ESSAYS ON MARKET MICROSTRUCTURE:

MARKET TRANSPARENCY, LIQUIDITY, AND PRICE DISCOVERY

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DECLARATION OF ORIGINALITY

I, Ayşe Çağlayan Gümüş, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution.
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution.
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ABSTRACT

Essays on Market Microstructure: Market Transparency, Liquidity, and Price Discovery

This thesis consists of two different studies on market microstructure, specifically on liquidity, transparency, and informativeness of the order book as measured with its contribution to the price discovery process. In the first study, the liquidity impact of a switch to the post-trade transparency regime i.e., disclosure of broker identifiers in real-time data feeds, which was implemented by Borsa İstanbul in April 2017 is analyzed. In addition to classical spread measures frequently used in the literature, liquidity is measured with more sophisticated measures like XLM, MCI, and order book depth that incorporate all the available order book information. Results show that post-trade transparency increases liquidity for stocks other than constituents of the BIST30 Index for which the change was implemented directly. For BIST30 stocks, the liquidity effect of the gradual switch to transparency implemented in an empirical setting is limited. In the second study, the contribution of the limit order book to the price discovery process is analyzed. Information shares of different price series are estimated with three different methods. The analysis that is performed with two different samples that include 30 different stocks included in the BIST30 Index in January and February of 2016 and in May and June of 2019 show that the orders beyond best bid and ask contribute significantly to the price discovery process. It is also found out that the contribution of orders in price levels that are close to the best price level is higher than in price levels that are farther away.

ÖZET

Piyasa Mikroyapısı Üzerine Makaleler: Şeffaflık, Likidite ve Fiyat Keşfi

Bu tez piyasa mikroyapısı alanında likidite, şeffaflık ve emir defterinin fiyat keşfi sürecine katkısı konularında iki farklı çalışmadan oluşmaktadır. İlk çalışmada Borsa İstanbul'da 2017 yılının Nisan ayında devreye alınan, işlemlerde taraf bilgisinin eşzamanlı olarak gösterilmesi uygulamasının likidite üzerindeki etkisi incelenmiştir. Çalışmada, literatürde sıklıkla kullanılan yöntemlerden olan alım satım marjlarının yanı sıra emir defteri bilgisini kullanan XLM, MCI ve derinlik gibi çok yönlü yöntemlerle likidite ölçülmüştür. Sonuçlar BIST30 endeksi dışındaki paylarda tek seferde gerçekleşen işlem sonrası şeffaflığın likiditeye olumlu etkisinin olduğunu göstermiştir. BIST30 endeksine dahil olan paylarda ise kademeli olarak gerçekleştirilen bu değişikliğin likiditeye olan etkisinin sınırlı olduğu belirlenmiştir. İkinci çalışmada ise emir defterinin fiyat keşfi sürecine olan katkısı analiz edilmiştir. Farklı fiyatların fiyat keşfi sürecine olan etkisi 3 farklı yöntem ile ölçülmüştür. 2016 yılının Ocak ve Şubat ayları ile 2019 yılının Mayıs ve Haziran aylarında BIST30 endeksine dahil olan 30 farklı payı içeren iki farklı örneklem ile yapılan analizlerde emir defterinin en iyi alım ve satım kademeleri dışında yer alan emirlerin de fiyat keşfi sürecine önemli oranda katkı sağladığı anlaşılmıştır. Sonuçlar en iyi fiyat seviyesine yakın olan fiyat kademelerinde yer alan emirlerin katkısının uzak olan fiyat kademelerine kıyasla daha yüksek olduğunu göstermiştir.

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To my daughter,

Esma Bilge

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ABBREVIATIONS

APM	Adverse Price Movement
ASX	Australian Stock Exchange
CCP	Central Counter-Party
DWS	Depth Weighted Spread
ESMA	European Securities and Markets Authority
HFT	High Frequency Trading
HIO	High Institutional Ownership
IOSCO	International Organization of Securities Commission
KAP	Public Disclosure Platform
LIO	Low Institutional Ownership
LOB	Limit Order Book
LP	Liquidity Premium
MCI	Marginal Cost of Immediacy
MIS	Modified Information Share
MiFID	Markets in Financial Instruments Directive
NZX	New Zealand Stock Exchange
OFI	Order Flow Imbalance
PT	Permanent-Transitory
SROs	Self-Regulated Organizations
VAR	Vector Auto Regression
VECM	Vector Error Correction
XLM	Xetra Liquidity Measure

CHAPTER 1

INTRODUCTION

Market microstructure is defined as “the study of the process and outcomes of exchanging assets under specific trading rules” (O’Hara, 1995) and as the study of “the process by which investors’ latent demands are translated into executed trades” (Madhavan, 2000). As it is clear from these definitions, market microstructure is about “trading, the people who trade securities and contracts, the marketplaces where they trade, and the rules that govern trading” (Harris, 2003).

Since the time when the term “market microstructure” has first been introduced by Garman (1976) in his article about market making and inventory costs, financial markets have changed tremendously. Due to the technological developments, at first traditional floor trading and dealership markets have been replaced with electronic limit order books, and trading through algorithms and high-frequency channels have become the popular way of trading thereafter. Apart from technological advances, competition among trading venues and increased fragmentation of markets have had a strong effect on the microstructure of markets. That is to say, today’s financial markets are characterized by technological innovations, high speed of trading, competition to get information rapidly, and increased fragmentation of trading venues. All these developments have created regulatory changes, especially with risk management and transparency requirements in all jurisdictions, and opened up a new area of research for academicians and practitioners working in this field.

As put forth by Madhavan (2000), the study of market microstructure can be grouped into four different categories. The first category is price formation and price discovery that look into the process of how new information is reflected into prices over time. The second category is research of trading structure and market design that examines the impact of different trading rules and regulations on market quality. The third category relates to information and disclosure, specifically market transparency, which explore how the information disclosed in different stages of the trading process affects strategies of traders and market quality. Finally, studies in the last category are about research about informational issues arising from the intersection of market microstructure with other fields of finance, including asset pricing, corporate finance, behavioral finance, etc.

This thesis aims to touch upon three specific areas of market microstructure through two different studies. All these issues have both practical and policy implications. First, the liquidity impact of change in the market structure of Borsa İstanbul from post-trade anonymous to transparent trading will be studied. Second, using the order book information of Borsa Istanbul, the information content of the limit order book, particularly the incremental content of the book aside from the best bid and best ask prices along with the order book depth, will be analyzed.

The first study empirically analyzes the liquidity impact of post-trade transparent trading on liquidity. To this end, the switch to the post-trade transparency regime implemented by Borsa İstanbul starting from April 2017 is treated as a quasi-natural experimental design. The fact that the rule change regarding the transparency regime is applied with two different methods for different stocks depending on which index they belong to has made it possible to employ two different analyzes in this study. Because the experiment was applied in a unique setting for BIST30 stocks that allowed only five stocks to become transparent in each month and then switching them back to anonymity afterward, it is possible to perform an analysis with five stocks in the treatment group each month and 25 stocks in the control group. All the other non-BIST30 stocks have become post-trade transparent in a direct way, creating an exogenous variation to analyze the impact of introducing transparency.

Previous empirical studies provided mixed evidence on the relation between post-trade anonymity and liquidity. On the one hand, Meling (2020), Dennis and Sandas (2020), Friedrich and Payne (2011), and Hachmeister and Schiereck (2010) documented an increase in liquidity after the switch to anonymous trading. On the other hand, Waisburd (2003), Pham, Swan, and Westerholm (2016), and Poskitt, Marsden, and Nguyen (2011) showed that liquidity had deteriorated with anonymity.

This part of the thesis contributes to the literature in several ways. While majority of the existing studies analyzed the change from post-trade transparent to the anonymous regime, we study the opposite case in which the change is from anonymity to transparency. Additionally, disclosure of broker identifiers is not limited to the counterparty of the transaction, but it is the real-time display of counterparty information which is available for all participants. Furthermore, the rule change has been implemented for BIST30 stocks in such a way that each month a control and a treatment group have been formed among blue-chip stocks traded in the Equity Market, enabling to test the impact of transparency without confounding factors. Finally, to be able to cover all its dimensions, liquidity is measured in a variety of ways, including more sophisticated measures like XLM, MCI, and Depth in addition to effective spreads.

In the second study, using the data from Borsa Istanbul, the informativeness of the limit order book both in the best-bid and best-ask prices and in the orders behind the first level of the order book is analyzed. Considering that price discovery is one of the principal functions of a financial market, the contribution of the orders placed in the order book to the price discovery process deserves attention.

There is a scarce number of studies on the contribution of the limit order book to the price discovery process (Martins, 2019). This part of the dissertation contributes to the literature by analyzing the informativeness of the order book for blue-chip stocks traded at Borsa İstanbul. To do so, using three different price discovery measures, the contribution of the order book beyond best prices is calculated. Moreover, the effect of disclosing price and volume information of five more price steps is investigated. Finally, the question of how information content of the order book changes with respect to changes in pre-trade transparency rule or in different market conditions is addressed.

The ultimate objectives of this thesis are twofold. First, it contributes to the literature of market microstructure by analyzing the effects of different trading rules governing the transparency in trading on market liquidity. Second, it adds upon the knowledge on the effect of information inherent in the order book on price discovery. To the best of our knowledge, this study is the first to analyze the information content of the limit order book and market transparency issues for Borsa Istanbul. The findings of this thesis can be useful for researchers, professionals, and regulators to better understand market dynamics and develop new trading methods.

The remainder of the dissertation is organized as follows. Chapter 2 introduces the institutional structure of Borsa İstanbul and explains the changes in post-trade and pre-trade transparency regimes in detail. Chapter 3 studies the impact of post-trade transparency on liquidity. Chapter 4 analyzes the contribution of the limit order book to the price discovery process. In Chapter 3 and Chapter 4 of the thesis, the introduction, literature review, data, methodology, and results parts are provided individually. Chapter 5 summarizes the findings and concludes.

CHAPTER 2

INSTITIONAL STRUCTURE AND TRANSPARENCY REFORM

The objective of this chapter is to introduce Borsa İstanbul's institutional structure and present details regarding post-trade and pre-trade transparency rule changes implemented by Borsa İstanbul.

2.1 Institutional Structure of Borsa Istanbul

Borsa Istanbul is the only securities exchange in Turkey in which equities, exchange-traded funds, warrants, certificates, options, futures, various debt instruments together with precious metals and diamonds instruments are traded under four separate markets: Equity Market, Derivatives Market, Debt Securities Market and Precious Metals and Diamonds Market. Since the scope of this study is limited to equities, details of the market rules for Equity Market will be summarized below.

Borsa Istanbul uses the BISTECH trading system, which is developed based on NASDAQ's Genium INET platform during the technological transformation project held between years 2014-2019. After this transformation project, which was conducted in partnership with Nasdaq OMX, the technological infrastructure of Borsa Istanbul has been renewed, and all the markets began to operate in a single platform.

BISTECH trading platform is used for the Equity Market as well in which securities are traded either with continuous auction or single price trading methods. At the time period of analysis for Chapter 3 (Chapter 4), trading took place between 09:40 (09:15) and 18:10 (17:40) with a trading model of continuous trading with auctions. Continuous trading starts with the order collection phase of the opening auction between 09:40 (09:15) and 09:55 (09:30) and is followed by the price determination and matching stage at 09:55 (09:30). Continuous auction is interrupted with a midday auction between 13:00 (12:30) and 13:55 (13:25) and resumes at 14:00 (13:30). Trading ends with a closing call auction and trades at the closing price stage that took place between 18:00 (17:30) and 18:10 (14:40). In the call auctions, price is determined by uncrossing the orders by a special call auction algorithm that will basically maximize the traded volume as well some other variables such as remaining quantity, etc. Order book depth is concealed during the order collection phase of the call auctions, and only indicative equilibrium prices and volumes are published.

According to Equity Market Directive (Borsa İstanbul, 2021), Borsa İstanbul is an order-driven market in which orders are matched according to price and time priority rules. Together with limit orders which are submitted with price and quantity information, entering other order types such as market, market to limit, and iceberg orders during the whole trading session and imbalance orders during the call auctions is also possible. Market orders are submitted only with quantity information and match the best bid or best ask until the specified quantity is reached, if the whole quantity is not reached, the remaining part is deleted. Market to limit orders are similar to market orders, but the remaining part is converted to limit orders and placed in the order book with the traded price instead of being deleted. Iceberg orders are submitted with partial display condition and only a predefined part of the order is disclosed to other participants. When the disclosed part is traded, the same quantity is re-entered in the order book like a new order until the total quantity is finished. In terms of the validity of the orders, it can be daily (order stays in the order book until the end of the session), immediate (also known as fill and kill order where the unmatched part is deleted by the system immediately), or good till date (stays in the order book until the specified date unless it is deleted by the trader). Using the classification suggested by De Jong and Rindi (2009), Table 1 summarizes order types available at Equity Market.

