturity Group	# of Bonds (daily avg.)	# of Bonds (daily avg.)	# of Bonds (daily avg.)	# of Bonds (daily avg.)
0-1m	1311 (1.7)	1417 (1.8)	1306 (1.37)	1608 (1.7)
1m-1y	5623 (7.2)	5926 (7.6)	6248 (6.58)	7228 (7.6)
1-3y	6584 (8.4)	7338 (9.4)	5781 (6.1)	7130 (7.5)
3-5y	2975 (3.8)	3352 (4.3)	4329 (4.56)	4666 (4.9)
5-10y	2117 (2.7)	2374 (3.0)	7389 (7.8)	7613 (8.0)
TOTAL	18610 (23.8)	20407 (26)	25053 (26.4)	28245 (29.8)

Panel B: Bond characteristics by type

	Jan 2010- May 2013			May 2013-Dec 2016		
	# of Bonds	# of Trades (daily avg.)	Trade Volume (daily avg.)	# of Bonds	# of Trades (daily avg.)	Trade Volume (daily avg.)
Zero-Coupon	7852	514152 (656)	590.9B (755 M)	3361	35098 (37)	44.4 (46.8M)
Fixed Coupon	12671	262299 (334)	319.3B (408M)	20614	476981 (502)	579.3 (610M)
Floating	1776	5737 (7.3)	16.92B (22M)	781	5183 (5.5)	25.0 (26M)
Sukuk	124	323 (0.4)	.094B (0.1M)	2413	9957 (10.5)	3 (3.2M)
TOTAL	22423	782516 (999)	927.3B (1.18B)	27169	527219 (555.5)	651.7 (686.7 M)

In Panel B of the table, we can observe the breakdown of the bonds according to their characteristics in terms of their type, trade volume and number. Both number of zero-coupon bonds and trade size significantly decrease in the second period compared to first period. While daily trade volume of zero coupon bonds decreases from 755 million TL to 468 million TL, daily trade volume of coupon-bearing bonds (excluding floating) increases from 408 million to 610 million TL. We can also observe that sukuk trading becomes more popular in the second period. Another aspect worth to mention is that, both total trade number and volume significantly decrease in the second period: the daily trade number decreases from 999 to 555 and daily trade volume decreases from 1.18 billion TL to 687 million TL. Actually, these results are also in line with our results that the mean and standard deviation of bid-ask spread increases in the second period: Daily mean goes from 2255 bps to 3528 bps while it has a daily mean of 2933 bps in the overall period. Furthermore, its daily standard deviation goes from 964 to 1533 while it has a daily standard deviation of 1445 in the overall period.

3.1. Dataset, Descriptive Statistics and Time Series Properties

In this subsection, we will present descriptive statistics of variables and analyze univariate time series properties of each variable.

Noise as information for liquidity in Turkey

There are totally 44498 government bond observations (after excluding strips, floating, sukuks and Eurobonds) between 2 January 2010 to 31 December 2016. We take the bond time-series data (high, low and weighted average prices) from BIST Daily Bulletin. Furthermore, the static properties of each bond (issue date, maturity, coupon type, coupon frequency etc.) is taken from Bloomberg terminal. We eliminate, beforehand, some bonds having the yields below a threshold level. After elimination, each day, in average, there are 21 bonds traded. Noise measure fluctuates around its time series average of 12 bps with a standard deviation of 4 bps (See Table 3).

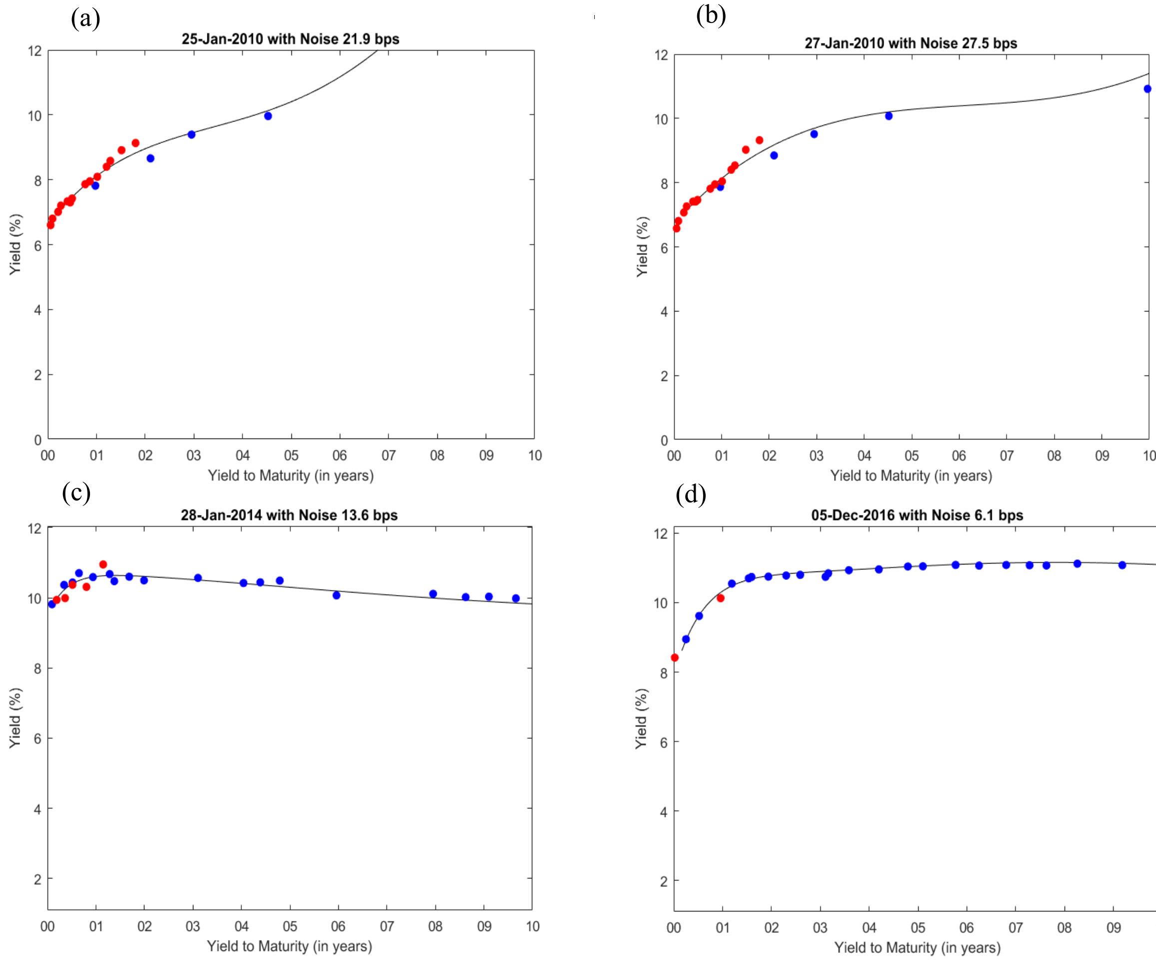

Figure shows yield curve plots for four different dates. Points represent the simple yields observed in the market; red ones are for zero-coupon and blue ones are for coupon-bearing bonds, while black curve represents the fitted curve using Svensson curve fitting model.

Figure 3: Yield Curve Fitting Examples

Turkish government started issuing 10-year bonds on 27 January 2010 (see Figure 3.a & 3.b). Before that, zero-coupon and short-maturity bonds hold heavy weight in term structure (Please see Table 2 and also see Figure 3 for comparison). For instance, from January 2008 to January 2010, no bonds are observed between 5-year and 10-year maturity segment. Because of this, we feel that it would not be wise to use this measure before 2010 since our noise measure is constructed by using bonds having maturity up to 10 years. Although 10-year bonds started trading after 2010, the date we consistently observe at least one bond in 5-to10-year maturity segment is 14 April 2010. After this date, we only observed one day when no 5-to10-year bonds are traded, which is 12 July 2010. So, we set the start date for the noise measure as 14 April 2010.

