

**ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF ARTS AND
SOCIAL SCIENCES**

**BID-ASK SPREAD, LIQUIDITY AND THE EFFECTS OF FIRM-LEVEL AND
MARKET-LEVEL FEATURES**

Ph.D. THESIS

Zeynep GÜLOĞLU

Department of Management

Management Programme

MAY 2018

**ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF ARTS AND
SOCIAL SCIENCES**

**BID-ASK SPREAD, LIQUIDITY AND THE EFFECTS OF FIRM-LEVEL AND
MARKET-LEVEL FEATURES**

Ph.D. THESIS

**Zeynep GÜLOĞLU
(403122005)**

Department of Management

Management Programme

Thesis Advisor: Assoc. Prof. Dr. Cumhur EKİNCİ

MAY 2018

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ SOSYAL BİLİMLER ENSTİTÜSÜ

**ALIM SATIM FARKI, LİKİDİTE VE ŞİRKETE VE PİYASAYA ÖZGÜ
KOŞULLARIN ETKİLERİ**

DOKTORA TEZİ

**Zeynep GÜLOĞLU
(403122005)**

İşletme Anabilim Dalı

İşletme Programı

Tez Danışmanı: Doç. Dr. Cumhuri EKİNCİ

MAYIS 2018

Zeynep GÜLOĞLU, a Ph.D. student of ITU Graduate School of Arts and Social Sciences student ID **403122005**, successfully defended the thesis/dissertation entitled “**BID-ASK SPREAD, LIQUIDITY AND THE EFFECTS OF FIRM-LEVEL AND MARKET-LEVEL FEATURES**”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor : **Assoc. Prof. Dr. Cumhuri EKİNCİ**
Istanbul Technical University

Jury Members : **Prof. Dr. Oktay TAŞ**
Istanbul Technical University

Prof. Dr. Burç ÜLENGİN
Istanbul Technical University

Assoc. Prof. Dr. Yaman Ömer ERZURUMLU
Bahçeşehir University

Assoc. Prof. Dr. Recep BİLDİK
Borsa Istanbul

Date of Submission : 2 May 2018

Date of Defense : 28 May 2018

To my family,

FOREWORD

I would like to express my sincere gratitude to my supervisor Assoc. Prof. Cumhuri Ekinci for his valuable support and guidance during the whole period of my thesis. I am very grateful for all of his contributions, advice, criticism, encouragements and insight throughout the research.

I am also grateful to my thesis jury members, Prof. Oktay Taş and Assoc. Prof. Yaman Ömer Erzurumlu for their expertise and their recommendations.

This study was financially supported by TÜBİTAK (The Scientific and Technological Research Council of Turkey), National PhD Scholarship Program no.2211.

Lastly, I would like to offer my endless gratitude to my family for their endless support, encouragement and love.

May 2018

Zeynep GÜLOĞLU

TABLE OF CONTENTS

	<u>Page</u>
FOREWORD	ix
TABLE OF CONTENTS	xi
ABBREVIATIONS	xv
LIST OF TABLES	xvii
LIST OF FIGURES	xix
SUMMARY	xxi
ÖZET	xxiii
1. INTRODUCTION	27
2. LIQUIDITY: DEFINITIONS, DIMENSIONS AND MEASURES	29
2.1 Introduction	29
2.2 Definitions of Liquidity.....	30
2.3 Dimensions and Causes of Liquidity	33
2.4 Liquidity Measurement: A Comparative Review of the Literature	38
2.4.1 Dimensional features.....	44
2.4.2 Various specificity	46
2.4.3 Data features	47
2.4.4 Potential usage	48
2.5 Remarks and Discussion	49
2.6 Conclusion.....	51
3. A COMPARISON OF SPREAD PROXIES: EMPIRICAL EVIDENCE FROM BORSA ISTANBUL FUTURES	53
3.1 Introduction	53
3.2 Literature	54
3.3 Spread Measures	56
3.3.1 High-frequency spread benchmarks.....	56
3.3.2 Low-frequency spread proxies.....	56
3.3.2.1 Roll measure.....	57
3.3.2.2 LOT-Mixed measure.....	57
3.3.2.3 Effective tick measure.....	58
3.3.2.4 High-low spread measure.....	58
3.3.2.5 Closing percent quoted spread measure	59
3.4 Data and Methodology	59
3.5 Findings and Discussions	61
3.6 Conclusion.....	64
4. EFFECTS OF FIRM-LEVEL AND MARKET-LEVEL CHARACTERISTICS ON STOCK LIQUIDITY: AN INTERNATIONAL ANALYSIS	65
4.1 Introduction	65
4.2 Literature	66
4.3 Hypotheses	69
4.4 Data	70
4.5 Methodology	74

4.6 Results	80
4.7 Discussion of the Results.....	83
4.8 Conclusion	85
REFERENCES	89
APPENDICES	95
APPENDIX A	96
APPENDIX B.....	104
CURRICULUM VITAE	107

ABBREVIATIONS

ACD	: Autoregressive Conditional Volume Duration
AD	: Average Depth
ALR	: Amihud Illiquidity Measure
AMEX	: American Stock Exchange
AMV	: Amivest
CAPM	: Capital Asset Pricing Model
CET	: Coefficient Elasticity of Trading
CFR	: Complete Fill Rate
CHL	: Close-High-Low
CPQS	: Closing Percent Quoted Spread
CR	: Cancellation Rate
CRT	: Cost of a Round Trip Trade
EAM	: Extended Amihud Measures
EC	: Execution Cost
EROLL	: Extended Roll
ET	: Effective Tick
FR	: Flow Ratio
GMM	: Gamma
HL	: High-Low
IS	: Implementation Shortfall
ISO	: International Organization for Standardization
ISSM	: The Institute for the Study of Security Markets
LHH	: Hui-Heubel Liquidity Ratio
LOB	: Limit Order Book
LOTM	: LOT-Mixed
LOTYS	: LOT Y-Split
LR	: Liquidity Ratio
MLI	: Martin Index
MROLL	: Modified Roll
NYSE	: New York Stock Exchange
OR	: Order Ratio
OV	: Order Value
PES	: Percent Effective Spread
PFR	: Partial Fill Rate
PPI	: Percent Price Impact
PQS	: Percent Quoted Spread
QS	: Quote Slope
REIT	: Real Estate Investment Trust
RL	: Regressed Lambda
ROR	: Relative Odds Ratio
SC	: Speed of Cancellation
SCE	: Speed of Complete Execution

SEC	: U.S. Securities and Exchange Commission
SPE	: Speed of Partial Execution
TAQ	: Trade and Quote
TF	: Trading Frequency
TR	: Turnover Ratio
TV	: Transaction Volume
VIOP	: Borsa Istanbul Futures and Options Market
VN	: VNET
VR	: Variance Ratio
VV	: Volume Volatility
WA	: Weighted Ask
WB	: Weighted Bid
WD	: Weighted Durations
WFE	: World Federation of Exchanges
XLM	: Xetra Liquidity Measure
ZRS	: Zeros

LIST OF TABLES

	<u>Page</u>
Table 2.1 : Liquidity measures with various features.	40
Table 2.2 : Summary of liquidity measures.	50
Table 3.1 : Summary statistics of the benchmarks and spread proxies.	61
Table 3.2 : Correlations for spread estimates of each contract.	63
Table 3.3 : Root mean square errors between the benchmarks benchmarks.	63
Table 4.1 : Indices and numbers/market caps of selected stocks by country (as of December 2015).....	71
Table 4.2 : Definitions of all variables.	75
Table 4.3 : Summary statistics of all variables.	76
Table 4.4 : The correlation matrix for all the variables.	79
Table 4.5 : Least squares regression results.	80
Table 4.6 : % changes in liquidity with a 10% increases in independent variables..	82
Table A.1 : Formulas/ models of liquidity measures.	96
Table B.1 : Residual test for heteroskedasticity.	104
Table B.2 : Test for multicollinearity.	105

LIST OF FIGURES

	<u>Page</u>
Figure 2.1 : Dimensions of liquidity.	35
Figure 2.2 : Measures of liquidity.	39
Figure 3.1 : Effective spread pattern.	62
Figure 3.2 : Quoted spread pattern.	62
Figure 4.1 : Variable groups, variables and their expected effects.	76
Figure B.1 : Residual test for linearity.	104
Figure B.2 : Residual test for normality.	104

BID-ASK SPREAD, LIQUIDITY AND THE EFFECTS OF FIRM-LEVEL AND MARKET-LEVEL FEATURES

SUMMARY

Market liquidity is defined as the ability to trade quickly, with low transactions costs, at any time and with no or a minimal impact on price. Liquidity is crucial for well functioning of markets. It has many implications for traders, investors, exchanges, regulators, and the listed firms. Thus, an accurate understanding of liquidity concepts and its determinants is essential.

This dissertation consists of three main sections relating to liquidity.

We start with a comprehensive review of the frameworks currently available for understanding definitions and determinants of liquidity. We put a special emphasis on various liquidity measures discussed in the literature about equity markets. Indeed, measures that we present have specific properties and capture certain aspects of liquidity. Our purpose, however, is to highlight the differences and similarities of these measures and produce a more complete understanding of their limitations and extensions. To do this, we review and categorize virtually all the equity market liquidity measures.

Secondly, we empirically evaluate the performance of five different methods appearing in the market microstructure literature in predicting the cost dimension of market liquidity, in other words “bid-ask spread”. Microstructure literature proposes models that attempt to estimate bid-ask spread using low-frequency data. However, the question is whether low-frequency spread proxies really measure what researchers want to measure. This questioning is essential since inaccurate estimates of spreads can create misleading information about actual market liquidity and functioning of financial markets. Thus, we investigate the performance of these proxies on index, currency and gold futures trading in Borsa Istanbul Futures and Options Market (VIOP).

Although market liquidity is widely investigated from the markets perspective, the effects of corporate level features mostly are neglected. To fill this gap, in the last section, we develop a log-linear model that combines both corporate-level and market-level aspects in determining the market liquidity of stocks worldwide. The results indicate highly significant effects of the selected features and yield policy implications.

ALIM SATIM FARKI, LİKİDİTE VE ŞİRKETE VE PİYASAYA ÖZGÜ KOŞULLARIN ETKİLERİ

ÖZET

Piyasa likiditesi, fiyat üzerinde önemli bir değişiklik olmaksızın, hızlı, düşük maliyetle ve istendiği anda işlem yapabilme yeteneği olarak tanımlanmaktadır. Piyasaların iyi bir şekilde işleyişi için likidite çok önemlidir. Likiditenin yatırımcılar, borsalar, düzenleyici kuruluşlar ve borsalara kote firmalar için çok sayıda etkileri vardır. Bu nedenle, likidite kavramının ve likiditeyi belirleyen faktörlerin doğru bir şekilde anlaşılması esastır. Son yıllarda mikroyapı teorileri likiditeyi anlamaya ve analiz etmeye çalışmış ve birçok bulgu ortaya konmuştur.

Bu tez, likidite üzerine yapılan üç ana araştırmadan oluşmaktadır.

Çalışmanın ilk kısmında, likiditenin tanımını ve belirleyicileri anlamak için mevcut kavramları gözden geçiriyoruz. Likidite tanımlanması kolay olmakla birlikte, doğrudan gözlemlenemediği için likiditeyi ölçmek ve tüm yönleri ile yakalamak zordur. Likiditeyi ölçmek için işlem hacmi veya miktarı, efektif (effective) veya afişe edilen (quoted) alım satım farkı, işlem ve/veya emir sayısı, emir defterinde bekleyen derinlik (depth) ve maliyet (tightness) gibi birçok gösterge önerilmiştir. Halbuki likidite büyüklük, maliyet ve zaman gibi boyutları içeren çok boyutlu bir olgudur. Önerilen likidite ölçüm yöntemleri genellikle likiditeyi yalnızca belirli bir açıdan yakalar. Bu nedenle, likiditeyi ölçen en geçerli yöntem hakkında fikir birliği yoktur. Bu nedenle tez çalışmasının ilk kısmında özellikle hisse senedi piyasalarının likiditesini ölçen çeşitli likidite ölçüm yöntemlerinin üzerinde duruyoruz. Gerçekten de, sunduğumuz birçok likidite ölçüm yönteminin belirli bazı özellikleri vardır ve bunlar likiditeyi birtakım yönlerden yakalar. Amacımız, bu ölçüm yöntemlerinin farklılıklarını ve benzerliklerini ortaya koymak, böylelikle onların artı ya da eksi yönlerini anlamaktır. Bunu yapmak için de, hisse senedi piyasalarında likiditeyi ölçmek için ortaya konan hemen hemen tüm likidite ölçüm yöntemlerini gözden geçiriyor ve sınıflandırıyoruz. İlk olarak, likidite ölçüm yöntemleri likiditenin bir boyutunu veya birden fazla boyutunu gösterebilir. Bu ölçüm yöntemleri likit olma durumunu ya da likit olmama durumunu gösterebilir. Dahası, likiditeyi ölçerken belirli bir anın likiditesini ölçebildikleri gibi, bir süre boyunca gerçekleşen işlemlerden de likiditeyi ölçebilirler. Bunların dışında, bazıları geçmişteki mevcut likiditeyi gösteren (ex post) ölçüm yöntemleri iken, bazıları ilerdeki beklenen likiditeyi simüle eden (ex ante) ölçüm yöntemleridir. Ayrıca bazı ölçüm yöntemleri alım-satım farkını modellemek için ortaya çıkmıştır. Bazı likidite ölçüm yöntemleri kotasyon sistemine göre fiyat güdümlü (piyasa yapıcı, quote driven) piyasalara uygunken; bir diğer kısmı emir güdümlü (limit emirli, order driven) piyasalar için geliştirilmiştir ve daha uygundur. Bu ölçüm yöntemlerinin hesaplanmasında kullanılan girdi verileri birbirinden farklı veya veri sıklığı da düşük ya da yüksek

olabilir. Ayrıca, bazı likidite ölçüm yöntemleri, zamana veya miktara göre ağırlıklandırıldığında potansiyel periyodikliğe sahip olabilmektedirler. Sonuç olarak, likidite ölçüm yöntemlerinin belirli özellikler etrafında yoğunlaştığı sonucuna vardık. Bununla birlikte, likiditeyi ölçen iyi ölçüm yöntemleri var olmakla birlikte bu yöntemlerin de bir takım sınırlamaları olduğu sonucuna vardık.

Ardından, piyasa likiditesinin maliyet boyutunun, diğer bir deyişle ‘fiyat aralığı’nın, tahmini için, piyasa mikroyapı literatüründe ortaya çıkan beş farklı yöntemin (Roll, LOT Mixed, Effective Tick, High-Low ve Closing Percent Quoted Spread) performansını değerlendiriyoruz. Alım-satım farkı, diğer bir deyişle en iyi alım (bid) ve en iyi satım (ask) fiyatları arasındaki fark, likiditenin maliyet boyutunu göstermesi bakımından önemlidir. Yatırımcılar genellikle fiyat aralığının dar olduğu kıymetleri tercih ederler. Bu nedenle, fiyat aralığı çok sayıda araştırmaya konu olmuştur ve yatırımcılar ve piyasa oteriterileri tarafından yakından takip edilmektedir. Ayrıca, birçok çalışmada alım-satım farkı likidite göstergesi olarak kullanılmıştır. Alım-satım farkını hesaplamak için ise gün içinde afişe edilen bütün en iyi alım ve satım fiyatlarının verisi, yani yüksek frekanslı veri gerekmektedir. Çoğu durumda, gün içi veriler birkaç yıldan fazla geriye gitmez. Bununla birlikte, piyasa likiditesi zaman serisi olarak ve çeşitli uluslararası pazarlarda analiz edilmek istenebilir. Fakat bu tür bir analiz, genellikle bulunması (özellikle gelişmekte olan piyasalar için) veya çalışılması zor olan büyük miktarlardaki yüksek frekanslı veriyi gerektirir. Bu nedenle, mikroyapı literatürü, düşük frekanslı veya diğer verileri kullanarak fiyat aralığı tahmin etmeye çalışan modeller önermektedir. Fakat asıl sorulması gereken soru düşük frekanslı bu tahmin yöntemlerinin gerçekten araştırmacının ölçmek istediğini ölçüp ölçmedikleridir. Bu sorgulama önemlidir çünkü fiyat aralığı konusundaki yanlış tahminler piyasa likiditesi ve finansal piyasaların işleyişi hakkında yanıltıcı bilgiler verebilir. Bu nedenle çalışmanın bu kısmında bu ölçüm yöntemlerinin performansını Borsa İstanbul Vadeli İşlem ve Opsiyon Piyasası’nda (VIOP) işlem gören endeks, döviz ve altına dayalı vadeli işlem sözleşmeleri üzerinde araştırıyoruz. Düşük frekanslı modellerin ölçüm performansını değerlendirmek için literatürde benzer çalışmalarda uygulanmış belirli kriterleri kullanıyoruz. Bunlar zaman serisi korelasyonu (önem düzeyi için de test edilmiştir) ve ortalama hata kareleri kareköküdür (RMSE). Sonuç olarak bu beş yöntem içinden “Effective Tick” en iyi performansı gösterse de, yöntemlerin hiçbiri alım-satım farkını yeterince iyi tahmin etmediğini söylüyoruz.

Çalışmanın son bölümünde, logaritmik doğrusal bir model yardımıyla firma temelli ve piyasa temelli faktörlerin likidite üzerindeki etkisi araştırılmıştır. Piyasa likiditesi, piyasa temelli faktörlerle geniş çapta incelenmiş olmakla birlikte, firma temelli faktörlerin likidite üzerindeki etkisi pek incelenmemiştir. Mikroyapı literatüründe, bir firmanın piyasa değerini belirlemek için, şirketin beklenen nakit akışlarını, sermaye maliyetine eklenen bir likidite primi ile indirmesi gerektiğini belirten bir bulgu ortaya atılmıştır. Sonrasında, birçok ampirik makale bu bulguyu doğrulamış ve genişletmiştir. Ayrıca, bazı araştırmacılar firmaların kaldıraç oranlarını düşürmek, etkili açıklama yapmak veya yatırımcı tabanını artırmak gibi bazı kurumsal politikaları uygulayarak piyasa likiditesini artırabileceğini savunmaktadır. Sonuç olarak, çeşitli çalışmalar firma özellikleri ile piyasa likiditesi arasındaki bağlantıyı araştırmıştır. Firma seviyesindeki faktörler, kaldıraç, kârlılık ve ödenen kar payları

gibi finansal oranlar ile fiili dolaşım oranı ve kote olma süresi gibi yatırımcı erişiminin göstergelerini içermektedir. Piyasa seviyesindeki faktörleri, yatırımcı ilgisi (örneğin hisse senedini takip eden analistlerin sayısı ve kurumsal mülkiyet oranı); piyasa riski (gün içi ve uzun vadeli dalgalanmalar) veya işlemin doğası gereği olan teknik konuları (fiyat adımı büyüklüğü ve fiyat seviyesi) içermektedir. Bu analizde sadece bir ülkeye odaklanmak yerine uluslararası bir veri seti kullanılmıştır. Literatürde şu ana kadar yapılan çalışmaların çoğu, şu ana kadar ABD piyasaları için firma düzeyindeki veya piyasa düzeyindeki özelliklerin likidite üzerindeki etkilerini araştırmıştır. Bildiğimiz kadarıyla, bu faktörleri likiditeye ilişkilendiren az sayıda uluslararası ampirik kanıt bulunmaktadır. Biz uluslararası düzeyde kanıt sunan bazı çalışmaların aksine, likiditeyi gün içi varyasyonları yakalayan alım-satım farkı ile hesaplıyoruz. Bu bağlamda piyasa seviyesindeki faktörlere ek olarak firma seviyesindeki faktörlere bağlı olarak likiditenin belirleyicilerini uluslararası bir veri setiyle araştırarak literatüre katkıda bulunmaya çalışıyoruz. Tüm bu faktörlerin likidite üzerine etkisini değerlendirmek için, 31 ülkeden 2,556 firmanın verileriyle kesitsel regresyon uyguluyoruz. Sonuçlar yüksek kaldıraç, yüksek kârlılık, yüksek fiili dolaşım oranı ve uzun kote olma süresi, hisse senedini takip eden analistlerin sayısının fazla olması, yüksek beta ve yüksek fiyat seviyesinin yanı sıra düşük kurumsal mülkiyet oranı, düşük gün içi dalgalanmalar ve düşük fiyat adımı büyüklüğünün yüksek piyasa likiditesi ile ilişkili olduğunu söylemektedir. Tüm bu sonuçlar, firma düzeyinde ve piyasa seviyesinde özelliklerin likidite üzerindeki etkilerini anlamamızı sağlar. Elde edilen sonuçlar modelde yer alan faktörlerin büyük ölçüde etkili olduğunu gözler önüne sermektedir ve çeşitli piyasa düzenlemeleri konusunda ışık tutmaktadır.

1. INTRODUCTION

Liquidity is crucial for well-functioning of financial markets. It has major implications for traders, investors, exchanges, regulators, and the listed firms. Though easy to define, liquidity is not directly observable. For, it is very hard to quantify it and capture all its aspects. For several decades, microstructure theories have been trying to understand and analyze liquidity and several stylized facts have already been documented.

We have several purposes in this dissertation.

The first purpose is to review all the definitions, determinants and measures of liquidity. Liquidity measurement literature have designed various measures to capture various features of liquidity. However, there is still no consensus on which liquidity measure is the best. We intend to contribute to the literature by providing an exhaustive review and categorization of virtually all the equity market liquidity measures, highlighting their differences and similarities. To do this, we review and categorize virtually all the equity market liquidity measures.

The cost dimension of liquidity, in other words “bid-ask spread”, is particularly important for many practitioners. Microstructure literature proposes many models to estimate bid-ask spread. Our second purpose is to contribute to this literature by identifying the estimator that performs best in predicting actual spreads. To evaluate the performance of five different methods, we conduct an empirical test on index, currency and gold futures trading in Borsa Istanbul Futures and Options Market (VIOP).

Our final purpose is to provide empirical evidence on the determinants of liquidity. Market liquidity is widely investigated from the markets perspective. However, there are other factors affecting stock liquidity at corporate level. For this purpose, we investigate the determinants of liquidity based upon factors at corporate level in addition to factors at market level by employing an international dataset. In our analysis, we base our liquidity calculation upon minutely data which capture intraday

variations. We hope to contribute to the literature by combining different factors for explaining liquidity all over the world.

The dissertation is organized as follows. This chapter is an introduction of the thesis and provides various purposes for the research undertaken. Chapter 2 provides a review of definitions, dimensions and measures of liquidity. Chapter 3 gives a comparison of bid-ask spread proxies with an empirical evidence from Borsa Istanbul Borsa Istanbul futures. In Chapter 4, the effects of market level and firm level characteristics on stock liquidity are empirically investigated. Chapter 5 concludes all the results.

2. LIQUIDITY: DEFINITIONS, DIMENSIONS AND MEASURES

2.1 Introduction

Market microstructure is a branch of finance that studies trading processes, price formation and the organization of financial markets. It has gained considerable interest after October 1987 financial crisis when present theories failed to explain price formation, and in these passing thirty years has evolved dramatically along with technological developments and the globalization of markets.