Table 1. Order Types for the Equity Market at Borsa İstanbul

Price Instructions	
Limit Order	Entered with price and volume information
Market Order	Entered with volume information only, executed from best available price on the opposite side, remaining part is deleted
Market to Limit Order	Entered with volume information only, executed from best available price on the opposite side, remaining part rests in the book with last price
Imbalance Order	Entered only in call-auctions to be traded from call-auction price
Mid-point Order	Entered only with volume information, used for large orders only in BIST 30 stocks, matched with mid-point orders only
Quotes	Used by market makers and liquidity providers
Maturity Instructions	
Day Order	Valid for the day, automatically canceled at the end of the session if not executed or deleted
Good Till Date Order	Valid until the date speficied on order entry
Good Till Cancel Order	Valid until canceled, used only in primary market orders
Quantity Instructions	
Fill and Kill	Unfilled part of the order is automatically cancelled
Hidden (iceberg orders)	Entered with partial display condition

Borsa Istanbul applies lower and upper price limits within which stocks can be traded during the trading day. At the analysis period of this study, price limits are calculated by applying ±20% to the base price, which is the closing price of the previous day. In addition to daily price limits, a circuit breaker is triggered in case of price change which is calculated using the last trade price, and the price of the last call auction exceeds 10%. In case of a circuit breaker, continuous auction in the related stock is temporarily halted and carried out to the order collection phase of a call auction.

Moreover, orders are entered according to tick sizes determined by the exchange. Tick size is defined as the minimum price movement that a financial instrument can increase/decrease. It is determined based on the order's price, i.e. a higher tick size level is applied for stocks with higher prices. Tick size levels set by Borsa Istanbul at the time period of this study are shown in Table 2.

Table 2. Tick Table

Price Level		
Minimum Price (TL)	**Maximum Price (TL)**	**Tick Size (TL)**
0.010	19.999	0.010
20.000	49.999	0.020
50.000	99.999	0.050
100.000	above	0.100

2.2 Post-trade Transparency Rule Changes

Since 1993, when Borsa Istanbul (formerly known as İMKB or Istanbul Stock Exchange) introduced an automated trading system, until 2010, a fully post-trade transparent policy had been implemented. The policy was allowing disclosure of broker identifiers on the buy and sell-side of trades.

However, starting from October 8, 2010, Borsa Istanbul revised its transparency regime and abandoned the transparent post-trade reporting regime that had been in place since 1993 (Borsa İstanbul, 2011). After this date, post-trade reporting became anonymous in the Equity Market. Broker identifiers of the buy and sell-side of trades were started to be concealed in all real-time market data feeds during the session and not shared with intermediary institutions.

The post-trade anonymity rule that had been in force since 2010 had been abolished with the introduction of a transparency regime on April 03, 2017 (Borsa İstanbul, 2018). After this date, post-trade transparent reporting was implemented for all stocks in the Equity Market except the ones that are constituents of the BIST30 Index which includes most liquid stocks with highest market capitalization.

For stocks that are constituents of the BIST30 Index, the rule change was implemented in an experimental setting. The purpose of not implementing the change in immediately for BIST 30 stocks was to be able to analyze the effect of transparency on market quality before the ultimate implementation takes place.

As mentioned above, the rule change was implemented in a stepwise manner for the BIST30 stocks. In the first stage, five stocks were randomly selected, and information about which stocks were selected for the post-trade transparency regime was published through Public Disclosure Platform (KAP) as BISTECH Equity Market trading system announcements on equity market counterparty information dissemination . For the selected stocks, broker identifiers were started to be shown for each trade in all real-time market data feeds. As opposed to the selected five stocks, broker codes remained anonymous for the remaining 25 stocks. In the following month, broker identity information was removed again for the five stocks while another five stocks were selected. Broker codes were started to be disclosed for the newly selected stocks. At the end of a 6-months period (as of the end of September 2017), broker codes for each trade had become transparent for a month for all the BIST 30 stocks. In Table 3, stocks that are selected for the transparency regime in the first stage are shown on a monthly basis.

Table 3. Stocks Selected for Post Trade Transparency in the First Stage

Month	**Announcement Date**	**Start Date**	**End Date**	**Selected Stocks**					
April	31.03.2017	03.04.2017	28.04.2017	YKBNK	TOASO	VAKBN	ULKER	EREGL	
May	28.04.2017	02.05.2017	31.05.2017	AKBNK	ASELS	KCHOL	KRDMD	TAVHL	
June	31.05.2017	01.06.2017	30.06.2017	BIMAS	FROTO	ISCTR	PETKM	SISE	
July	30.06.2017	03.07.2017	31.07.2017	DOHOL*	EKGYO	HALKB	MAVI*	THYAO	
August	31.07.2017	01.08.2017	31.08.2017	ENKAI	GARAN	OTKAR	SAHOL	TUPRS	
September	31.08.2017	05.09.2017	29.09.2017	ARCLK	KOZAL	SODA	TCELL	TKFEN	TTKOM

**As of 21/06/2017, broker codes had become anonymous for MAVI and had become transparent for DOHOL with respect to the change in BIST 30 Index constituents.*

In the second stage, starting from October 2017, for each month, broker codes had become anonymous for five stocks in BIST 30 Index while they had become transparent for the remaining 25 stocks. In the next month, broker codes for these five stocks were publicized, and another five stocks were selected again, and broker code information for these newly selected stocks was hidden in the same way. This process had continued for six months (until the end of April 2018). In Table 4, stocks that are selected for the transparency regime in the second stage are shown on a monthly basis.

Table 4. Stocks Selected for Post Trade Transparency in the Second Stage

Month	**Announcement Date**	**Start Date**	**End Date**	**Stocks**					
October, 2017	29.09.2017	02.10.2017	31.10.2017	ARCLK	KOZAL	TCELL	TKFEN	TTKOM	
November,2017	31.10.2017	01.11.2017	30.11.2017	AKBNK	YKBNK	THYAO	DOHOL	KOZAA	
December,2017	01.12.2017	01.12.2017	29.12.2017	BIMAS	ECILC	EKGYO	PGSUS	SISE	
January, 2018	29.12.2017	02.01.2018	31.01.2018	HALKB	ISCTR	KCHOL	KRDMD	VAKBN	
February, 2018	31.01.2018	01.02.2018	28.02.2018	EREGL	GARAN	SAHOL	SKBNK*	OTKAR	
March, 2018	28.02.2018	01.03.2018	30.03.2018	ASELS	PETKM	TAVHL	TOASO	TUPRS	ENJSA
April, 2018	30.03.2018	02.04.2018	30.04.2018	AKBNK	KOZAL	TKFEN	TTKOM	YKBNK	

**As of 14/02/2018, broker codes had become transparent for SKBNK with respect to the change in BIST 30 Index constituents.*

In the third stage broker identifiers were started to be disseminated real-time in market data feeds for all stocks that are constituents of the BIST30 Index starting from May 02, 2018, based on the evaluation that post-trade transparency mechanism did not cause any negative impact on the market.

For all the stocks except the ones in the BIST 30 Index, the post-trade transparency rule change was implemented in a more direct way i.e., broker code information for the buy and sell-side of each trade has been published in real-time starting from April 03, 2017.

Adapted from Meling (2021), the following table illustrates post-trade transparent and post-trade anonymous trade feeds. As it is clear from Table 5, broker

IDs for both buy and sell sides are disclosed in the post-trade transparency regime while they are not in the post-trade anonymity.

Table 5. Post Trade Transparent and Anonymous Trade Feeds

Panel A - Post-trade Transparent Trade Feed				
Stock Code	Buy Broker ID	Price	Volume	Sell Broker ID
AAAAA.E	XXX	10.10	1,500	PPP
BBBBB.E	YYY	20.10	2,300	SSS
CCCCC.E	ZZZ	13.80	5,000	KKK
DDDDD.E	TTT	18.20	150,000	LLL
FFFFF.E	VVV	115.20	15	UUU
Panel B - Post-trade Anonymous Trade Feed				
Stock Code	Buy Broker ID	Price	Volume	Sell Broker ID
AAAAA.E	-	10.10	1.,500	-
BBBBB.E	-	20.10	2,300	-
CCCCC.E	-	13.80	5,000	-
DDDDD.E	-	18.20	150,000	-
FFFFF.E	-	115.20	15	-

2.3 Pre-Trade Transparency Rule Changes

In terms of pre-trade transparency, a rule change was implemented on February 01, 2016, that made markets more transparent in terms of market depth information disseminated on a real-time basis. From that date onwards, information regarding best ten price steps has started to be broadcasted to data vendors. Before the change, only five best price steps were being disseminated. Moreover, in trading workstations, which are used only by licensed traders, it is possible to get market depth information up to the best 25 price steps. Broker identity information is not disclosed in market depth screens.

CHAPTER 3

THE EFFECT OF MARKET TRANSPARENCY ON LIQUIDITY

This chapter explores the liquidity effect of the post-trade transparency regime implemented by Borsa İstanbul in April 2017. The first part of this chapter introduces the concept of market transparency with a focus on different participants' viewpoints towards transparency. In the second part, theoretical and empirical explanations that explain the relationship between transparency and market quality are provided. The next part introduces the concept of liquidity together with various liquidity measures that will be employed in the analysis. Afterward, the sample and data used in the study will be explained together with descriptive statistics. Model specification and variables will be defined, and empirical findings will be presented in the last part.

3.1 Introduction

Market transparency is described as "the quantity and quality of the information provided to market participants during the trading process." (Madhavan, 2000). As it is clear from this definition, market transparency is limited to the level of information that is available during the trading process, which starts from the order collection phase and ends with the settlement of trades. Information disclosures made by listed companies about matters such as the financial situation of the company and other material developments are not covered under this concept.

Different levels of transparency can be applied to different stages in the trading process, so transparency is broadly categorized as either pre-trade transparency or post-trade transparency depending on the stage in which the transparency regime is adopted (De Jong and Rindi (2009)).

- Pre-trade or quote transparency is real-time display of unexecuted bid or ask orders resting in the order book before they are traded or deleted.
- Post-trade transparency is the real-time display of trades. It consists of information such as execution time, direction, volume, and price.

In addition to the above explanation, it should be noted that one of the most critical aspects of both pre and post-trade transparency is “anonymity” i.e., the decision to disclose or conceal participants’ identities entering the buy/sell orders.

Apart from the type of information that is revealed to market participants, the extent of dissemination (e.g. brokers, customers, or public), timing (e.g. whether to display information real-time or at day-end), and frequency (at what intervals information becomes available) are important as well (Madhavan, 2000).

Market transparency, as defined above, is a key market design issue concerning different stakeholders, including regulators, trading venues, and market participants, each of which has conflicting interests and different preferences with respect to the optimal level of information that should be displayed through the trading process.

Regulators set transparency as one of the main objectives that should be achieved for the well-functioning of the markets. International Organization of Securities Commission (IOSCO), which is accepted as the global standard-setter for the securities industry, considers transparency as a central principle and reflects this in “Objectives and Principles of Securities Regulation” by saying that one of the three core objectives of securities regulation is “Ensuring that markets are fair, efficient and transparent” (IOSCO, 2017).

It is emphasized as an objective in the Turkish regulation as well. In the first Article of the Capital Markets Law, the purpose of the Law is said to be "to regulate and supervise capital markets to ensure the functioning and development of capital markets in a secure, transparent, efficient, stable, fair and competitive environment and to protect the rights and interests of investors."

Transparency issues have become especially important after the global financial crisis, and regulators from different jurisdictions have taken actions to make financial markets more transparent. European Securities and Markets Authority (ESMA) updated the Markets in Financial Instruments Directive (MiFID), and new requirements are defined in terms of transparency under the new regulation, MIFID II, to increase the level of information available to market participants and to reduce the use of over the counter markets and dark pools (ESMA, 2020a).

Changing the level of information that is disclosed during the trading process is used as a policy response by capital markets regulatory institutions to changes in financial and macroeconomics conditions. To give a recent example, as a response to extreme stock market volatility resulting from the Covid-19 pandemic, ESMA increased the transparency requirement of short-sell transactions by lowering the notification threshold of short-selling reporting from %0,2 to %0,1, i.e. net short-sell positions above 0,1% instead of 0,2% required to be reported to the regulatory authorities (ESMA, 2020b).

Transparency varies to a large extent for different types of trading venues. At the one extreme, there are regulated exchanges which are also known as self-regulated organizations (SROs), that emphasize transparency as a core objective. At the other extreme, there are dark pools that are characterized by a lack of transparency. Dark pools are opaque markets in which trading is conducted in a confidential manner. Due to their opaque nature, these platforms are generally preferred by institutional investors for their trades with large quantities not to reveal their trading intentions to the market and to minimize the price impact of trades (Petrescu and Wedow, 2017). Despite their common emphasis on transparency, regulated exchanges differ in terms of their pre-trade and post-trade transparency rules, and these rules change over time depending on market conditions and regulatory needs.