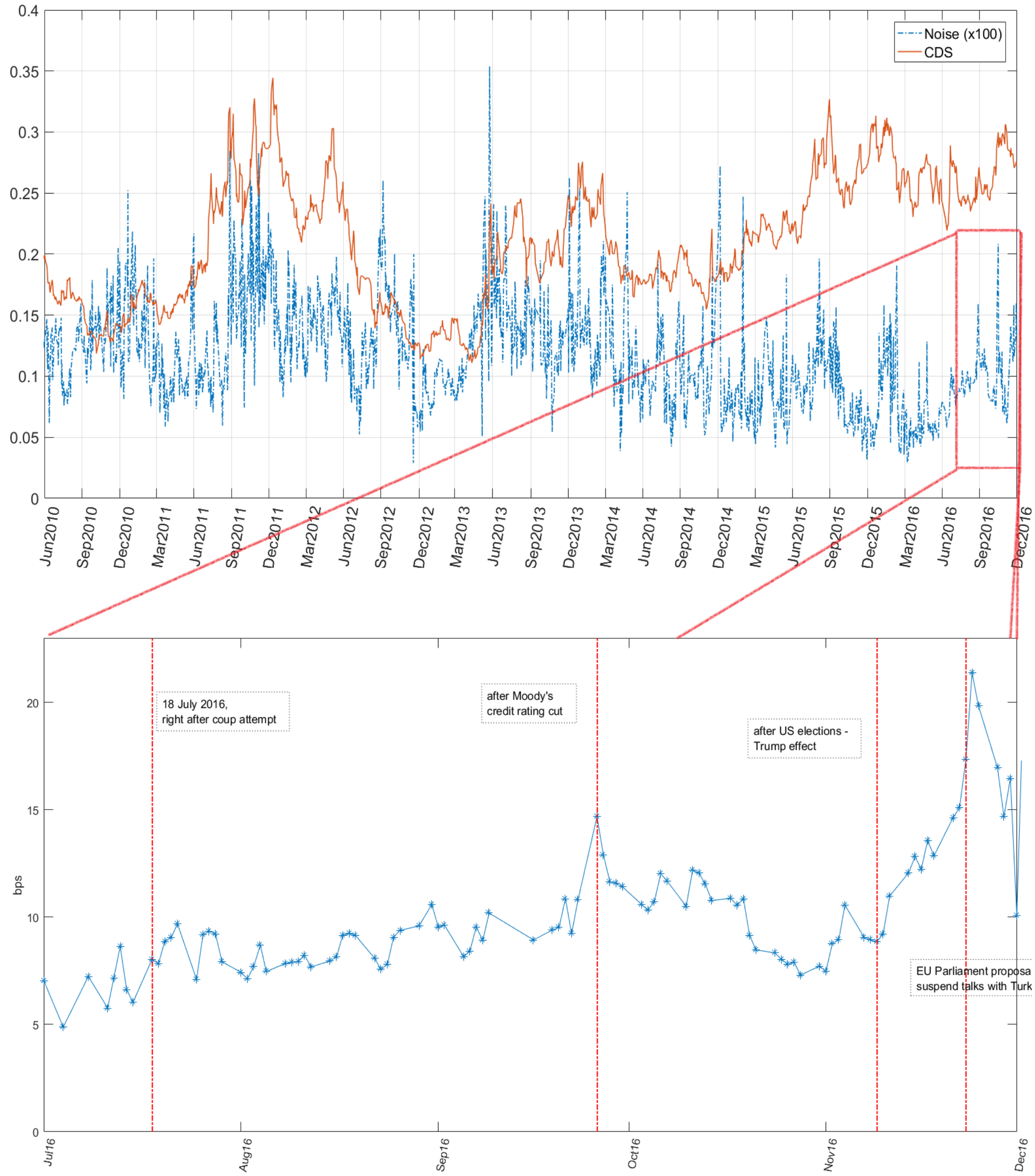

Figure 4: Noise Measure and CDS (Daily)

In order to observe whether the noise measure gives meaningful results for Turkey, we plot the noise measure for the 2nd half of 2016 in which significant events occurred. We can observe from Figure 4 that the noise measure reflects possible liquidity shocks as a result of significant political events well and the movement of noise measure is meaningful. We observe a level increase after July 15th of 2016 (coup attempt) and the effect of illiquidity seems more pronounced after US elections-Trump effect.

Bid-Ask Spread

In order to construct daily average of bid-ask spreads, different from what we did in yield curve fitting where we use only zero-coupon and fixed-coupon government bonds, we include all government bonds/bills with zero coupon, fixed-coupon, floating-coupon bonds and sukuks (excluding strips, Eurobonds) between 2 January 2010 to 31 December 2016. So, there are totally 49592 government bond data. we eliminate, beforehand, bonds traded each day with following properties: ask or bid price (yield) is missing (not quoted), ask price is lower than bid price, bonds having negative yields. After elimination, each day, in average, there are approximately 20 bonds traded that we use for calculating bid-ask spread. Rather than using high and low prices given by BIST daily bulletin (BIST does not provide quoted prices, but provides executed transactions) we used bid and ask (quoted) prices from Bloomberg. Bid-ask spread fluctuates around its time series average of 2933 bps with a standard deviation of 1445 bps.

High-Low Measure

In order to construct monthly High-Low spread measure, we used the same pool of bond data while forming bid-ask spread. Here, we used the daily high- and low-prices of government bonds that we obtained from BIST Debt Securities Market Data, Daily Bulletin. After elimination, each day, in average, there are approximately 20 bonds traded that we use for calculating high-low spread. High-low spread fluctuates around its (monthly) time series average of 1.60 bps with a standard deviation of 0.87 bps. Although not reported, we observe again that high-low measure increased in the second period.

Other Variables

We obtained other variables from Bloomberg terminal and from Central Bank reports. These are 5-year CDS spreads for Turkish sovereigns, US VIX data, cross currency swap spread (CCSS) calculated by using the difference between TEB 2-year benchmark interest rates and swap rates data, and (TRBill-USBill) which is the difference in yields between 3-month Turkish USD Eurobond and 3-month US government bill. We use these data as exogenous variables to control the relation between credit risk and our liquidity variables. Furthermore, we also obtained from Central Bank of Turkey the 'Debt' and 'Net' data which respectively represents the portfolio investments on debt and overall (debt+equity) financial markets. This data is provided by the Central Bank in monthly terms under financial account in Balance of Payments report. We use them in order to observe the relation between the liquidity measures and short-term foreign

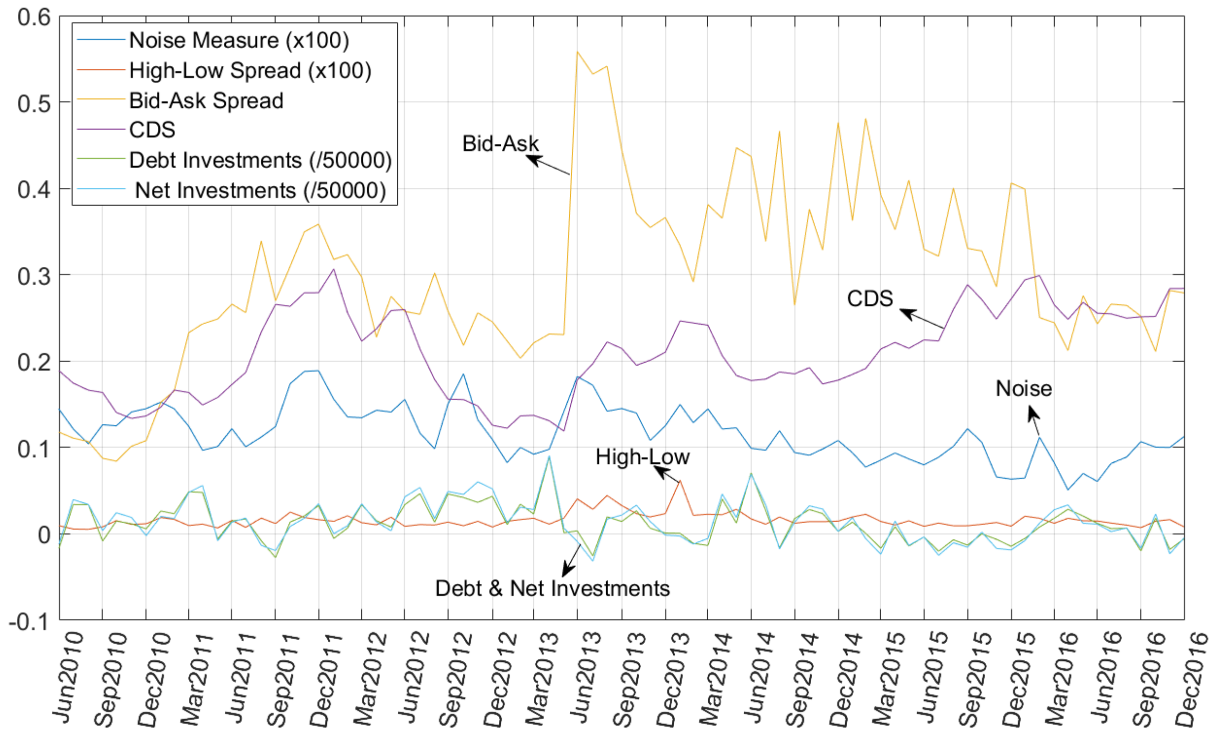

Figure 5: Liquidity Variables and CDS (Converted to Monthly and Scaled)

investments in Turkey.