It is a well-known fact that one of the most important fields of study in market microstructure is liquidity. For several decades, microstructure theories have been trying to understand and analyze liquidity. Especially in recent years, with the development of high-frequency databases, a large portion of microstructure literature has been dealing with liquidity and several stylized facts have already been documented.

Market liquidity is defined as the ability to trade quickly, with low transactions costs, at any time and with no or a minimal impact on price. Though easy to define, liquidity is not directly observable and thus it is very hard to quantify it and capture all its aspects. Several indicators have been proposed to measure liquidity such as trading volume or turnover, quoted and effective bid-ask spreads, number of trades and/or orders, depth and tightness visible in the limit order book and so forth. However, liquidity is a multi-dimensional phenomenon, encompassing quantity, cost, and time dimensions. Liquidity measures generally capture only one of several aspects. Thus, there is no consensus about the most applicable measure (e.g. Bernstein, 1987; Aitken and Comerton-Forde, 2003; Lybek, and Sarr, 2002).

In this part of the dissertation, we contribute to the literature in several ways. Firstly, we intend to provide a comprehensive review of the frameworks currently available for understanding definitions and determinants of liquidity. We put a special emphasis on various liquidity measures discussed in the previous literature about equity markets. Indeed, many measures that we present have some specific properties and capture certain aspects of liquidity. Our purpose, however, is to highlight the

differences and similarities of these measures and produce a more complete understanding of their limitations and extensions. To do this, we review and categorize virtually all the equity market liquidity measures. To begin with, liquidity measures can cover a single dimension or several dimensions of liquidity. They indicate either liquidity or illiquidity. Moreover, they do this at a point in time (as a stock variable) or cumulatively over a period of time (as a flow variable). Furthermore, some are ex post, which show the available liquidity in the past and some are ex ante, which simulate the expected liquidity in the future. Besides, some liquidity measures directly or indirectly relate to bid-ask spread. Some of them are originally developed and more appropriate for quote-driven markets while others are developed and more appropriate for order-driven markets. The frequency of the data to produce these measures (input data) or the frequency of the measures themselves (output data) can be low or high. Moreover, some liquidity measures have potential periodicity if weighted by time or quantity.

This comparative survey allows us to examine liquidity measures thoroughly and understand their advantages, limitations and extensions. We conclude that liquidity measures concentrate around specific properties. Overall, liquidity has many dimensions and a desirable liquidity measure should take into account many dimensions of liquidity such as immediacy, large transactions walking through the book or hidden orders. Moreover, a desirable liquidity measure should be ex ante in the sense that it can predict the available liquidity in the future. Good measures exist, yet with some limitations.

2.2 Definitions of Liquidity

An objective of stock exchanges around the world is to provide a liquid market where liquidity is straightforwardly defined as the ability to trade large sizes quickly and at low cost whenever you want to trade. Alternatively, it can be defined as “the ability of the market to handle immediate execution for an incoming order flow” and “the ability of the market to trade large orders without large changes in the market price”.

Liquidity is an important topic in market microstructure discussions and though easy to define, due to its multi-dimensional nature, it is hard to capture with a scalar quantity.

The relevance of liquidity actually arises from trading. Trading itself is a phenomenon about search in which buyers look for sellers and sellers look for buyers. Illiquidity generally results from the non-synchronicity of buyers and sellers. The main role of markets is financial intermediation, i.e., bringing buyers and sellers together, and by this way minimizing this bilateral search cost. The structure of a market depends on several issues such as its establishment, regulation, transparency, quotation systems, trade sequences or automation in order registering, matching and executions. All these aspects tend to influence each other by playing a crucial role in market liquidity. ‘Better’ markets provide liquidity more cheaply, allowing buyers to pay less and sellers to get more (O’Hara, 2007, p.827). Harris (1990) indicates, in a liquid market, the cost of a round trip of any amount of a security is minimized. If costs are too high, no one wants to trade, thus, market becomes “illiquid” and ability of trading disappears.

Buyers and sellers in the market are called “traders” and the purpose of traders generally is to invest, to borrow, to speculate, to diversify or hedge a risk, to gamble or to deal (Harris, 2003). Traders can be in the form of brokers, dealers, speculators, investors, borrowers or hedgers. They all participate in the market in order to profit or rebalance their portfolio. Measuring market liquidity with a scalar quantity depends on understanding the committed liquidity supply by traders. Therefore, before discussing how to measure liquidity, it is important to review the concept of liquidity supply.

Traders’ orders, submitted in order to execute transactions, may provide or consume liquidity in the market. Orders are trade instructions, specifying what traders want to trade, whether to buy or sell, how much and when they want to trade (Harris, 2003). Traders indicate price, quantity, validity (day order, good-till-date, good-till-cancelled, fill and kill, fill or kill), anonymity and other conditions with their orders. Supplying liquidity through a market order results in an immediate execution while supplying liquidity over time by submitting a passive limit order feeds limit order book (LOB). Finally, supplying liquidity depends on transaction size.

Understanding the supply of liquidity usually means the analysis of traders’ order submission. The most important order types are market orders and limit orders. Several studies have analyzed different order submission strategies in order to understand liquidity supply and demand (e.g. Biais, Hillion and Spatt, 1995;

Foucault, 1999 and Parlour, 1998). The basic idea in these studies is that traders' decisions to send market or limit orders have an impact on liquidity supply and demand. A market order is an order to buy or sell a security immediately at the current available market price and it commonly consumes the liquidity in the market. They are generally used by impatient and liquidity demander traders. Market orders give guarantee to order execution at the current or near the current bid/ask prices. The execution price of a market order depends on the size of an order and available liquidity. The execution price is uncertain since market prices can change in the time interval between the submission of an order and the actual execution. Especially for large orders, this uncertainty gets bigger. In order to avoid execution price uncertainty, traders can choose to submit limit orders. A limit order is an order to trade at the buy, sell a security at a specific price, or better. They are generally used by patient and liquidity supplying traders. Limit orders limit the execution prices but do not guarantee execution. A buy limit order is given to be executed at the specified limit price or a better lower price; a sell limit order is given to be executed at the specified limit price or better higher price. In a continuous market, the best limit order to buy and the best limit order to sell establish the market and the order sizes establish the market depth. Thus, limit orders provide liquidity to the market.

The distinction between market and limit orders does not exist in all types of markets, though. Three kinds of trading mechanisms exist: quote driven (dealers market), order driven (limit orders markets) or hybrid markets. Quote driven markets are traditionally designed in a way to accept market orders only. In quote driven markets, market makers generally hold inventory and offer liquidity to immediate buyers or sellers, and trades take place if other traders accept these prices. Market makers are exchange specialists who also accept the risk of holding inventory to provide liquidity in a security. Each market maker stands ready for complete clients' orders by offering buy and sell quotations. Once an order received, the market maker immediately sells from its inventory or seeks an offsetting order immediately. Bagehot (1971), defined the role of market maker as "The role of the market maker is, of course, to provide liquidity by stepping in and transacting whenever equal and opposite orders fail to arrive in the market at the same time" (Bagehot, 1971, p.13). In this type of market, traders do not trade directly with each other and their quotes are valid for a limited size and time. Thus, in a quote driven market there is a sharp

difference between liquidity suppliers, which are dealers, and liquidity demanders who send market orders.

Order driven markets (limit orders markets) are today's dominant market structure, especially for trading equities, where limit order provides liquidity and market orders demand liquidity. Traders interact directly with each other, without intervention of intermediaries, over a platform such as LOB. Orders are matched via LOB and their priority determines which order is to be matched first.

However, with the rapid development of technology in the last two decades, quote driven markets turn into hybrid markets, where market makers and order book, coexist. Furthermore, with the new decade, developing infrastructure of limit order markets allows algorithmic trades. According to Boehmer et al. (2015), algorithmic trading increasingly dominates manual trading on a global basis and in various asset classes. Hendershott et al. (2011) state that algorithms typically determine the timing, price, quantity, and routing of orders, dynamically monitor market conditions across different securities and trading platforms and reduce market impacts. They employ both limit orders and marketable orders. Thus, sometimes, they function as liquidity demanders, and sometimes, they supply liquidity. Algorithmic trading results with the existence of high-frequency traders. High-frequency traders, according to Securities and Exchange Commission (SEC) definitions, are professional traders who use high-speed and sophisticated computer programs for generating, routing, and executing orders and they establish and liquidate their positions in very short time-frames. As Easley et al. (2012) states, high frequency traders typically act as market makers, providing liquidity to passive limit orders at various levels of the electronic order book.

We can finally say that despite the evolving form of markets, the main function of markets which is to provide liquidity will not change.

2.3 Dimensions and Causes of Liquidity

Black (1971) is the first who indicates the dimensions of liquidity. He proposes that “a liquid market is a continuous market, in the sense that almost any amount of stock can be bought or sold immediately; and an efficient market, in the sense that small amounts of stock can always be bought or sold very near the current market price,

and in the sense that large amounts can be bought or sold over long periods of time at prices that, on average, are very near the current market price” (Black, 1971, p. 30). Black (1971)’s proposition suggests us that in a liquid market a trader can sell or buy small amounts quickly by exposing small spreads, while she/he should pay a liquidity premium in order to sell or buy large amounts. His arguments indicate that handling large amounts without any price increment in a liquid market is an unrealistic assumption since markets are not infinitely deep. Kyle (1985), defines liquidity alike Black (1971), and states that defining market liquidity is slippery and difficult since it compromises number of properties of markets. According to Kyle (1985), market liquidity includes “tightness” (the cost of turning around a position over a short period of time), “depth” (the size of an order flow innovation required to change prices a given amount), and “resiliency” (the speed with which prices recover from a random, uninformative shock) (Kyle, 1985, p.1316)

We can summarize the five dimensions of liquidity as follows:

1. Tightness: It shows the price dimension of liquidity and refers to trading costs, in other words “spread”. If it is narrow, then the market can be defined to be liquid.
2. Depth: It shows market's ability to sell/buy with minimal price impact. In other words, it shows potential volume at best buy and sell prices. If it is high then the market can be defined to be liquid.
3. Resilience: It shows market ability to turn back the initial level after a large amount of buy or sell. If market shifts fast then the market can be defined to be liquid.
4. Breadth: It refers to the overall size of the volume traded. If it is large, then the market can be defined to be liquid.
5. Immediacy: It refers to availability of buyers and sellers at any time. If buyers and sellers is available all time then the market can be defined to be liquid.

Figure 2.1 shows a graphic of LOB at some instant in time. This figure illustrates dimensions of liquidity. The buy orders are displayed in orange, while sell orders are displayed in green. The horizontal line shows price, the vertical line shows quantity. Blocks show the order quantities in each price level. The horizontal line within the blocks at each individual price level demonstrate available quotation at that price at a

point in time. As shown in Figure 2.1, several orders can have the same price at a given time (more than one block at a price level). Priority is given to active orders with the best price. If some of the blocks at buy or sell side is missing, then the market lacks immediacy. Depth of the market displays bid and ask quantities at the currently best prices as shown in Figure 2.1. LOB has a dynamic structure where quantity and price change continuously. The spread between bid and ask prices get wider if the quantities at the best bid or best ask are depleted. If a trader submits a large sell order, it is expected to see a drop in prices as visualized in Figure 2.1. The total number of blocks at each price levels show the breadth of the market.

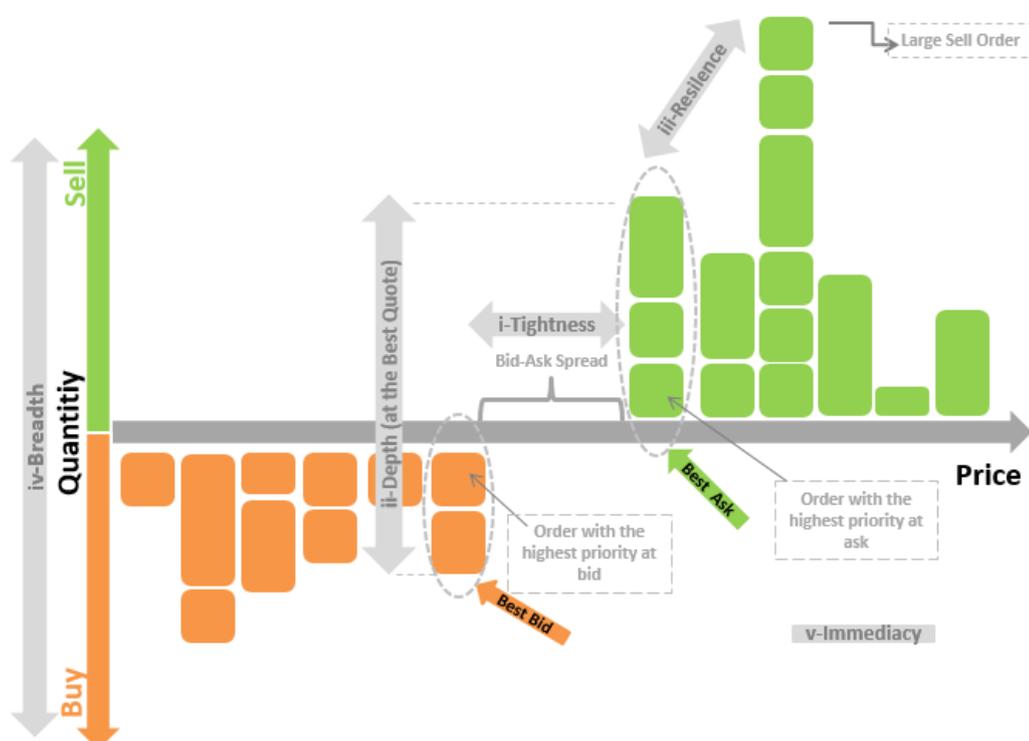


Figure 2.1 : Dimensions of liquidity.

In the absence of liquidity, trading will be costly; therefore, the researches on liquidity are usually associated with liquidity costs. Demsetz (1968) is first who pointed at the bid-ask spread as the cost of liquidity. He states, “The inclusion of the ask-bid spread in transaction costs can be understood best by considering the neglected problem of “immediacy” in supply and demand analysis. The ask-bid spread is the markup that is paid for predictable immediacy of exchange in organized markets” (Demsetz, 1968, p.35-36). As Demsetz (1968), Bagehot (1971), points that liquidity is inversely related to bid-ask spread.

In market microstructure literature, there has been an extensive research on bid-ask spread. The early literature focuses on the determinants of the spread and states that it has three major components: order processing costs, inventory holding costs and adverse selection costs.

Order processing cost is the follow on the cost of doing business in the market, which is first emphasized by Demsetz (1968) as a spread component. The cost includes order routing, execution, clearing, and staff wages, trading system developments, telecommunications and other such items.

Amihud and Mendelson (1980), Ho and Stoll (1981), and Stoll (1978) are the first who emphasize the inventory holding costs of liquidity suppliers. Ho and Stoll (1981) state that since liquidity suppliers hold an inventory, they should adjust the stock quotations in return to trades to keep inventory levels. Stoll (1978) and Ho and Stoll (1981)'s main statement are that the spread does not depend on the dealer's inventory position. However, it depends on the dealer's ability to adjust prices in response to inventory changes in time. According to them, liquidity suppliers adjust the quote midpoint relative to the fundamental value based on accumulated inventory in order to induce inventory-equilibrating trades (Huang and Stoll, 1997). Amihud and Mendelson (1980) state that bid-ask prices depends on market-maker's stock inventory position and market maker's inventory adjustments leads to a dynamic pricing policy.

The adverse selection cost component of the bid-ask spread, which has received the highest interest in the microstructure literature, arises in order to prevent traders from losses due to asymmetric information. Asymmetric information defines the situation when information is asymmetrically distributed among traders, in other words when some traders possess greater material information than others. The component is called adverse selection since traders who have better information, choose the side of the market they trade, and dealers are always in the wrong side, so prices tend to move against them before they trade (Harris, 2003). Therefore, dealers or liquidity suppliers in the market widen the spread between bid-ask prices in order to compensate the losses of adverse selection.

Bagehot (1971), states the role of market maker and the existence of informed traders for the first time. According to him, market maker confronts three kinds of traders;

first the one who has special information; second the liquidity motivated investors and third the traders who believe that prices do not reflect the information they have but which in fact already have. He further states that market maker always fails to win against informed investors. As he noted, uninformed traders must pay a spread to compensate the losses to informed investors.

Alike Bagehot (1971), Amihud and Mendelson (1980) state that even knowledge of the market maker's current inventory position and his pricing policy cannot produce a profitable trading rule due to the superior information of informed traders. They say that insiders have a more accurate assessment of the demand and supply functions than market maker does, and they may use their superior information to make profit in excess of their cost implied in the bid-ask spread.

Copeland and Galai (1983), Kyle (1985), Glosten and Milgrom (1985) and Easley and O'Hara (1987), also concentrate on the adverse selection costs in their studies and they commonly have the idea that the spread is the value of the information lost to more timely and well informed traders. Copeland and Galai (1983)'s paper models the dealer behavior in the existence of asymmetric information. According to them, a rational dealer will always set an ask price higher and a bid price lower than what he believes the "true" market price to be (Copeland and Galai, 1983, p. 1468). Kyle (1985) develops a dynamic model of insider trading in order to examine the informativeness of prices, liquidity of the market and the value of private information of insiders. Kyle (1985) proposes that a market maker is not able to distinguish whether quantities traded in the market come from the insiders or noise traders, they set bid-ask prices as the increasing function of the imbalances in the order flow to protect from adverse selection. Glosten and Milgrom (1985), state the adverse selection by itself is the reason of the spread and the width of the spread depends on many parameters, such as arrival patterns of insiders and liquidity traders, the imbalance of supply and demand among liquidity traders, and the quality of insiders' information. Easley and O'Hara (1987) investigate the effect of trade sizes on trading and state that trade size introduces an adverse selection problem since informed traders prefer to trade larger amounts at any given price.

The common feature of the literature mentioned above is; they are all constructed for quote driven markets where market makers exist. However, markets are generally order driven nowadays. Handa and Schwartz (1996), state that bid-ask spread is

related to equilibrium levels of buying and selling orders, and to the degree of asymmetric information in order driven markets. Foucault et al. (2005), further states that narrowness of spread in the order driven market is related to proportion of patient limit order traders. Furthermore, electronic trading systems in order driven markets make it possible for traders to cancel and resubmit limit orders rapidly in response to market conditions. This is an important aspect to determine the bid-ask spread since traders may want to resubmit or cancel their limit orders with the increase in the volatility of value changes. With this intuition, Harris (2003) states that the most important factors that determine the spread in order driven markets are, the degree of information asymmetry among the traders, how quickly traders can cancel their limit orders, and the volatility of the security.

Besides bid-ask spread, depending on the willingness of investors to provide liquidity, market depth, breadth and resiliency will vary over time and may lack in certain times. Suspicion of asymmetric information in the market makes traders reluctant to submit limit orders in order driven markets; it also makes dealers to widen spread in quote driven markets and they all drain the market liquidity. In this manner, Hasbrouck (1991)'s study says that price effect for a given trade size is generally held to be a positive function of the proportion of potentially informed traders in the population. Glosten and Harris (1988) also suggest that effects of asymmetric information are presumably to be captured in the price impact of trade size.

Lastly, immediacy dimension generally occurs in trading systems which offer continuous trading. The reason is that only a continuous quote driven market can supply liquidity for immediacy demanding impatient traders at all time. Therefore, this dimension is interrelated to market features that affect trading speed of markets and trading interest of liquidity suppliers.

2.4 Liquidity Measurement: A Comparative Review of the Literature

In this part, we put a special emphasis on various liquidity measures discussed in the previous literature about equity markets. To begin with, liquidity measures can cover a single dimension or several dimensions of liquidity and these dimensions differ. They indicate either liquidity or illiquidity. Moreover, they do this at a point in time (as a stock variable) or cumulatively over a period of time (as a flow variable).

Furthermore, some are ex post, which show the available liquidity in the past and some are ex ante, which simulate the expected liquidity in the future. Besides, some liquidity measures directly or indirectly relate to bid-ask spread. Some of them are originally developed and more appropriate for quote-driven markets while others are developed and more appropriate for order-driven markets. The frequency of the data to produce these measures (input data) or the frequency of the measures themselves (output data) can be low or high. Moreover, some liquidity measures have potential periodicity if weighted by time or quantity. Our purpose, however, is to highlight the differences and similarities of these measures and produce a more complete understanding of their limitations and extensions. To do this, we review and categorize virtually all the equity market liquidity measures and all are listed in Table 2.1 and graphically presented in Figure 2.2. We report 50 different liquidity measures about equity markets which are discussed below. The mathematical models/formulas of these measures are given in Table A.1 in the Appendix A.

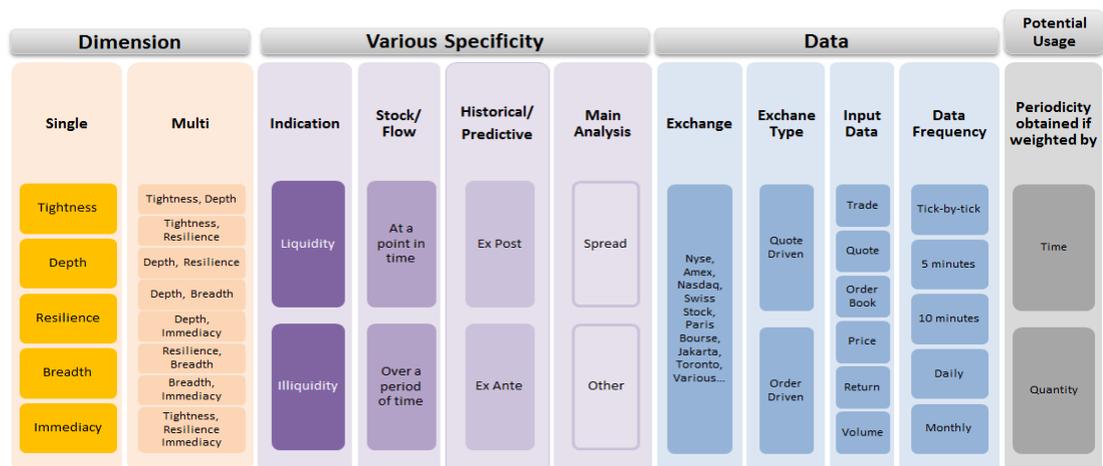


Figure 2.2 : Measures of liquidity.

Table 2.1 : Liquidity measures with various features.