Market participants i.e., investors, brokers, and traders differ with respect to the level of their private information (informed vs. uninformed traders), liquidity characteristics (liquidity providers vs. liquidity takers), and their trading directions (buy-side vs. sell-side). Since different types of market participants have different transparency preferences, changing transparency rules create different outcomes for them (Harris, 2003). For example, informed traders generally prefer not to reveal their private information, so they favor anonymous trading, while uninformed traders prefer more transparency to be able to benefit from the private information of informed traders.

Given their different natures, sometimes conflicting interests and preferences of different stakeholders, finding the optimal degree of transparency is a challenging issue that attracts the interests of academicians and professionals. In the academic literature, there is a number of studies investigating the potential effects of different transparency regimes on market quality. These studies approach the subject by assuming either a theoretical or an empirical perspective, or both.

Initial studies, both theoretical and empirical, focus on the preference of traders between anonymous and non-anonymous markets and provided explanations for the main determinants of their choice. Afterward, with stock exchanges' tendency to alter their transparency regimes, which provide a quasi-natural experiment setting, academicians start to study the effects of such changes on market quality. In the existing literature, although there is an agreement that transparency changes have an effect on market quality, empirical results do not provide a conclusive result about the direction of this effect, mainly because of different market structures and different market rules implemented by different exchanges.

This part of the thesis aims to make a contribution to market transparency literature by analyzing how the switch to a post-trade transparent reporting regime in Borsa İstanbul Equity Market affected liquidity. Starting from April 2017, all the stocks except constituents of the BIST30 Index have become post-trade transparent. This rule change has been implemented in a unique way for BIST30 stocks allowing each stock to become both anonymous and transparent in a six months period. Exploiting this experimental design as a proxy of market transparency and using limit order book liquidity measures in addition to classical spread measures, this study analyzes the effect of post-trade transparency on liquidity.

3.2 Literature Review

In the following parts, theoretical and empirical studies that provide an explanation for the relationship between market transparency and market quality will be briefly summarized.

3.2.1 Theoretical Background on Market Transparency and Market Quality

As per the theoretical perspectives to the subject of the relationship between transparency and market quality, Friederich and Payne (2011) suggest that there are basically two theoretical frameworks explaining that relationship, namely the asymmetric information and predatory trading frameworks. Asymmetric information theory is based on the idea that market participants possess different levels of information, while in predatory trading, some traders exploit the information of large traders' positions and profit at their expense.

3.2.1.1 Asymmetric Information

In financial markets, there are multiple trader types that differ along with a variety of dimensions, including the level of information endowments they have. On the one hand, there are informed traders who have private information about the fundamental value of the asset. On the other hand, there are uninformed traders who do not have any private information (Harris, 2003).

Since acquiring information is costly, only some traders prefer to get the information while others do not get the information as they do not prefer to incur this cost. However, depending on the market rules related to information flows, uninformed traders may have the chance to observe the signals of informed traders without incurring a cost. Not to reveal their private information, informed traders prefer less transparency. Therefore acquiring the optimal level of information depends, among other things, on transparency rules set by regulators and trading venues.

Because market participants have different levels of information endowments and different objective functions, their reaction to a change in a market rule is not the same. Therefore, the existence of information asymmetries among agents is a key issue to explain the impact of transparency rule changes on market quality.

In summary, according to the studies based on asymmetric information theory summarized below, informed traders prefer anonymity while uninformed traders, also known as liquidity traders, prefer transparency. The explanation behind this argument is that transparency makes trading costly for informed traders because they signal the information that they acquire with a cost to uninformed traders such that uninformed traders may better predict the probability of informed trading and engage in activities such as piggybacking or front-running. Since informed traders prefer anonymity, an increase in anonymity increases informed traders' transactions which also increases adverse selection risk. As a result, spreads widen, and liquidity decreases.

Seppi (1990) developed an intertemporal model in which an investor has a choice to trade either in upstairs or downstairs markets and showed that informed traders prefer to trade in upstairs markets in block trades instead of trading in multiple small trades in the primary market. Similar to Seppi (1990), Madhavan (1995) developed a two-period dynamic model with post-trade information disclosure to identify the effect of disclosure policy on market consolidation and showed that large traders prefer nondisclosure and trade on upstairs markets not to reveal their trading strategies or not to be front-run. Even with voluntary disclosure, traders choose not to reveal their identity to take advantage of the reduction in price competition.

Pagano and Roell (1996) tested the impact of transparency on liquidity using different trading systems with varying transparency levels, including different auction markets and a dealer market. In their model, transparency is defined as increased visibility of the agents' order flows who are not necessarily the end-users of the market. They also assume that there are traders with informational advantages who create an adverse selection problem. They conclude that transparency of the market mechanism enhances liquidity and make several policy suggestions, including public dissemination of the order flow and immediate trade publication.

The study of Huddart, Hughes, and Levine (2001) is based on the rational expectations trading model of Kyle (1985), in which an insider has private information about the fundamental value of the asset. They extend this model by adding disclosure requirements for insider trades. With disclosure requirements, insiders continue to trade on their private information. However, since market makers start to observe their private information, insiders add noise to their trades. As a result, insider trades become less profitable, yet there is still positive profit. Moreover, the authors conclude that, with disclosure, information is incorporated into prices more rapidly, i.e. the price discovery process is accelerated, and trading costs decline.

Foucault, Moinas, and Theissen (2007) developed a theoretical model based on the idea that a limit order book carries information about future volatility. They showed that if volatility information is symmetric, anonymity does not matter, but when it becomes asymmetric, the order book becomes informative for uninformed traders. However, with a switch to anonymity, the informativeness of the limit order book becomes less precise depending on the participation rate of informed traders. When the participation rate is low, traders who do not have any private information become more aggressive, and they more frequently send best quotes leading to the smaller average size of the quoted spread and smaller informativeness. On the other hand, when the participation rate is high, a wide bid-ask spread leads uninformed traders to behave less aggressively. In summary, the authors concluded that when the participation rate of informed traders is low, the correlation between bid-ask spread and volatility declines together with the size of the bid-ask spread after the switch to anonymity. With anonymity, for a given participation rate, the size of the bid-ask spread and its informativeness evolves in the same direction.

According to Rindi (2008), if the number of informed traders is given, liquidity is improved with transparency by a reduction in adverse selection costs. By observing the order flow of informed traders through their identification codes, uninformed traders get the information at no cost and submit more aggressive orders, which increases liquidity. However, with endogenous information acquisition, this mechanism reduces informed traders' incentive to acquire information and thus reduces the number of informed traders, which decreases liquidity. Moreover, another result of the model is that in stock markets, the strictness of insider trading rules matters. If they are not strict enough, then insiders can continue to trade on their private information, so the number of informed agents does not change. Therefore, transparency increases liquidity. With strict insider trading regulations, since information acquisition becomes costly, transparency can reduce the incentive to get information, and liquidity declines.

Another strand of research that explains the relation between asymmetric information and market quality is "stealth trading", under which shrewd traders adopt trading strategies to hide their trading intentions and to prevent information leakages (Yin, 2014). Previous studies showed that informed traders arrange either size of their orders or the timing of their trades so as to conceal their monopolized information at the beginning of the trading session and enter informed orders or execute informed trades near to end of the session. In this way, they used their information as a strategic tool and released it at the optimal time with the optimal size (Foster and Viswanathan, 1994, 1996 and Back, Cao, and Willard, 2000). Relation between stealth trading and transparency is clear; with increased transparency, the stealth trading motivation of traders will increase while there is no need to conceal their motivation under anonymity.

In summary, results provided by theoretical studies that are based on asymmetric information arguments are inconclusive. On the one hand, transparency decreases information asymmetries since individual investors will have more information regarding the market conditions after the switch to anonymity. On the other hand, institutional investors who have an informational advantage will have an incentive to conceal their trading intentions through noise trading not to reveal their private information, or they may abuse their advantage to influence the trading of individual investors and manipulate the price, which will further increase information asymmetry.

3.2.1.2 Predatory Trading

The predatory trading argument of Brunnermeier and Pedersen (2005) also provides a theoretical framework to explain the relationship between anonymity and liquidity. In the predatory trading theory, a large investor who has a market impact and who trades continuously is followed by predators who buy (sell) alongside the large investor and benefit from the price pressure by selling (buying) at a high (low) price. Predatory trading increases systematic risk, and is harmful to the market. For instance, a hedge fund that has to liquidate its position because of a margin call can be known by other participants who will sell alongside the hedge fund, withdraw the liquidity and accelerate the price decline of the asset. This argument is also relevant in the case of a short-squeeze when a short-seller recovers his position when there is a significant price increase. In summary, strategic traders trade in the same direction as large traders when their positions are known and consume liquidity instead of providing it, causing a systemic risk for the whole market.

According to Brunnermeier and Pedersen (2005), predatory trading can be considered as an argument against transparency however, they do not specifically explain the link between predatory trading and market liquidity. This relation is explained by Friedrich and Payne (2011). According to their explanation, the presence of predators executing trades based on positions of large informed traders and at the expense of others badly affects market quality. Since predatory trading becomes possible under full transparency, with increased transparency, informed traders conduct more liquidity consuming aggressive trades not to reveal their trading intentions. On the other hand, under anonymity, their aggressiveness decline, and they contribute much to liquidity. In summary, according to the predatory trading argument, transparency has a negative effect on liquidity.

3.2.2 Empirical Literature Review on Market Transparency and Market Quality

Foucault et al. (2007) tested their theoretical hypothesis using data from Paris Bourse, which switched to pre-trade anonymity on April 3, 2001. Their results show that pre-trade anonymity leads to an increase in liquidity, i.e. a decrease in spreads. Moreover, after anonymity, spreads become less informative about future volatility. In that sense, empirical findings support their theoretical hypothesis that when volatility information is asymmetric, the order book contains more information than what is publicly available.

Comerton-Forde and Tang (2009) studied the impact of the simultaneous introduction of pre-trade and post-trade anonymity on different market quality aspects, including liquidity, order aggressiveness, and market selection, exploiting the rule change implemented by Australian Stock Exchange (ASX) in 2005. They first showed that anonymity leads to an improvement in liquidity which is measured by effective and quoted spreads. In addition to this, their results showed that the opportunity to hide their identity leads large traders to use limit instead of market orders, and they become less aggressive while executing trades. As a result, the depth of the order book increases. Moreover, traders prefer to submit their orders to the anonymous market instead of the non-anonymous upstairs market. Finally, they demonstrate that liquidity increase and order flow concentration effects of anonymity are more prevalent for liquid stocks, for which level of information asymmetry is lower as compared to illiquid stocks. The results provided by Comerton-Forde and Tang (2009) are generally consistent with the predictions of Foucault et al. (2007).

Friederich and Payne (2011) studied the impact of introducing post-trade anonymity after London Stock Exchange launched a central counter-party (CCP) on February 26, 2001 for the SETS order book, which accounts for a high percentage of UK equity market activity. As the control sample, the authors used two other trading markets in which no anonymity change is implemented: the SEAQ dealership system and Euronext. Their results show that liquidity is improved, the price impact of trades is reduced, and execution costs declined after the switch to post-trade anonymity while no such change is observed in control samples. They also tested for the source of improvements in market quality and clarified that reductions in predatory trading are the main reason of such an improvement. They do not find evidence in favor of asymmetric information arguments, i.e., information asymmetries do not decline with anonymity as predicted by Huddart et al. (2001) and Rindi (2008).

Using a transparency regime change in German Stock Exchange that takes place in 2003, Hachmeister and Schiereck (2010) tried to answer the question of how post-trade anonymity affected liquidity and informed trading. Their findings suggest that liquidity is increased, and the arrival rate of informed traders is reduced after the switch to post-trade anonymity.

Dennis and Sandas (2020) studied the effect of anonymity on market quality based on a quasi-natural experiment provided by Nasdaq Nordic exchanges. In 2008, post-trade anonymity was applied by Nordic exchanges of Helsinki, Reykjavik, Stockholm (limited to the five most liquid stocks). For Copenhagen and for the remaining stocks in Stockholm, broker codes continued to be displayed in real-time market feed. A year later, the change is reversed, and all the exchanges except five stocks in Helsinki get back to transparency. Using this experimental setting, the authors applied difference-in-difference regressions and found out that spreads tightened with anonymity and widened with transparency. Price impact and order book depth measures also show better liquidity under anonymity.