As explained before, the CDS spread is a proxy for measuring credit risk. The US VIX data, which is assumed to measure global systemic risk and widely known as 'fear gauge', is the implied volatility index of S&P 500 Index options. Cross currency swap spread, on the other hand, is the spread for a cross currency swap between Turkish Lira and US dollar London Interbank Offered Rate (LIBOR) which is discussed in the literature to proxy global funding liquidity for a country. This relies on the fact that when liquidity is available to arbitrageurs, deviations from uncovered interest rate parity should be eliminated. So, lasting deviations is considered as a sign of lack of funding liquidity (Brunnermeier, Nagel, and Pedersen (2008) as cited in Pelizzon et al., 2016).

Table 3: Descriptive Statistics and Unit Root Tests for Daily/Monthly Variables

This table shows the descriptive statistics of the variables used in our model. While rows represent the variables, columns represent the statistics such as mean and standard deviation. The 'Unit Root Test' column shows the result of Dickey-Fuller tests for unit root for each variable both in levels and differences. (***) indicates %1 significance, where (**) indicates %5 significance for unit root tests, meaning that the variables with stars don't show unit root characteristic.

Variables Statistics

	(in basis points)					**Unit Root Test**	
Variable	**Mean**	**STD**	**5^{th} Pct**	**Median**	**95^{th} Pct**	**Level**	**Difference**
Noise	12	4	6	11	20	-5.17^{***}	-58.05^{***}
Bid-Ask Spread	2933	1445	1028	2672	5442	-8.02^{***}	-64.07^{***}
High-Low (monthly)	1.60	0.87	0.75	1.46	3.05	-2.32^{**}	-14.36^{***}
Turkish CDS	209.3	51.2	129.90	205.80	290.70	-0.20	-34.68^{***}
USVIX	17.90	5.94	12.10	16.19	31.33	-1.83	-43.15^{***}
CrossCurr Swap	63	78	-38	59	206	-2.12^{**}	-47.51^{***}
TRBill-USBill	172	99	89	159	293	-6.48^{***}	-50.43^{***}

3.2. Univariate time-series properties of variables

Table 3 also shows the summary statistics of unit root tests for each variable. We applied Dickey-Fuller test to check for unit root. In levels, while the daily liquidity measures do not show unit root characteristics, the unit root tests fail to reject the null hypothesis of unit root for the other variables. It can also be seen that, first level differencing eliminates the unit root and all differenced variables become order if integration zero, *I(0)*. Moreover, although it is not reported, the Dickey-Fuller tests fail to reject the null hypothesis of unit root for all the variables (in levels) that we convert from daily to monthly by taking simple average.

Furthermore, we also checked the models that each variable best fits whether AR(p), MA(q) or ARMA (p,q) processes and determine their optimal lag length by using Akaike information criteria. We also checked the residuals for normality and whether they show heteroscedasticity and serial correlation. The summary results are given in Table 4. For the sake of comparability, we regress the difference of variables to their lags of differences since some variables show unit root characteristics. We do not report the lags bigger than 4 either.

Table 4: Univariate Time Series Processes

This table shows the univariate process of each variable in differences that is used to construct our empirical model. The lags of ARMA (p,q) processes are chosen according to Akaike Information Criteria. Lags beyond 4 are not reported.

No. of lags	ΔNoise	ΔBid-Ask Spread	ΔHigh-Low (monthly)	ΔTurkish CDS	ΔUSVIX	ΔCrossCurr Swap	ΔTRBill-USBill
Constant	-4×10^{-07}	2.6×10^{-05}	-2.8×10^{-09}	-1.4×10^{-05}	-1.7×10^{-03}	5.4×10^{-06}	-0.25
AR(1)	-0.1	0.24	0.03	1.29^{***}	0.92^{***}	0.04	-0.012
MA(1)	-0.42	-0.91^{***}	-0.67^{***}	-1.17^{***}	-1.07^{***}	-0.23^{**}	-0.31^{***}
AR(2)	0.35^{**}	0.86^{***}	-	-0.49^{***}	-0.17^{**}	-0.68^{***}	-0.042
MA(2)	-0.49	0.87^{**}	-	0.34^{**}	0.29^{**}	0.67^{***}	-0.15^{***}
AR(3)	0.11^{**}	0.50^{*}	-	-	-0.77^{***}	-0.10^{***}	0.55^{***}
MA(3)	-	-1.0^{**}	-	-	0.67^{***}	-	-0.47^{***}
AR(4)	-	-0.37	-	-	0.68^{***}	-0.05^{*}	-
MA(4)	-	0.48	-	-	-0.73^{***}	-	-

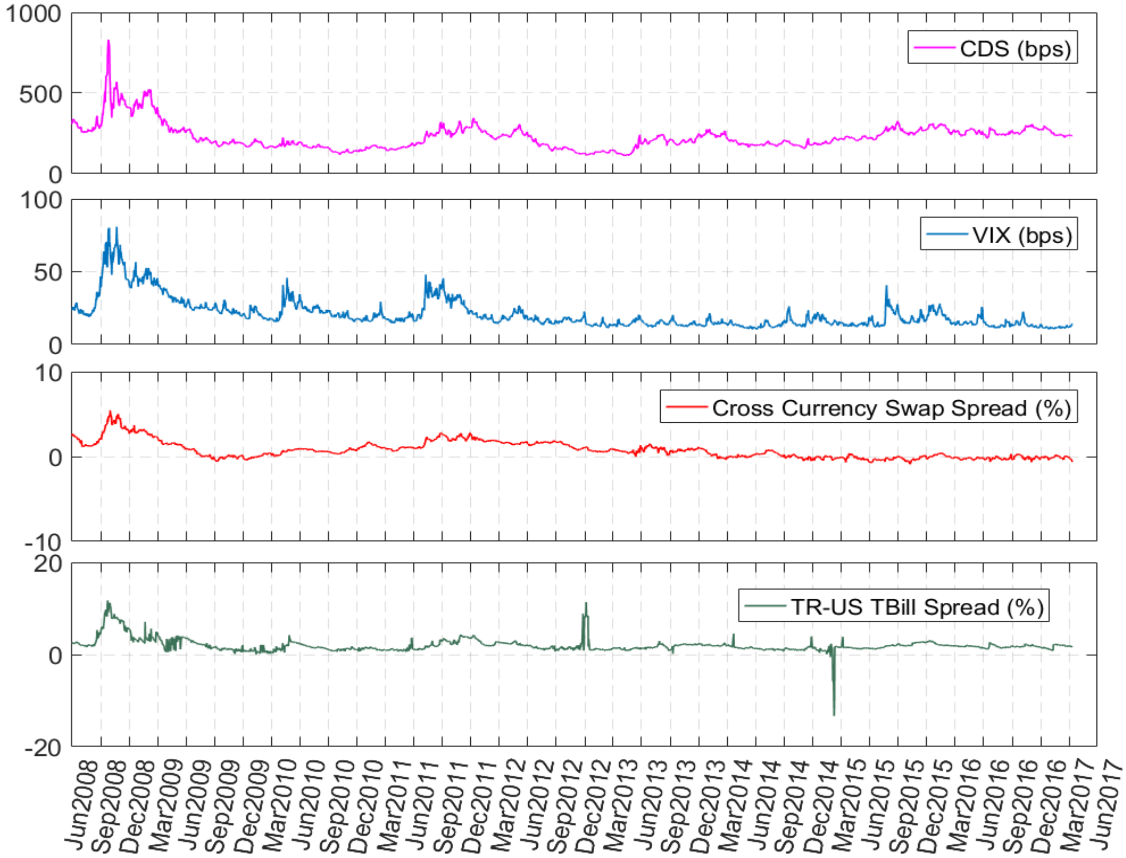

Figure 6: CDS and Exogenous Variables Plots

3.3. Correlations among variables

Table 5 shows the correlation among variables in two periods (Panel A and B): one is 2010 to 2016 which represents the whole period, and the other is 2013 to 2016 in which Turkish sovereigns have been awarded investment grade. The upper triangle shows the daily correlations among the differences of variables while the lower triangle shows the monthly correlations. There are ‘not applicable’ boxes in the upper triangle (daily terms) due to the fact that some variables are only available in monthly terms. While most of our variables are available in daily frequency, high-low measure and short term portfolio investments (debt and net) is available in monthly terms. Monthly measures of daily variables are obtained by taking simple average over a month. On the other hand, we calculated the correlations in differences because most of our variables show unit root characteristics. So, it is more reliable to observe correlations in differences rather than in levels. We also show the level correlations of liquidity measures in parenthesis to observe the strong correlation among them.