No	Abbr.	Measure	Source	Year	Dimension		Various Specificity				Data				Potential Usage
					S/M	DN	Indication	Stock/Flow	Historical/Predictive	Main Analysis	Exchange	Exchange Type	Input Data	Data Frequency	Periodicity obtained if weighted by
1	PQS	Percent Quoted Spread	Demsetz	1968	S	i	IL	AT	Ex Ante		Nyse	Quote Driven	Quote	Tick by tick	Time, Quantity
2	IS	Implementation Shortfall	Perold	1988	S	i	IL	AT	Ex Post		Nyse/Amex/Nasdaq	Quote Driven	Trade and Quote	Tick by tick, periodic	
3	ET	Effective Tick	Goyenko, Holden, Trzcinka; Holden	2009	S	i	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Price, Spread	Daily	
4	CPQS	Closing Percent Quoted Spread	Chung, Zhang	2014	S	i	IL	AT	Ex Ante		Nyse/Amex/Nasdaq	Hybrid	Trade	Daily	
5	EC	One-Way, Execution Cost	Perold, Holden	1988, 2014	S	i	IL	AT	Ex Post		Nyse/Amex/Nasdaq	Quote Driven	Trade and Quote	Tick by tick, periodic	
6	AD	Average Depth	Mann, Ramanlal	1996	S	ii	L	AT	Ex Ante		Nyse	Quote Driven	LOB	Tick by tick	
7	ZRS, ZRS2	Zeros, Zeros2	Lesmond, Ogden, Trzcinka	1999	S	ii	IL	OT	Ex Post	Spread	Nyse/Amex	Quote Driven	Return	Monthly	
8	OR	Order Ratio	Rinaldo	2000	S	ii	IL	OT	Ex Ante		Swiss SE	Order Driven	Trade and Quote	10 minutes	
9	VN	VNET	Engle, Lange	2001	S	ii	L	OT	Ex Ante		Nyse	Quote Driven	Trade and Quote	Tick by tick	
10	WB, WA, OV	Weighted Bid, Ask and Order Value	Aitken, Comerton-Forde	2003	S	ii	L	OT	Ex Ante		Jakarta SE	Order Driven	LOB	Tick by tick, periodic	
11	ROLL	Roll	Roll	1984	S	iii	IL	OT	Ex Post	Spread	Nyse/Amex	Quote Driven	Price	Daily	
12	VR	Variance Ratio	Hasbrouck, Schwartz	1988	S	iii	IL	OT	Ex Post		Nyse/Amex/Nasdaq	Quote Driven	Price	Daily	
13	ROR	Relative Odds Ratio	Kluger and Stephan	1997	S	iii	IL	OT	Ex Post		Nyse	Quote Driven	Trade	Daily	

Note: S: single dimensional; M: multi-dimensional, DN: dimension name, i: tightness, ii: depth, iii: resilience, iv: breadth, v: immediacy, L: liquidity, IL: illiquidity, AT: at a point in time, OT: over a period of time.

Table 2.1 (continued) : Liquidity measures with various features.

No	Abbr.	Measure	Source	Year	Dimension		Various Specificity				Data				Potential Usage
					S/M	DN	Indication	Stock/Flow	Historical/Predictive	Main Analyses	Exchange	Exchange Type	Input Data	Original Data Frequency	Periodicity obtained if weighted by
14	CET	Coefficient Elasticity of Trading	Datar	2000	S	iii	L	OT	Ex Post		Nyse	Quote Driven	Price, Volume	Monthly	
15	MROLL	Modified Roll	Goyenko, Holden, Trzcinka	2009	S	iii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Price	Daily	
16	EROLL	Extended Roll	Holden	2009	S	iii	IL	OT	Ex Post	Spread	Nyse	Quote Driven, Order Driven	Price	Daily	
17	TR	Turnover Ratio	Datar, Naik, Radcliffe	1998	S	iv	L	OT	Ex Post		Nyse	Quote Driven	Price, Volume	Monthly	
18	TV	Transaction Volume	Black; Cooplend, Galai	1971, 1983	S	iv	L	OT	Ex Post		Nasdaq	Quote Driven	Volume	Daily	
19	TF	Trading Frequency	Demsetz	1968	S	v	IL	OT	Ex Post		Nyse	Quote Driven	Trade	Tick by tick, periodic	
20	ACD	Autoregressive Conditional Volume Duration	Engle, Russell	1998	S	v	IL	OT	Ex Ante		Nyse	Quote Driven	LOB	Tick by tick	
21	WD	Weighted Durations	Gouriéroux, Jasiak, Le Fol	1999	S	v	IL	OT	Ex Ante		Paris Bourse	Order Driven	LOB	Tick by tick	
22	SPE	Speed of Partial Execution	Holden	2014	S	v	L	AT	Ex Post			Order Driven	LOB	Tick by tick	Quantity
23	SCE	Speed of Complete Execution	Holden	2014	S	v	L	AT	Ex Post			Order Driven	LOB	Tick by tick	Quantity
24	SC	Speed of Cancellation	Holden	2014	S	v	IL	AT	Ex Post			Order Driven	LOB	Tick by tick	Quantity
25	HL	High-Low	Corwin, Schultz	2012	M	i, iii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Price	Daily	
26	CHL	Close-High-Low	Abdi, Rinaldo	2013	M	i, iii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Price	Daily	

Note: S: single dimensional; M: multi-dimensional, DN: dimension name, i: tightness, ii: depth, iii: resilience, iv: breadth, v: immediacy, L: liquidity, IL: illiquidity, AT: at a point in time, OT: over a period of time.

Table 2.1 (continued) : Liquidity measures with various features.

No	Abbr.	Measure	Source	Year	Dimension		Various Specificity				Data				Potential Usage
					S/M	DN	Indication	Stock/Flow	Historical/Predictive	Main Analysis	Exchange	Exchange Type	Input Data	Original Data Frequency	Periodicity obtained if weighted by
27	CRT	Cost of a Round Trip Trade	Irvine, Benston, Kandel	2000	M	i, iii,v	IL	AT	Ex Ante		Toronto SE	Order Driven	Trade, Quote and LOB	Tick by tick	
28	XLM	Xetra Liquidity Measure	Deutsche Borse	2002	M	i, iii,v	IL	AT	Ex Ante		Deutsche Borse	Order Driven	Trade, Quote and LOB	Tick by tick	
29	PPI	Percent Price Impact	Huang, Stoll	1996	M	i,ii	IL	AT	Ex Post		Nyse/Nasdaq	Quote Driven	Quote	Tick by tick	Quantity
30	PES	Percent Effective Spread	Huang, Stoll	1996	M	i,ii	IL	AT	Ex Post		Nyse/Nasdaq	Quote Driven	Trade and Quote	Tick by tick	Quantity
31	LOTM	LOT-Mixed	Lesmond, Ogden, Trzcinka	1999	M	i,ii	IL	OT	Ex Post	Spread	Nyse/Amex	Quote Driven	Return	Daily	
32	BLM	BLM	Pascual, Escribano, Tapia	2004	M	i,ii	IL	AT	Ex Ante		Nyse	Quote Driven	Trade and Quote	Tick by tick, 10 minutes	Time
33	QS	Quote Slope	Hasbrouck, Seppi	2001	M	i,ii	IL	AT	Ex Ante		Nyse/Amex/Nasdaq	Quote Driven	Trade and Quote	Tick by tick, 15 minutes	Time
34	LOTYS	LOT Y-Split	Goyenko, Holden, Trzcinka	2009	M	i,ii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Return	Daily	
35	FHT	FHT	Fong, Holden, Trzcinka	2014	M	i,ii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq/Various	Quote Driven, Order Driven	Return	Daily	
36	AMV	Amivest	Cooper, Groth, Avera	1985	M	ii, iii	L	OT	Ex Post		Nasdaq	Quote Driven	Return, Volume	Daily	
37	LR	Liquidty Ratio	Ranaldo	2000	M	ii, iii	L	OT	Ex Post		Swiss SE	Order Driven	Return, Volume	Daily	
38	ALR	Amihud Illiquidity	Amihud	2002	M	ii, iii	IL	AT	Ex Post		Nyse	Quote Driven	Return, Volume	Daily	

Note: S: single dimensional; M: multi-dimensional, DN: dimension name, i: tightness, ii: depth, iii: resilience, iv: breadth, v: immediacy, L: liquidity, IL: illiquidity, AT: at a point in time, OT: over a period of time

Table 2.1 (continued) : Liquidity measures with various features.

No	Abbr.	Measure	Source	Year	Dimension		Various Specificity				Data				Potential Usage
					S/M	DN	Indication	Stock/Flow	Historical/Predictive	Main Analysis	Exchange	Exchange Type	Input Data	Original Data Frequency	Periodicity obtained if weighted by
39	GMM	Gamma	Pastor, Stambaugh	2003	M	ii, iii	IL	OT	Ex Ante		Nyse/Amex	Quote Driven	Return, Volume	Daily	
40	RL	Regressed Lambda	Goyenko, Holden, Trzcinka; Holden	2009	M	ii, iii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Return, Volume	5 minutes	
41	EAM	Extended Amihud	Goyenko, Holden, Trzcinka	2009	M	ii, iii	IL	OT	Ex Post		Nyse/Amex/Nasdaq	Quote Driven, Order Driven	Return, Volume and Specific	Daily	
42	VOV	VoV	Fong, Holden, Tobek	2017	M	ii, iii	IL	OT	Ex Post	Spread	Nyse/Amex/Nasdaq/Various	Quote Driven, Order Driven	Return, Volume	Daily	
43	VV	Volume Volatility	Foster, Viswanathan	1993	M	ii, iv	IL	OT	Ex Post		Nyse/Amex	Quote Driven	Volume	Daily	
44	FR	Flow Ratio	Rinaldo	2000	M	ii, v	IL	OT	Ex Post		Swiss SE	Order Driven	Trade	10 minutes	
45	LM	LM	Liu	2006	M	ii, v	IL	OT	Ex Post		Nyse/Amex/Nasdaq	Quote Driven	Return	Daily	
46	MLI	Martin Index	Martin	1975	M	iii, iv	IL	OT	Ex Post		Nyse/Amex/Nasdaq	Quote Driven	Price, Volume	Daily	
47	LHH	Hui-Heubel Liquidity Ratio	Hui-Heubel	1984	M	iii, iv	IL	OT	Ex Post		Nyse	Quote Driven	Price, Volume	Daily	
48	PFR	Partial Fill Rate	Holden	2014	M	iv, v	L	AT	Ex Post			Order Driven	LOB	Tick by tick	Quantity
49	CFR	Complete Fill Rate	Holden	2014	M	iv, v	L	AT	Ex Post			Order Driven	LOB	Tick by tick	Quantity
50	CR	Cancellation Rate	Holden	2014	M	iv, v	IL	AT	Ex Post			Order Driven	LOB	Tick by tick	Quantity

Note: S: single dimensional; M: multi-dimensional, DN: dimension name, i: tightness, ii: depth, iii: resilience, iv: breadth, v: immediacy, L: liquidity, IL: illiquidity, AT: at a point in time, OT: over a period of time

2.4.1 Dimensional features

Liquidity measures can cover a single dimension or several dimensions of liquidity. Their dimensional properties of liquidity measures are given in sixth and seventh columns of Table 2.1.

The first dimension is tightness which is the bid-ask spread and it is generally measured in percent terms (*percent quoted spread*, PQS) to balance different stock price levels. Additionally, we find that single dimensional *implementation shortfall* (IS), *one-way execution cost* (EC), *closing percent quoted spread* (CPQS) and *effective tick* (ET) measures capture the tightness of liquidity.

The second dimension is called depth and it is defined through corresponding volume of best bid and best ask prices. Mann and Ramanlal (1996) suggest *average depth* (AD) which simply averages the best bid and best ask quantities to measure the depth. Furthermore, single dimensional *order ratio* (OR), *weighted bid value* (WB), *weighted ask value* (WA), *order value* (OV), *VNET* (VN), *zeros* (ZRS) and *zeros2* (ZRS 2) measures capture the depth dimension of liquidity.

Resilience is the third dimension that shows market ability to turn back the initial level after a large amount of trade. Hasbrouck and Schwartz (1988) state that for a given permanent price movement, the transitory shifts tend to be minor in resilient markets and they provide *variance ratio* (VR) as a liquidity measure. Roll (1984) proposes a serial first-order covariance model (ROLL) to estimate the liquidity in the market and states that price reversals are caused by traders' buying and selling activity. The ROLL measure and its versions, *modified Roll* (MROLL) and *extended Roll* (EROLL), capture the resilience of liquidity. Kluger and Stephan (1997)'s relative odds ratio (ROR) estimates the relative probability that a firm will experience after a critical price movement. Datar (2000)'s coefficient elasticity of trading (CET) capture the resilience dimension as well.

The fourth dimension is the breadth that shows overall size of the volume traded. The simplest measure of breadth is the *transaction volume* (TV) which is first mentioned by Black (1971) and Copelend and Galai (1983). This an indirect measure and captures only one dimension of liquidity. However, TV is highly used as a liquidity measure; since there is general empirical evidence on active markets tending to be

liquid. Similar to the TV, *turnover ratio* (TR) which scales transaction volumes to the size of the asset traded is suggested by Datar, Naik and Radcliffe (1998).

The final dimension is immediacy. It shows the time needed to execute a trade of a given size at a given cost and generally measured with trading frequency, durations and speed of transacting. Immediacy can also be interpreted as availability of buyers and sellers at all time in the market. Demsetz (1968) is the first who mentioned waiting costs of trading, and states high *trading frequency* (TF) will lower the cost of waiting in a trading queue of specified length. Gouriéroux, Jasiak, Le Fol (1999) state that *weighted durations* (WD) capture dependencies between intra-trade durations, transaction volumes and prices, thus they can be interpreted as liquidity measures. In this manner, Engle and Russell (1998)'s *autoregressive conditional volume duration* (ACD) model can be used as a liquidity measure to capture the immediacy dimension of liquidity. Furthermore, Holden (2014) mentions "an order that has not been completely executed" may expire, be cancelled, or continue effectively in continuous markets. According to him, *speed of partial execution* (SPE), *speed of complete execution* (SCE) and *speed of cancellation* (SC) may be used to capture immediacy dimension of liquidity.

Multi-dimensional liquidity measures combine the features of different single dimensional liquidity measures. As an example, tightness and depth or tightness and resilience may be determined together. Copeland et al. (1983) states that for a given point in time, tightness (spread) is a negative function of measures of depth and market activity (trading volume or turnover). We find that the liquidity measures which capture tightness and depth together are, *percent effective spread* (PES), *percent price impact* (PPI), *bi-dimensional liquidity measure* (BLM), *quote slope* (QS), *LOT mixed* (LOTM), *LOT y-split* (LOTYS) and FHT. Furthermore, *high-low* (HL) and *close-high-low* (CHL) capture tightness by simultaneously using daily high and low prices, they capture also transitory price effects of large orders, in other words immediacy.

Resilience and depth have a strong interrelation. Kyle (1985) proposes that spread is an increasing function of the imbalance in the order flow and this creates a positive relationship between the order flow and price changes. In this manner, Amihud (2002) introduces a price impact illiquidity measure, the *Amihud illiquidity measure* (ALR), that captures daily stock price reaction to a dollar of trading volume. ALR is

very similar to the *Amivest* (AMV) of Cooper, Groth, Avera (1985). Pastor and Stambaugh (2003) suggest a price impact model (*Gamma*, GMM) alike Amihud (2002) which measures price reverses per unit volume. Moreover, *extended Amihud measures* (EAM), *liquidity ratio* (LR), *regressed lambda* (RL) and VOV measures capture resiliency and depth dimension of liquidity. Besides, liquidity measures which use price volatility over volume or turnover such as *Hui-Heubel liquidity ratio* (LHH), *Martin liquidity index* (MLI) capture both resilience and breadth. Meanwhile, *volume volatility* (VV) captures both depth and breadth of the market. Depth and immediacy are also related. Rinaldo (2000) suggests a liquidity measure called *flow ratio* (FR) with respect to the interrelation of number of trades and waiting time. Liu (2006) introduces the *liquidity measure* (LM), which standardizes the turnover-adjusted number of zero daily trading volumes over a certain period time to capture the risk in extreme cases. Holden (2014) mentions a set of liquidity measures that combine breadth and time dimension by examining set of submitted orders, over a certain time interval. These are cancellation rate (CR), complete fill rate (CFR) and partial fill rate (PFR).

Irvine, Benston and Kandel (2000) are the first who define a market impact liquidity measure (*cost of a round trip*, CRT). It computes costs of simultaneous buy and sell orders of the same size at a certain point in time by aggregating status of the limit order book. This measure captures tightness, resiliency and immediacy dimension of liquidity. Similar version of this measure is the *Xetra Liquidity Measure* (XLM) which is designed by Deutsche Boerse AG. It is implemented in the Xetra trading system. The calculation of the CRT and XLM are based on all orders in the limit order book, including hidden orders.

Consequently, we can say that 24 measures present a single dimension of liquidity; and 26 measures present multi dimensions of liquidity.

2.4.2 Various specificity

Measures for equity market liquidity are generally called as “liquidity measures”; however, most of them are in fact measures of “illiquidity”. This distinction is important when interpreting the results, for example, higher results of illiquidity measures indicate lower liquidity. Moreover, they indicate either liquidity or illiquidity at a point in time (as a stock variable) or cumulatively over a period of

time (as a flow variable). For example, PPI, PES and QS are calculated from certain time transactions and give the illiquidity situation at a time. However, AMV or OR necessitates cumulative order flow to measure liquidity or illiquidity. We find that 13 liquidity measures show illiquidity at a point in time; 25 liquidity measures show illiquidity over a period of time; 5 liquidity measures show liquidity at a point in time; 7 liquidity measures show liquidity over a period in time. These properties are given in eighth and ninth columns of Table 2.1

Furthermore, some are ex post, which show the available liquidity in the past and some are ex ante, which simulate the expected liquidity in the future. Aitken and Comerton-Forde (2003) are the first ones who mention the distinction. Ex post liquidity measures are transaction based measures which show the available liquidity in the past; however ex ante measures are order based measures which simulate the expected liquidity in the future. Ex post liquidity measures show the general market features however their ability to predict future is limited. Besides, ex ante liquidity measures can predict future liquidity. Ex ante measures are preferred over ex post measures since they are more indicative of what is presently available. However, we find that, ex post liquidity measures dominated in the literature; 37 of all 50 measures show ex post liquidity; and 13 of them show ex ante liquidity. This distinction is presented at tenth column of Table 2.1

Additionally, some liquidity measures directly or indirectly relate to bid-ask spread. The bid-ask spread is used as a liquidity benchmark in various studies withstanding its interrelation to other liquidity factors and its ability to show intraday features of the market. However, the computational difficulties and more importantly, the lack of long-term intraday data necessitate other measures, which can estimate spread from readily available low-frequency data such as daily price or volume. Nevertheless, literature proposes models to estimate bid-ask spread using low frequency data. We find that 12 liquidity measures are developed in this purpose. The measures are marked at the eleventh column of Table 2.1.

2.4.3 Data features

Liquidity measures vary within their origination. The usage of pioneer liquidity measures are originated for New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ. The obvious reason is availability of transaction

data of these exchanges. For US markets, the Trade and Quote (TAQ) database provides historical tick-by-tick data back to 1993; the Institute for the Study of Security Markets (ISSM) database provides tick-by-tick data covering the NYSE and AMEX between 1983 and 1992, and NASDAQ between 1987 and 1992. However, in many countries, transaction data are not available at all.

Moreover, some of them are originally developed and more appropriate for quote-driven markets while others are developed and more appropriate for order-driven markets. For example, Gouriéroux, Jasiak and Le Fol (1999) model is appropriate for order-driven market, and they test their model in Paris Bourse. Rinaldo (2000)'s model is developed for order driven Swiss Stock exchange. Irvine, Benston and Kandel (2000) liquidity measure CRT is originally developed for Toronto Stock Exchange and it is appropriate for order-driven markets. The list of origin exchange and origin exchange type of the measures are given in the twelfth and thirteenth column of Table 2.1.

The frequency of the data to produce these measures (input data) or the frequency of the measures themselves (output data) can be low or high. We find that 4 measures use trade data and two of them use quote data which are collected at a certain interval within a time series. Seven of them use trade and quote data (trade prices and bid-ask quotes with their time stamps), while ten of the measures use order book data (tick-by-tick order with their time stamps). Besides, 2 of the liquidity measures (CRT, XLM) necessitate both trade and quote and order book data which are very specific (e.g., NASDAQ ITCH, Xetra Order Book). In order to reduce computational time or/and to study time series, 25 liquidity measures use price, volume and return data which are obviously the easiest to calculate and inexpensive to obtain. Corresponding to necessitated data sets, the frequency of data sets differs. We find 24 liquidity measures use intraday tick by tick, while 23 use daily and 3 use monthly data. The data types and frequencies of the measures are listed in fourteenth and fifteenth column of Table 2.1.

2.4.4 Potential usage

Finally, we find that some liquidity measures have potential periodicity if weighted by time or quantity. Measures can be used in different periodicities such as tick-by-tick, hourly, daily, monthly or yearly. However, some measures that show

liquidity/illiquidity at a point in time necessitate simple time or quantity weighed aggregation in order to have periodicity. For example, PQS, QS and BLM can be aggregated by computing time weighted where each observation is weighted by the amount of time of observed quote; PQS, PPI, PES, SPE, SCE, SC, PFR, CFR and CR measures can be aggregated by quantity where each observation is weighted by the amount of currency volume of the observed trade or quote. This is reported in the last column of Table 2.1.

2.5 Remarks and Discussion

Liquidity is the one of the most important determinant of market microstructure. It affects transaction costs, trading strategies, market quality and so forth. Concerning its importance, its measurement has been subject of many studies.

Liquidity measurement is complicated due to its interrelation to many dynamics. In this regard, a desirable liquidity measure should take into account many dimensions of liquidity such as immediacy, the overall depth of the market and possibility of immediate transaction especially in the event of liquidity shocks. Furthermore, a desirable liquidity measure should take into account liquidity any time in the market, large transactions and/or hidden orders (Gomber, Schweickert, Theissen, 2004; Irvine, Benston, Kandel, 2000). Therefore, a rightful determination of liquidity should rely on large number of transactions over long period of time (Bernstein, 1987). Thus, the frequency of the data to produce these measures should be high.

Furthermore, a desirable liquidity measure should be ex ante in the sense that it can predict the available liquidity in the future (Irvine, Benston, Kandel, 2000, Aitken, Comerton-Forde, 2003). Indeed, many measures have some specific properties and capture certain aspects of liquidity.

We review and categorize virtually all the equity market liquidity measures. The summary of the equity market liquidity measures according to some certain aspects are given in the Table 2.2.

Table 2.2 : Summary of liquidity measures.