Meling (2021) used a regression discontinuity design to explore the liquidity effect of post-trade anonymity regime adopted by the Oslo Stock Exchange on June 2, 2008. The rule change was implemented only for 25 stocks involved in the OBX list for which the constituents were selected semi-annually. All the other stocks, including the ones leaving the OBX list have remained post-trade transparent. Exploiting the changes in the OBX list as a source of exogenous variation, the author used a regression discontinuity design for just-included and just-excluded stocks. Results show that anonymous trading has increased trading volume and reduced stock liquidity as measured by bid-ask spreads. The author also finds out that the improvement in stock liquidity was due to increased trading of institutional investors while no change was observed in the trading activity of retail traders.

As opposed to the empirical studies mentioned above, there are studies that document a negative relation between anonymity and liquidity. Maher, Swan, and Westerholm (2008) studied five exchanges, namely Euronext Paris and Brussels, the Tokyo Stock Exchange, the Australian Stock Exchange who removed broker identity, and Korea Stock Exchange who introduced broker identification. The authors show that the previous studies are sensitive to the econometric model employed, and they suffer from endogeneity problem which seriously affects results. To overcome this problem, they used instrumental variables estimation, and opposite to previous studies, show that anonymity is associated with an increase in bid-ask spread, intraday volatility, and a decline in total volume.

Linnainmaa and Saar (2012) used a dataset from Finland where investor detailed information is available. They find that although it is possible for investors to trade with different brokers and thus conceal their trading intentions, broker identity can still be used as a signal about the identity of investors, and it affects prices where the market processes the information content of broker identity. According to the authors, anonymity improves market liquidity in such a way that prices adjust less efficiently to order flow information.

Swan and Westerholm (2019) undertake a broader study for a sample of 33 major exchanges and investigates the impact of different market transparency regimes on trading activity using simultaneous equation systems. Their results show that small and large stocks are affected differently from transparency levels in the order book. For large stocks, disclosing minimum information on the bid and ask steps of the order book causes positive results. However, for small stocks and intermediate stocks, to some extent, transparency of the order book is the suggested policy as it leads to a reduction in transaction costs and volatility. They also demonstrate that the possibility to enter iceberg orders, i.e. large orders that are split into smaller portions to conceal the actual quantity, is suggested for large stocks while it is not for the small and intermediate stocks. Lastly, the authors found out that pre-trade and post-trade transparency rules such as displaying Broker IDs before the trade and disclosing block trades reduce information asymmetries, so it is suggested for most of the stocks.

Poskitt et al. (2011) documented a negative relationship between anonymity and liquidity for New Zealand Stock Exchange (NZX) that adopted anonymous trading in 2007 and started to disclose broker identities to market participants only two trading days after the transaction date. They showed that spreads become wider and liquidity decreased after the rule change together with increased adverse selection costs. In their study, the authors also emphasized that a similar anonymity regime was adopted by the Australian Stock Exchange (ASX), and they found out that the market share of NZX increased for cross-listed stocks after NZX has become anonymous as well.

Empirical studies that analyzed the relationship between liquidity and anonymity are summarized in Appendix A.

3.3 Liquidity

Liquidity is considered as a critical aspect of market quality which is desired by all the market participants. Investors demand liquidity because it affects their transaction costs. Marketplaces set liquidity as a goal to achieve because it affects the trading decisions of investors between different exchanges. Although it is difficult to define liquidity which is a multidimensional concept, Pastor and Stambaugh (2003) define this concept as “the ability to trade large quantities easily and without a large effect on price”. As it is clear from this definition, liquid markets enable their investors to immediately execute their large orders with a minimum effect on price so that they can open and close their positions at a low cost.

As specified by Rösch (2012), market liquidity has four cost components: price impact, search costs, delay costs, and direct trading costs. Direct trading costs, which are exchange fees, brokerage commissions, and taxes incurred by the government, are generally neglected since they are smaller compared to other components. Moreover, they are easier to measure and determined exogenously by stock exchanges, brokerage firms, and governments. Search costs can also be neglected for assets like stocks since they are continuously traded in regulated exchanges, and finding a counterparty is not an important issue. Contrary to direct trading costs and search costs, price impact and delay costs are substantial components of market liquidity. Price impact involves the cost of immediately executing a transaction which is the difference between realized transaction price and the fair value of the asset. Small orders can be executed from the best bid or best ask prices without causing a significant change in price. However, large orders cannot be fulfilled only with orders pending at the best level in the order book. Therefore, order book volume beyond best bid and ask levels become important, which makes liquidity measurement more complex. Delay costs involve the cost of not immediately executing a transaction. Market participants may delay their orders on purpose with an expectation of more favorable prices in the future, or their orders may not be executed due to market conditions. In both cases, there is a risk of not being able to execute the order or facing a worse price.

The existing literature about liquidity asserts that there are different aspects of liquidity which are known as different dimensions of liquidity. Although there is no consensus on its number, as specified by Hasbrouck and Schwartz (1988), there are four dimensions of liquidity: market breadth, market depth, immediacy in execution, and market resiliency.

Market breadth refers to transaction costs that can be measured by bid-ask spread and associated with trades even with smaller amounts. Immediacy in execution is related to the amount of time it takes for an order to be executed. Market depth is the availability of orders in the buy and sell sides of the order book both below and above the current price, showing the capacity to trade without causing large price movements. Lastly, resiliency is the market’s ability to recover and revert to normal after shocks in the order flow.

In summary, liquidity is an important aspect of market quality that is desired by all market participants. However, it is a complex feature that include various components and dimensions, so it is difficult to define and measure. In the academic literature that examines liquidity, numerous measures have been suggested so far. These measures can be classified along with a variety of ways, such as indirect measures or direct measures, high-frequency measures or low-frequency measures, price-based, volume-based, or transaction cost measures. However, none of these measures is able to cover all the components and dimensions of liquidity.

In this study, different liquidity measures will be used to estimate the effect of post-trade transparency rule change implemented by Borsa Istanbul on liquidity. These measures are Xetra Liquidity Measure (XLM), Marginal Cost of Immediacy (MIC), Depth Weighted Spread (DWS), Effective Spread (EffSpread), and Volume

Weighted Effective Spread (VWES). Details of these liquidity measures are explained below.

3.3.1 Xetra Liquidity Measure (XLM)

Xetra Liquidity Measure (XLM) was first developed by Gomber and Schweickert (2002) and introduced by Deutsche Börse to measure the cost of immediately executing a transaction. It measures the liquidity of the market at a certain moment by taking all the orders available in the limit order book into account, including the undisclosed part of the iceberg orders.

XLM has two components which are liquidity premium (LP) and adverse price movement (APM). The liquidity premium is the extra return requested by investors for relatively illiquid assets and equals to the minimum cost of consuming liquidity. It is measured by half of the bid-ask spread and covers the width dimension of the liquidity.

However, liquidity premium becomes insufficient to measure price impact if the order is larger than the total volume available at the best level of the book. In such cases, market depth needs to be considered as it is done in the adverse price movement component of XLM.

For each stock and for a specific time t, let $P_{B,l}$ be the bid and $P_{A,l}$ be the ask price of the lth step of the book and $Q_{B,l}$ be the bid volume and $Q_{A,l}$ be the ask volume available at step l.

The liquidity premium is measured with the formula $LP = (P_{A,1} - P_{B,1})/2P_{MID}$ where midpoint price which is accepted as the fair price of the asset calculated as $P_{MID} = (P_{B,1} + P_{A,1})/2$.

Adverse price movement (APM) is measured as the volume-weighted average price incurred by an investor who wants to buy or sell a hypothetical order of size V measured in Turkish Liras (TL) at a specific time $t.$ Average volume-weighted price $VWAP_B, VWAP_A$) of buying or selling an order with size V is calculated as follows:

$$VWAP_B(V) = \frac{\sum_{l=1}^{L} P_{B,l}\, Q_{B,l}}{Q_B}$$

$$VWAP_A(V) = \frac{\sum_{l=1}^{L} P_{A,l}\, Q_{A,l}}{Q_A}$$

where $Q_B = \sum_{l=1}^{L} Q_{B,l}$ and $Q_A = \sum_{l=1}^{L} Q_{A,l}$

Accordingly, adverse price movement for the bid and ask side is calculated by taking the difference of best price level and the average price of trading V as follows:

$$APM_B(V) = (P_{B,1} - VWAP_B(V))/P_{MID}$$

$$APM_A(V) = (VWAP_A(V) - AP_{A,1})/P_{MID}$$

XLM is calculated for the bid and ask side as the sum of liquidity premium (LP) and adverse price movement (APM) and measured as follows:

$$XLM_B(V) = (LP + APM_B(V)) \times 100$$

$$XLM_A(V) = (LP + APM_A(V)) \times 100$$

$$XLM(V) = XLM_B(V) + XLM_A(V)$$

In summary, XLM measures liquidity at a specific point in time by taking all the information available in the order book into consideration. Therefore, XLM covers three dimensions of liquidity: market breadth is measured through liquidity premium component, market depth is measured through adverse price movement component, and immediacy in execution is covered through the computation logic of XLM since it calculates the immediate cost of execution at a certain point in time.

Adapted from Fullwood and Massacci (2018), the following figure visually represents the logic of XLM.

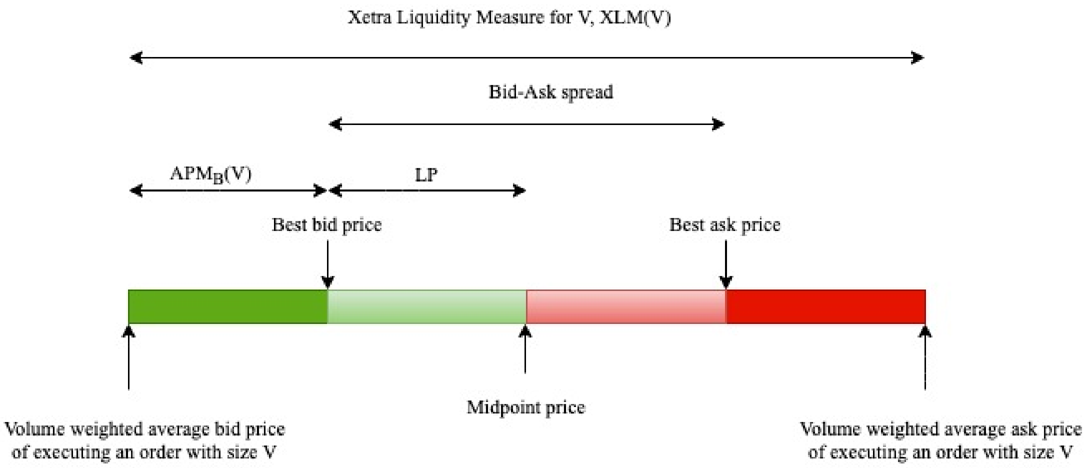

Figure 1. Visual Representation of XLM

Although XLM is an informative liquidity measure that covers many dimensions of liquidity, it has a limitation. It depends on the position size that is selected by the researcher, and different position sizes may result in different outcomes. Therefore, making stock-wide and time-series comparisons with XLM become difficult in some cases.

3.3.2 Marginal Cost of Immediacy (MCI)

Cenesizoglu and Grass (2017) suggested an alternative order book liquidity measure, Marginal Cost of Immediacy (MCI), which aggregates the information in the order book to calculate the cost of immediately executing buy and sell trades at a given point in time.

The rationale behind MCI was summarized by the authors with a quotation from Grossman and Miller (1988), who say that “the cost of trading immediately rather than delaying the order, particularly when the order is a large one, is the essence of market liquidity”.

As Cenesizoglu and Grass (2017) point out, MCI is a good liquidity measure for a variety of reasons. First of all, it aggregates the information in the order book by taking price and volume information of unexecuted orders into account. Second, it has a high correlation with Amihud’s illiquidity measure, which is an accepted liquidity measure widely used in the related literature. Finally, it allows making comparisons over time and across stocks. In this respect, it eliminates the shortcomings of XLM, which depends on the hypothetical order size, making comparisons across stocks difficult.

MCI_B (MCI_A) is calculated as the volume-weighted average price paid by an investor who trades all the bid orders pending in the order book up to 10 price levels divided by the total TRY volume of these trades.

For a given state of the order book at time t and for the Lth step at the bid side $VWAPM_{B,L}$ is defined as

$$VWAPM_{B,L} = \ln(\frac{VWAP_{B,L}}{P_{MID}})$$

where $VWAP_{B,L} = \frac{Vlm_{A,}}{\sum_{l=1}^{L} Q_{A,l}}$

and $Vlm_{B,L} = \sum_{l=1}^{L} P_{B,l} \times Q_{B,l}$

$P_{B,l}$ shows the price and $Q_{B,l}$ shows the volume at level l for the bid side of the order book. MP denotes midpoint price which is calculated as the average of the best bid and best ask quotes as

$$P_{MID} = (P_{A,1} + P_{B,1})/2$$

$$MCI_A = \frac{VWAPM_{A,10}}{Vlm_{A,10}}$$

$$MCI_B = \frac{-VWAPM_{B,10}}{Vlm_{B,10}}$$

In summary, MCI for the bid (ask) side shows the logarithmic return of volume-weighted average price of an investor who trades all the orders pending in the bid side of the order book up to 10 price levels relative to midpoint price. Logarithmic returns are scaled by the total TL volume of the trades.