While bid-ask spread and high-low measure are strongly correlated in both periods (52.3% and 45.5% monthly correlations respectively), our noise measure performs poorly for the first period. Even, in the first period we see a negative correlation with bid-ask spread that is unexpected. We feel that it is due to lack of sufficient government bonds in 5-to10-year segment of the term structure for that period. The average number (in month) of bonds having maturity between 5-to10 years becomes consistently more than 2 after January 2012.

Table 5: Correlations of Variables and Other Metrics

This table shows the correlations among variables. All correlations are calculated among differences of variables. While figures in lower triangle represent the correlations among variables in monthly terms, figures in upper triangle represent the results in daily terms. Since some of variables are monthly in nature (High-Low, Debt, and Net), the boxes are marked as NA: not applicable in daily terms. The results in parenthesis represent the correlations in level and are only reported for liquidity variables. Panel A shows the correlations for the whole period and Panel B shows the correlations for the second period.

Panel A: Correlations 2010-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) ΔNoise	1	-1.0% (-1.5%)	NA	5.7%	3.7%	0.04%	-4.8%	NA	NA	-1.1%
(2) ΔBid-Ask Spread	13.7% (-8%)	1	NA	3.8%	3.0%	-0.06%	0.3 %	NA	NA	-2.2%
(3) ΔHigh-Low	19.2% (26%)	34.3% (52.3%)	1	NA	NA	NA	NA	NA	NA	NA
(4) ΔTurkish CDS	32.7%	25.5%	21.2%	1	42.5%	-.0%	4.3%	NA	NA	-57.4%
(5) ΔUSVIX	23.1%	18.0%	8.9%	48.7%	1	6.0%	4.5%	NA	NA	-33.0%
(6) ΔCrossCurr Swap	24.4%	13.4%	11.5%	34.8%	34.8%	1	3.6%	NA	NA	-2.2%
(7) ΔTRTBill-USTBill	-.4%	13.6%	1.2%	22.4%	16.0%	22.9%	1	NA	NA	-1.9%
(8) ΔDebt	-8.8%	-11.8%	-1.2%	-20.5%	-13.1%	-13.0%	0.0%	1	NA	NA
(9) ΔNet (D+E)	-12.6%	-19.2%	-6.8%	-21.1%	-16.0%	-13.6%	-0.8%	96.4%	1	NA
(10) BIST Ret (ΔP)	-29.3%	-36.0%	-14.1%	-79.7%	-51.2%	-28.5%	-14.9%	11.7%	18.5%	1

Table 5 (cont'd)

Panel B: Correlations 2013-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) ΔNoise	1	-0.0% (24%)	NA	7.7%	3.9%	-4.8%	-4.9%	NA	NA	-2.3%
(2) ΔBid-Ask Spread	24.5% (45.9%)	1	NA	5.3%	5.7%	-0.7%	-0.8%	NA	NA	-2.0%
(3) ΔHigh-Low	23.9% (63.8%)	30.9% (45. 5%)	1	NA	NA	NA	NA	NA	NA	NA
(4) ΔTurkish CDS	47.4%	34.4%	31.6%	1	37.7%	-7.9%	2.0%	NA	NA	-58.3%
(5) ΔUSVIX	24.1%	16.9%	12.5%	49.5%	1	0.7%	3.0%	NA	NA	-28.9%
(6) ΔCrossCurr Swap	27.0%	18.4%	22.7%	22.1%	12.3%	1	3.5%	NA	NA	4.6%
(7) ΔTRTBill-USTBill	-6.5%	23.0%	5.6%	23.2%	8.9%	10.3%	1	NA	NA	-2.0%
(8) ΔDebt	-29.1%	-24.2%	4.8%	-16.1%	-1.2%	-11.8%	20.5%	1	NA	NA
(9) ΔNet (D+E)	-27.1%	-34.0%	-2.6%	-20.1%	-2.8%	-10.2%	21.3%	96.1%	1	NA
(10) BIST Ret (ΔP)	-35.9%	-39.3%	-19.8%	-86.5%	-44.7%	-10.9%	-12.8%	24.2%	30.8%	1

This is why the relation among our noise measure with other liquidity measures becomes very strong in the second period, 63.8% with high-low spread and 45.9% with bid-ask spread, in levels.

It is easily observed that the relation between liquidity measures and CDS spreads (in differences) is consistently positive and even becomes stronger in 2013 - 2016 period. The noise measure has the strongest relation (47.4%) while the bid-ask spread comes the second (34.4%), and then high-low spread with 31.6% correlation in differences. That means that when CDS spreads increase, so do the liquidity measures. On the other hand, the liquidity measures are negatively correlated with stock returns and short-term portfolio investments. When debt and net short-term portfolio investments are positive, meaning a capital inflow to Turkey, this improves the liquidity of the market and so the liquidity measures decrease, as expected. On the other hand, we observe that CDS prices of Turkish sovereigns is also strongly correlated with global risk factor of US VIX, while it is very strongly and negatively correlated with stock returns both daily and monthly terms, -57.4% and -79.7%, respectively for the whole period. These relations become, again, stronger in the second period.

CHAPTER 5

EMPIRICAL ANALYSIS AND RESULTS

In this section we will present the results we obtained by estimating the model and using methodology explained in Chapter 4. We test the model in both daily and monthly terms. While, high-low measure is already a monthly measure itself, we obtained monthly variables for daily liquidity measures, CDS data and other exogenous variables by simply taking averages of variables over a month.

1. Results in Daily Frequency

First, we used whole sample from 2010 to end-2016. You can see the VAR results from Table 6, in which we use daily noise measure and bid-ask spread for liquidity and daily sovereign CDS spreads for credit risk. Even if we choose the lag length as p=20 for endogenous variables, we see that liquidity measures are very persistent and significant up to p=15, while credit risk loses its significance after p=8. So, although Akaike information criterion gives p=5 for noise measure and p=8 for bid-ask spread, in daily terms we choose the lag length of endogenous variables as p=9 and p=12, respectively, in order to remove serial correlation among residuals (see Figure 7). We didn't report all of the lags. Instead, we reported the lags which are significant.

For VAR structure in which Bid-Ask spread is used as liquidity measure, liquidity lags are very persistent and significant on explaining present change of the variable itself. On the other hand, although early lags of liquidity do not significantly explain the change of credit risk, as expected, we begin to see the significance on the lag 6; 6th lag is significant on explaining CDS change when we use noise measure as our liquidity variable. In this setting, CDS lags are also explaining itself. Although some are not significant, we see significance on lags 1, 5, and 8. More importantly, CDS lags are significant on explaining the change in liquidity; lag 1 of CDS is highly significant when we use noise measure. We also test the Granger-causality by using likelihood ratio test. Our results confirm that, for the whole sample period, the test fails to reject that CDS Granger-cause Liquidity at %1 significance level but not vice versa, although converse relation has significance at %10 level. Here, we see that causality is more significant when we use the noise measure. As for exogenous variables, while USVIX is significant in explaining credit risk, it loses its significance on explaining liquidity. In this setting, other exogenous variables are not significant for explaining neither liquidity nor credit risk.

Similar results can be found when we use bid-ask measure as liquidity variable in VAR setting. Here, no liquidity lags are significant on explaining the variation of CDS spreads. However, we see the significance of lag 4 of CDS on liquidity when we use bid-ask measure as our liquidity variable. Granger-causality tests fails to reject that CDS Granger-cause Liquidity and vice versa at %10 significance level but it is not strong. Again, among exogenous variables only US VIX is significant on explaining credit risk, while others are not significant on explaining neither liquidity nor credit component.

Table 6: VAR Results for Daily Liquidity Measures

This table shows the VAR regression results when daily Noise measure and Bid-Ask Spread are used as liquidity variables. Results cover the whole period from 2010 to end-2016. Columns represent the zero lags for both liquidity variables (respectively) and CDS, while rows represent the other lags of variables. (***) represents level of significance at %1 and (**) for %5 and (*) for %10.