Data Frq.	Ex Ante /Ex Post	Single Dimension					Multi Dimension								
		i	ii	iii	iv	v	i, iii	i, ii	ii, iii	ii, iv	ii, v	iii, iv	iv, v	i, iii, v	
High	Ex Ante	PQS	AD, OR, VN, WB, WA, OV			ACD, WD		BLM, QS							CRT, XLM
	Ex Post	EC, IS				SC, SCE, SPE, TF		PES, PPI			FR		CFR, CR, PFR		
Low	Ex Ante	CP QS							GMM						
	Ex Post	ET	ZRS, ZRS 2	CET, EROLL, MROLL, ROLL, ROR, VR	TR, TV		CHL, HL	FHT, LOT M, LOT YS	ALR, AMV, EAM, LR, RL, VOV	VV	LM	LHH, MLI			

Note: Liquidity measures names are given as abbreviations in the table. Frq: Frequency, i: tightness, ii: depth, iii: resilience, iv: breadth, v: immediacy

As shown in Table 2.2, liquidity measures concentrate around specific properties. For example, half of the measures are ex post and they use low frequency data sets. Moreover, ex ante measures are mostly single dimensional. The five dimensions allow a complete mapping of market liquidity, however we could not find out any measure that represents all dimensions. Measures those are able to capture several dimensions, such as CRT and XLM may be preferred. Those two measures dominate other equity liquidity measures in the sense that they are multidimensional, they indicate ex ante liquidity and their determination depend on high frequency data. The challenge of these measures is to obtain the required data. A researcher or investor who wants to analyze liquidity for several years on various international markets, she/he should obtain large sets of high-frequency (tick-by-tick) data. Intraday data do not go back to more than a few years and in many markets (especially in emerging markets). The data problem surely stands for other liquidity measures, which use high frequency data sets as stated in Table 2.1 and Table 2.2. As O' Hara (2015) states, with trading electronic, the data sets are becoming more available, but they are expensive to purchase, store, study and manipulate.

Besides, these certain properties, some measures have been used many times in researches. For example, intraday spread measures (PQS, PES, PPI) are used as liquidity benchmarks in many studies (e.g. Lesmond, 2005, Goyenko, Holden,

Trzcinka, 2009; Fong, Holden, and Trzcinka, 2014; Holden, 2014 and many others). Spread measures are important since they can answer certain cost-based questions about market liquidity. However, they have some drawbacks such as capturing the costs beyond best bid-ask quotes.

Moreover, these spread measures are originally developed for quote driven markets (dealer's market), rather than order driven markets. Despite this fact, small differences between bid and ask prices make these measures applicable even in order driven markets. In order driven markets, spread and tick sizes are very interrelated (Harris, 1994; Ahn, Charles, and Hyuk, 1996; Angel, 1997; Huang and Stoll, 2001; Foucault et al., 2005). In fact, for equities, which have high tick sizes, spread is usually one tick and it rarely changes. This tick size discreteness makes spread measures meaningless for high tick size equities and markets.

We further observe that, volume based measures are dominant. These measures use relative or actual transactions in order to understand depth and breadth as shown in Table 2.1. These measures generally use low frequency data sets, such as daily turnover or daily volume. The widespread availability of data makes them popular liquidity measures, however their single dimensional nature and their deficiencies to show intraday liquidity behavior makes them problematic (Bernstein, 1987). Amihud (2002) develops liquidity measure that is calculated as absolute value of the stock's realized daily return divided by its daily dollar volume over all positive-volume days (measure is undefined for zero volume days). This measure is one of the most popular measures in the finance literature due to its simple construction, availability of data and easy interpretation. This low-frequency measure captures both depth and immediacy however neglects other dimensions of liquidity. Goyenko, Holden, and Trzcinka (2009) also find that Amihud measure is not appropriate to be used as proxies for effective or realized spreads.

2.6 Conclusion

In summary, we can say that liquidity measurement literature have designed various measures to capture various features of liquidity. However, there is still no consensus on which liquidity measure is the best. This comparative survey allows us to examine liquidity measures thoroughly and understand their advantages, limitations and extensions. Good measures exist, yet with some limitations.

3. A COMPARISON OF SPREAD PROXIES: EMPIRICAL EVIDENCE FROM BORSA ISTANBUL FUTURES

3.1 Introduction

Bid-ask spread, i.e. the difference between the best available buying and selling prices available to investors, is important in market microstructure research since it can answer certain cost-based questions about market's liquidity. Investors prefer assets in which narrow spreads are observed. Thus, spread has been of great concern in various research and closely followed by investors and market authorities. Furthermore, in many studies (e.g. Lesmond, 2005, Goyenko, Holden, Trzcinka, 2009; Fong, Holden, and Trzcinka, 2014; Holden, 2014 and many others) effective and quoted bid-ask spreads are used as liquidity benchmarks.

Withstanding the importance of spread, there are several studies that explain spread dynamics over time or its time-series determinants. However, existing studies of bid-ask spread analysis have all been performed over short time periods such as a year or a few months. The reason for this is computational difficulties and more importantly the lack of long-term intraday data. In order to compute either quoted spread or effective bid-ask spread for long periods, large sets of high-frequency data that consist of quotes and trades are needed. In most cases, intraday data do not go back more than a few years. However, one might be interested in analyzing market liquidity for several years and on various international markets. Thus, this kind of analysis requires extensive amounts high-frequency data, which usually are unavailable (especially in emerging markets) or hard to work with. Instead, if bid-ask spread can be estimated with readily available low-frequency data such as daily price or volume, this can allow for the investigation about liquidity for much longer time periods.

In effect, microstructure literature proposes models that attempt to estimate bid-ask spread using low frequency or other data. A wide variety of researchers has used these low frequency proxies in their analysis. However, the question is whether low-

frequency spread proxies really measure what researchers want to measure. This questioning is essential since inaccurate estimates of spreads can create misleading information about actual market liquidity and functioning of financial markets. In this part of the thesis, we evaluate the performance of five different methods appearing in the market microstructure literature in predicting effective and quoted bid-ask spreads (Roll, LOT Mixed, Effective Tick, High-Low and Closing Percent Quoted Spread proxies). Our investigation about the performance of these proxies on index, currency and gold futures trading on Borsa Istanbul Futures and Options Market (VIOP). While few studies test all these liquidity proxies' performance for stocks, not much is known about liquidity proxies' performance for futures contracts. Our study contribute literature in that it extends the analysis on available spread proxies as well as providing evidence on futures market. In fact, we have other reasons for studying futures contracts rather than stocks. Tick sizes in Borsa Istanbul stock market are so high that the bid-ask spread is usually one tick for most stocks and changes very rarely. Therefore, we believe making such an analysis makes more sense in futures market rather than stock market in the case of Borsa Istanbul. Moreover, with this comprehensive assessment, we will have market evidence in a different futures market perspective.

3.2 Literature

Roll (1984) is first to estimate bid-ask spreads from observed price movements. Roll approach is attractive since it gives an estimate using just price data. However, it is criticized since its performance is poor when longer-term data are used. Thus, starting from popular Roll (1984) measure, various new models have been proposed. Lesmond, Ogden and Trzcinka (1999) develop "Zeros" measure to estimate transaction costs using only the time series of daily security returns, which outperforms Roll measure. Their method is based on the idea that lower liquidity is a result of zero volume thus zero return days (Goyenko, Holden, Trzcinka, 2009). Their bid-ask spread measure is defined as the proportion of zero return days to total trading days in a month. Thus, their percent cost proxy shows monthly liquidity rather than daily liquidity. For the same reason, they launched a new measure called LOT-Mixed based on the relationship between trading costs and observed stock returns. They state that observed stock returns can change due to buying and selling

costs and their liquidity proxy is simply the difference of buying and selling costs. Furthermore, they indicate that true return of a stock is unobserved and a market model could estimate these unobserved returns. Using these relations, they estimate cost parameters by maximizing the likelihood function of daily stock returns. Hasbrouck (2004) estimates effective costs of trading with a Gibbs procedure. The study uses Roll model and assumes that public information in the model is distributed normally. In fact, we can argue that both LOT-Mixed and Hasbrouck (2004) measures are useful low-frequency spread proxies but require iterative and computer-intensive calculations. Holden (2009) develops an extended Roll model. This model is a more implicit version of Roll since it takes the idiosyncratic adjusted price change by generating a market model. Developed by Holden (2009) and Goyenko, Holden and Trzcinka (2009), Effective Tick estimator assumes that the relation between spreads and effective tick sizes help researchers infer spreads from price clustering. This spread proxy is simply the probability weighted average of each effective spread size divided by average price. Recently, Corwin and Schultz (2012) generate a new spread proxy using daily high and daily low prices. More recently, Chung and Zhang (2014) suggest a percent-cost proxy called 'Closing Percent Quoted Spread' using closing ask and closing bid prices and show that it performs better for U.S. data. Fong, Holden and Trzcinka (2014), generate a new monthly spread proxy called FHT, which is a simplified version of LOT Mixed.

So far, several studies in the literature have tested the performance of these low-frequency spread estimators on stock markets. For instance, Lesmond (2005) tests the LOT Mixed proxy to provide liquidity estimates for thirty-one emerging markets for a period from 1991 to 2000. The study finds that estimates are more than 80% correlated with the proportional bid-ask spread recorded for twenty-three of thirty-one markets. Goyenko, Holden, and Trzcinka (2009) compare TAQ-based effective spread with various low-frequency liquidity measures using a sample of 400 randomly selected stocks over the period from 1993 through 2005. They show that the simplest dominant measure is the Effective Tick among Holden, Gibbs, LOT Mixed, Zeros and Roll proxies. Corwin and Schultz (2012) compare Roll, Effective Tick, LOT Mixed and High-Low estimators with NYSE data from 1993 through 2006. Their results show that High-Low spread estimator dominates Roll and LOT estimators, and does better than Effective Tick estimator does for most stocks. Chung

and Zhang (2014) test Closing Percent Quoted spread for US data and find that it performs better than Roll, Effective Tick, Gibbs and Zeros. Fong, Holden and Trzcinka (2014) do the most comprehensive study. They calculate a variety of liquidity proxies including newest Closing Percent Quoted and High-Low proxy for forty-three exchanges around the world and test the performance of these proxies by comparing with daily liquidity benchmarks calculated from intraday data. They find that Closing Percent Quoted Spread and High-Low estimator show the best performance.

3.3 Spread Measures

This section presents high-frequency spread benchmarks and low-frequency spread proxies used in our research.

3.3.1 High-frequency spread benchmarks

Spread can be defined in several ways. Quoted spread is simply the difference between bid and ask prices at any time in the market. In its turn, effective spread is the difference between trading price and mid-point of the bid-ask spread (also called mid-price). Taking into account large transactions walking through the book, hidden orders or internalization of orders by market makers, effective spread usually is considered a more realistic indicator of market liquidity than quoted spread. Two of the most common measures of market liquidity are relative percent effective spread (PES) and percent quoted spread (PQS). Both spread measures are generally used in percent terms in order to take into account differences in stock price levels. The mathematical models/formulas of PES and PQS are given in Table A.1. These measures are calculated directly with high-frequency data.

3.3.2 Low-frequency spread proxies

Low-frequency spread proxies include Roll (Roll, 1984), LOT-Mixed (Lesmond, Ogden and Trzcinka, 1999), Effective Tick (Goyenko, Holden, and Trzcinka, 2009; and Holden, 2009), High-Low (Corwin and Schultz, 2012) and Closing Percent Quoted Spread (Chung and Zhang, 2014). These are defined and discussed below.

3.3.2.1 Roll measure

Roll (1984) developed an estimator of the effective spread based on observed price changes. His effective spread estimation methodology depends on the idea that the true value of the stock price follows a random walk and in an efficient market the bid-ask spread fluctuates randomly around the true price. Thus, effective bid-ask spread can be inferred from the first-order serial covariance of price changes. Under these conditions, subsequent price changes yield negative expected autocorrelation. Therefore, effective spread estimator ROLL is defined in equation (3.1).

$$\text{Roll} = 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})} \quad (3.1)$$

When serial covariance is positive, the formula in equation (3.1) is undefined. Thus, Goyenko et al. (2009) as defined in equation (3.2) suggest the following modified roll measure.

$$\text{Roll} = \begin{cases} 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})} / \bar{P} & \text{when } \text{Cov}(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{when } \text{Cov}(\Delta P_t, \Delta P_{t-1}) > 0 \end{cases} \quad (3.2)$$

In equation (3.1) and equation (3.2) P_t is trade price at time t and \bar{P} is average price. Roll approach is attractive since it gives an estimate by using price data only. However, researchers criticize this model because its performance is poor when longer term data are used since the covariance of price changes is frequently positive for long term.

3.3.2.2 LOT-Mixed measure

Lesmond, Ogden and Trzcinka (1999) developed a new measure called LOT-Mixed that depends on the relation between trading costs and observed stock returns. The authors argue that observed stock returns change due to buying and selling costs. Their model is defined in equation (3.3).

$$\text{LOT - Mixed} = \alpha_{2j} - \alpha_{1j} \quad (3.3)$$

where $\alpha_{1j} < 0$ denote the cost of selling and $\alpha_{2j} > 0$ the cost of buying s . The unobserved return of a stock j on day t (R_{jt}^*) can be estimated by $R_{jt}^* = \beta_j R_{mt} + \varepsilon_{jt}$ where R_{mt} is the market return. The observed return is

$$R_{jt} = \begin{cases} R_{jt}^* - \alpha_{1j} & \text{when } R_{jt}^* < \alpha_{1j} \\ 0 & \text{when } \alpha_{1j} < R_{jt}^* < \alpha_{2j} \\ R_{jt}^* - \alpha_{2j} & \text{when } R_{jt}^* > \alpha_{2j} \end{cases}$$

The model's parameters are estimated by maximizing a likelihood function.

3.3.2.3 Effective tick measure

Holden (2009) as well as Goyenko, Holden and Trzcinka (2009) jointly developed an effective spread proxy based on the observable price clustering. Their model is given in equation (3.4).

$$\text{Effective Tick} = \frac{\sum_{j=1}^J \hat{\gamma}_j s_j}{\bar{P}} \quad (3.4)$$

In equation (3.4) \bar{P} is average price. For each possible spread s_j , the probability of price clustering F_j is calculated as: $F_j = \frac{N_j}{\sum_{j=1}^J N_j}$ for $j = 1, 2, \dots, J$ where N_j is the number of the trades on prices corresponding to the j^{th} spread. Then, the unconstrained probability of the effective spread is defined as:

$$U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \dots, J-1 \\ F_j - F_{j-1}, & j = J \end{cases} \quad (3.5)$$

Further; they add the following constraints to generate proper probabilities.

$$\hat{\gamma}_j = \begin{cases} \text{Min}[\text{Max}\{U_j, 0\}, 1], & j = 1 \\ \text{Min}[\text{Max}\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k], & j = 2, 3, \dots, J \end{cases} \quad (3.6)$$

3.3.2.4 High-low spread measure

Corwin and Schultz (2012) proposed a new measure simply by using daily high and low prices. They state that daily high (low) prices are usually buyer-initiated (seller-initiated) trades. Therefore, the ratio of the high to low prices reflects both the fundamental volatility of stock and its bid-ask spread. They add that variance component grows proportionally with time while spread component does not. Thus, high-low ratios estimated over a two-day period should have a variance that is twice the variance over a one-day period. This fact helps them to create an innovative high-low spread. Their effective spread estimator is given in equation (3.7).

$$\text{High} - \text{Low} = \frac{2(e^\alpha - 1)}{1 + e^\alpha} \quad (3.7)$$

where $\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$ and β and γ values in equation are obtained from daily high and low prices and defined as $\beta = \sum_{j=0}^1 [\ln(\frac{H_{t+j}}{L_{t+j}})]^2$ and $\gamma = [\ln(\frac{H_{t,t+1}}{L_{t,t+1}})]^2$ where $H_{t,t+1}$ and $L_{t,t+1}$ are highest and lowest prices over a two-day period, respectively.

This low-frequency spread measure allows the study of liquidity over relatively long periods since only daily high and low prices are needed and these are easily available even in long-term historical data. The estimator is easy to calculate and the authors claim that it performs better than other spread proxies do, i.e. it results in higher correlations with spread benchmarks. In their study, they state that this measure performs better in U.S. data than any other proxy. Further, the estimator is not limited to daily data but can be applied to intraday data when the quote data are unavailable or trades cannot be reliably matched with the quotes.

3.3.2.5 Closing percent quoted spread measure

Chung and Zhang (2014) suggest a percent-cost proxy called Closing Percent Quoted Spread using closing ask and bid prices. Their effective spread proxy is calculated as given in equation (3.8).

$$\text{Closing Percent Quoted Spread} = \frac{(\text{Closing Ask}_t - \text{Closing Bid}_t)}{(\text{Closing Ask}_t + \text{Closing Bid}_t)/2} \quad (3.8)$$

The main criticism about this proxy is that it only considers the closing moment of the day leaving out all the intraday spread patterns.

3.4 Data and Methodology

Using a sample of futures data from Borsa Istanbul Futures and Options Market (VIOP) through March 25 to August 25, 2014 (98 trading days), we first calculated our high frequency spread benchmarks. We work on three contracts: BIST 30 Index future contract (Index Future), USDTRY future contract (Currency Future) and USD/OUNCE Gold future contract (Gold Future). These are the most heavily traded futures contracts and represent approximately %98 of trading at that time. In VIOP, contracts with three different expiration months are traded; we only take the nearest-to-maturity contracts since these are the most liquid.

VIOP is a fully automated market. It operates continuously from 9:15 am to 17:45 pm. A lunch break exists for equity derivatives from 12:30 to 13:55. As an example, there are on average 20,000 timestamp records daily for the index future. However, other contracts are not liquid; only 3000 records for currency future exist on the same screen page and only 200 records for gold future.

We calculated effective and quoted bid-ask spreads from the tick-by-tick quote and transaction data as trades occur for 98 trading days from Thomson Reuters Eikon trade and quote screen page. We record data as trades occur and end up with 2,210,695 data points for index future contract, 196,161 data points for currency future contract and 18,131 data points for gold future contract. Our high-frequency dataset differs from periodic datasets since it relies on price observation drawn at variable time intervals.

In our analysis, we first constructed our high-frequency bid-ask spread benchmarks by calculating percent effective spread and percent quoted spreads from intraday data. At each moment of transaction in each contract, we determined percent quoted spread and then calculated the time-weighted average for a day. The quoted spread is the implicit cost of trading when a trade occurs at the quoted price. In order to measure the spread beyond the quoted bid-ask prices, we also calculated the effective spread at each moment of transaction in each contract and then calculated the average effective spread for the day.

In addition to our high-frequency benchmarks, we calculated each low frequency spread estimators (Roll, LOT Mixed, Effective Tick, High-Low and Closing Percent Quoted Spread). The Roll estimates are calculated as in modified version by setting positive monthly autocovariance estimates to zero. The Effective Tick is based on the observable price clustering and is a function of the tick increment used in trade prices. LOT Mixed is estimated by maximizing the likelihood function of daily stock returns. High-Low estimator is calculated exactly as in Corwin and Schultz (2012) and Closing Percent Quoted Spread is calculated using daily closing ask and bid prices.

Following the literature (Corwin & Schultz, 2012; Fong, Holden, & Trzcinka, 2014; Goyenko et al., 2009), we identified certain criteria in order to assess the measurement performance of the low frequency spread estimators. These are time

series correlation (tested as well for significance) and root mean square errors (RMSE). Therefore, we test the performance of these daily low-frequency spread measures by comparing correlations and root mean square errors with our benchmark spread.

3.5 Findings and Discussions

Table 3.1 provides the summary statistics for the estimators considered in this study. For comparison purposes, Effective Spread and Quoted Spread (the benchmarks) are presented first. Simple average effective spreads are 0.0361%, 0.0352% and 0.1441% and time-weighted quoted spreads are 0.0281%, 0.0274%, 0.1019% for index, currency and gold futures, respectively. A comparison of the left and right sides of the table reveals that a majority of proxies underestimate effective and quoted spreads (for example, mean values of Roll, Effective Tick and High-Low respectively are 0.0137%, 0.0264% and 0.0168% in index futures while effective and quoted spreads are 0.0361% and 0.0281%, respectively). However, LOT Mixed and Closing Percent Quoted Spread overestimate index future spreads (0.0535% and 0.1772% vs. 0.0361%) and currency future spreads (0.0398% and 0.4849% vs. 0.0352%). For gold future, Lot Mixed largely under estimate spreads (0.0116% vs. 0.1441%) while Closing Percent Quoted Spread overestimate them (0.8305% vs. 0.1441%). In this preliminary analysis, out of all the proxies, the values of Effective Tick generally are the closest to the benchmarks.

Table 3.1 : Summary statistics of the benchmarks and spread proxies.

	<i>Effective Spread</i>	<i>Quoted Spread</i>	Roll	LOT Mixed	Effective Tick	High-Low	Closing Percent Quoted Spread
Index Future							
Mean	0.0361%	0.0281%	0.0137%	0.0535%	0.0264%	0.0168%	0.1772%
Median	0.0353%	0.0276%	0.0132%	0.0506%	0.0259%	0.0158%	0.1506%
Standard Deviation	0.0043%	0.0025%	0.0022%	0.0742%	0.0015%	0.0072%	0.1264%
Range	0.0355%	0.0162%	0.0140%	0.7567%	0.0079%	0.0453%	0.9266%
N	98	98	98	98	98	98	98
Currency Future							
Mean	0.0352%	0.0274%	0.0114%	0.0398%	0.0234%	0.2779%	0.4849%
Median	0.0351%	0.0270%	0.0112%	0.0296%	0.0234%	0.2717%	0.4572%
Standard Deviation	0.0044%	0.0019%	0.0044%	0.0378%	0.0003%	0.1158%	0.2454%
Range	0.0218%	0.0094%	0.0284%	0.2401%	0.0018%	0.6703%	1.4349%
N	98	98	98	98	98	98	98
Gold Future							
Mean	0.1441%	0.1019%	0.0389%	0.0116%	0.0710%	0.7377%	0.8305%
Median	0.1327%	0.0976%	0.0407%	0.0096%	0.0651%	0.6878%	0.7827%
Standard Deviation	0.0545%	0.0365%	0.0288%	0.0192%	0.0326%	0.3619%	0.4251%
Range	0.3540%	0.1902%	0.1282%	0.1949%	0.1787%	2.4813%	2.2513%
N	98	98	98	98	98	98	98

In order to see the spread patterns over time, we plot daily effective and quoted spreads (the benchmarks) for the entire period, which are shown Figure 3.1 and Figure 3.2.

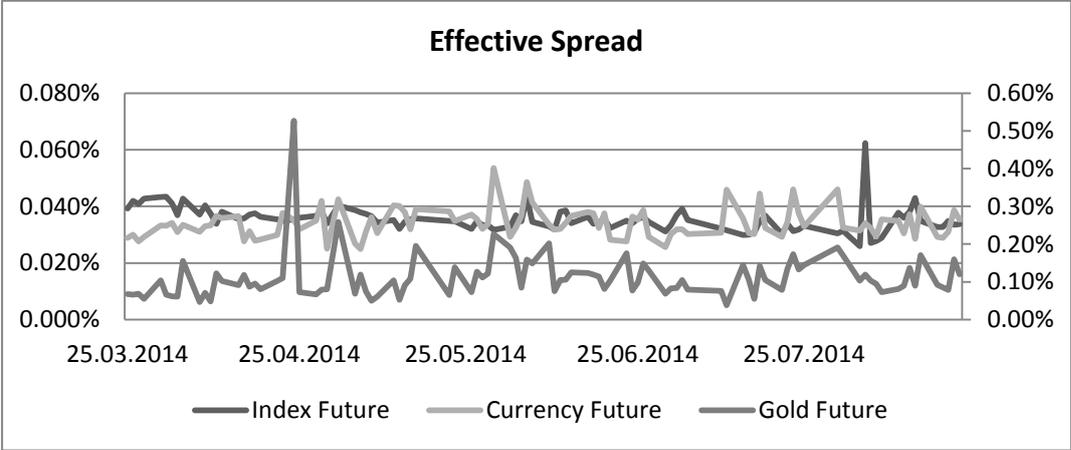


Figure 3.1 : Effective spread pattern.