3.3.3 Depth Weighted Spread (DWS)

Depth weighted spread (DWS), as it is also used by Martinez and Tapia (2021), is calculated as the difference of volume weighted average price of all the bid orders and volume weighted average price of all the ask orders available in the order book up to L price levels a specific time t.

$$DWS_t = \frac{100}{P_{MID}} \left(\frac{\sum_{l=1}^{L} P_{B,l} Q_{B,l}}{\sum_{l=1}^{L} Q_{A,l}} - \frac{\sum_{l=1}^{L} P_{A,l} Q_{A,l}}{\sum_{l=1}^{L} Q_{A,l}} \right)$$

3.3.4 Effective Spread

Effective spread is another measure of liquidity that is widely used in the literature, and it is defined as the difference of trade price and midpoint price prevailing at trade execution time. It is calculated for each trade i executed at time t as follows.

$$ESPR_t = 100 \times D_{i,t}(P_{i,t} - P_{MIDi,t})$$

where $D_{i,t}$ is a dummy variable that equals to 1 for buyer-initiated and -1 for seller-initiated trades, $P_{i,t}$ is the price of the trade executed at time t, and $P_{MIDi,t}$ is midpoint price which is calculated at time t with the formula $P_{MIDi,t} = (P_{Bi,t} + P_{Ai,t})/2$.

Aggregating over the trading day, a stock's Effective Spread is the weighted average of all effective spreads computed over all trades in the time interval. The weighting can be equal (dividing by the number of observations), by the number of shares traded (volume-shares), or by the number of shares traded times price (volume-TL).

3.3.5 Order Book Volume at Best Limit

Order book volume at best limit measures the volume available at the best bid and best ask prices measured in TRY terms. Higher volume at the best bid and ask prices imply higher liquidity. Following Roncalli and Zheng (2014), it is measured as follows:

$$BestAsk = P_{A,1}Q_{A,1} \text{ and } BestBid = P_{B,1}Q_{B,1}$$

$$BestVol = \frac{1}{100}(BestBid + BestAsk)$$

3.3.6 Order Book Depth

Order book depth measures the volume available at L steps of the order book. As it covers price levels behind the best limits, it contains more information than $BestVol$ measure. $Depth_{Ask}$ and $Depth_{Bid}$ are calculated as follows:

$$Depth_{Ask} = \frac{\sum_{l=1}^{L} P_{A,l} Q_{A,l}}{100} \quad \text{and } Depth_{Bid} = \frac{\sum_{l=1}^{L} P_{B,l} Q_{B,l}}{100}$$

Total depth is calculated as $Depth = Depth_{Ask} + Depth_{Bid}$

3.4 Data and Descriptive Statistics

The following parts explain the data used in the study, and present descriptive statistics.

3.4.1 Data and Sample Specification

As explained in Chapter 3, transparency was introduced in two different ways for stocks included in BIST 30 Index and for the remaining ones. For BIST 30 stocks, the change was implemented gradually in such a way that only five stocks became transparent each month until all the stocks became transparent for a month until the end of September. For the remaining stocks, the change was implemented in a direct way i.e., all the stocks had become post-trade transparent on April 03, 2017.

Based on different transparency regimes applied to BIST 30 stocks and the remaining ones, a separate analysis is conducted with two different samples to reflect this approach. The first sample consists of 70 stocks that are constituents of the BIST100 Index, but not BIST30 Index. Stocks in the BIST100 are selected as the first sample because BIST100, which is a market capitalization-based index, is the most widely followed benchmark index in Turkey, which tracks the performance of 100 selected stocks. As it is apparent from Table B2 in Appendix B, which shows stocks belonging to sample 1 together with their sectors, the first sample provides good sectoral coverage. In terms of market capitalization, these 70 stocks constitute around 17% of the whole market cap of all equities.

The second sample consists of 29 stocks that were components of the BIST30 Index and that were selected for the transparency rule change in the first stage. Two stocks, MAVI and DOHOL, are excluded from the sample since MAVI has started to be traded on June 15, 2017, and DOHOL was delisted from the BIST 30 Index and became transparent on June 21, 2017.

BIST 30 Index is mainly composed of blue-chip stocks that are traded in the Stars Market and also used as underlying in the Derivatives Market. Stocks in the second sample are shown in Table B1 in Appendix B with their sectors. This sample also provides good sectoral coverage and constitutes around 64% of the whole market cap of all equities.

In terms of trading activity, stocks in the BIST100 sample cover around 22%, and the BIST30 sample covers around 61% of the trading volume (TRY) of all stocks traded in the Equity Market.

Data for the first sample contains 70 stocks and 80 trading days with 40 trading days before (06/02/2017-31/03/2017) and 40 trading days after (03/04/2017-30/05/2017) the event date (03/04/2017). For the second sample, there is no single event date as the rule change had been implemented in an experimental setting within a six months period. Therefore, data for the second sample contains 29 stocks between the experiment period of 03/04/2017 and 29/09/2017. Half days are excluded (ie. 31/08/2020) from the second sample.

In summary, the final samples cover all the sectors including banks, holding and investment companies, telecommunication, consumer-trade, defense, food, beverage, and tobacco, chemicals, petroleum, rubber and plastic products, construction and public works, electricity, gas, and stem. Two samples cover around 81% of the total market capitalization and 83% of the trading volume of all stocks traded in the Equity Market.

For each stock, order and trade data is obtained from Borsa Istanbul. Liquidity variables of $XLM, MCI, DWS, Depth, BestVol$ are calculated using snapshots of the order book taken at every 5 minutes during the continuous auction stage of the trading session. In other words, order book liquidity measures of XLM, MCI, DWS, $Best$, and $Depth$ are calculated at every 5 minutes starting from 10:05 until 17:55. The start (at 10:00) and end (at 18:00) period of the continuous auction is not taken into account since, at the beginning of the session, the order book is not representative enough about the liquidity condition. Moreover, time intervals for midday call auction taking place between 13:00 and 13:55 and call auctions taking place as a result of circuit breakers which are triggered for volatile market conditions of a specific stock are excluded. Therefore, for each day in the sample period, these five liquidity measures are calculated using order book snapshots taken at 82 different time points (if no circuit breaker is triggered for the related stock).

XLM is calculated for ten different hypothetical order sizes of 10,000 TRY, 25,000 TRY, 50,000 TRY, 75,000 TRY, 100,000 TRY, 250,000 TRY, 500,000 TRY, 750,000 TRY, 1,000,000 TRY, and 1,500,000 TRY. In addition to these, given the difficulty of finding an optimal position size value that will apply to all stocks for the calculation of XLM due to different amount of orders available in the order book for different stocks, 1 percent and 5 percent of the average trading volume in TRY terms for each stock calculated in the sample period are also taken as hypothetical order size values.

For the BIST100 sample, there are enough orders available in the order book to fill the position sizes of 10,000 TRY, 25,000 TRY, 50,000 TRY, 75,000 TRY, 100,000 TRY, 250,000 TRY, 500,000 TRY, and 1 percent of the average trading volume for more than 70% of the data points. For the BIST30 sample, the total position available in the order book fulfills all the order sizes except 5% of the average trading volume for more than 70% of data points. If the order volume available in the order book at a specific point in time is not enough to fulfill a hypothetical order size, similar to the approach of Şensoy (2016), XLM is calculated with an assumption that the remaining part of the order is traded from the worst price level (i.e., highest ask for bid orders and lowest bid for ask orders).

To calculate effective spreads, transaction-level data is used, i.e., effective spreads are calculated for each trade executed during the continuous auction state of the session and averaged across the day. The average operation is either equal (dividing by the number of observations), by the number of shares traded (volume-shares), or by the number of shares traded times price (volume-TRY).

In the following two tables, correlation matrices for different liquidity measures are shown. Table 6 reports pairwise correlations for the BIST100 sample, while Table 7 reports pairwise correlations for the BIST30 sample.

For the BIST100 sample, XLM values with varying hypothetical position sizes are highly correlated if position sizes are close to each other. For instance, the correlation of XLM_500 with XLM_250 is 0.91 while it is even not correlated with XLM_10. XLM_1PC, which is calculated by taking 1% of each stock's average trading value as the hypothetical order size, has the highest correlation with

XLM_25. The value of MCI's correlation with other liquidity measures ranges from 0.03 (with XLM_1PC) and 0.75 (with XLM_250). DEPTH has the highest correlation with DWS, and BESTVOL has the highest correlation with DEPTH. For the BIST30 sample, XLM_1PC has the highest correlation with XLM_250, and MCI has the highest correlation with XLM_500, and it is positively correlated with XLM_250, XLM_750 and XLM_1000 with a correlation value of more than 0.80.

Table 6. Pairwise Correlations of Liquidity Measures for BIST100 Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) XLM_10	1.00															
(2) XLM_25	0.98*	1.00														
(3) XLM_50	0.87*	0.94*	1.00													
(4) XLM_75	0.70*	0.80*	0.95*	1.00												
(5) XLM_100	0.55*	0.68*	0.88*	0.98*	1.00											
(6) XLM_250	0.16*	0.29*	0.53*	0.70*	0.81*	1.00										
(7) XLM_500	0.00	0.12*	0.33*	0.48*	0.60*	0.91*	1.00									
(8) XLM_1PC	0.91*	0.92*	0.84*	0.70*	0.58*	0.23*	0.07*	1.00								
(9) MCI	-0.07*	0.11*	0.39*	0.58*	0.68*	0.75*	0.64*	0.03	1.00							
(10) DWS	0.93*	0.89*	0.73*	0.54*	0.39*	0.03	-0.08*	0.83*	-0.22*	1.00						
(11) DEPTH	0.59*	0.53*	0.38*	0.22*	0.11*	-0.18*	-0.29*	0.48*	-0.34*	0.63*	1.00					
(12) BESTVOL	0.66*	0.62*	0.50*	0.35*	0.24*	-0.05*	-0.16*	0.56*	-0.23*	0.60*	0.91*	1.00				
(13) ESPR_V	-0.14*	-0.11*	-0.06*	-0.01	0.02	0.06*	0.04*	-0.10*	0.15*	-0.25*	-0.19*	-0.13*	1.00			
(14) ESPR_TL	-0.14*	-0.11*	-0.06*	-0.02	0.01	0.06*	0.04*	-0.10*	0.14*	-0.25*	-0.19*	-0.13*	0.99*	1.00		
(15) ESPR_PC	0.99*	0.95*	0.81*	0.62*	0.46*	0.07*	-0.07*	0.89*	-0.18*	0.95*	0.62*	0.68*	-0.17*	-0.17*	1.00	
(16) LIQPREM	0.99*	0.95*	0.80*	0.61*	0.45*	0.06*	-0.08*	0.89*	-0.19*	0.95*	0.62*	0.68*	-0.17*	-0.17*	1.00*	1.00

* *p<0.01*

Table 7. Pairwise Correlations of Liquidity Measures for BIST30 Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) XLM_25	1.00															
(2) XLM_50	0.98*	1.00														
(3) XLM_100	0.83*	0.93*	1.00													
(4) XLM_250	0.42*	0.58*	0.83*	1.00												
(5) XLM_500	0.21*	0.38*	0.67*	0.95*	1.00											
(6) XLM_750	0.14*	0.30*	0.60*	0.90*	0.98*	1.00										
(7) XLM_1000	0.11*	0.26*	0.55*	0.85*	0.95*	0.99*	1.00									
(8) XLM_1PC	0.22*	0.36*	0.55*	0.65*	0.60*	0.55*	0.50*	1.00								
(9) MCI	0.04	0.23*	0.56*	0.90*	0.94*	0.92*	0.89*	0.65*	1.00							
(10) DWS	0.91*	0.84*	0.61*	0.13*	-0.07*	-0.12*	-0.13*	-0.01	-0.24*	1.00						
(11) DEPTH	0.32*	0.23*	0.03	-0.27*	-0.39*	-0.45*	-0.48*	-0.21*	-0.47*	0.47*	1.00					
(12) BEST	0.66*	0.58*	0.35*	-0.06*	-0.24*	-0.31*	-0.35*	-0.09*	-0.38*	0.70*	0.84*	1.00				
(13) ESPR_V	-0.10*	-0.04	0.07*	0.19*	0.20*	0.20*	0.19*	0.11*	0.23*	-0.21*	-0.23*	-0.21*	1.00			
(14) ESPR_TL	-0.12*	-0.05*	0.06*	0.19*	0.21*	0.21*	0.20*	0.10*	0.24*	-0.24*	-0.25*	-0.23*	0.98*	1.00		
(15) ESPR_PC	0.98*	0.92*	0.72*	0.26*	0.06*	0.00	-0.03	0.10*	-0.13*	0.95*	0.39*	0.71*	-0.11*	-0.14*	1.00	
(16) LIQPREM	0.98*	0.93*	0.73*	0.27*	0.06*	0.00	-0.02	0.09*	-0.13*	0.95*	0.39*	0.72*	-0.17*	-0.18*	0.99*	1.00

* *p<0.01*

3.4.2 Descriptive Statistics

The following two tables report summary statistics for trading activity and liquidity variables for BIST100 and BIST30 samples. For each stock, average market capitalization, trading volume (TL), volume available at the best price level (BESTBID), volume available at best ask price level (BESTASK), volume available at bid side (BIDVAL), and volume available at ask side (ASKVAL) are reported in millions TL, and trading volume (shares) is reported in million shares. INS_INV shows the average percent of shares owned by institutional investors calculated separately for each stock and for each day. Liquidity variables of XLM, DWS, and Effective Spreads are daily averages for each stock in percentages. MCI is the daily average for each stock measured in basis points per 1000 TL traded.