	2010-2016 (Noise)		**2010-2016 (Bid-Ask Spread)**	
Variables	$\Delta\mathbf{Liq_t}$	$\Delta\mathbf{CDS_t}$	$\Delta\mathbf{Liq_t}$	$\Delta\mathbf{CDS_t}$
$\Delta\mathbf{Liq_{t-1}}$	**-0.5193*****	0.0930	**-0.7173*****	0.0004
$\Delta\mathbf{CDS_{t-1}}$	**0.0056*****	**0.1154*****	0.6558*	**0.1176*****
$\Delta \boldsymbol{Liq_{t-2}}$	**-0.3377** ***	-0.3373	**-0.5527*****	0.0007

Table 6 (cont'd)				
ΔCDS_{t-2}	0.0002	0.0101	0.4314	0.0063
ΔLiq_{t-3}	**-0.2603*****	-0.4016	**-0.4956*****	0.0017
ΔCDS_{t-3}	0.0007	-0.0345	0.1902	-0.0362
ΔLiq_{t-4}	**-0.2445*****	-0.3681	**-0.4594*****	0.0001
ΔCDS_{t-4}	0.0006	-0.0373	**1.2289*****	-0.0395*
ΔLiq_{t-5}	**-0.1906*****	0.0630	**-0.3347*****	0.0022
ΔCDS_{t-5}	0.0003	**-0.0584****	0.0252	**-0.0642*****
ΔLiq_{t-6}	**-0.1095*****	**1.2620****	**-0.3329*****	0.0011
ΔCDS_{t-6}	0.0020*	-0.0434*	0.3113	-0.0380
ΔLiq_{t-7}	**-0.1264*****	-0.7491	**-0.3036*****	0.0011
ΔCDS_{t-7}	-0.0002	-0.0021	-0.1266	-0.0028
ΔLiq_{t-8}	**-0.1262*****	-0.6420	**-0.2469*****	0.0041*
ΔCDS_{t-8}	0.0003	**-0.0512****	0.0120	**-0.0584****
$\Delta Liq_{t-9/12}$	-0.0449*	0.2893	**-0.0847*****	0.0026*
$\Delta CDS_{t-9/12}$	0.0013	0.0140	0.3564	0.0033
$\Delta USVIX_t$	4.96e-6	**0.0016*****	0.0028*	**0.0016*****
$\Delta CCBSS_t$	-0.0037	-0.1865	0.4107	-0.2030
$\Delta TR - US\ 3M\ Tbill_t$	-0.0020*	0.0299	-0.1558	0.0220
Intercept	-2.08e-6	7.7e-5	3.5e-4	7.3e-5
Granger-causality test				
$\Delta Liq \overset{GC}{\Rightarrow} \Delta CDS$	p=0.093*		p=0.0785*	
$\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq$	**p=0.000327*****		p=0.0956*	

It is a known fact that the investment funds monitor credit ratings and they are allowed to invest in those countries which have investment grade at least by two rating agencies. In order to observe the effects of ratings (if any), we divided the sample into two periods: 2010 to 2013 and 2013 to 2016, due to the fact that, Turkish sovereigns were warranted as investment grade between 16 May 2013 and 24 September 2016 by at least two of credit rating agencies. Table 7 shows the results of our model separately for these

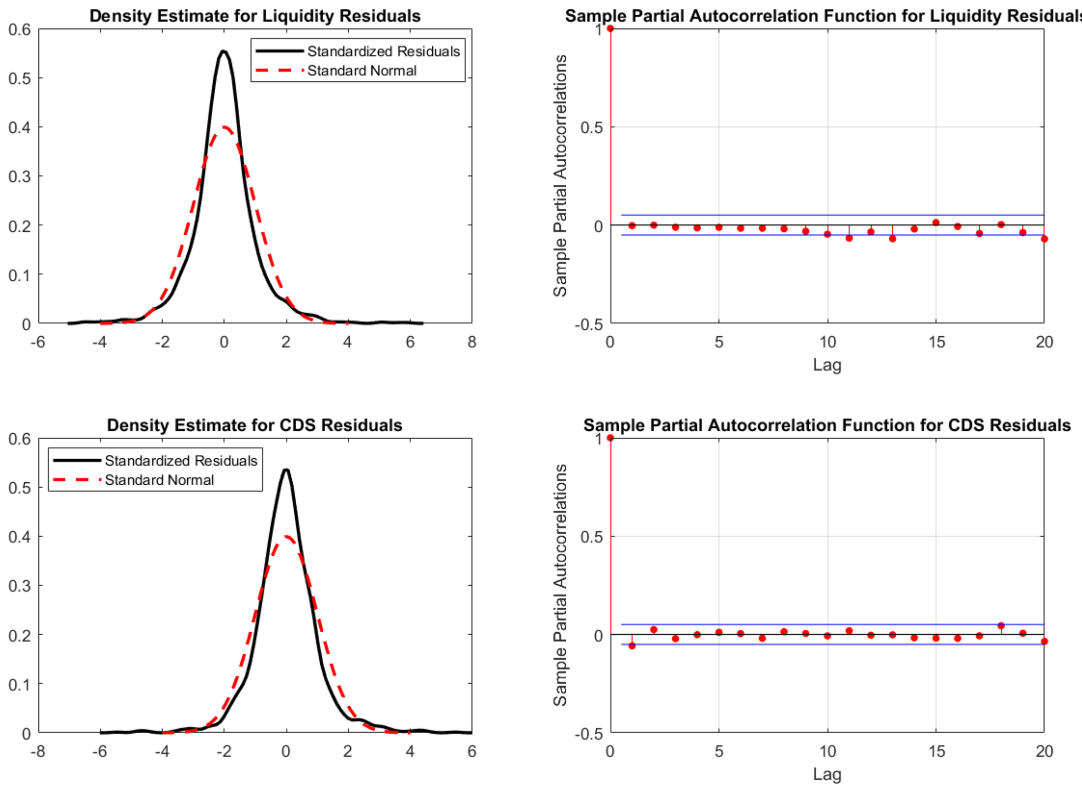

Figure 7: Residual Analysis Plots

periods when we use again daily liquidity measures: noise and bid-ask spread with CDS to proxy credit risk. In the first period, while we do not observe any causality when we use bid-ask spread, the Granger-causality tests results conform with the whole-period results when we use noise measure. In addition, we observe a feedback relation in the first period. In the second period, however, while we see significance for feedback relation on 10% level for bid-ask spread, Granger-causality test show that only ($\Delta\text{CDS} \overset{\text{GC}}{\Rightarrow} \Delta\text{Liq}$) but the converse relation does not exist for the noise measure.

Table 7: VAR Results for Daily Measures and Sub-periods

This table shows the VAR regression results in two sub-periods using daily Noise measure and Bid-Ask Spread as liquidity variables. Columns represent the zero lags for both liquidity variables and CDS for corresponding sub-period, while rows represent other lags of variables. (***) represents level of significance at %1 and (**) for %5 and (*) for %10.

	2010 - 2013				2013 - 2016			
	Noise		Bid-Ask		Noise		Bid-Ask	
Variables	ΔLiq_t	ΔCDS_t	ΔLiq_t	ΔCDS_t	ΔLiq_t	ΔCDS_t	ΔLiq_t	ΔCDS_t
ΔLiq_{t-1}	**-0.55*****	-1.0248	**-0.7015*****	-0.0027	**-0.49*****	1.0045	**-0.7218*****	0.0009
ΔCDS_{t-1}	**0.0052*****	**0.1022*****	-0.0157	**0.1031*****	**0.0060*****	**0.1253*****	1.1453*	**0.1393*****
ΔLiq_{t-2}	**-0.30*****	-1.3677	**-0.6065*****	-0.0016	**-0.36*****	0.5346	**-0.5451*****	0.0014
ΔCDS_{t-2}	0.0003	0.0505	-0.0629	0.0385	0.0006	-0.0295	0.8750	-0.0288
ΔLiq_{t-3}	**-0.18*****	0.1819	**-0.4297*****	-0.0016	**-0.30*****	-0.8230	**-0.5062*****	0.0026
ΔCDS_{t-3}	0.0008	-0.0290	-0.2788	-0.0151	0.0005	-0.050	0.4109	**-0.0629****
ΔLiq_{t-4}	**-0.19*****	-0.1716	**-0.4147*****	-0.0012	**-.2683*****	-0.1658	**-0.4760*****	0.0003
ΔCDS_{t-4}	0.0016	-0.0420	0.3254	-0.0455	-.0008	-0.0272	**2.0660*****	-0.0244
ΔLiq_{t-6}	**-0.16*****	**2.47*****	**-0.335*****	0.0070	**-.1991*****	-0.2023	**-0.3442*****	0.0035
ΔCDS_{t-6}	0.0025	-0.047	0.4287	**-0.0344****	0.0010	-0.0583*	-0.3070	-0.0618*
ΔLiq_{t-8}	-0.10***	-0.3920	**-0.1872*****	0.0086*	-0.13***	-0.8050	**-0.2620*****	0.0039*
ΔCDS_{t-8}	-0.0020	**-0.094*****	0.0866	**-0.1078*****	0.0026*	-0.0137	-0.0714	-0.0155
$\Delta USVIX_t$	2.1e-6	**0.0015*****	-3.65e-5	**0.0015*****	5.71e-6	**0.0017*****	**0.0064****	**0.0018*****
$\Delta CCBSS_t$	0.0161	**0.5575****	4.4346	**0.5388****	-.0099	**-0.4569*****	-0.2754	**-0.54*****
$\Delta TR - US\ 3M\ Tbill$	-0.0029*	0.0483	0.5437	0.0401	-.0014	0.0032	-0.6736	0.0032
Intercept	-1.69e-6	-8.25e-5	5.44e-4	-7.73e-5	-2.65e-6	2e-4	5.8e-4	1.9e-4
Granger-causality test								
$\Delta Liq \overset{GC}{\Rightarrow} \Delta CDS$	**p=0.00427*****		p=0.444			p=0.458		p=0.0725*
$\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq$	**p=0.0425****		p=0.648			**p=0.0151****		p=0.0844*