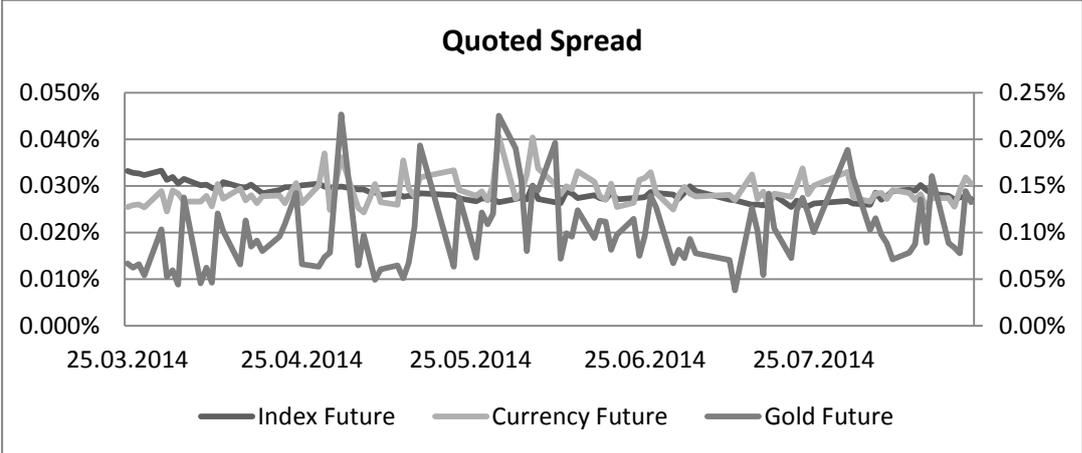


Figure 3.2 : Quoted spread pattern.

These charts gives the daily percent average effective spread and daily percent time-weighted quoted spread in index and currency futures (left axis) and gold futures (right axis). Both charts indicate that the level and the volatility of gold futures spreads are considerably higher than index and currency futures.

Table 3.2 presents results about the correlation between the benchmarks and the spread estimates. In Table 3.2, dashed boxes mean the highest correlation in the row; bold-faced numbers are statistically significant or have predictive power that is significant at the 5% level.

Table 3.2 : Correlations for spread estimates of each contract.

	Roll	Lot Mixed	Effective Tick	High-Low	Closing Percent Quoted Spread
Index Future					
<i>Effective Spread</i>	40.57%	-8.42%	31.83%	28.05%	16.83%
<i>Quoted Spread</i>	37.03%	-14.69%	73.21%	32.46%	29.86%
Currency Future					
<i>Effective Spread</i>	29.65%	12.40%	32.57%	16.32%	-15.01%
<i>Quoted Spread</i>	42.51%	-0.58%	40.00%	10.63%	-9.98%
Gold Future					
<i>Effective Spread</i>	31.77%	8.28%	77.94%	27.40%	-6.82%
<i>Quoted Spread</i>	46.41%	2.03%	84.02%	3.76%	-9.94%
Average					
<i>Effective Spread</i>	34.00%	4.09%	47.44%	23.92%	-1.67%
<i>Quoted Spread</i>	41.98%	-4.41%	65.74%	6.02%	3.31%

A clear result is that Effective Tick has the highest correlation coefficients in all the futures except one (the correlation coefficient between effective spread (respectively quoted spread) and Roll's measure is 41% (43%)). Moreover, coefficients are fully significant in Effective Tick, partially significant in Roll and High-Low and almost insignificant in Closing Percent Quoted Spread and LOT Mixed proxies. The average coefficient of correlation between Effective Tick proxy and effective (quoted) spread benchmark is 47% (66%). This implies that Effective Tick is more successful in predicting quoted spread rather than effective spread. Another interesting result is the relatively low coefficients in currency futures. For instance, as far as quoted spread is concerned, the coefficients of Effective Tick are as high as 73% and 84% in index and gold futures, but only 40 % in currency futures. The root mean square errors (RMSE) between the benchmarks and proxies that help determine whether the relevant proxy captures the level of the benchmark are given in Table 3.3. In Table 3.3, dashed boxes mean the lowest RMSE value in the row.

Table 3.3 : Root mean square errors between the benchmarks benchmarks.

	Roll	Lot Mixed	Effective Tick	High-Low	Closing Percent Quoted Spread
Index Future					
<i>Effective Spread</i>	0.00392%	0.00427%	0.00406%	0.00411%	0.00422%
<i>Quoted Spread</i>	0.00236%	0.00251%	0.00173%	0.00240%	0.00243%
Currency Future					
<i>Effective Spread</i>	0.00426%	0.00443%	0.00422%	0.00440%	0.00441%
<i>Quoted Spread</i>	0.00172%	0.00190%	0.00174%	0.00189%	0.00189%
Gold Future					
<i>Effective Spread</i>	0.05196%	0.05461%	0.03434%	0.05270%	0.05467%
<i>Quoted Spread</i>	0.03252%	0.03670%	0.01991%	0.03669%	0.03653%
Average					
<i>Effective Spread</i>	0.02005%	0.02110%	0.01421%	0.02041%	0.02110%
<i>Quoted Spread</i>	0.01220%	0.01371%	0.00779%	0.01366%	0.01361%

In general; Effective Tick has the lowest RMSE in all the futures indicating its relatively good performance. However, one should notice that there is a large gap between the RMSE of effective and quoted spreads. RMSE are very high in effective spreads compared to quoted spreads. Especially in currency futures, the performance of Effective Tick is not really different from the performance of other proxies.

Results show that none of the proxies is successful enough in estimating effective or quoted spread although under normal market conditions; Effective Tick appears to perform best. Although, this evidence is in line with Goyenko, Holden, and Trzcinka (2009) comparative study, it is contradictory with Corwin and Schultz (2012) and Fong, Holden and Trzcinka (2014) comparative studies for stocks. Although controversial and highly criticized, Roll measure performs relatively well. Its correlations with the benchmarks are higher than LOT Mixed or Closing Percent Quoted Spread proxies and to a lesser extent High-Low proxy.

Furthermore, results also show that the level and the volatility of gold futures spreads are higher than index and currency future spreads. This is not surprising since index and currency futures are more liquid than gold futures.

3.6 Conclusion

In this study, our aim is to contribute to the literature by identifying the estimator that performs best in predicting actual spreads for futures market. We compare five proxies to the spreads calculated directly with high-frequency data. Our findings show that bid–ask spread estimates are thoroughly biased. Imprecise market liquidity estimates can create misinformation about actual spread dynamics. Thus, we conclude that one should be cautious in using these proxies proposed in the literature. Moreover, a detailed check is necessary about method suitability to market type, market specific regulations (e.g. tick size) and instrument-specific features before starting any study.

The most important direction for further research may be about finding more robust proxies of bid-ask spreads that work with low-frequency data and keeping computational ease. Besides, spread estimation for other markets may bring about different results.

4. EFFECTS OF FIRM-LEVEL AND MARKET-LEVEL CHARACTERISTICS ON STOCK LIQUIDITY: AN INTERNATIONAL ANALYSIS

4.1 Introduction

Market liquidity mostly is investigated within the field of market microstructure and is not considered among the primary factors affecting stock value by traditional finance theory. Although essential for the proper functioning of financial markets and widely investigated from the market perspective, the role of liquidity is not represented enough in asset pricing models. In this regard, Amihud and Mendelson (1986)'s study is an exception and has attracted keen attention. Amihud and Mendelson (2000) states that in order to determine a firm's market value, one should discount the company's expected cash flows at a liquidity premium added to the cost of capital. Several empirical papers confirmed and extended these findings (Brennan and Subrahmanyam, 1996; Datar, Naik and Radcliffe, 1998; Chordia, Subrahmanyam and Anshuman, 2001; Pastor and Stambaugh, 2003; Fang, Noe and Tice, 2009; Nguyen, Duong and Singh, 2016). Furthermore, Amihud and Mendelson (2008) argue that firms can increase their market liquidity by carrying out some corporate policies such as lowering leverage ratios, making effective disclosure or increasing their investor base. Consequently, various studies have suggested links between firm characteristics and stock market liquidity (e.g., Brennan and Subrahmanyam, 1995, Heflin and Shaw 2000, Banerjee and Gatchev, 2007, Lipson and Mortal, 2009, Lang, Lins and Maffett, 2012, Chung, Elder and Kim, 2010)

In this part of the thesis, we attempt to contribute the literature by investigating the determinants of liquidity based upon factors at firm level in addition to factors at market level. Firms-level factors include financial ratios such as leverage, profitability and dividends in excess of earnings as well as indicators of investor access such as free float ratio and length of listing period. Market-level factors are generated in the market in the form of investor interest (e.g., number of analysts following the stock and institutional ownership); market risk (intraday and long-term

volatilities) or just technical issues due to the nature of trading such as tick size and price level.

In that sense, we hope to contribute to the literature by combining these two groups of factors for explaining bid-ask spreads all over the world. Rather than focusing in a single country or exchange, we conduct an analysis on thirty-two exchanges in thirty-one countries. Unlike previous studies offering international evidence for corporate characteristics affecting market liquidity (e.g., Bekaert, Harvey and Lundblad, 2007; Lang, Lins, Maffett, 2012; Gao and Zhu, 2015), we base our bid-ask spread calculation upon minutely data which capture intraday variations. This research also adds to existing literature on determinants of market liquidity.

4.2 Literature

Market liquidity is a major concern for those who offer liquidity, demand liquidity and regulate the whole financial infrastructure. It is an issue for investors as well, not only because it engenders a cost but also affects the value of firms as argued by some researchers. For instance, in a seminal work, Amihud and Mendelson (1986) state that asset returns include a significant premium for quoted spread. Thus, they point out to a relation between asset returns and liquidity. Eleswarapu and Reinganum (1993) find positive relation between bid-ask spreads and average returns, but only during the month of January in the US markets while Brennan and Subrahmanyam (1996), using intraday data, find the same relation for the US markets for a whole year. Datar, Naik and Radcliffe (1998) state that liquidity has a significant role in explaining the cross sectional variation in stock returns for the US markets. Bekaert, Harvey and Lundblad (2007) suggest that the “Zeros” measure significantly predicts returns and unexpected liquidity shocks are positively associated with returns and negatively correlated with dividend yields. By using intraday Trade and Quote Data (TAQ), Fang, Noe and Tice (2009) assert that in the US, firms with liquid stocks have better performance as measured by market-to-book ratio. Chang, Faff and Hwang (2010) conduct an empirical study on Tokyo Stock Exchange and find a significantly negative relation between liquidity proxies and stock returns. Cheung, Chung and Fung (2015) study the effects of stock liquidity on firm value and corporate governance for US Real Estate Investment Trust (REIT) firms and find that REIT stock liquidity has a positive effect on firm value and is conducive to better

corporate governance through the channel of institutional ownership. More recently, Nguyen, Duong and Singh (2016) conduct an empirical investigation on the Australian market and confirm the prior literature by stating higher stock market liquidity is associated with higher firm value.

The research linking liquidity to expected return naturally brings into question how liquidity affects capital structure decisions and leverage in a firm. Lesmond and Senbet (2008), on a sample of 276 firms that experienced a leverage recapitalization from 1980 to 2006, find that equity liquidity costs increase by 0.89% for leverage increasing firms and decrease by -1.95% for leverage decreasing firms. Further, they state that leverage increasing firms experience an increase of 1% in the bid-ask spread and leverage decreasing firms experience a decrease of 2% in the bid-ask spread. Lipson and Mortal (2009) confirm these findings by stating due to adverse selection, firms will prefer internal equity financing over debt, and debt over external equity. Frieder and Martell (2006) extend Lipson and Mortal (2009) analysis to explore possibility of reverse-causality and state that leverage increases when transaction costs are high and equity is expensive to issue. Moreover, in opposite relation they state that increases in leverage decrease spreads since debt forces managers to be more disciplined and thereby reduces information asymmetry between borrowers and lenders. Im (2014) also states firms with more liquid shares tend to have higher target leverage ratios. They interpret this finding as a result of presence of more informative share prices as well as more active information production in the stock market allow firms to obtain additional debt finance at lower costs.

Literature also addresses the question of how stock market liquidity and the dividend policy relate. Existing work argues that as trading costs exist in the market, dividend payments may be a less costly mechanism to fulfil liquidity needs than selling shares. For instance, Banerjee, Gatchev and Spindt (2007), Brockman, Howe and Mortal, (2008), Griffin (2010) empirically find that firms with less liquid stocks are more likely to pay dividends to satisfy investors' need for liquidity.

Researchers also handle the role of analysts in stock liquidity. Brennan and Subrahmanyam (1995) show that greater analyst following tends to reduce adverse selection costs and increase market liquidity. Roulstone (2003) supports this idea and empirically states the positive relation between stock liquidity and number of

analysts following the company. Lang, Lins and Maffett (2012) confirm these studies and they state analysts gather and analyze information from various public and private sources and so that the published information reduces asymmetries among traders and this leads lower bid-ask spreads and greater liquidity.

Findings about the effects of ownership structure on liquidity are mixed. On one side, Heflin and Shaw (2000) document a strong positive relation between percentage of outstanding shares held by blockholders and liquidity. They state that increased block ownership brings about information asymmetry and this makes an increase in bid-ask spread. Rubin (2007) states that liquidity in the US-traded shares is positively related to total institutional holdings but negatively related to institutional blockholdings. He claims that an increase in the level of institutional ownership causes an increase in trading activity while the concentration of ownership causes an increase in adverse selection. Sarin et al. (1996) find that a higher level of institutional ownership increases illiquidity due to higher inventory carrying costs. On the contrary, Jennings et al. (2002) state that the proportion of the spread attributable to adverse selection declines as institutional ownership increases. In a more recent study, Chung, Elder and Kim (2010) argue that firms that are held by institutional investors may be pressured to adopt better corporate governance and exhibit lower spreads.

Ding, Ni, Zhong (2016) put forward the relation between free float ratio and stock liquidity by employing low-frequency liquidity proxies on an international sample and find that stocks with higher free float have a higher level of liquidity

Prior empirical research also mentions relations between spread and well-known liquidity determinants, such as price, volatility and tick size. For instance, trading price is negatively related to quoted spread (e.g. Demsetz (1968), Cooplend and Galai (1983), Glosten and Milgrom (1985), Chordia, Roll and Subrahmanyam (2000)). Stoll (2000) states that more volatile stocks associated with more uncertainty and which results with wider spreads. Moreover, reduction in tick sizes yields an improvement in liquidity (Bacidore, 1997; Bollen and Whaley, 1998, Harris et al., 1999, Bacidore et al. 2003).

4.3 Hypotheses

Our main research question is to determine the role of both firm level and market-level factors on liquidity.

Firm-level factors include *financial ratios* and such as leverage, profitability and dividends in excess of earnings as well as *accessibility of stocks by investors* such as free float ratio or how old the firm is in the stock market (age). The first hypothesis we explore about firm-level factors is the positive effect of high leverage ratio on liquidity. In line with the idea put forth by Frieder and Martell (2006), we hypothesize that increases in leverage result in decreased information asymmetry between managers and investors and, thus, increase a stocks' liquidity. On the other hand, high profitability ratio increases the trading interest; our second hypothesis addresses the positive effect of high profitability ratio on liquidity. Thirdly, as reported by the existing literature, we expect a negative relation with dividend payment and liquidity. Nevertheless, Ding, Ni, Zhong (2016) state free float could reduce real trading friction by introducing more trading, our fourth hypothesis is that a stocks' liquidity may increase with the level of free float. We finally examine whether long trading years in the market (age) leads to high stock liquidity.

Market-level factors are generated in the market in the form of *investor interest* (e.g., number of analysts following the stock and the share of institutional ownership), *market risk* (intraday volatility and long-term volatility) or *quote features* such as tick size and price level. Parallel to Subrahmanyam (1995), Roulstone (2003) and Lang, Lins and Maffett (2012), we believe that firms that are widely followed by analysts have much more information in the market and this information reduces adverse selection costs. Correspondingly, our first hypothesis that links market-level factors to stock market liquidity is whether high number of followers give rise to stocks' liquidity. According to Jennings et al. (2002), high institutional ownership leads to decline in inside information, which would increase liquidity. So, our second hypothesis is whether a positive relation between institutional ownership and liquidity exists. The third hypothesis is the negative relation between liquidity market risk factors (short-term volatility and long-term volatility). Besides, we take into account technical issues arising from the nature of trading such as tick size and price

level. We expect a positive relation between liquidity and stock price level and a negative relation between liquidity and tick size, as documented in the literature.

Additionally, we control firm size, and country group in our analysis. Because large firms are traded and are monitored by various investors, we expect a positive relation between firm size and liquidity. Emerging market exchanges are financially open and accessible worldwide nowadays; therefore, we do not expect a significant relation between country group and liquidity.

4.4 Data

We collected accounting data, market data, institutional holdings data, detailed company information and tick-by-tick stock price data (time and sales) that include bid and ask quotes. Our sample space contains all-share (composite) indices of 32 exchanges from 31 countries. Exchanges are also categorized as large, medium and small exchanges following the classification of World Federation of Exchanges.

Liquidity has many dimensions and indicators such as transaction volume, bid-ask spread, order flow and depth/width in the limit order book (LOB). Instant liquidity is mostly visible on intraday figures. Hence, the best one of these alternatives is to work on LOB aggregates. However, it is generally hard to gather historical LOB data especially for emerging markets. Therefore, we rather choose bid-ask spread as measure of liquidity. We collected tick-by-tick trade and quote data from September 2015 to January 2016 (five months). We choose a representative sample of stocks from each exchange by taking into account both size of exchange and size of firm¹. We select only non-financial firms and exclude firms for which accounting data, market data, institutional holdings data, detailed company information or liquidity data are missing as of the end of fiscal year 2015. Furthermore, we remove some erroneous data and extreme observations. Finally, our sample contains 2,556 firms from 31 countries. Table 4.1 gives a list of indices, countries and number of stocks used in our sample.

¹ We run a cluster algorithm in order to find BIG, MEDIUM and SMALL firms. We cluster stocks according to their market capitalization within each exchange.

Table 4.1 : Indices and numbers/market caps of selected stocks by country (as of December 2015).

Index	Exchange	Cntry	Size	Number of Stocks in the Sample				Market Cap of Stocks in the Sample				Number of Stocks in the Index				Market Cap of Stocks in the Sample				Ratio
				L	M	S	ALL	L	M	S	ALL	L	M	S	ALL	L	M	S	ALL	
NYSE Composite	NYSE	USA	L	84	176	17	277	6833	2356	36	9225	272	893	445	1610	14245	4472	206	18923	49%
TOPIX	Japan Exch.	JPN	L	134	148	31	313	2560	436	3	2999	241	748	784	1773	3091	915	115	4121	73%
Shanghai Se Composite	Shanghai Stock Exch.	CHN	L	20	28	7	55	672	108	8	788	61	387	514	962	1325	1389	540	3254	24%
Hang Seng Composite	Hong Kong Exch.	CHN	L	12	60	60	132	562	598	120	1280	32	155	245	432	1493	1055	271	2819	45%
Ftse All Share	LSE Group	GBR	L	62	88	72	222	1426	222	33	1681	90	181	124	395	2219	380	53	2652	63%
Germ CDAX Performance	Deutsche Boerse AG	DEU	L	61	44	8	113	1173	10	0.12	1184	152	185	46	383	1761	32	0.23	1793	66%
Cac All Share	Euronext	FRA	L	32	32	6	70	1011	197	5	1213	72	209	162	443	1167	277	11	1456	83%
Swiss Market	SIX Swiss Exchange	CHE	L	18	23	29	70	518	54	11	583	27	70	60	157	1112	109	14	1235	47%
S&P Bse 500	BSE India Limited	IND	L	17	43	49	109	417	272	20	710	66	226	124	416	657	459	38	1154	61%
Kospi	Korea Exchange	KOR	L	52	33	10	95	575	3	0.09	578	103	294	306	703	744	122	22	887	65%
S&P/TSX Composite	TMX Group	CAN	L	25	66	66	157	457	230	53	741	29	89	96	214	525	284	74	884	84%
All Ordinaries	Australian Securities Exch.	AUS	L	9	58	73	140	308	15	6	328	73	215	148	436	671	146	15	832	39%
Large Exchanges Total				526	799	428	1753	16512	4503	295	21309	1218	3652	3054	7924	29010	9641	1358	40009	53%

Notes: Cntry: Country; Size: Exchange size; L: Large; M: Medium; S: Small; Ratio: Market cap of the sample stocks over market cap of all the stocks in the index. Country names are given with ISO country codes. Market capitalization (bn. USD).

Table 4.1 (continued) : Indices and numbers/market caps of selected stocks by country (as of December 2015).

Index	Exchange	Cntry	Size	Number of Stocks in the Sample				Market Cap of Stocks in the Sample				Number of Stocks in the Index				Market Cap of Stocks in the Sample				Ratio
				L	M	S	ALL	L	M	S	ALL	L	M	S	ALL	L	M	S	ALL	
AEX All Share	Euronext	NL	M	39	12	12	63	613	17	0.29	631	52	25	25	102	684	22	0.65	706	89%
OMX Stockholm All Share	Nasdaq OMX	SWE	M	20	18	19	57	276	34	6	316	64	116	87	267	575	84	9	668	47%
BEL All Share	Euronext	BEL	M	1	8	16	25	200	42	15	256	21	65	24	110	438	52	15	505	51%
FTSE Italia All Share	LSE Group	ITA	M	20	27	20	67	258	25	2	285	52	85	71	208	367	43	4	414	69%
OMX Helsinki	Nasdaq OMX	FIN	M	16	22	19	57	110	9	0.52	120	26	54	40	120	311	29	1	341	35%
Bovespa Broad	Bm&F Bovespa S.A.	BRA	M	10	37	13	60	100	70	1	171	17	67	17	101	233	96	3	331	52%
FTSE/JSE Africa All Share	Johannesburg Stock Exch.	ZAF	M	13	28	14	55	15	17	3	36	25	54	47	126	233	83	15	331	11%
Russian RTS	Moscow Exch.	RUS	M	12	8	7	27	214	27	5	247	14	18	12	44	241	65	9	315	78%
Stock Exch. of Thai	Stock Exch. of Thailand	THA	M	13	15	12	40	90	1	0.61	91	102	208	169	479	224	36	6	265	34%
Oslo SE All Share	Oslo Bors	NOR	M	2	7	4	13	70	45	4	119	3	66	78	147	77	89	8	174	69%
Bolsa General	BCBA	ARG	M	1	3	12	16	55	55	0.50	111	11	28	16	55	90	64	0.54	154	72%
Chile Stock Mkt General	Bolsa Comercio Santiago	CHL	M	9	3	14	26	56	6	0.73	63	23	33	23	79	111	25	2	137	46%
BIST All Share	Borsa Istanbul	TUR	M	19	37	60	116	73	22	3	98	33	113	120	266	87	38	5	130	76%
Tel Aviv 100 Adv	Tel-Aviv Stock Exch.	ISR	M	1	7	14	22	59	18	4	82	1	32	45	78	59	51	13	124	66%
Medium Exchanges Total				176	232	236	644	2190	389	46	2625	444	964	774	2182	3729	776	89	4594	57%

Notes: Cntry: Country; Size: Exchange size; L: Large; M: Medium; S: Small; Ratio: Market cap of the sample stocks over market cap of all the stocks in the index. Country names are given with ISO country codes. Market capitalization (bn. USD).