Summary statistics in Table 8 and Table 9 for BIST100 and BIST30 indices, respectively show the diversity of stocks both between and within samples. The average market capitalization of stocks in the BIST 30 sample (7,008 million TL) is around 11 times higher than the ones in BIST 30 sample (642 million TL). Average institutional ownership is also higher for BIST 30 stocks. In terms of trading activity, the average daily trading volume is 13,5 million TL for BIST 100 stocks, and it is 109,4 million TL for BIST 30 stocks. Average trade size, which shows the average number of shares traded with a single trade, is close for both samples, but average order size, which shows the average number of shares of an order, is higher for BIST 100 sample. All the liquidity measures show higher liquidity and lower volatility for BIST 30 sample.

Table 8. Descriptive Statistics for BIST 100 Sample

VARIABLES	Mean	SD	Min	Max	P10	P25	P50	P75	P90
MARKETCAP	642.13	647.70	84.45	4,350.21	173.76	270.00	437.57	754.76	1,113.40
VOLUME(TL)	13.53	23.79	0.14	517.42	1.59	3.01	6.31	14.20	30.38
VOLUME(SHARES)	4.26	9.73	0.00	200.99	0.08	0.24	1.14	3.97	10.76
NUMOFTRADES	1,813.08	2,317.84	92.00	43,469.00	426.00	697.50	1,168.50	2,049.50	3,608.50
AVGTRDSIZE	2,398.40	3,571.31	6.58	29,349.37	88.39	231.25	898.80	2,866.23	7,196.03
AVGORDERSIZE	6,222.01	11,475.28	15.88	112,149.48	176.44	494.56	1,943.07	6,198.54	17,761.75
INS_INV	0.70	0.25	0.04	0.99	0.32	0.58	0.80	0.89	0.95
XLM_10K	0.39	0.39	0.06	2.75	0.12	0.16	0.26	0.45	0.83
XLM_25K	0.44	0.39	0.06	2.75	0.15	0.20	0.31	0.52	0.85
XLM_50K	0.52	0.42	0.06	6.07	0.19	0.26	0.38	0.63	0.98
XLM_75K	0.60	0.50	0.07	10.07	0.21	0.31	0.45	0.71	1.13
XLM_100K	0.68	0.60	0.07	12.29	0.24	0.35	0.52	0.81	1.30
XLM_250K	1.22	1.28	0.08	18.40	0.36	0.57	0.83	1.37	2.45
XLM_500K	2.04	2.22	0.10	21.49	0.54	0.83	1.31	2.42	4.24
XLM_750K	2.70	2.83	0.12	23.40	0.71	1.02	1.75	3.31	5.51
XLM_1M	3.26	3.28	0.15	25.56	0.83	1.25	2.18	4.07	6.72
XLM_1.5M	4.16	3.91	0.20	29.08	1.02	1.67	2.84	5.17	8.93
XLM_1PC	0.56	0.36	0.10	2.75	0.27	0.35	0.46	0.65	0.87
XLM_5PC	1.58	1.20	0.33	17.09	0.71	0.90	1.27	1.84	2.66
MCI	0.39	0.56	0.01	10.29	0.06	0.11	0.22	0.45	0.82
DWS	2.26	1.97	0.43	14.62	0.67	0.95	1.54	2.90	4.62
BESTBID	0.47	1.15	0.00	12.71	0.01	0.02	0.07	0.32	1.18
BESTASK	0.40	0.92	0.00	9.93	0.01	0.02	0.07	0.29	1.09
BIDVAL	2.24	3.51	0.04	34.46	0.25	0.42	0.90	2.47	5.68
ASKVAL	3.47	4.77	0.03	42.92	0.34	0.60	1.62	4.56	8.25
ESPR_VOL	3.99	9.02	0.90	107.70	1.00	1.00	1.11	2.21	7.07
ESPR_PC	0.36	0.40	0.06	2.76	0.10	0.13	0.21	0.38	0.83
ESPR_TL	3.71	8.24	0.93	92.70	1.00	1.01	1.09	1.97	6.61
VOL_MP	0.16	0.10	0.00	1.16	0.08	0.11	0.14	0.20	0.27
VOL_MINMAX1	2.43	1.72	0.37	21.78	1.04	1.42	2.02	2.88	4.17
VOL_MINMAX2	0.67	0.45	0.09	3.82	0.31	0.39	0.54	0.80	1.19
Number of Observations	5,600								

Table 9. Descriptive Statistics for BIST 30 Sample

VARIABLES	**Mean**	**SD**	**Min**	**Max**	**P10**	**P25**	**P50**	**P75**	**P90**
MARKETCAP	7,008.23	5,848.25	669.68	26,881.61	1,658.19	3,249.75	4,387.39	10,569.24	14,037.84
VOLUME(TL)	109.36	151.89	1.75	1,797.04	12.10	20.54	56.29	129.86	260.26
VOLUME(SHARES)	14.91	23.74	0.04	259.37	0.47	1.23	4.31	18.49	43.34
NUMOFTRADES	4,933.26	4,233.19	417.00	69,121.00	1,835.00	2,584.00	3,827.00	5,675.00	8,876.00
AVGTRDSIZE	2,631.89	3,228.88	21.05	20,541.24	177.33	338.90	1,358.54	3,825.66	6,695.85
AVGORDERSIZE	5,748.20	7,716.50	56.73	87,897.19	370.00	711.90	3,151.89	7,640.05	13,625.48
INS_INV	0.86	0.15	0.32	0.99	0.64	0.81	0.92	0.96	0.98
XLM_10K	0.16	0.11	0.06	0.89	0.09	0.10	0.13	0.18	0.24
XLM_25K	0.17	0.11	0.06	0.89	0.09	0.11	0.14	0.19	0.24
XLM_50K	0.18	0.11	0.06	0.89	0.09	0.11	0.16	0.21	0.27
XLM_75K	0.20	0.12	0.06	0.89	0.10	0.12	0.17	0.23	0.33
XLM_100K	0.21	0.13	0.06	0.94	0.10	0.12	0.18	0.25	0.35
XLM_250K	0.33	0.27	0.06	2.60	0.11	0.15	0.24	0.40	0.69
XLM_500K	0.53	0.51	0.06	4.54	0.13	0.19	0.34	0.66	1.23
XLM_750K	0.71	0.71	0.06	5.40	0.15	0.23	0.43	0.92	1.72
XLM_1000	0.88	0.87	0.06	6.61	0.17	0.26	0.53	1.23	2.14
XLM_1500	1.18	1.13	0.07	9.99	0.21	0.33	0.73	1.81	2.76
XLM_1PC	0.43	0.31	0.06	3.49	0.23	0.27	0.34	0.48	0.68
XLM_5PC	1.55	0.80	0.10	6.85	0.71	0.98	1.41	1.96	2.53
MCI	0.09	0.11	0.00	0.88	0.01	0.01	0.04	0.11	0.23
DWS	1.22	0.73	0.38	5.54	0.62	0.77	0.97	1.48	1.91
BESTBID	0.81	1.33	0.01	15.53	0.05	0.10	0.26	0.86	2.27
BESTASK	0.86	1.39	0.01	11.48	0.05	0.10	0.28	0.94	2.55
BIDVAL	7.80	10.22	0.15	75.47	0.66	1.35	3.12	9.47	23.74
ASKVAL	13.11	17.19	0.19	113.81	1.02	2.14	5.13	17.69	36.78
ESPR_VOL	2.49	3.73	1.00	122.87	1.00	1.02	1.10	2.38	6.10
ESPR_PC	0.16	0.11	0.06	0.89	0.08	0.10	0.12	0.17	0.23
ESPR_TL	2.39	3.17	1.00	77.06	1.00	1.02	1.09	2.34	6.03
VOL_MP	0.14	0.07	0.00	1.10	0.09	0.10	0.13	0.16	0.21
VOL_MINMAX1	2.15	1.27	0.38	22.21	1.05	1.37	1.84	2.57	3.54
VOL_MINMAX2	0.53	0.22	0.18	3.93	0.34	0.40	0.49	0.60	0.77
Number of Observations	4,205								

3.5 Research Methodology and Results

3.5.1 Univariate Analysis

Before proceeding to multivariate analysis, univariate analysis is performed before and after the event date of the post-trade transparency rule change. To do so, for the BIST100 sample, the average of each variable is calculated for each stock and each day. Afterward, averages are taken for each variable over the pre-event period (40 days before the rule change) and post-event period (40 days after the rule change). $Diff$ is calculated as the difference between pre-event and post-event values. T-statistics are calculated to see whether the change in figures is statistically significant or not with the null hypothesis that $Diff$ is zero.

Table 10. Univariate Analysis for BIST100 Sample

VARIABLES	Pre-event	Post-event	Diff	t-test
VOLUME(TRY)	13.760	13.290	-0.47	-0.740
VOLUME(SHARES)	4.505	4.008	-0.497	-1.910
NUMOFTRADES	1,877.774	1,748.395	-129.379*	-2.090
AVGTRDSIZE	2,388.627	2,408.177	19.55	0.200
AVGORDERSIZE	5,995.887	6,448.143	452.256	1.475
XLM_10	0.396	0.383	-0.013	-1.21
XLM_25	0.445	0.427	-0.018	-1.76
XLM_50	0.530	0.501	-0.029*	-2.57
XLM_75	0.620	0.578	-0.042**	-3.16
XLM_100	0.713	0.656	-0.057***	-3.56
XLM_250	1.297	1.147	-0.15***	-4.39
XLM_500	2.161	1.913	-0.248***	-4.19
XLM_750	2.834	2.568	-0.266***	-3.52
XLM_1000	3.390	3.125	-0.266**	-3.03
XLM_1500	4.304	4.021	-0.283**	-2.71
XLM_1PC	0.570	0.542	-0.028**	-2.92
XLM_5PC	1.669	1.499	-0.17***	-5.32
MCI	0.410	0.370	-0.041**	-2.750
DWS	2.290	2.229	-0.061	-1.170
DEPTH	5.739	5.690	-0.05	-0.230
BESTVOL	0.859	0.874	0.015	0.270
ESPR_VOL	4.141	3.842	-0.299	-1.240
ESPR_PC	0.364	0.356	-0.009	-0.820
ESPR_TL	3.841	3.575	-0.266	-1.210
VOL_MP	0.170	0.159	-0.012***	-4.260
VOL_MINMAX	0.690	0.660	-0.03*	-2.490
VOL_MINMAX2	2.495	2.364	-0.131**	-2.860

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

As it is evident from Table 10, all the liquidity variables except DEPTH show an improvement of liquidity (a decline in the liquidity variables of XLM, MCI, DWS, and Effective Spreads imply an improvement in liquidity while the increase in BESTVOL and DEPTH imply liquidity improvement). Decrease in main liquidity variables including XLM with hypothetical order sizes ranging from 50 thousand TL to 5PC and in MCI is statistically significant.

In the post-event period, there is a decline in trading volume as measured in TL amounts and in the number of shares traded, but this change is not found to be statistically significant. The number of trades declines after the rule change while both average trade size which is calculated by dividing trading volume to number of trades, and average order size, which is calculated by dividing total order volume by the number of orders increase. However, only the change in the number of trades is statistically significant.