2. Results in Monthly Frequency

Table 8 presents the results for monthly variables. For the variables which are originally generated in daily terms, we took simple average of the data over a month to get monthly variables. Other than that, the high-low measure is originally a monthly liquidity measure. We repeated the tests for three liquidity measures for the whole sample period (not reported) and for sub-periods, this time, in monthly terms. We chose the lag length p=6 in order to observe the effect of credit (liquidity) risk on 6-month-ahead liquidity (credit) risk. Although we observe some lags explaining the present change of itself, there is no lead-lag relationship between endogenous variables for the whole sample period (not reported) for all monthly measures. In this case, overall, the Granger-causality tests fail to reject the null hypothesis that the corresponding coefficients are zero (i.e. no causality).

In monthly terms the variables are not as persistent as in daily terms. As can be seen from Table 8, the results are mixed for different measures and for sub-periods. In Table 8 we only report the results where Granger-causality tests give significant results. In case Noise measure is used, we only observe significance in monthly terms for the second period and there seems to be a feedback relation. However, when we use bid-ask spread as our liquidity measure we observe significance on two different sub-periods.

For 2010-2013 period with bid-ask spread as the liquidity measure, some lags of liquidity (credit risk) explain the contemporaneous change in credit risk (liquidity) and the causality tests give significant and mixed results. While liquidity Granger-cause credit risk at %1 level in the first period, the converse relation is valid for the second period at 5% significance level. On the other hand, we have different results when we use noise measure as our liquidity variable. It seems that there is a feedback relation between liquidity and credit risk for the period 2013-2016. While we observe that second lag of CDS is significant on explaining variation in the noise measure, 3^{rd} lag of noise measure has significance on CDS change. The relation is positive. We can also observe the significance of some exogenous variables. However, we should note that exogenous variables generally fail to show significance in our regression results which contrasts with the existing literature.

Table 8: Causality Test for Monthly Measures for the whole sample period

This table shows VAR regression results in monthly terms. Monthly variables are obtained by simply averaging daily variables over a month. Here, only significant results are reported in terms of Granger-causality. While first two columns give the result for the noise measure covering only second period, other columns give results for Bid-Ask spread for both periods.

	2013-2016 (Noise)		**2010-2013 (Bid-Ask)**		**2013-2016 (Bid-Ask)**	
Variables	$\mathbf{\Delta Liq_t}$	$\mathbf{\Delta CDS_t}$	$\mathbf{\Delta Liq_t}$	$\mathbf{\Delta CDS_t}$	$\mathbf{\Delta Liq_t}$	$\mathbf{\Delta CDS_t}$
$\mathbf{\Delta Liq_{t-1}}$	-0.2652	-21.1784	**-0.3776****	0.0462	**-0.8893*****	-0.0398
$\mathbf{\Delta CDS_{t-1}}$	0.0013	0.0883	0.2517	**0.4860*****	-0.4520	0.1375
$\boldsymbol{\Delta Liq_{t-2}}$	**-0.4538****	-13.5794	0.0856	-0.0902	**-0.3824****	**-0.0930****
$\mathbf{\Delta CDS_{t-2}}$	**0.0047****	0.2771	0.5614*	**-0.2503****	-0.5563	0.0564
$\mathbf{\Delta Liq_{t-3/3/4}}$	0.1033	**45.01*****	**0.3847****	-0.0230	-0.1367*	-0.0239*
$\mathbf{\Delta CDS_{t-3/3/4}}$	**-0.0050*****	**-0.4514*****	0.1077	-0.0669	**-0.7647****	-0.4380
$\mathbf{\Delta Liq_{t-5/5/6}}$	0.0299	4.9358	**-0.5445*****	**0.3980*****	**-0.4857****	**0.0186****
$\mathbf{\Delta CDS_{t-5/5/6}}$	-0.0024	-0.0511	-0.2967	**0.2239****	**0.3722****	0.3169
$\mathbf{\Delta USVIX}_t$	0.0000	**0.0038*****	**0.0044****	0.0011	0.0024	**0.0025*****
$\mathbf{\Delta CCBSS}_t$	0.0183	-0.9425	-0.7684	**1.8589****	5.8492	-0.9225
$\mathbf{\Delta TR - US\ 3M\ Tbill}_t$	-0.0010	0.5932	**2.1935****	-0.3357	1.2937	0.8898
Intercept	2.3e-5	1.1e-3	**9.9e-3****	1.8e-3	8.3e-3	7.4e-4
Granger-causality test						
$\mathbf{\Delta Liq} \overset{GC}{\Rightarrow} \mathbf{\Delta CDS}$	**p=0.029****		p=**0.00047*****		p=0.15	
$\mathbf{\Delta CDS} \overset{GC}{\Rightarrow} \mathbf{\Delta Liq}$	**p=0.04****		p=0.077*		**p=0.025****	

*** *represents level of significance at %1 and* ** *for %5 and* * *for %10.*

Table 9: The results for monthly High-Low measure for liquidity

This table shows VAR regression results in monthly terms for only monthly High-Low measure. While first two columns give the results covering first period, other two columns give results for the second period.

	2010-2013		2013-2016	
Variables	$\Delta\mathbf{Liq_t}$	$\Delta\mathbf{CDS_t}$	$\Delta\mathbf{Liq_t}$	$\Delta\mathbf{CDS_t}$
$\Delta\mathbf{Liq_{t-1}}$	**-0.7266***	15.6972	**-0.8094***	35.5066
$\Delta\mathbf{CDS_{t-1}}$	0.0003	**0.4149***	0.0002	0.0002
$\Delta \boldsymbol{Liq_{t-2}}$	-0.1594	93.9937	**-0.7632***	12.4056
$\Delta\mathbf{CDS_{t-2}}$	0.0003	-0.2280*	0.0010	-0.0085
$\Delta\mathbf{Liq_{t-3}}$	-0.1717	**158.4792**	**-0.6431***	-38.6251
$\Delta\mathbf{CDS_{t-3}}$	-0.0007	-0.0063	-0.0007	-0.1819
$\Delta\mathbf{Liq_{t-4}}$	0.0790	-4.5214	-0.3990*	-59.4704
$\Delta\mathbf{CDS_{t-4}}$	0.0007*	0.0437	0.0008	0.1124
$\Delta\mathbf{Liq_{t-5}}$	-0.1684	86.4880	-0.1750	-61.7187
$\Delta\mathbf{CDS_{t-5}}$	-0.0002	**0.4359***	0.0015*	0.1373
$\Delta\mathbf{USVIX}_t$	1.86e-6	**0.0024***	-2.83e-6	**0.0022***
$\Delta\mathbf{CCBSS}_t$	0.0030	1.7096*	-0.0019	0.2055
$\Delta\mathbf{TR-US\ 3M\ Tbill}_t$	-0.0016	0.6372*	-4.3e-5	0.7781
Intercept	2.13e-6	4.3e-4	2.43e-5*	6.5e-4
Granger-causality test				
$\Delta\mathbf{Liq} \overset{GC}{\Rightarrow} \Delta\mathbf{CDS}$	**p=0.016**		p=0.43	
$\Delta\mathbf{CDS} \overset{GC}{\Rightarrow} \Delta\mathbf{Liq}$	p=0.43		p=0.29	

By using only monthly high-low measure, we, again, divided the whole sample period into two sub-periods as before in order to see the effect of sub-periods on causality test. The results are presented in Table 9. This time, we have different results for sub-periods when we only use monthly high-low measure as the liquidity variable. In first period, 3rd lag of liquidity is significant on explaining the CDS and Granger-causality test fails to reject that the liquidity Granger-cause credit risk. The results in the second period show that no causality exists between endogenous variables.