Table 4.1 (continued) : Indices and numbers/market caps of selected stocks by country (as of December 2015).

Index	Exchange	Cntry	Size	Number of Stocks in the Sample				Market Cap of Stocks in the Sample				Number of Stocks in the Index				Market Cap of Stocks in the Sample				Ratio
				L	M	S	ALL	L	M	S	ALL	L	M	S	ALL	L	M	S	ALL	
WSE WIG	Warsaw Stock Exch.	POL	S	4	12	36	52	25	16	5	46	26	134	161	321	47	30	7	84	55%
Irish Overall	Irish Stock Exch.	IRL	S	1	3	1	5	15	15	1	31	9	19	12	40	53	20	1	75	42%
Austrian Traded ATX	Wiener Borse	AUS	S	7	7	3	17	31	14	0.27	45	18	25	15	58	47	20	0.61	68	67%
PSI All Share	Euronext	PRT	S	7	14	7	28	16	3	0.28	20	13	15	14	42	52	3	0.34	56	35%
Athens General	Athens Stock Exch.	GRC	S	9	13	9	31	15	2	0.18	17	12	23	17	52	25	5	0.57	30	56%
EGX 100	Egyptian Exch.	EGY	S	5	12	9	26	6	0.52	0.06	7	19	27	35	81	16	3	0.62	20	34%
Small Exchanges Total				33	61	65	159	108	51	7	166	97	243	254	594	241	81	10	333	50%
Exchanges Total				735	1092	729	2556	18809	4943	348	24100	1759	4859	4082	10700	32980	10499	1457	44936	54%

Notes: Cntry: Country; Size: Exchange size; L: Large; M: Medium; S: Small; Ratio: Market cap of the sample stocks over market cap of all the stocks in the index. Country names are given with ISO country codes. Market capitalization (bn. USD).

4.5 Methodology

Our main research question is to determine the role of both firm level and market-level factors on liquidity. Firm-level factors include financial ratios and such as leverage, profitability and dividends in excess of earnings as well as accessibility of stocks by investors such as free float ratio or how old the firm is in the stock market (age). These are either determined by firms (dividend policy, the part of the capital to float freely, when to go public etc.) or are result of corporate policies (leverage and profitability). In their turn, market-level factors are not directly related to the firm, but rather are generated in the market in the form of investor interest (e.g., number of analysts following the stock and the share of institutional ownership), market risk (intraday and long-term volatility) or just technical issues due to the nature of trading such as tick size and price level. Besides, with dummy variables added, we control for firm size, and country group.

We measure liquidity by the inverse of relative quoted bid-ask spread. Let Bid_t be the bid price, Ask_t be the ask price, $Midpoint_t$ be the midpoint of the prevailing bid and ask quotes at time t . Relative quoted spread is defined as in equation (4.1):

$$\text{Relative Quoted Spread}_t = (Ask_t - Bid_t) / Midpoint_t \quad (4.1)$$

For each stock, we retrieve minute-by-minute bid-ask spread data during trading hours of each market for a period of five months². In order to eliminate day-of-the-week or intraday seasonality bid-ask spread may exhibit, we take the median value over the whole period. Then, our liquidity measure (LIQ) is defined as in equation (4.2).

$$LIQ = 1 / \text{Relative Quoted Spread}_t \quad (4.2)$$

To assess the role of all these firm level and market-level factors on the market liquidity of stocks, we run cross-sectional regressions with the data of 2,556 firms from 31 countries. The empirical model with firm size and country group dummies is given in equation (4.3)

² The data are filtered for any extreme values witnessed for instance in case of an absence of quotation on one side of trading.

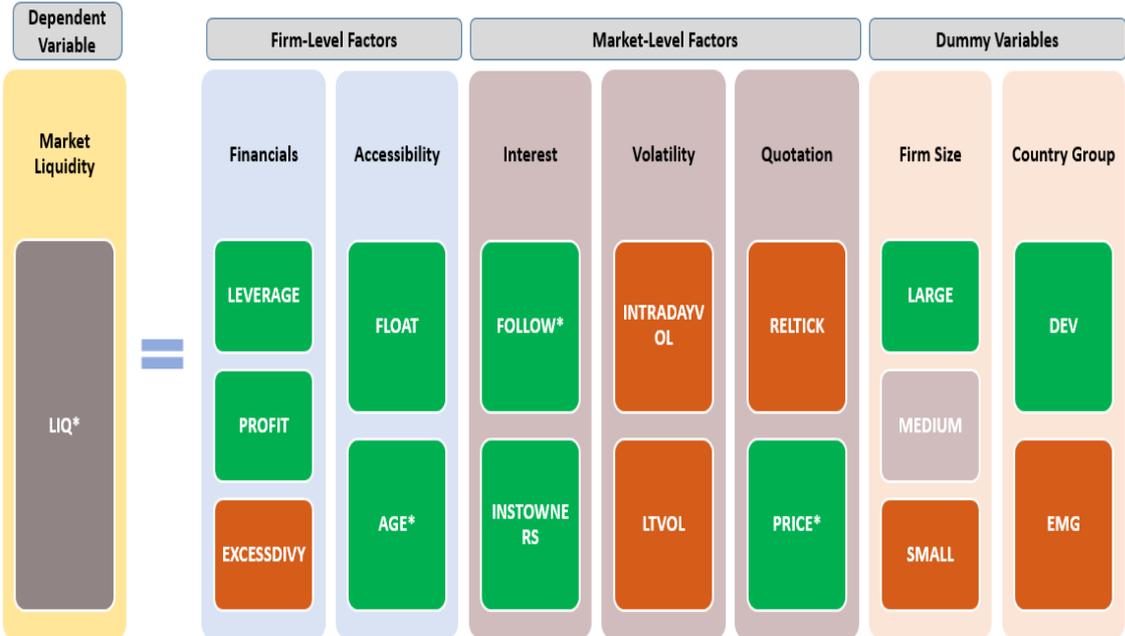
$$\text{LOG(LIQ)} = C_1 + C_2 * \text{LEVERAGE} + C_3 * \text{PROFIT} + C_4 * \text{EXCESSDIVY} + C_5 * \text{FLOAT} + C_6 * \text{LOG(AGE)} + C_7 * \text{LOG(FOLLOW)} + C_8 * \text{INSTOWNERS} + C_9 * \text{INTRADAYVOL} + C_{10} * \text{LTVOL} + C_{11} * \text{RELTICK} + C_{12} * \text{LOG(PRICE)} + C_{13} * \text{LARGE} + C_{14} * \text{SMALL} + C_{15} * \text{EMG} \quad (4.3)$$

The variables in the models are defined and explained in Table 4.2.

Table 4.2 : Definitions of all variables.

	Variable Name	Definition
Dependent Variable	LOG(LIQ)	The variable is liquidity and measured by logarithm of the inverse of relative bid-ask spread as explained in equation (4.3).
Firm-Level Variables	LEVERAGE	The variable is measured by the debt to asset ratio.
	PROFIT	The variable is profitability and measured by return on asset (ROA).
	EXCESSDIVY	The variable is excess dividend yield and measured by the difference between dividend payments per share and earnings per share over the prior twelve months, divided by stock price.
	FLOAT	The variable is the free float ratio and measured by the percent of outstanding shares traded in the exchange by the end of fiscal year 2015.
	LOG(AGE)	The variable is the logarithm of the number of years the stock trades in the exchange.
Market-Level Variables	LOG(FOLLOW)	The variable is followers and measured the logarithm of number of analysts making recommendations for the security.
	INSTOWNERS	The variable is institutional ownership and measured by the percent of shareholding by large financial organizations, pension funds or endowments (as defined by Bloomberg holdings database) by the end of fiscal year 2015.
	INTRADAYVOL	The variable is intraday volatility and measured by the difference between daily high and daily low prices divided by the average of daily high and low prices.
	LTVOL	The variable is long-term volatility and measured by the CAPM beta calculated over two-year weekly data.
	RELTICK	The variable is relative tick size and measured by the tick size defined by the exchange divided by stock price.
	LOG(PRICE)	The variable is the price level and measured by the logarithm of stock price in local currency.
Dummy Variables	LARGE	The variable is the dummy for large firms.
	MEDIUM	The variable is the dummy for medium firms.
	SMALL	The variable is the dummy for small firms.
	DEV	The variable is the dummy for developed countries.
	EMG	The variable is the dummy for emerging countries.

Among firm-level characteristics, we expect liquidity be positively associated with such as leverage, profitability, free float ratio and age and negatively associated with excess dividend yields. Among market-level characteristics, we expect liquidity be positively associated with price, and negatively associated with intraday volatility, long-term volatility and relative tick. Figure 4.1 summarizes the variable groups, the variables as well as their expected signs.



* indicates the variable is in logarithm form.

Figure 4.1 : Variable groups, variables and their expected effects.

Table 4.3 provides summary statistics for all the variables used in our model.

Table 4.3 : Summary statistics of all variables.

	Mean	Median	Max.	Min.	Std. Dev.	Observations
LOG(LIQ)	1.52	1.76	4.75	-3.26	1.39	2556
LEVERAGE (%)	25.69	24.00	194.04	0.00	19.36	2556
PROFIT (%)	2.38	3.59	234.14	-200.05	13.48	2556
EXCESSDIVY (%)	2.51	1.84	80.18	-3.92	3.48	2556
FLOAT (%)	66.45	70.97	102.20	0.50	27.88	2556
LOG(AGE)	2.96	3.09	3.89	0.69	0.57	2556
LOG(FOLLOW)	2.09	2.48	4.04	0.00	1.15	2556
INSTOWNERS (%)	55.34	55.58	161.06	0.00	32.80	2556
INTRADAYVOL (%)	3.24	2.84	13.85	0.00	1.52	2556
LTVOL	0.87	0.86	3.47	-0.99	0.45	2556
RELTICK (%)	0.18	0.04	12.41	0.00	0.52	2556
LOG(PRICE)	4.05	3.86	14.02	-4.84	2.93	2556

Table 4.3 reports statistics for our dependent variable as well as firm-level and market-level factors. The market liquidity variable LIQ is dispersed between 0.04 and 116 and has a median 5.81 for 2556 firms³.

Statistics for financial ratios are as follows. Median leverage is 24%, median profitability is 3.59% and median dividends in excess of earnings is 1.84%. LEVERAGE is dispersed between 0% and 194% while PROFIT is dispersed between -200% and 234% and EXCESSDIVY is dispersed between -4% and 80%. The table also shows investors' accessibility statistics. Median free float ratio (FLOAT) for our sample is 71%. Length of listing period (AGE) of our sample firms is 22 years on average; which is 2 years minimum and 49 years maximum.

Statistics for our market level factors are as follows. Our sample firms are followed by 12 analyst on average. In our sample, there are also firms those are not followed by any analysts and those followed by maximum 57 analysts. The median share of institutional ownership for our sample is 55%. Turning to market risk factors, our sample consists firms with 2.84% intraday volatility and 0.86 beta values. Among market-level factors, the median of tick size and price level are 0.04% and 47, respectively. Further, tick size levels strongly vary across stocks, with a dispersion between 0.0016% and 3.4831%.

Overall, an advantage of our sample we employ is that it includes wide range of firms with different corporate level and market level features. Thus, wide range of different features let us examine the relation between firm-level factors and market-level factors and liquidity. In order to minimize the effects of outliers, we winsorize data at 1% (the average of the 0.05th to 0.995th percentile of the data).

Table 4.4 present the correlation matrix for all the variables used in cross-sectional regressions⁴. Table 4.4 shows that there are relatively strong positive correlations between LOG(FOLLOW) and INSTOWNERS (0.44), LOG(FOLLOW) and FLOAT (0.35), FLOAT and INSTOWNERS (0.33), FLOAT and LOG(AGE) (0.27), LOG(AGE) and LOG(PRICE) (0.29) and INTRADAYVOL and RELTICK (0.32) as well as negative correlations between LOG(PRICE) and RELTICK (-0.44),

³ Remind that in Table 4.3, LIQ, FOLLOW, AGE and PRICE variables are given in natural logarithm.

⁴ As a robustness check, we add some extra variables to correlation matrix such as number of news, return on equity and total debt to total equity. Then, we omit highly auto correlated variables.

INTRADAYVOL and LOG(PRICE) (-0.29). Considered mutually, these correlations make sense.

As shown in Table 4.4, LOG(LIQ) has strong positive correlations with some of the firm-level characteristics such as PROFIT, FLOAT and LOG(AGE). For market-level characteristics, LOG(LIQ) has positive correlations with LOG(FOLLOW), INSTOWNERS, LTVOL, LOG(PRICE) and negative correlations with INTRADAYVOL, RELTICK. INSTOWNERS and LTVOL correlation results are in the wrong sign as we have not expected. In fact, correlations only takes into binary relations, thus we run regression and control other variables in order to interpret the effects. Furthermore, LOG(LIQ) has positive correlation with LARGE (0.44) while it has negative correlation with SMALL (-0.55). These results appear to imply that large firms are have greater liquidity than small firms have. Besides, LOG(FOLLOW) has positive correlation with LARGE (0.49) while it has negative correlation with SMALL (-0.54). These correlations make sense since many investors follow large firms. Several relations are apparent for country group dummy variables. Developed country firms have positive correlations with firm-level characteristics such as FLOAT and LOG(AGE) as well as market-level characteristics such as LOG(FOLLOW) and INSTOWNERS.

Table 4.4 : The correlation matrix for all the variables.

	LOG(LIQ)	LEVERAGE	PROFIT	EXCESSDIVY	FLOAT	LOG(AGE)	LOG(FOLLOW)	INSTOWNERS	INTRADAYVOL	LTVOL	RELTICK	LOG(PRICE)	LARGE	MEDIUM	SMALL	DEV	EMG
LOG(LIQ)	1.00																
LEVERAGE	0.09	1.00															
PROFIT	0.30	-0.19	1.00														
EXCESSDIVY	-0.01	0.02	-0.09	1.00													
FLOAT	0.36	0.01	0.01	0.06	1.00												
LOG(AGE)	0.29	-0.04	0.06	-0.04	0.27	1.00											
LOG(FOLLOW)	0.72	0.08	0.19	0.06	0.35	0.19	1.00										
INSTOWNERS	0.31	0.05	0.15	0.05	0.33	0.10	0.44	1.00									
INTRADAYVOL	-0.29	0.07	-0.39	0.02	-0.13	-0.17	-0.14	-0.16	1.00								
LTVOL	0.28	0.12	-0.13	0.02	0.14	0.11	0.35	0.09	0.36	1.00							
RELTICK	-0.42	-0.03	-0.32	0.06	-0.11	-0.13	-0.26	-0.21	0.32	0.03	1.00						
LOG(PRICE)	0.40	-0.11	0.32	-0.08	0.18	0.29	0.28	0.16	-0.29	0.01	-0.44	1.00					
LARGE	0.44	0.00	0.15	0.00	0.12	0.17	0.49	0.08	-0.19	0.13	-0.16	0.30	1.00				
MEDIUM	0.10	0.03	0.02	-0.03	0.06	0.07	0.04	0.11	0.03	0.02	-0.08	0.01	-0.55	1.00			
SMALL	-0.55	-0.03	-0.18	0.03	-0.19	-0.24	-0.54	-0.20	0.16	-0.16	0.25	-0.32	-0.40	-0.55	1.00		
DEV	0.18	0.02	-0.05	0.01	0.39	0.21	0.23	0.28	-0.14	0.02	-0.10	-0.09	0.05	0.06	-0.12	1.00	
EMG	-0.18	-0.02	0.05	-0.01	-0.39	-0.21	-0.23	-0.28	0.14	-0.02	0.10	0.09	-0.05	-0.06	0.12	-1.00	1.00

Our model, which is stated in equation 4.3, is estimated using ordinary least squares (OLS) regression. We run residual analysis (linearity, homoscedasticity, normality and multicollinearity) for statistical assumptions for regression equation 4.3. The test results are given in Appendix B. We did not detect any violations of the regression assumptions except heteroskedasticity. In order to remove heteroskedasticity, we estimate equation 4.3 with t statistics calculated with White heteroskedasticity-consistent standard errors & covariance.

4.6 Results

Regression results for equation 4.3 are given in Table 4.5. In the Table 4.5, the adjusted R square value, which shows the explanatory power of regression, appears significant and powerful with 66.40%. The results indicate that except excess dividend yield and country group dummy, all the variables are significant.

Table 4.5 : Least squares regression results.

Dependent Variable: LOG(LIQ)
Method: Least Squares
Sample: 1 2556
Included observations: 2556
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.383647	0.124233	-3.088126	0.0020
LEVERAGE	0.005157	0.000936	5.507578	0.0000
PROFIT	0.012389	0.001801	6.877508	0.0000
EXCESSDIVY	-0.005802	0.005995	-0.967896	0.3332
FLOAT	0.005291	0.000698	7.577805	0.0000
LOG(AGE)	0.167917	0.031023	5.412693	0.0000
LOG(FOLLOW)	0.556031	0.022559	24.64819	0.0000
INSTOWNERS	-0.002225	0.000611	-3.641138	0.0003
INTRADAYVOL	-0.120953	0.016229	-7.452698	0.0000
LTVOL	0.403079	0.044956	8.966132	0.0000
RELTICK	-0.501737	0.046723	-10.73859	0.0000
LOG(PRICE)	0.020724	0.007108	2.915626	0.0036
LARGE	0.122947	0.036966	3.325939	0.0009
SMALL	-0.466708	0.048374	-9.647818	0.0000
EMG	0.047371	0.045610	1.038608	0.2991
R-squared	0.665775	Mean dependent var		1.524628
Adjusted R-squared	0.663933	S.D. dependent var		1.382667
S.E. of regression	0.801550	Akaike info criterion		2.401312
Sum squared resid	1632.547	Schwarz criterion		2.435620
Log likelihood	-3053.876	Hannan-Quinn criter.		2.413753
F-statistic	361.5469	Durbin-Watson stat		1.940303
Prob(F-statistic)	0.000000	Wald F-statistic		325.7567
Prob(Wald F-statistic)	0.000000			

Among firm-level factors, coefficients of financial ratios (leverage, profitability) and coefficients of accessibility (free float ratio and length of listing period) are all positive and significant.

Among market-level factors, coefficients of investor interest are significant; they indicate positive significant relation between number of analysts following the stock as well as negative relations with institutional ownership ratio. Coefficients of volatility are also significant which suggests increases in short-term volatility are associated with lower liquidity while increases in long-term volatility higher liquidity. The positive coefficient of long-term volatility is interesting because it suggests that high beta has a positive effect on liquidity. Quotation factors among market-level variables indicate significant relations between liquidity: positive relation with price level as well as negative relations with tick size.

As expected, large firms have greater liquidity than small firms have. Finally, these individual relations hold apart from development level of the country.

Together, the observed relations are consistent with our hypotheses, suggesting that firm-level and market-level characteristics importance on market liquidity. These results overall suggest that high leverage, high profitability, high free float ratio and long length of listing period, greater number of followers, high beta and high price level as well as low institutional ownership ratios, low intraday volatility and low tick size levels are all associated with greater market liquidity.

In our model, dependent variable and some of independent variables are in log-linear format. Because of these log-linear formats, the significance of results in Table 4.5 is not immediately distinguishable. However, these log-linear formats allow us to analyze coefficients as the percentage changes: dependent variable change given the percentage changes in independent variables. We analyze the effects of 10% changes in the independent variables when they are in high, medium or low levels. Table 4.6 summarizes the magnitude and it gives univariate differences in liquidity based on independent variables levels.

Table 4.6 : Percentage changes in liquidity with a 10% increases in independent variables.

	Independent Variable	High	Median	Low	High-Low
Firm-Level Variables	LEVERAGE	2.63	1.24	0.04	2.59
	PROFIT	1.47	0.45	-0.81	2.28
	EXCESSDIVY	-0.31	-0.11	0	-0.31
	FLOAT	5.41	3.83	1.39	4.02
	AGE	1.61	1.61	1.61	0
Market-Level Variables	FOLLOW	5.44	5.44	5.44	0
	INSTOWNERS	-2.17	-1.24	-0.21	-1.96
	INTRADAYVOL	-5.94	-3.37	-2.19	-3.75
	LTVOL	5.78	3.51	1.39	4.39
	RELTICK	-1.98	-0.19	-0.06	-1.92
	PRICE	0.2	0.2	0.2	0

High, Median and Low mean the firm is one for which the independent variable is at its top 10%, 50% and 90% level.

Results in Table 4.6 indicate that among firm-level characteristics, for a median level firm, a 10% increase in FLOAT increases liquidity 3.83%; a 10% increase in the AGE increases liquidity 1.61% and a 10% increase in LEVERAGE increases liquidity 1.24%. Compared with the other firm-level characteristics, effect of 10% increase in PROFIT is significantly lower (increases liquidity 0.45%). The results indicate that, in respect to liquidity, among corporate level features, a change in investors' accessibility is more important than a change in firm's financial ratios.

Among market-level characteristics, for a median level firm, a 10% increase in FOLLOW increases liquidity 5.44%; a 10% increase in LTVOL increases liquidity 3.51%, while 10% increase in INTRADAYVOL decreases liquidity 3.37% and a 10% increase in the INSTOWNERS decreases liquidity 1.24%. Compared with other market-level characteristics, effect of 10% increase in RELTICK (decreases liquidity 0.19%) and PRICE (increases liquidity 0.2%) are significantly lower. Overall, at median levels, a 10% increase FOLLOW has the highest effect on liquidity. Nevertheless, with a 10% increase in FLOAT, INTRADAYVOL and LTVOL have considerable effect on liquidity. In sum, among market level factors a change in investors' interest (FOLLOW and FLOAT) and a change in volatility (INTRADAYVOL and LTVOL) have a significant effect on liquidity.

The last column of Table 4.6 shows the differences of percentage change in liquidity when independent variables are in high or low levels. Within this context, LTVOL has the highest dispersion. This means that in a high beta firm, a 10% change in LTVOL has significant effect on liquidity when compared to a 10% change in

LTVOL in a low beta firm. A similar relation holds for FLOAT and INTRADAYVOL. In fact, LEVERAGE, PROFIT, INSTOWNERS and RELTICK follow them.