For the BIST30 sample, there is no single event date since the rule change was implemented gradually in a six month period in which only five stocks have become transparent each month. In this experimental setting, stocks that have become post-trade transparent form the treatment group while others that remain anonymous in and before the experiment month form the control group. Therefore, similar to the methodology employed by Dennis and Sandas (2020), a difference-in-difference approach is used such that difference in variables for treatment and control samples before and after the event date is analyzed. The scope of this experimental setting is limited to stocks included in BIST 30 index, and its composition changes quarterly. Moreover, according to the announcement of Borsa İstanbul, stocks are selected in a random way. Therefore, it is assumed that anonymity is randomly assigned to five stocks for each month (it should be noted that because only six stocks remained in the last month of the experiment, stocks that will become transparent were apparent before it was announced).

Table 11 reports the average of trading volume and liquidity variables before and after the event date for each month together with the difference of differences for control and treatment samples. Diff-and-diff of trading volume is positive for stocks in the treatment group on April, May, June, and July and negative for August and September. For April and May, this value is statistically significant, showing that trading volumes of stocks in the treatment group increased after the rule change.

The diff-and-diff of liquidity variables is not statistically significant for April, May, and June. In July, there is a significant increase in MCI, which means a decrease in liquidity. In August, XLM calculated for hypothetical order sizes of 500, 1000, and 1pc and MCI are all negative and statistically significant, implying an improvement in liquidity. In September, there is a significant increase in order book depth and a significant increase in MCI, meaning a decrease in liquidity.

In addition to diff-and-diff approach, a univariate analysis is also performed separately for each stock. As it can be seen from Appendix C, which reports the results for each stock and for each variable, there is a statistically significant change in at least one liquidity variable for 25 stocks. However, results are mixed in terms of the direction of the change such that there is an increase in liquidity for some stocks while liquidity is worsened for the others. In summary, univariate analysis for BIST 100 sample shows that liquidity has been increased after stocks in this sample had become transparent. However, for stocks in BIST 30 sample, these analyses are inconclusive.

Table 11. Diff-and-Diff Analysis for BIST30 Sample

Period	**Sample**	**Event**	**Volume**	**XLM_100k**	**XLM_500k**	**XLM_1000**	**XLM_1pc**	**MCI**	**DWS**	**Best**	**Depth**	**ESPR_TL**
April	Treatment	Before	63.411	0.228	0.624	1.008	0.398	0.100	1.302	1.429	16.382	1.460
		After	102.751	0.224	0.572	0.908	0.344	0.094	1.263	1.586	19.185	1.531
		Diff	39.339	-0.004	-0.052	-0.100	-0.054	-0.006	-0.039	0.157	2.804	0.070
	Control	Before	102.415	0.237	0.573	0.955	0.535	0.099	1.267	1.906	19.960	2.321
		After	112.640	0.224	0.512	0.844	0.475	0.083	1.260	1.977	22.750	2.235
		Diff	10.225	-0.012	-0.061	-0.111	-0.059	-0.016	-0.007	0.071	2.790	-0.086
		T-C Diff	*29.114**	*0.008*	*0.009*	*0.011*	*0.005*	*0.011*	*-0.032*	*0.086*	*0.014*	*0.156*
May	Treatment	Before	94.191	0.272	0.449	0.657	0.527	0.052	1.475	2.960	20.895	1.162
		After	169.482	0.236	0.373	0.546	0.423	0.041	1.570	2.848	28.499	1.364
		Diff	75.291	-0.036	-0.076	-0.111	-0.104	-0.011	0.096	-0.112	7.604	0.202
	Control	Before	117.495	0.212	0.528	0.893	0.462	0.091	1.204	1.719	23.238	2.517
		After	137.807	0.196	0.473	0.806	0.386	0.081	1.160	1.884	25.720	2.568
		Diff	20.312	-0.016	-0.055	-0.087	-0.076	-0.010	-0.044	0.166	2.482	0.051
		T-C Diff	*54.979***	*-0.020*	*-0.022*	*-0.025*	*-0.028*	*-0.001*	*0.139*	*-0.278*	*5.123*	*0.151*
June	Treatment	Before	78.919	0.215	0.566	0.981	0.308	0.099	1.235	1.257	18.148	2.694
		After	61.022	0.213	0.549	0.872	0.315	0.098	1.189	1.129	16.850	2.715
		Diff	-17.897	-0.002	-0.017	-0.110	0.007	-0.001	-0.046	-0.128	-1.298	0.021
	Control	Before	140.917	0.202	0.506	0.831	0.402	0.085	1.171	1.911	25.717	2.345
		After	107.420	0.195	0.475	0.799	0.381	0.076	1.159	1.732	24.090	2.393
		Diff	-33.497	-0.007	-0.031	-0.033	-0.021	-0.009	-0.012	-0.179	-1.626	0.048
		T-C Diff	*15.600*	*0.006*	*0.015*	*-0.077*	*0.028*	*0.009*	*-0.034*	*0.051*	*0.329*	*-0.027*
July	Treatment	Before	262.914	0.188	0.202	0.226	0.355	0.008	1.485	5.743	73.196	1.035
		After	310.111	0.176	0.193	0.218	0.334	0.008	1.403	5.651	73.158	1.052
		Diff	47.197	-0.011	-0.009	-0.008	-0.021	0.000	-0.082	-0.092	-0.038	0.018
	Control	Before	85.265	0.202	0.486	0.811	0.386	0.078	1.194	1.327	17.467	2.343
		After	86.440	0.188	0.433	0.748	0.362	0.065	1.164	1.226	16.239	2.596
		Diff	1.175	-0.014	-0.053	-0.063	-0.024	-0.013	-0.030	-0.101	-1.228	0.253
		T-C Diff	*46.021*	*0.003*	*0.044*	*0.055*	*0.003*	*0.013***	*-0.052*	*0.009*	*1.191*	*-0.235*

Period	Sample	Event	Volume	XLM_100k	XLM_500k	XLM_1000	XLM_1pc	MCI	DWS	Best	Depth	ESPR_TL
August	Treatment	Before	111.600	0.148	0.281	0.454	0.299	0.039	1.031	1.157	19.592	5.544
		After	111.107	0.166	0.347	0.575	0.324	0.055	1.027	1.043	17.374	5.997
		Diff	-0.493	0.017	0.066	0.121	0.025	0.016	-0.004	-0.114	-2.219	0.453
	Control	Before	74.851	0.197	0.481	0.828	0.357	0.073	1.184	1.257	15.862	1.931
		After	74.413	0.229	0.675	1.200	0.462	0.110	1.194	1.003	13.346	2.215
		Diff	-0.438	0.032	0.194	0.372	0.104	0.037	0.009	-0.254	-2.517	0.284
		T-C Diff	*-0.055*	*-0.014*	*-0.128***	*-0.250****	*-0.079****	*-0.021***	*-0.013*	*0.141*	*0.298*	*0.168*
September	Treatment	Before	50.117	0.230	0.840	1.660	0.541	0.136	1.014	0.324	4.619	1.915
		After	50.263	0.260	0.962	1.742	0.646	0.175	1.053	0.330	4.394	1.881
		Diff	0.146	0.030	0.122	0.082	0.105	0.039	0.039	0.006	-0.225	-0.034
	Control	Before	121.415	0.220	0.541	0.885	0.423	0.085	1.291	1.826	24.178	2.126
		After	134.880	0.222	0.582	0.917	0.483	0.093	1.260	1.493	19.058	2.010
		Diff	13.465	0.002	0.042	0.032	0.060	0.008	-0.031	-0.333	-5.120	-0.116
		T-C Diff	*-13.319*	*0.028*	*0.080*	*0.050*	*0.045*	*0.031**	*0.070*	*0.339**	*4.895***	*0.082*

3.5.2 Multivariate Analysis

In order to assess the effect of post-trade transparency on liquidity in a more effective manner, in addition to univariate analysis, which is not explanatory of the changes in liquidity measures, a multivariate approach is necessary, which takes other factors that may have an influence on liquidity into account.

Similar to previous literature, including Foucault et al. (2007) and Hachmeister and Schiereck (2010), the following equation is specified to measure the effect of transparency on liquidity.

$$Liquidity_{i,t} = \alpha + \beta_1 \ln(Volume)_{i,t} + \beta_2 Volatility_{i,t} + \beta_3 RelTickSize_{i,t} + \beta_4 Transparency_{i,t}$$

where subscript i represents individual stock and t represents the day. $Liquidity$ as a dependent variable is measured either with $XLM(V)$ with different values of V, MCI, DWS, $BestVol$, $Depth$, or $ESPR$. Explanatory variables in this specification are $\ln(Volume)$, $Volatility$, and $RelTickSize$. $\ln(Volume)$ is natural logarithm of daily traded volume measured in TL. $Volatility$ ($VOL\_MINMAX1$) is calculated as the ratio of maximum and minimum prices calculated at every 15 minutes and then averaged per day per stock to obtain a single figure of volatility as follows:

$$Volatility_{minmax} = \frac{\sum \frac{High}{Low}}{n}$$

$RelTickSize$ is $Tick$ which is the minimum price movement that a financial instrument can increase/decrease in each trade divided by the closing price of stock i for day t.

$$Tick = \frac{Tick_{it}}{ClosingPrice_{it}}$$

$Transparency$ is a period dummy that takes the value of 0 before the transparency rule change implemented by Borsa Istanbul and 1 after the rule change. Earlier studies show that $\beta_1 > 0, \beta_2 < 0$ and $\beta_3 < 0$.

Using this model, panel regressions are estimated for each of the liquidity variables. Stock fixed effects are included to capture stock level differences in the sample. As suggested by Hoechle (2007), Driscoll-Kraay standard errors are used because of the presence of cross-sectional dependence observed in the data together with heteroscedasticity and autocorrelation.

Table 12 reports estimation results for the BIST100 sample. It shows that liquidity has been improved after the switch to post-trade transparency regime for all the liquidity variables except $Depth$ and $Best$ for which there is a decrease after the rule change. $lnVolume$ has a positive effect on liquidity as expected but $Volatility$ has a negative effect implying that the cost of trading becomes higher in volatile market conditions. Finally, results provide mixed evidence for the relationship between $RelTickSize$ and liquidity.

Table 12. Estimation Results for BIST100 Sample

VARIABLES	XLM_50	XLM_75	XLM_100	XLM_250	XLM_500	XLM_1PC	MCI	DWS	ESPR_V	ESPR_TL	Depth	Best
Transparency	-0.015**	-0.025***	-0.037***	-0.115***	-0.193***	-0.011**	-0.023**	-0.034*	-0.237**	-0.211***	-0.272**	-0.007
	(0.006)	(0.009)	(0.013)	(0.035)	(0.052)	(0.005)	(0.010)	(0.019)	(0.091)	(0.064)	(0.119)	(0.020)
LnVolume	-0.114***	-0.167***	-0.223***	-0.550***	-0.906***	-0.134***	-0.237***	-0.008	-0.510***	-0.507***	1.702***	0.111***
	(0.008)	(0.012)	(0.016)	(0.039)	(0.051)	(0.006)	(0.017)	(0.013)	(0.123)	(0.072)	(0.091)	(0.020)
Volatility	0.297***	0.413***	0.531***	1.156***	1.716***	0.347***	0.621***	0.538***	2.402***	2.121***	-2.236***	-0.444***
	(0.028)	(0.041)	(0.056)	(0.124)	(0.161)	(0.025)	(0.060)	(0.052)	(0.364)	(0.262)	(0.245)	(0.058)
RelTickSize	0.382***	0.115	-0.161	-1.657***	-2.507***	0.436***	-0.837***	1.553***	-2.962***	-2.839***	-16.582***	-0.825
	(0.074)	(0.108)	(0.147)	(0.381)	(0.634)	(0.092)	(0.150)	(0.464)	(0.699)	(0.514)	(2.159)	(0.560)
Constant	1.988***	2.922***	3.894***	9.686***	16.031***	2.292***	3.976***	1.528***	11.478***	11.277***	-13.927***	-0.304
	(0.130)	(0.194)	(0.271)	(0.669)	(0.924)	(0.104)	(0.263)	(0.283)	(1.911)	(1.114)	(1.754)	(0.372)
Observations	5,600	5,600	5,600	5,600	5,600	5,600	5,600	5,600	5,600	5,600	5,600	5,600
# of groups	70	70	70	70	70	70	70	70	70	70	70	70
Adj.R2	88.1	77.6	71.3	62.2	67.9	91.4	74.0	96.7	90.7	93.0	93.5	93.0

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Previous studies, including Linnainmaa and Saar (2012) and Meling (2021) assumed that institutional investors are more likely to have private information and they take institutional investors as a proxy of informed investors. Meling (2021) also showed that retail investors do not respond to the change in the anonymity regime by adjusting their trading behavior, while the increase in liquidity observed after the anonymous trading regime was due to the increased activity of institutional investors.

Considering these findings observed in the earlier literature, stocks included in the BIST100 sample is divided into two groups based on their institutional ownership levels in the analysis period. In the resulting groups, stocks with average institutional ownership larger than 70% are assigned to high institutional ownership sample (HIO), and remaining stocks are assigned to low institutional low institutional ownership (LIO) sample. In the final analysis, there are 35 stocks in each of the samples.