Finally, Table 10 shows the summary results of Granger-causality tests using different liquidity measures for different periods reported both in daily and monthly frequencies.

Table 10: Summary Results for Granger-causality tests

This table shows summary results for Granger-causality test for different periods while Noise, Bid-Ask spread or High-Low spread is used as liquidity variable. While Panel A shows the summary results for each liquidity variables in daily frequency, Panel B shows the results in monthly frequency. The results in bold represent significance of the tests. (***) represents level of significance at %1, (**) for %5 and (*) for %10.

Panel A: Summary Results in Daily Frequency

	Noise	**Bid-Ask**
2010-2016	$\boldsymbol{\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq}$ *** $\Delta \mathrm{Liq} \overset{GC}{\Rightarrow} \Delta \mathrm{CDS}$ *	$\Delta \mathrm{CDS} \overset{GC}{\Rightarrow} \Delta \mathrm{Liq}$ * $\Delta \mathrm{Liq} \overset{GC}{\Rightarrow} \Delta \mathrm{CDS}$ *
2010-2013	$\boldsymbol{\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq}$ *** $\boldsymbol{\Delta Liq \overset{GC}{\Rightarrow} \Delta CDS}$ ***	No significance
2013-2016	$\boldsymbol{\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq}$ **	$\Delta \mathrm{CDS} \overset{GC}{\Rightarrow} \Delta \mathrm{Liq}$ * $\Delta \mathrm{Liq} \overset{GC}{\Rightarrow} \Delta \mathrm{CDS}$ *

Panel B: Summary Results in Monthly Frequency

	Noise	**Bid-Ask**	**High-Low**
2010-2016	No significance	No significance	No significance
2010-2013	No significance	$\boldsymbol{\Delta Liq \overset{GC}{\Rightarrow} \Delta CDS}$ ***	$\boldsymbol{\Delta Liq \overset{GC}{\Rightarrow} \Delta CDS}$ **
2013-2016	$\boldsymbol{\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq}$ *** $\boldsymbol{\Delta Liq \overset{GC}{\Rightarrow} \Delta CDS}$ ***	$\boldsymbol{\Delta CDS \overset{GC}{\Rightarrow} \Delta Liq}$ **	No significance

CHAPTER 6

CONCLUSION

In this thesis, given the theoretical framework by Pelizzon et al. (2016), we test the causality between liquidity and sovereign credit risk which are both proxied by some measures widely used in the literature. While we use, in line with the literature, sovereign CDS spreads for Turkey as a proxy for credit risk, we used three different liquidity measures that may capture, we believe, different aspects of liquidity. Some of our results are in line with the results in the literature which says that CDS Granger-cause liquidity but not vice versa. However, we also show that converse relation is also possible and significant with different measures and time scale.

We used two conventional spread measures, which are proxy for transaction costs, and one noise measure which is claimed to have a strong relation with the availability of arbitrage (speculators') capital in financial markets. The spread measures are daily bid-ask spread and the high-low measure proposed by Corwin and Schulz (2012). By this way, we were able to observe the contemporaneous effect of liquidity measures with different characteristics on credit risk and vice versa.

The results are mixed and changing according to the measures we used as the liquidity variable and to the period. In daily terms, for the whole period covering the years from 2010 to 2016, we find that there is strong evidence that credit risk Granger-causes liquidity for noise and bid-ask measure, although significance is at %10 level for bid-ask measure. When we divide the sample period into two sub-periods (2010-to-2013 and 2013-to-2016), the daily results are mixed. In the first period and while using noise measure as the liquidity variable, we observed a significant feedback relation between credit risk and liquidity. That means; when credit risk Granger-cause liquidity, the converse relation is also true at the same time. The results are significant at %1 level. As expected, the relation is positive.

We also repeated our tests in monthly terms in the sense that liquidity effects (on credit risk) may be better observed in mid- and long-terms. To this end, we use the monthly high-low measure and daily liquidity measures which are converted to monthly frequency by simply averaging over a month. Using whole sample period (2010-to-2016), we couldn't observe any causality between liquidity and credit risk in monthly terms; all of the Granger-causality tests fail to reject the null hypothesis that the corresponding coefficients are zero (i.e. no causality). This time, as in previous case, we repeated the tests in sub-periods. The results are mixed again. While we don't see any causality for noise measure in the first period, we see significant feedback relation in the second period. On the other hand, using bid-ask measure as our liquidity variable, in the first period we see that liquidity significantly Granger-cause CDS, while the converse relation is true for the second period. The results for the monthly high-low measure are different for the sub-periods. While in the first sub-period (2010-to-2013), the Granger-causality test fails to reject that the liquidity Granger-cause credit risk, in the second period, however, we do not observe any causality.

There are also some drawbacks of this study that we should mention. First, our main liquidity measure, noise, is constructed using daily available data in treasury market. Although the data is readily available in daily terms and does not require high-frequency data handling, the process of yield curve fitting is computationally complex and requires to figure out the fundamentals of yield curve fitting, which is not an easy task. Furthermore, the noise measure is sensitive to the parameters to be estimated. Since this is literally an optimization procedure, during the process we observed that the estimation of parameters is sometimes stuck to sub-optimal values that decrease the explaining power of our noise measure. In addition, another shortfall worth to mention may be the characteristic of the term structure. We observed that, especially in early periods, Turkish term structure doesn't include sufficient bonds to infer interest rates for

5-to-10-year maturity segment. This questions the efficiency of the noise measure given the fact that this measure is computed from average dispersion of yields of 1-to-10 year bonds around the yield curve. On the other hand, our results show mixed properties according to which measures and periods are chosen. So, we can't precisely say that there is a certain rule that determines the relation between liquidity and credit risk, which prevents us from generalizing our results. Most probably, investor preferences may change over time and there may be some other factors that affect the relation between these two risk factors.

We constructed our liquidity measures using daily available data from only Turkish bond market. Future study may include constructing a liquidity measure that represents three main markets in Borsa Istanbul: stock market, bond market, and futures and options market. Maybe it is possible to infer different and consistent results by using a common and/or systemic liquidity measure constructed from the data available in these three markets.

REFERENCES

Acharya, V., & Pedersen, L. (2005, 08). Asset pricing with liquidity risk. *Journal of Financial Economics, 77*(2), 375-410. doi:10.1016/j.jfineco.2004.06.007

Ahn, H., Cai, J., Hamao, Y., & Ho, R. Y. (2002, 11). The components of the bid–ask spread in a limit-order market: Evidence from the Tokyo Stock Exchange. *Journal of Empirical Finance, 9*(4), 399-430. doi:10.1016/s0927-5398(02)00003-8

Amihud, Y. (2002, 01). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31-56. doi:10.1016/s1386-4181(01)00024-6

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2005). Liquidity and Asset Prices. *Foundations and Trends® in Finance, 1*(4), 269-364. doi:10.1561/0500000003

Amihud, Y., & Mendelson, H. (1986, 05). Liquidity and Stock Returns. *Financial Analysts Journal, 42*(3), 43-48. doi:10.2469/faj.v42.n3.43

Amihud, Y., & Mendelson, H. (1987, 07). Trading Mechanisms and Stock Returns: An Empirical Investigation. *The Journal of Finance, 42*(3), 533-553. doi:10.1111/j.1540-6261.1987.tb04567.x

Atilgan, Y., Demirtas, K. O., & Gunaydin, A. D. (2016, 04). Liquidity and equity returns in Borsa Istanbul. *Applied Economics, 48*(52), 5075-5092. doi:10.1080/00036846.2016.1170935

Beber, A., Brandt, M. W., & Kavajecz, K. A. (2008, 02). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *Review of Financial Studies, 22*(3), 925-957. doi:10.1093/rfs/hhm088

Black, F., & Cox, J. C. (1976, 05). Valuing Corporate Securities: Some Effects of Bond Indenture Provisions. *The Journal of Finance, 31*(2), 351. doi:10.2307/2326607

Blanco, R., Brennan, S., & Marsh, I. W. (2005, 09). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. *The Journal of Finance, 60*(5), 2255-2281. doi:10.1111/j.1540-6261.2005.00798.x

Bliss, R., (1997) Testing term structure estimation methods, *Advances in Futures and Options Research*, 9, 197-231.