These relations are economically important. For example, among firm-level characteristics, a firm who has high free float ratio can increase its stock liquidity at 5.41% by simply increasing its free float at 10 percent. Furthermore, changes in PROFIT in a low profit firm have a negative effect on its market liquidity, while changes in PROFIT in a high profit firm have a positive effect on its market liquidity. Similarly, changes in LEVERAGE in a low leveraged firm has a insignificant effect on its market liquidity, while changes in LEVERAGE in a high leveraged firm has a positive and significant effect on its market liquidity. Among market-level characteristics changes in RELTICK in a high tick size stock has a significant negative effect on its market liquidity, while changes in RELTICK in a low tick size stock has a insignificant effect on its market liquidity.

4.7 Discussion of the Results

This research contributes to the literature by investigating various corporate level factors as well as various market level factors on market liquidity by employing an international data.

Much of the literature so far investigated effects of several firm-level or market-level characteristics on liquidity for US markets (e.g. Jiang, Kim, Zhou, 2011; Diaz, Frieder and Martell, 2006 and Chung, Elder, Kim, 2010; Fang, Noe and Tice, 2009; Lipson and Mortal, 2007). To our knowledge, there is few international evidence that relatively links these factors to liquidity. Contrary to some of the studies offering international evidence for corporate level characteristics affecting market liquidity (e.g., Bekaert, Harvey and Lundblad, 2007; Lang, Lins, Maffett, 2012; Gao and Zhu, 2015), we base our bid-ask spread calculation upon minutely data which capture intraday variations. We hope to add to the literature by combining different factors for explaining bid-ask spreads all over the world.

This research also adds to the existing literature on determinants of market liquidity. The study is a follow up of Amihud and Mendelson (2000) who argue that firms can increase their market liquidity by carrying out some corporate policies such as

lowering leverage ratios, making effective disclosure or increasing their investor base.

We draw many empirical results in this study which have many implications for companies, policy makers and investors. They are summarized as follows:

- Liquidity is significantly affected by corporate policies (leverage and profitability) of firms. The positive relation between leverage and liquidity is probably the result of decreased information asymmetry. Our findings confirm Frieder and Martell (2006) who state that debt forces managers to be more disciplined and thereby reduces information asymmetry between borrowers and lenders. On the other hand, liquidity tends to be high in companies which have high profitability ratios. In this context, corporate managers can increase the liquidity by changing their leverage and profitability ratios. Nonetheless, the effects on liquidity are limited to companies' leverage and profitability levels.
- We did not find any significant relation with dividends in excess of earnings and liquidity.
- High liquidity is associated with accessibility of stocks by investors such as free float ratio or how old the firm is in the stock market (age). Corporate managers can increase the liquidity by changing their free float ratios. Nevertheless, the effects on liquidity gets bigger if the company already has high free float levels.
- In respect to liquidity, among corporate level features, a change in investors' accessibility is more important than a change in firm's financial ratios.
- Liquidity is significantly affected by investor interest (e.g., number of analysts following the stock and the share of institutional ownership). We find positive relation between the number of followers and liquidity which confirms previous literature (e.g. Subrahmanyam, 1995, Roulstone, 2003 and Lang, Lins and Maffett, 2012). Perhaps, the public information provided by analysts decreases asymmetric information and increases liquidity. It follows that the companies can improve their liquidity by voluntarily providing more information. Differently, we find a negative relation between the level of institutional ownership and liquidity. Alike Sarin et al. (1996), we can say that increased institutional ownership leads increased inside information.

- Increases in short-term volatility make liquidity lower while increases in long-term volatility make liquidity higher. We measure long-term volatility via CAPM beta. Frazzini (2010) states that since investors prefer unleveraged risky assets to leveraged safe assets, they hold portfolios of high-beta assets that have lower alphas and Sharpe ratios than portfolios of low-beta assets. Consistent with Frazzini (2010), the positive relation between long-term volatility and stocks' liquidity is possibly a result of traders' attention towards high beta stocks.
- In line with the widely documented literature, we find that liquidity is positively related to price level and negatively related to tick size. Interestingly, compared to other variables used in our model, for a median level firm, the effect of an increase in the tick size and price level is relatively lower. However, if the company already has high tick size levels, the effects on liquidity get bigger.
- To sum up, among market level factors, a change in investors' interest and a change in volatility have a significant effect on liquidity.
- We find a positive relation between firm size and liquidity. This probably occurs since large firms are traded and are monitored by various investors.
- We did not find significant relation between country development level and liquidity.
- Overall, we find that for a median level firm, an increase in numbers of followers has the highest positive effect on liquidity. This is followed by an increase in free float ratios and an increase in long term volatility. Besides, for a median level firm, an increase in intraday volatility has the highest negative effect on liquidity. This is followed by an increase in institutional ownership ratios.

4.8 Conclusion

In this study, we attempt to contribute to the literature by investigating the determinants of liquidity based upon factors at firm level in addition to factors at market level. The results indicate that except excess dividend yield and country group dummy, all the variables are significant. These results overall suggest that high leverage, high profitability, high free float ratio and long length of listing period,

greater number of analysts following the stock, high beta and high price level as well as low institutional ownership, low intraday volatility and low tick sizes are associated with greater market liquidity.

All these add to our understanding about the effects of firm-level and market-level characteristics on liquidity. However, some limitations of the work remain. For example, we choose bid-ask spread as a measure of liquidity although liquidity has many dimensions and measures. The best one of these alternatives is to work on limit order book (LOB) aggregates. Nonetheless, it is generally hard to gather historical LOB data especially for emerging markets. Furthermore, we conduct our analysis over a five-month period. A major step would be to repeat the analysis for longer periods. A time series analysis is required to check the robustness of the results. In fact, liquidity not only varies across different securities and countries, but the liquidity of a given security can vary over years.

5. CONCLUSION

This dissertation consists of three sections, all conducting research about market liquidity.

We begin with a comprehensive review of the definitions and determinants of liquidity. We put a special emphasis on various liquidity measures discussed in the literature about equity market. Our study is unique in its way of categorizing all the equity market liquidity measures. We conclude that liquidity measures concentrate around specific properties. Overall, liquidity has many dimensions and a desirable liquidity measure should take into account many dimensions such as immediacy, large transactions walking through the book or hidden orders. Moreover, a desirable liquidity measure should be *ex ante* in the sense that it can predict the available liquidity in the future. The liquidity measures that we examine have some advantages, limitations and extensions. Good measures exist, yet with some limitations.

Then, we empirically evaluate the performance of five different methods appearing in the market microstructure literature in predicting cost dimension of market liquidity, in other words “bid-ask spread”. We analyze the performance of five different methods (Roll, LOT Mixed, Effective Tick, High-Low and Closing Percent Quoted Spread proxies) in predicting effective and quoted bid-ask spreads. Results show that bid–ask spread estimates are thoroughly biased and none of the proxies is successful enough in estimating effective or quoted spread although under normal market conditions, Effective Tick appears to perform best. Thus, we conclude that one should be cautious in using these proxies. Moreover, a detailed check is necessary about the suitability of the method to market type, market-specific regulations (e.g. tick size) and instrument-specific features before starting any study. Besides, we conclude that spread estimation for other markets may bring about different results.

Finally, we empirically test the determinants of liquidity based upon factors at corporate level in addition to factors at market level. Rather than focusing in a single country or exchange, we conduct an international analysis. Further, our study is

unique in its way of using intraday data for all over the world. We obtain highly significant results in this study, which have implications for companies, policy makers and investors. These results overall suggest that high leverage, high profitability, high free float ratio and long length of listing period, greater number of analysts following the stock, high beta and high price level as well as low institutional ownership, low intraday volatility and low tick sizes are associated with greater market liquidity. All these results add to our understanding about the effects of firm-level and market-level characteristics on liquidity.

REFERENCES

- Abdi, F., Ranaldo, A.** (2017). A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices. *The Review of Financial Studies*, 30(12), 4437-4480.
- Aitken, M., Comerton-Forde, C.** (2003). How should liquidity be measured?. *Pacific-Basin Finance Journal*, 11(1), 45-59.
- Amihud, Y.** (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.
- Amihud, Y., Mendelson, H.** (1980). Dealership market: Market-making with inventory. *Journal of Financial Economics*, 8(1), 31-53.
- Amihud, Y., Mendelson, H.** (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2), 223-249.
- Amihud, Y., Mendelson, H.** (2000). The liquidity route to a lower cost of capital. *Journal of Applied Corporate Finance*, 12(4), 8-25.
- Amihud, Y., Mendelson, H.** (2008). Liquidity, the value of the firm, and corporate finance. *Journal of Applied Corporate Finance*, 20(2), 32-45.
- Bacidore, J., Battalio, R. H., Jennings, R. H.** (2003). Order submission strategies, liquidity supply, and trading in pennies on the New York Stock Exchange. *Journal of Financial Markets*, 6(3), 337-362.
- Bacidore, J., Boquist, J. A., Milbourn, T. T., Thakor, A. V.** (1997). The search for the best financial performance measure. *Financial Analysts Journal*, 53(3), 11-20.
- Bagehot, W.** (1971). The only game in town. *Financial Analysts Journal*, 27(2), 12-14.
- Banerjee, S., Gatchev, V. A., Spindt, P. A.** (2007). Stock market liquidity and firm dividend policy. *Journal of Financial and Quantitative Analysis*, 42(2), 369-397.
- Bekaert, G., Harvey, C. R., Lundblad, C.** (2007). Liquidity and expected returns: Lessons from emerging markets. *The Review of Financial Studies*, 20(6), 1783-1831.
- Bernstein, P. L.** (1987). Liquidity, stock markets, and market makers. *Financial Management*, 54-62.
- Biais, B., Hillion, P., Spatt, C.** (1995). An empirical analysis of the limit order book and the order flow in the Paris Bourse. *The Journal of Finance*, 50(5), 1655-1689.
- Black, F.** (1971). Toward a fully automated stock exchange, part I. *Financial Analysts Journal*, 27(4), 28-35.

- Boehmer, E., Fong, K., Wu, J.** (2015). International evidence on algorithmic trading. *Social Science Research Network website*. Retrieved March, 2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2022034
- Bollen, N. P., Whaley, R. E.** (1998). Are "teenies" better?. *Journal of Portfolio Management*, 25(1), 10.
- Brennan, M. J., Subrahmanyam, A.** (1995). Investment analysis and price formation in securities markets. *Journal of Financial Economics*, 38(3), 361-381.
- Brennan, M. J., Subrahmanyam, A.** (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, 41(3), 441-464.
- Brockman, P., Howe, J. S., Mortal, S.** (2008). Stock market liquidity and the decision to repurchase. *Journal of Corporate Finance*, 14(4), 446-459.
- Chang, Y. Y., Faff, R., Hwang, C. Y.** (2010). Liquidity and stock returns in Japan: New evidence. *Pacific-Basin Finance Journal*, 18(1), 90-115.
- Cheung, W. M., Chung, R., Fung, S.** (2015). The effects of stock liquidity on firm value and corporate governance: Endogeneity and the REIT experiment. *Journal of Corporate Finance*, 35, 211-231.
- Chordia, T., Subrahmanyam, A., Anshuman, V. R.** (2001). Trading activity and expected stock returns. *Journal of Financial Economics*, 59(1), 3-32.
- Chung, K. H., Elder, J., Kim, J. C.** (2010). Corporate governance and liquidity. *Journal of Financial and Quantitative Analysis*, 45(2), 265-291.
- Chung, K. H., Zhang, H.** (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, 17, 94-120.
- Cooper, S. K., Groth, J. C., Avera, W. E.** (1985). Liquidity, exchange listing, and common stock performance. *Journal of Economics and Business*, 37(1), 19-33.
- Copeland, T. E., Galai, D.** (1983). Information effects on the bid-ask spread. *The Journal of Finance*, 38(5), 1457-1469.
- Corwin, S. A., Schultz, P.** (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, 67(2), 719-760.
- Datar, M. K.** (2000). Stock market liquidity: Measurement and implications. In *Proceedings of the 4th Capital Market Conference*.
- Datar, V. T., Naik, N. Y., Radcliffe, R.** (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1(2), 203-219.
- Demsetz, H.** (1968). The cost of transacting. *The Quarterly Journal of Economics*, 82(1), 33-53.
- Ding, X. S., Ni, Y., Zhong, L.** (2016). Free float and market liquidity around the world. *Journal of Empirical Finance*, 38, 236-257.

- Easley, D., López de Prado, M. M., O'Hara, M.** (2012). Flow toxicity and liquidity in a high-frequency world. *The Review of Financial Studies*, 25(5), 1457-1493.
- Easley, D., O'Hara, M.** (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, 19(1), 69-90.
- Eleswarapu, V. R., Reinganum, M. R.** (1993). The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics*, 34(3), 373-386.
- Engle, R. F., Lange, J.** (2001). Predicting VNET: A model of the dynamics of market depth. *Journal of Financial Markets*, 4(2), 113-142.
- Engle, R. F., Russell, J. R.** (1998). Autoregressive conditional duration: a new model for irregularly spaced transaction data. *Econometrica*, 1127-1162.
- Fang, V. W., Noe, T. H., Tice, S.** (2009). Stock market liquidity and firm value. *Journal of Financial Economics*, 94(1), 150-169.
- Fong, K. Y., Holden, C. W., Trzcinka, C. A.** (2017). What are the best liquidity proxies for global research?. *Review of Finance*, 21(4), 1355-1401.
- Fong, K., Holden, C., Tobek, O.** (2017). Are Volatility Over Volume Liquidity Proxies Useful For Global Or US Research?. *Social Science Research Network website*. Retrieved March, 2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2989367
- Foster, F. D., Viswanathan, S.** (1993). Variations in trading volume, return volatility, and trading costs: Evidence on recent price formation models. *The Journal of Finance*, 48(1), 187-211.
- Foucault, T.** (1999). Order flow composition and trading costs in a dynamic limit order market1. *Journal of Financial Markets*, 2(2), 99-134.
- Foucault, T., Kadan, O., Kandel, E.** (2005). Limit order book as a market for liquidity. *The Review of Financial Studies*, 18(4), 1171-1217.
- Frazzini, A., Pedersen, L. H.** (2014). Betting against beta. *Journal of Financial Economics*, 111(1), 1-25.
- Frieder, L., Martell, R.** (2006). On capital structure and the liquidity of a firm's stock. *Social Science Research Network website*. Retrieved March, 2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=880421
- Gao, W., Zhu, F.** (2015). Information asymmetry and capital structure around the world. *Pacific-Basin Finance Journal*, 32, 131-159.
- Glosten, L. R., Harris, L. E.** (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics*, 21(1), 123-142.
- Glosten, L. R., Milgrom, P. R.** (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1), 71-100.

- Gomber, P., Schweickert, U., Theissen, E.** (2004). Zooming in on Liquidity. *Social Science Research Network website*. Retrieved March, 2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=559406
- Gourieroux, C., Jasiak, J., Le Fol, G.** (1999). Intra-day market activity. *Journal of Financial Markets*, 2(3), 193-226.
- Goyenko, R. Y., Holden, C. W., Trzcinka, C. A.** (2009). Do liquidity measures measure liquidity?. *Journal of Financial Economics*, 92(2), 153-181.
- Griffin, C. H.** (2010). Liquidity and dividend policy: international evidence. *International Business Research*, 3(3), 3.
- Handa, P., Schwartz, R. A.** (1996). Limit order trading. *The Journal of Finance*, 51(5), 1835-1861.
- Harris, L.** (1990). *Liquidity, trading rules and electronic trading systems* (No. 91-8).
- Harris, L.** (1999). Trading in pennies: a survey of the issues. *Unpublished working paper, University of Southern California*, 1-13.
- Harris, L.** (2003). *Trading and exchanges: Market microstructure for practitioners*. Oxford University Press, USA.
- Hasbrouck, J.** (1991). Measuring the information content of stock trades. *The Journal of Finance*, 46(1), 179-207.
- Hasbrouck, J.** (2004). Liquidity in the futures pits: Inferring market dynamics from incomplete data. *Journal of Financial and Quantitative Analysis*, 39(2), 305-326.
- Hasbrouck, J., Schwartz, R. A.** (1988). Liquidity and execution costs in equity markets. *The Journal of Portfolio Management*, 14(3), 10-16.
- Hasbrouck, J., Seppi, D. J.** (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics*, 59(3), 383-411.
- Heflin, F., Shaw, K. W.** (2000). Blockholder ownership and market liquidity. *Journal of Financial and Quantitative Analysis*, 35(4), 621-633.
- Hendershott, T., Jones, C. M., Menkveld, A. J.** (2011). Does algorithmic trading improve liquidity?. *The Journal of Finance*, 66(1), 1-33.
- Ho, T., Stoll, H. R.** (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics*, 9(1), 47-73.
- Holden, C. W., Jacobsen, S., Subrahmanyam, A.** (2014). The empirical analysis of liquidity. *Foundations and Trends® in Finance*, 8(4), 263-365.
- Huang, R. D., Stoll, H. R.** (1997). The components of the bid-ask spread: A general approach. *The Review of Financial Studies*, 10(4), 995-1034.
- Hui, B., Heubel, B.** (1984). *Comparative liquidity advantages among major US stock markets* (Vol. 84081). Data Resources Inc.
- Im, H. J.** (2014). Does share liquidity increase the propensity to raise debt finance?. *Social Science Research Network website*. Retrieved March, 2018 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2200285

- Irvine, P. J., Benston, G. J., Kandel, E.** (2000). Liquidity beyond the inside spread: Measuring and using information in the limit order book. *Social Science Research Network website*. Retrieved September, 2017 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=229959
- Jennings, W. W., Schnatterly, K., Seguin, P. J.** (2002). Institutional ownership, information and liquidity. *Innovations in Investments and Corporate Finance* (pp. 41-71). Emerald Group Publishing Limited.
- Kluger, B. D., Stephan, J.** (1997). Alternative liquidity measures and stock returns. *Review of Quantitative Finance and Accounting*, 8(1), 19-36.
- Kyle, A. S.** (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315-1335.
- Lang, M., Lins, K. V., Maffett, M.** (2012). Transparency, liquidity, and valuation: International evidence on when transparency matters most. *Journal of Accounting Research*, 50(3), 729-774.
- Lesmond, D. A.** (2005). Liquidity of emerging markets. *Journal of Financial Economics*, 77(2), 411-452.
- Lesmond, D. A., O'Connor, P. F., Senbet, L. W.** (2008). Capital structure and equity liquidity. *Social Science Research Network website*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=229959
- Lesmond, D. A., Ogden, J. P., Trzcinka, C. A.** (1999). A new estimate of transaction costs. *The Review of Financial Studies*, 12(5), 1113-1141.
- Lipson, M. L., Mortal, S.** (2009). Liquidity and capital structure. *Journal of Financial Markets*, 12(4), 611-644.
- Liu, W.** (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82(3), 631-671.
- Lybek, M. T., Sarr, M. A.** (2002). *Measuring liquidity in financial markets (No. 2-232)*. International Monetary Fund.
- Mann, S. V., Ramanlal, P.** (1996). The Dealers' Price/Size Quote and Market Liquidity. *Journal of Financial Research*, 19(2), 243-271.
- Martin, P.** (1975). Analysis of the Impact of Competitive Rates on the Liquidity of NYSE Stocks. *Economic Staff Paper*, 75(3).
- Nguyen, T., Duong, H. N., Singh, H.** (2016). Stock market liquidity and firm value: an empirical examination of the Australian market. *International Review of Finance*, 16(4), 639-646.
- O'Hara, M.** (2003). Presidential address: Liquidity and price discovery. *The Journal of Finance*, 58(4), 1335-1354.
- O'Hara, M.** (2007). Optimal microstructures. *European financial management*, 13(5), 825-832.
- Parlour, C. A.** (1998). Price dynamics in limit order markets. *The Review of Financial Studies*, 11(4), 789-816.
- Pascual, R., Escribano, Á., Tapia, M.** (2004). On the bi-dimensionality of liquidity. *The European Journal of Finance*, 10(6), 542-566.

- Pástor, L., Stambaugh, R. F.** (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3), 642-685.
- Perold, A. F.** (1988). The implementation shortfall: Paper versus reality. *The Journal of Portfolio Management*, 14(3), 4-9.
- Ranaldo, A.** (2000). Intraday trading activity on financial markets: The Swiss evidence. *PhD diss., University of Fribourg, Fribourg.*
- Roll, R.** (1984). A simple implicit measure of the effective bid- ask spread in an efficient market. *The Journal of Finance*, 39(4), 1127-1139.
- Roulstone, D. T.** (2003). Analyst following and market liquidity. *Contemporary Accounting Research*, 20(3), 552-578.
- Rubin, A.** (2007). Ownership level, ownership concentration and liquidity. *Journal of Financial Markets*, 10(3), 219-248.
- Sarin, A., Wright, P., Ferris, S. P., Awasthi, V.** (1996). Impact of corporate insider, blockholder, and institutional equity ownership on firm risk taking. *Academy of Management Journal*, 39(2), 441-458.
- Stoll, H. R.** (1978). The supply of dealer services in securities markets. *The Journal of Finance*, 33(4), 1133-1151.
- Url-1** <<http://www.xetra.com/xetra-en/trading/market-quality/xlm-xetra-liquidity-measure>>, date retrieved 01.09.2017.

APPENDICES

APPENDIX A: Formulas/ models of liquidity measures.

APPENDIX B: Residual analysis for statistical assumptions of regression.