Brunnermeier, M., Nagel, S., & Pedersen, L. (2008, 11). Carry Trades and Currency Crashes. *NBER Macroeconomics Annual,* 23(1), 313-348. doi:10.3386/w14473

Brunnermeier, M. K. (2009, 01). Deciphering the Liquidity and Credit Crunch 2007–2008. *Journal of Economic Perspectives, 23*(1), 77-100. doi:10.1257/jep.23.1.77

Brunnermeier, M. K., & Pedersen, L. H. (2008, 11). Market Liquidity and Funding Liquidity. *Review of Financial Studies, 22*(6), 2201-2238. doi:10.1093/rfs/hhn098

Chordia, T., Roll, R., & Subrahmanyam, A. (2000, 04). Commonality in liquidity. *Journal of Financial Economics, 56*(1), 3-28. doi:10.1016/s0304-405x(99)00057-4

Corwin, S. A., & Schultz, P. (2012, 03). A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. *The Journal of Finance, 67*(2), 719-760. doi:10.1111/j.1540-6261.2012.01729.x

Duffie, D., & Singleton, K. J. (1999, 07). Modeling Term Structures of Defaultable Bonds. *Review of Financial Studies, 12*(4), 687-720. doi:10.1093/rfs/12.4.687

Eckbo, B. E., & Norli, O. (n.d.). Pervasive Liquidity Risk. *SSRN Electronic Journal*. doi:10.2139/ssrn.996069

Ejsing, J., Grothe, M., and Grothe, O. (2012) Liquidity and credit risk premia in government bond yields. ECB Working paper no 1440.

Ericsson, J., & Renault, O. (2006, 09). Liquidity and Credit Risk. *The Journal of Finance, 61*(5), 2219-2250. doi:10.1111/j.1540-6261.2006.01056.x

Guloglu, Z. C. (2016, 09). A comparison of bid-ask spread proxies: Evidence from Borsa Istanbul futures. *Pressacademia, 3*(3), 244-244. doi:10.17261/pressacademia.2016321992

Gürkaynak, R. S., Sack, B., & Wright, J. H. (2007, 11). The U.S. Treasury yield curve: 1961 to the present. *Journal of Monetary Economics, 54*(8), 2291-2304. doi:10.1016/j.jmoneco.2007.06.029

Hamao, Y., & Hasbrouck, J. (1995, 07). Securities Trading in the Absence of Dealers: Trades and Quotes on the Tokyo Stock Exchange. *Review of Financial Studies, 8*(3), 849-878. doi:10.1093/rfs/8.3.849

Hamao, Y., & Hasbrouck, J. (1995, 07). Securities Trading in the Absence of Dealers: Trades and Quotes on the Tokyo Stock Exchange. *Review of Financial Studies, 8*(3), 849-878. doi:10.1093/rfs/8.3.849

Handa, P., Schwartz, R., & Tiwari, A. (2003, 08). Quote setting and price formation in an order driven market. *Journal of Financial Markets, 6*(4), 461-489. doi:10.1016/s1386-4181(02)00041-1

Hasbrouck, J. (2009, 05). Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data. *The Journal of Finance, 64*(3), 1445-1477. doi:10.1111/j.1540-6261.2009.01469.x

He, Z. and Milbradt, K. (2014). Endogenous Liquidity and Defaultable Bonds. (2014). *Econometrica, 82*(4), 1443-1508. doi:10.3982/ecta11039

Hu, G. X., Pan, J., & Wang, J. (2013, 11). Noise as Information for Illiquidity. *The Journal of Finance, 68*(6), 2341-2382. doi:10.1111/jofi.12083

Hull, J., & Hull, J. (2015). *Options, futures, and other derivatives (9th ed.)*. Upper Saddle River, NJ: Pearson.

Hull, J. C., & White, A. D. (2000, 01). Valuing Credit Default Swaps I. *The Journal of Derivatives, 8*(1), 29-40. doi:10.3905/jod.2000.319115

Hull, J. C., & White, A. D. (2001, 01). Valuing Credit Default Swaps II. *The Journal of Derivatives, 8*(3), 12-21. doi:10.3905/jod.2001.319153

Hund, J., & Lesmond, D. A. (n.d.). Liquidity and Credit Risk in Emerging Debt Markets. *SSRN Electronic Journal*. doi:10.2139/ssrn.1107586

Imf. Monetary And Capital Markets Department. (2013). Global Financial Stability Report, April 2013: Old Risks, New Challenges. *Global Financial Stability Report*. doi:10.5089/9781475589580.082

Jarrow, R. A., Lando, D., & Yu, F. (2008, 10). Default Risk And Diversification: Theory And Empirical Implications. *Financial Derivatives Pricing,* 455-480. doi:10.1142/9789812819222_0019

Korajczyk, R. A., & Sadka, R. (2008, 01). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics, 87*(1), 45-72. doi:10.1016/j.jfineco.2006.12.003

Kyle, A. S. (1985, 11). Continuous Auctions and Insider Trading. *Econometrica, 53*(6), 1315. doi:10.2307/1913210

Küçük, U. N. (2010, 03). Non-Default Component of Sovereign Emerging Market Yield Spreads and Its Determinants:Evidence from the Credit Default Swap Market. *The Journal of Fixed Income, 19*(4), 44-66. doi:10.3905/jfi.2010.19.4.044

Longstaff, F. A., Mithal, S., & Neis, E. (2005, 09). Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market. *The Journal of Finance, 60*(5), 2213-2253. doi:10.1111/j.1540-6261.2005.00797.x

Longstaff, F. (2004, 04). Financial Claustrophobia: Asset Pricing in Illiquid Markets. doi:10.3386/w10411

Longstaff, F. A. (2004, 07). The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices. *The Journal of Business, 77*(3), 511-526. doi:10.1086/386528

Longstaff, F. A., & Schwartz, E. S. (1995, 06). Valuing Credit Derivatives. *The Journal of Fixed Income, 5*(1), 6-12. doi:10.3905/jfi.1995.408138

Madhavan, A. (2000, 08). Market microstructure: A survey. *Journal of Financial Markets, 3*(3), 205-258. doi:10.1016/s1386-4181(00)00007-0

Marshall, B. R., & Young, M. (2003, 04). Liquidity and stock returns in pure order-driven markets: Evidence from the Australian stock market. *International Review of Financial Analysis, 12*(2), 173-188. doi:10.1016/s1057-5219(03)00006-1

Monfort, A., & Renne, J. (2013, 11). Decomposing Euro-Area Sovereign Spreads: Credit and Liquidity Risks. *Review of Finance, 18*(6), 2103-2151. doi:10.1093/rof/rft049

Nelson, C. R., & Siegel, A. F. (1987, 01). Parsimonious Modeling of Yield Curves. *The Journal of Business, 60*(4), 473. doi:10.1086/296409

Pelizzon, L., Subrahmanyam, M. G., Tomio, D., & Uno, J. (2016, 10). Sovereign credit risk, liquidity, and European Central Bank intervention: Deus ex machina? *Journal of Financial Economics, 122*(1), 86-115. doi:10.1016/j.jfineco.2016.06.001

Pástor, Ľ, & Stambaugh, R. (2003, 06). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy, 111*(3), 642-685. doi:10.1086/374184

Roll, R. (1984, 09). A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market. *The Journal of Finance, 39*(4), 1127. doi:10.2307/2327617

Sadka, R. (2006, 05). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics, 80*(2), 309-349. doi:10.1016/j.jfineco.2005.04.005

Schestag, R., Schuster, P., & Uhrig-Homburg, M. (2016, 01). Measuring Liquidity in Bond Markets. *Review of Financial Studies, 29*(5), 1170-1219. doi:10.1093/rfs/hhv132

Schwarz, K. (n.d.). Mind the Gap: Disentangling Credit and Liquidity in Risk Spreads. *SSRN Electronic Journal*. doi:10.2139/ssrn.1486240

Svensson, L. E. (1994, 09). Estimating and Interpreting Forward Interest Rates: Sweden 1992 – 1994 (No. w 4871). National Bureau of Economic Research. doi:10.3386/w4871

Vassalou, M., & Xing, Y. (2004, 03). Default Risk in Equity Returns. *The Journal of Finance, 59*(2), 831-868. doi:10.1111/j.1540-6261.2004.00650.x