APPENDIX A

Table A.1 : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
1	PQS	Percent Quoted Spread	Demsetz, 1968	Percent Quoted Spread _t = (Ask _t – Bid _t)/Midpoint _t
29	PPI	Percent Price Impact	Huang and Stoll, 1996	Percent Price Impact _t = 2 * Midpoint _{t+5} – Midpoint _t /Midpoint _t
30	PES	Percent Effective Spread	Huang and Stoll, 1996	Percent Effective Spread _t = 2 * (P _t – Midpoint _t) /Midpoint _t
2	IS	Implementation Shortfall	Perold, 1988	$IS = \sum_{j=1}^J x_j (p_j - m_d) + \left(X - \sum_{j=1}^J x_j \right) (p_N - m_d)$ <p>where x_j is the size, p_j is the price of j th trade, m_d is the current midpoint of bid and ask prices; X is the requested trade size, p_N is the price of the last trade.</p>
5	EC	One-Way, Execution Cost	Perold, 1988, Holden, 2014	$\text{One - Way, Execution Cost} = \sum_j x_j (p_j - b_j) I_j$ <p>where x_j is the size, p_j is the price of j th trade, b_j is the benchmark price, I_j is trade sign (1 if it is a buy and –1 if it is a sale). Benchmark price may be volume or time weighted average price.</p>
8	OR	Order Ratio	Ranaldo, 2000	$OR = \frac{\text{market imbalance}}{\text{turnover}} = \frac{ Q_A - Q_B }{P \cdot Q}$ <p>where Q_A is ask quantities and Q_B is bid quantities</p>
32	BLM	BLM	Pascual, Escribano, Tapia, 2000	$BLM = \frac{\text{Corrected Ratio of Quoted Depth by time}}{\text{Time Weighted Relative Spread}}$
33	QS	Quote Slope	Hasbrouck, Seppi, 2001	$\text{Quote Slope} = \frac{ Ask_t - Bid_t }{\ln(q_t^A) + \ln(q_t^B)}$ <p>where q_t^A represents ask quantities, q_t^B represents bid quantities at time t.</p>

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
9	VN	VNET	Engle and Lange, 2001	$VNET = \ln \left \sum_i d_i vol_i \right $ <p>where d is trade sign (1 if it is a buy and -1 if it is a sale) and vol is the total number of stocks traded during a specific price duration(time interval) which is called as PTIME. PTIME is expected via autoregressive conditional duration (ACD) model.</p>
19	TF	Trading Frequency	Demsetz, 1968	$\text{Trading Frequency} = \frac{1}{n-1} \sum_{i=2}^n tr_i - tr_{i-1}$ <p>tr_i denotes the time of the trade at time t, n denotes number of trade times in a day.</p>
13	ROR	Relative Odds Ratio	Kluger and Stephan, 1997	$ROR = \frac{h(V, X_1)}{h(V, X_2)} = e^{b(X_1 - X_2)}$ <p>where X_1 represents characteristics of company 1 and X_2 represents characteristics of company 2, V is random variable representing trading volume from the start of the day until a 3 percent change; $h(V)$ is the hazard function which is the conditional probability of a critical price change at V and b is regression coefficient which is estimated by maximum likelihood.</p>
44	FR	Flow Ratio	Ranaldo, 2000	$FR = \frac{\text{turnover}}{\text{trading frequency}} = \frac{\sum_{i=1}^n p_i q_i}{\frac{1}{n-1} \sum_{i=2}^n tr_i - tr_{i-1}}$ <p>tr_i denotes the time of the trade at time t, n denotes number of trade times in a day.</p>
4	CPQS	Closing Percent Quoted Spread	Chung and Zhang, 2014	$\text{Closing Percent Quoted Spread} = \frac{(\text{Closing Ask}_t - \text{Closing Bid}_t)}{(\text{Closing Ask}_t + \text{Closing Bid}_t)/2}$
21	WD	Weighted Durations	Gouriéroux, Jasiak, and Le Fol, 1999	<p>volume duration = $\tau_{vol}(t, v) = \inf\{\tau: V_{t+\tau}(m) \geq V_t(m) + v\}$ value duration = $\tau_w(t, v) = \inf\{\tau: W_{t+\tau}(m) \geq W_t(m) + w\}$ V volume, W capital and t indicate time, τ represents the time necessary to observe an increment v of cumulated volume or w of cumulated capital.</p>

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
20	ACD	Autoregressive Conditional Volume Duration	Engle and Russell, 1998	<p>ACD framework models a dynamic process of volume durations where mean equation is written as follows:</p> $X_i = \Psi_i \cdot \varepsilon_i$ <p>and</p> $\Psi_i = w + \sum_{j=1}^p \alpha_j X_{i-j} + \sum_{k=1}^q \beta_k \Psi_{i-k}$ <p>where X_i represents volume duration and Ψ_i is the conditional expectation of duration according to available information at time t_{i-1} and ε_i is independent and identically distributed sequence, ACD models can be varied by differentiating functional forms Ψ_i or by differentiating distributional assumptions on ε_i.</p>
6	AD	Average Depth	Mann and Ramanlal, 1996	$\text{Depth} = (q_t^A + q_t^B)/2$ <p>where q_t^A represents ask quantities, q_t^B represents bid quantities at time t.</p>
10	WB, WA, OV	Weighted Bid, Ask and Order Value	Aitken, Comerton-Forde, 2003	$\text{Weighted Ask Value} = \sum \text{Askordervalue}_b * \text{Askorderweight}_b$ $\text{Weighted Bid Value} = \sum \text{Bidordervalue}_b * \text{Bidorderweight}_b$ <p>where b is the price band which orders are placed.</p> $\text{Weighted Order Value} = \sum \text{Weightedaskvalue}_b * \text{Weightedbidvalue}_b$
22	SPE	Speed of Partial Execution	Holden, 2014	$\text{Speed of partial execution}_k = pt_k - st_k$ <p>where pt_k represents fully or partially execution time of k-th order which is submitted at time st_k.</p>
23	SCE	Speed of Complete Execution	Holden, 2014	$\text{Speed of complete execution}_k = ct_k - st_k$ <p>where ct_k represents complete execution time of k-th order which is submitted at time st_k.</p>
24	SC	Speed of Cancellation	Holden, 2014	$\text{Speed of cancellation}_k = canct_k - st_k$ <p>where $canct_k$ represents cancellation time of k-th order which is submitted at time st_k.</p>

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
48	PFR	Partial Fill Rate	Holden, 2014	Partial Fill Rate = np/ns where np represents number of orders that are partially or fully executed and ns represents total number of submitted orders.
49	CFR	Complete Fill Rate	Holden, 2014	Complete Fill Rate = nc/ns where nc represents number of orders that are completely executed and ns represents total number of submitted orders.
50	CR	Cancellation Rate	Holden, 2014	Cancellation Rate = $ncanc/ns$ where ncanc represents number of orders that are cancelled and ns represents total number of submitted orders.
27	CRT	Cost of a Round Trip Trade	Irvine, Benston, Kandel, 2000	$CRT(D) = (\sum_{k=0,infy} I_k P_k Q_k - \sum_{k=0,infy} I_{-k} P_{-k} Q_{-k})/D$ where I_k is buying order, P_k is ask price, Q_k is ask quantities; I_{-k} is selling order, P_{-k} is bid price, Q_{-k} is bid quantities at depth k. D represents the dollar amount of orders.
28	XLM	Xetra Liquidity Measure	Deutsche Borse, 2002	Xetra Liquidity Measure = $XLM_t(V) = XLM_{B,t}(V) + XLM_{S,t}(V)$ $XLM_{B,t}(V) = 10,000 * \frac{P_{B,t}(V) - M_{Q,t}}{M_{Q,t}}$ and $XLM_{S,t}(V) = 10,000 * \frac{M_{Q,t} - P_{S,t}(V)}{M_{Q,t}}$ $M_{Q,t}$ is the quote midpoint at time t. B indicates buyer initiated trades, while S indicates seller initiated trades. V is order size, $P_{B,t}(V)$ buyer initiated price, $P_{S,t}(V)$ seller initiated price.
11	ROLL	Roll	Roll, 1984	$Roll = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}$
12	VR	Variance Ratio	Hasbrouck, Schwartz, 1988	Variance Ratio = $\frac{\sigma_{Price_{ST}}}{\sigma_{Price_{LT}}}$ where $\sigma_{Price_{ST}}$ shows short term price variance such as 10 minute interval, $\sigma_{Price_{LT}}$ shows long term price variance such as 1 day.
15	MROLL	Modified Roll	Goyenko, Holden, Trzcinka, 2009	$Roll = \begin{cases} 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})} / \bar{P} & \text{when } Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{when } Cov(\Delta P_t, \Delta P_{t-1}) > 0 \end{cases}$

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
16	EROLL	Extended Roll	Holden, 2009	$\text{Extended Roll} = \begin{cases} 2\sqrt{-\text{Cov}(\Delta P_t^*, \Delta P_{t-1}^*)} / \bar{P} & \text{when } \text{Cov}(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{when } \text{Cov}(\Delta P_t, \Delta P_{t-1}) > 0 \end{cases}$ <p>where the specially adjusted price change $\Delta P_t^* = u_t * P_{t-1}$ and u_t is the regression residual from market model $r_t - r_f = \alpha + \beta(r_{mt} - r_f) + u_t$.</p>
25	HL	High-Low	Corwin and Schultz, 2012	$\text{High} - \text{Low} = \frac{2(e^\alpha - 1)}{1 + e^\alpha}$ <p>where $\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$ and β and γ values in equation are obtained from daily high and low prices and defined as: $\beta = \sum_{j=0}^1 [\ln(\frac{H_{t+j}}{L_{t+j}})]^2$ and $\gamma = [\ln(\frac{H_{t,t+1}}{L_{t,t+1}})]^2$ where $H_{t,t+1}$ and $L_{t,t+1}$ are highest and lowest prices over a two-day period, respectively.</p>
26	CHL	Close-High-Low	Abdi, Rinaldo, 2016	$\text{CHL} = \sqrt{\max\left\{\frac{4}{N} \sum_{t=1}^N (C_t - \eta_t) \cdot (C_t - \eta_{t+1}), 0\right\}}$ <p>where C_t is close log price on day t and $\eta_t = (\text{daily high} + \text{daily low})/2$</p>
46	MLI	Martin Index	Martin, 1975	$\text{MLI}_t = \sum_{i=1}^N \frac{(P_{i,t} - P_{i,t-1})^2}{V_{i,t}}$ <p>where $P_{i,t}$ is the closing price and $V_{i,t}$ is traded volume at day t.</p>
47	LHH	Hui-Heubel Liquidity Ratio	Hui-Heubel, 1984	$L_{HH} = \frac{(P_{\max} - P_{\min})/P_{\min}}{V/(S * \bar{P})}$ <p>P_{\max} is the highest daily price, P_{\min} is the lowest daily price, V total volume traded, S number of instruments, \bar{P} average closing price over 5 day.</p>
17	TR	Turnover Ratio	Datar, Naik, Radcliffe, 1998	$\text{Turnover}_t = V_t / (S_t * P_t)$ <p>where S_t is number of instruments at time t.</p>

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
14	CET	Coefficient Elasticity of Trading	Datar, 2000	$CET = \frac{\%Change\ in\ Trading\ Volume}{\%Change\ in\ Price}$
3	ET	Effective Tick	Goyenko, Holden, and Trzcinka, 2009 and Holden, 2009	$Effective\ Tick = \frac{\sum_{j=1}^J \hat{V}_j s_j}{\bar{P}}$ <p>For each possible spread s_j, the probability of price clustering F_j is calculated as: $F_j = \frac{N_j}{\sum_{j=1}^J N_j}$ for $j = 1, 2, \dots, J$ where N_j is the number of the trades on prices corresponding to the j_{th} spread. Here:</p> $U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \dots, J - 1 \text{ and} \\ F_j - F_{j-1}, & j = J \end{cases}$ $\hat{V}_j = \begin{cases} \text{Min}[\text{Max}\{U_j, 0\}, 1], & j = 1 \\ \text{Min} \left[\text{Max}\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \hat{V}_k \right], & j = 2, 3, \dots, J \end{cases}$
18	TV	Transaction Volume	Black, 1971, Cooplend and Galai, 1983	$V_t = \sum_{i=1}^n P_{it} Q_{it}$ <p>where i is number of instruments.</p>
43	VV	Volume Volatility	Stoll, 2000	$\sigma_{vol_t} = \frac{1}{n-1} \sum_{i=1}^n Vol_t - \overline{Vol}_t$ <p>where transaction volume of an asset/market on the day i of month t and \overline{Vol}_t is average volume, n represents the number of trading days.</p>
36	AMV	Aminvest	Cooper, Groth, Avera, 1985	$Aminvest = \text{Average} \left(\frac{Volume_t}{ r_t } \right)$ <p>where r_t is the stock return and $Volume_t$ is the currency value of volume on day t. The average is computed over positive volume days.</p>

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t = time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
38	ALR	Amihud Illiquidity Measure	Amihud, 2002	$\text{Amihud} = \text{Average}\left(\frac{ r_t }{\text{Volume}_t}\right)$ <p>where r_t is the stock return and Volume_t is the currency value of volume on day t. The average is computed over positive volume days.</p>
39	GMM	Gamma	Pastor and Stambaugh, 2003	$r_{t+1}^e = \theta + \beta * r_t + \text{Gamma} * \text{sign}(r_t^e) * \text{volume}_t + \varepsilon_t$ <p>r_t^e is the stock's excess return above the market portfolio on day t in a month. θ is the intercept, β and Gamma are the regression coefficients, ε_t is the error term.</p>
40	RL	Regressed Lambda	Goyenko, Holden, and Trzcinka, 2009 and Hasbrouck, 2009	$r_n = \lambda S_n + u_n$ <p>For n-th 5 min period, r_n is the stock return, $S_n = \text{sign}(v_{kn})/\sqrt{ v_{kn} }$, v_{kn} is the signed square root of volume of the k-th trade.</p>
42	VOV	VoV	Fong, Holden, and Tobek, 2017	$\text{VoV} = \frac{a \cdot \sigma^b}{V^c}$ <p>where a, b, c are positive constants and σ is the standard deviation of daily returns, V is average daily volume.</p>
41	EAM	Extended Amihud Measures	Goyenko, Holden, and Trzcinka, 2009	$\text{Extended Amihud} = \frac{\text{Spread Proxy}_t}{\text{Average Daily Volume}_t}$ <p>Spread Proxy_t can be any liquidity/illiquidity proxy. For example Roll, LOT-Mixed or Zeros; then this measure as an example called as Roll Impact or Zeros Impact.</p>
45	LM	LM	Liu, 2006	$\text{LM} = \left[\text{Numberofzerodailyvolumesinprior } x \text{ months} + \frac{1/x\text{th month turnover}}{\text{Deflator}} \right] \frac{21x}{\text{NoTD}}$ <p>where xth month turnover is turnover the prior x months cumulated from daily turnovers and NoTD is the total number of trading days over x months and Deflator chosen in order to</p> $0 < \frac{1/x\text{th month turnover}}{\text{Deflator}} < 1$

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

Table A.1 (continued) : Formulas/ models of liquidity measures.

No	Abbr.	Measure	Source, Year	Formula/ Model
31	LOTM	LOT-Mixed	Lesmond, Ogden and Trzcinka, 1999	$\text{LOT - Mixed} = \alpha_{2j} - \alpha_{1j}$ <p>where $\alpha_{1j} < 0$ denote the cost of selling and $\alpha_{2j} > 0$ the cost of buying. s. The unobserved return of a stock j on day t (R_{jt}^*) can be estimated by $R_{jt}^* = \beta_j R_{mt} + \varepsilon_{jt}$ where R_{mt} is the market return. The observed return is:</p> $R_{jt} = \begin{cases} R_{jt}^* - \alpha_{1j} & \text{when } R_{jt}^* < \alpha_{1j} \\ 0 & \text{when } \alpha_{1j} < R_{jt}^* < \alpha_{2j} \\ R_{jt}^* - \alpha_{2j} & \text{when } R_{jt}^* > \alpha_{2j} \end{cases}$ <p>The model's parameters are estimated by maximizing a likelihood function.</p>
34	LOTYS	LOT Y-Split	Goyenko, Holden, and Trzcinka, 2009	$\text{LOT Y - Split} = \alpha_{2j} - \alpha_{1j}$ <p>The model is similar to LOT-Mixed however the model's parameters are estimated in different spatial regions.</p>
7	ZRS, ZRS2	Zeros, Zeros2	Lesmond, Ogden and Trzcinka, 1999	$\text{Zeros} = \frac{\text{Number of days with zero returns}}{\text{Trading days in a month}}$ $\text{Zeros2} = \frac{\text{Number of positive volume days with zero returns}}{\text{Trading days in a month}}$
35	FHT	FHT	Fong, Holden, and Trzcinka, 2017	$\text{FHT} = S = 2\sigma N^{-1}\left(\frac{1+z}{2}\right)$ <p>The model is a simple LOT model. It combines assumptions of both LOT Mixed and Zeros measures. z comes from Zeros proxy, $N^{-1}(\cdot)$ is the inverse function of the cumulative distribution.</p>
37	LR	Liquidty Ratio	Ranaldo, 2000	$\text{Liquidity Ratio} = \text{Average}\left(\frac{\text{Volume}_t}{ r_t \cdot \text{Free Float Ratio}}\right)$ <p>where r_t is the stock return and Volume_t is the currency value of volume on day t. The average is computed over positive volume days</p>

Notes: P is the price and \bar{P} is the average price, Ask is the ask price, Bid is the bid price, Midpoint is bid-ask midpoint, V volume, Q quantity and subscripts indicate: t= time.

APPENDIX B

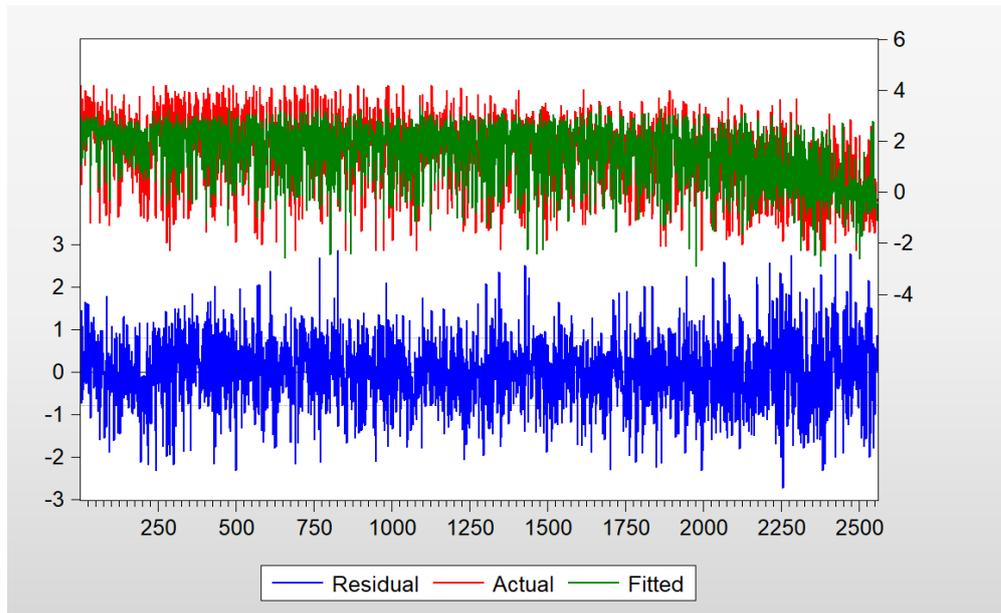


Figure B.1: Residual test for linearity.

Table B.1 : Residual test for heteroskedasticity.

Heteroskedasticity Test: White

F-statistic	7.114239	Prob. F(115,2440)	0.0000
Obs*R-squared	641.8266	Prob. Chi-Square(115)	0.0000
Scaled explained SS	725.1997	Prob. Chi-Square(115)	0.0000

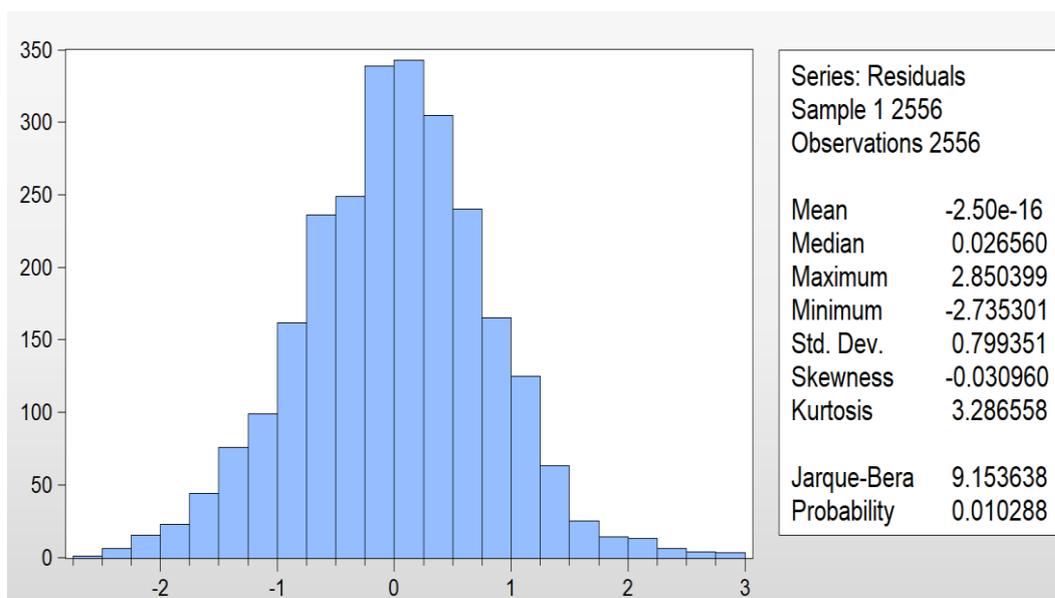


Figure B.2: Residual test for normality.

Table B.2 : Test for multicollinearity.

Variance Inflation Factors

Sample: 1 2556

Included observations: 2556

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.015434	71.70568	NA
LEVERAGE	8.77E-07	3.540940	1.116907
PROFIT	3.25E-06	1.657126	1.526770
EXCESSDIVY	3.59E-05	2.232198	1.069059
FLOAT	4.88E-07	12.31771	1.346291
LOG(AGE)	0.000962	41.34407	1.334271
LOG(FOLLOW)	0.000509	15.53378	2.102973
INSTOWNERS	3.73E-07	7.367478	1.417358
INTRADAYVOL	0.000263	13.78403	1.892629
LTVOL	0.002021	9.306136	1.411465
RELTICK	0.002183	1.783954	1.576332
LOG(PRICE)	5.05E-05	5.997803	1.761517
LARGE	0.001366	2.179767	1.434521
SMALL	0.002340	2.138903	1.653780
EMG	0.002080	1.583448	1.331278

CURRICULUM VITAE

Name Surname : Zeynep ÇOBANDAĞ GÜLOĞLU

Place and Date of Birth : Adana, May 1987

E-Mail : zeynecobandag@gmail.com

EDUCATION :

- **B.Sc.** : 2008, Cukurova University, Faculty of Science and Letters, Department of Mathematics
- **M.Sc.** : 2011, Middle East Technical University, The Institute of Applied Mathematics, Financial Mathematics

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **Cobandag, Z.**, Ekinci, C. 2015: A Comparison of Effective Bid-ask Spread Proxies: Evidence from Borsa İstanbul Futures. 55th Meeting of the EWGCFM, May 14-16, 2015 Ankara, Turkey.
- **Cobandag, Z.**, Ekinci, C. 2015: A Comparison of Effective Bid-ask Spread Proxies: Evidence from Borsa İstanbul Futures. 2nd Borsa İstanbul Finance & Economics Conference, October 1-2, 2015 Istanbul, Turkey.
- **Guloglu, Z. C.**, Ekinci, C. (2016). A comparison of bid-ask spread proxies: Evidence from Borsa Istanbul futures. *Journal of Economics Finance and Accounting*, 3(3).
- **Guloglu, Z. C.**, Ekinci, C. 2017: Effects of Corporate-Level and Market-Level Characteristics on Stock Liquidity. Global Business Research Congress, May 24-25, 2017 Istanbul, Turkey.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Guloglu, Z. C.**, Weber, G. W. (2014, February). Risk Modeling in Optimization Problems via Value at Risk, Conditional Value at Risk, and Its Robustification. In International Conference on Dynamics, Games and Science (pp. 133-145). Springer, Cham.