Panel A and Panel B of Table 13 report the results for HIO and LIO samples, respectively. As it is evident from these tables, liquidity has been improved after the switch to post-trade transparency for both samples. However, XLM_50, XLM_100, MCI, ESPR_V, and Depth measures are not statistically significant for the LIO sample, and the magnitude of the Transparency coefficient is relatively smaller in general. For the HIO sample, the transparency dummy is insignificant only for XLM_1pc and DWS measures.

One limitation of this analysis is that high institutional ownership does not always imply increased trading activity of these investors. For instance, institutional investors whose trading volume is large are not represented in this figure if they do not hold a position at the end of the day. Similarly, institutional investors that hold a large number of shares may not trade at all.

Table 13. Estimation Results for BIST 100 Sample with High/Low Institutional Ownership

Panel A – Estimation Results for Stocks with High Institutional Investor Ownership (HIO)											
VARIABLES	XLM_50	XLM_100	XLM_250	XLM_500	XLM_1pc	MCI	DWS	ESPR_V	ESPR_TL	Depth	Best
Transparency	-0.033***	-0.080***	-0.160**	-0.211**	-0.011	-0.046**	-0.003	-0.341**	-0.274**	-0.361***	-0.085**
	(0.010)	(0.025)	(0.065)	(0.097)	(0.007)	(0.018)	(0.019)	(0.160)	(0.126)	(0.083)	(0.035)
Volume	-0.137***	-0.263***	-0.603***	-0.902***	-0.140***	-0.284***	-0.019	-0.852***	-0.821***	1.684***	0.128***
	(0.011)	(0.024)	(0.055)	(0.070)	(0.007)	(0.023)	(0.014)	(0.169)	(0.099)	(0.099)	(0.027)
Volatility	0.410***	0.674***	1.252***	1.588***	0.426***	0.917***	0.489***	4.311***	3.773***	-2.856***	-0.440***
	(0.039)	(0.100)	(0.225)	(0.284)	(0.033)	(0.085)	(0.055)	(0.568)	(0.420)	(0.300)	(0.065)
RelTick	-0.551***	-2.263***	-6.024***	-7.584***	-0.306**	-2.183***	0.920	-8.020***	-7.337***	-16.193***	0.352
	(0.203)	(0.471)	(1.172)	(1.525)	(0.131)	(0.371)	(0.729)	(1.940)	(1.609)	(5.698)	(1.563)
Constant	2.559***	5.054***	11.700***	17.464***	2.520***	4.957***	1.633***	18.024***	17.275***	-14.783***	-0.946
	(0.208)	(0.472)	(1.102)	(1.387)	(0.121)	(0.394)	(0.246)	(2.749)	(1.714)	(2.404)	(0.571)
Observations	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
# of groups	35	35	35	35	35	35	35	35	35	35	35
Adj. R2	76.14	63.88	62.05	67.09	80.63	75.06	94.22	90.88	92.79	93.09	92.11
Panel B – Estimation Results for Stocks with Low Institutional Investor Ownership (LIO)											
VARIABLES	XLM_50	XLM_100	XLM_250	XLM_500	XLM_1pc	MCI	DWS1	ESPR_V	ESPR_TL	Depth	Best
Transparency	0.001	-0.002	-0.089***	-0.204***	-0.014**	-0.001	-0.070**	-0.123	-0.139**	-0.191	0.077***
	(0.005)	(0.010)	(0.022)	(0.048)	(0.006)	(0.009)	(0.027)	(0.082)	(0.058)	(0.186)	(0.028)
Volume	-0.093***	-0.188***	-0.509***	-0.931***	-0.133***	-0.195***	0.003	-0.183**	-0.204***	1.748***	0.098***
	(0.007)	(0.014)	(0.044)	(0.066)	(0.007)	(0.014)	(0.019)	(0.079)	(0.053)	(0.112)	(0.028)
Volatility	0.217***	0.421***	1.066***	1.809***	0.305***	0.424***	0.555***	1.075***	0.954***	-1.953***	-0.438***
	(0.024)	(0.047)	(0.123)	(0.178)	(0.026)	(0.045)	(0.091)	(0.252)	(0.180)	(0.290)	(0.085)
RelTick	0.597***	0.285***	-0.848**	-1.797***	0.560***	-0.484***	1.669***	-1.090***	-1.150***	-16.528***	-1.022*
	(0.053)	(0.108)	(0.328)	(0.619)	(0.084)	(0.093)	(0.559)	(0.348)	(0.257)	(2.455)	(0.571)
Constant	1.622***	3.211***	8.749***	16.060***	2.283***	3.278***	1.567***	5.575***	5.813***	-13.498***	0.020
	(0.109)	(0.221)	(0.714)	(1.129)	(0.112)	(0.212)	(0.393)	(1.186)	(0.799)	(2.075)	(0.560)
Observations	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800	2,800
# of groups	35	35	35	35	35	35	35	35	35	35	35
Adj. R2	95.46	83.28	61.72	68.59	94.59	71.22	97.26	89.97	93.74	93.85	94.33

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 14 presents results for the multivariate regression analysis applied to BIST 30 sample that includes blue-chip stocks with the highest market capitalization. The coefficients for other explanatory variables are all significant and as expected (except TickSize, which shows mixed results). Coefficients of the Transparency dummy show that there is a statistically significant decline in liquidity after the switch to transparency when liquidity is measured with five different methods (XLM_50, XLM_100, XLM_250, MCI, ESPR_TL), and there is an increase in order book depth. However, the magnitude of the change is relatively small, estimating an increase in these four XLM measures ranging from around 0.5 to 2 basis points.

Table 14. Estimation Results for BIST30 Sample

VARIABLES	XLM_50	XLM_100	XLM_250	XLM_500	XLM_1000	XLM_1pc	MCI	DWS	ESPR_V	ESPR_TL	Best	Depth
Transparency	0.005***	0.008***	0.020**	0.037	0.048	0.006	0.009**	0.007	0.098	0.133*	0.051	1.032**
	(0.002)	(0.003)	(0.010)	(0.023)	(0.042)	(0.008)	(0.004)	(0.011)	(0.071)	(0.071)	(0.067)	(0.492)
logVolume	-0.043***	-0.078***	-0.189***	-0.352***	-0.572***	-0.308***	-0.080***	-0.016**	-0.397	-0.345**	0.685***	9.786***
	(0.003)	(0.005)	(0.014)	(0.028)	(0.040)	(0.018)	(0.006)	(0.006)	(0.271)	(0.169)	(0.058)	(0.697)
Volatility	0.106***	0.186***	0.467***	0.898***	1.488***	0.681***	0.185***	0.193***	2.740***	2.193***	-1.899***	-21.066***
	(0.008)	(0.015)	(0.047)	(0.091)	(0.122)	(0.073)	(0.021)	(0.025)	(1.000)	(0.628)	(0.221)	(2.483)
TickSize	0.796***	0.655***	0.199**	-0.437**	-1.118***	-0.463***	-0.300***	3.066***	0.731	0.705	18.134***	45.549***
	(0.020)	(0.038)	(0.097)	(0.184)	(0.290)	(0.143)	(0.042)	(0.309)	(0.682)	(0.458)	(1.529)	(11.080)
Constant	0.785***	1.414***	3.421***	6.388***	10.430***	5.619***	1.453***	0.982***	7.996*	7.264***	-12.057***	-148.802***
	(0.053)	(0.091)	(0.241)	(0.479)	(0.705)	(0.313)	(0.102)	(0.118)	(4.421)	(2.765)	(1.015)	(12.181)
Observations	4,205	4,205	4,205	4,205	4,205	4,205	4,205	4,205	4,205	4,205	4,205	4,205
# of groups	29	29	29	29	29	29	29	29	29	29	29	29
Adj. R2	93.8	85.6	76.2	76.1	76.2	73.5	76.5	96.1	74.3	85.2	88.6	89.6

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.5.3 Robustness of Results

In this part, additional analyses are performed to check the robustness of results obtained for the BIST100 sample. First of all, in addition to the estimations with 40 trading days before and 40 days after the event date, the multivariate model is estimated with shorter ($\pm$30 days) and longer (±50 days) time periods. Moreover, to allow for a period of learning, one week before and one week after the event date is excluded from the BIST 100 sample.

In the related literature, volatility is measured with different methods. Following different methodologies used in the literature, in addition to the volatility measure explained above, the following two methods are used as well.

- VOL_MP: Daily standard deviation of midpoint returns calculated at every 15 minutes during the continuous trading session, averaged per stock per day
- $VOL\_MINMAX2$: Calculated as the ratio of daily maximum and daily minimum prices divided by daily volume-weighted average price.

All of these estimations show that the liquidity improvement that is observed for the BIST100 sample after the post-trade transparency regime is robust to length of the event window and selection of the volatility measure.

CHAPTER 4

INFORMATION CONTENT OF LIMIT ORDER BOOK

This chapter analyzes the informativeness of the limit order book by measuring the contribution of orders resting in the book beyond the best price levels to the price discovery process. The first part of the chapter summarizes findings of the previous literature on the limit order book to be followed by literature on price discovery measures. The second part introduces the methodology, including order book metrics and price discovery measures used in the analysis. The third part is about data and samples with summary statistics of the order book and trading activity of the sample stocks. The next two parts provide the results for two separate samples.

4.1 Introduction

As De Jong and Rindi (2009) point out "orders are traders' statements of their intention to trade". In electronic limit order markets, traders show their trading intentions by submitting different kinds of orders, with limit and market orders being the most common types. Limit orders are entered into the system with price and volume information specified by the traders. A limit ask order is being traded at or above, and a limit bid order is being traded at or below the order's price. If it is not executed, it rests in the order book until it is matched with an incoming order or canceled by the trader. Market orders are submitted only with volume information, and they are traded from the best available prices, and if there is any remaining part, it is automatically deleted. Marketable limit orders are similar to market orders submitted with a price equal to or better than the best price at the opposite side of the book. Given the characteristics of these orders, it can be generalized that limit orders are used by patient traders that increase the depth of the book and supply liquidity, while market orders are used by impatient traders that consume liquidity (De Jong and Rindi, 2009).

A limit order book is constructed from all the unexecuted limit orders ranked according to price and time priority rules. It consists of information regarding direction (bid or ask), price, volume, and timestamp of each order. In other words, for a specific point in time, the state of the order book contains information regarding all the unexecuted orders. Given the amount of information embedded in it, studying the limit order book may provide valuable information about the functioning of financial markets.

One important factor that determines whether the information in the order book provided valuable information is the type of traders submitting limit orders to the system and their strategies. If informed traders submit limit orders, then the limit order book is expected to carry their information. However, if they submit market orders instead, then their information is not reflected in the book.

O’Hara (2003) points out that financial markets have two primary functions: providing liquidity and facilitating price discovery. The first one is related to ease of buying and selling a security with a minimum cost, while the second one is related to the speed of how new information is reflected in prices of financial assets. Since price discovery is a key function of exchanges, understanding how limit order book contributes to the price discovery process, and how pre-trade transparency affects this process is two important questions to be answered.

The aim of this study is to understand the contribution of the information available in the limit order book to the price discovery process for the most liquid stocks traded at Borsa İstanbul. The analysis is performed by measuring information shares of different price series, including last trade price, best prices of the order book, and price steps beyond the best price levels so that it becomes possible to measure the contribution of orders beyond best prices to price discovery.

In February 2016, there has been an improvement in the pre-trade transparency policy of Borsa İstanbul, such that the top ten price levels instead of five started to be disseminated in real-time data feeds. Taking this rule change as an experiment, the effect of disclosing price and volume of order book steps between 6 and 10 on the information shares of these price steps is analyzed.

Finally, the information content of LOB is analyzed using more recent data for the months of May and June of 2019. This dataset allowed us to make an analysis for days with positive and negative returns and to see how the contribution of the LOB to price discovery changes with respect to changes in market conditions.

4.2 Literature on the Information Content of Limit Order Book

The question of whether limit order book (LOB) conveys any information is an active discussion in the market microstructure literature, and it is directly linked to the issue of whether market or limit orders are used by informed and uninformed traders to execute their trades. If informed traders who have private information about the fundamental value of the asset prefer to submit limit orders, then LOB is expected to reflect their information. However, if they choose to trade through market orders which are immediately executed without being placed in the book, then their information is not expected to be reflected in the book.

Earlier theoretical models that analyzed LOB, including Glosten (1994), Glosten and Milgrom (1985), Rock (1996), and Seppi (1997), are based on the assumption that uninformed traders are liquidity providers who submit limit orders which are executed only when market orders which are submitted by informed traders are entered into the trading systems. Therefore, these models implicitly imply that LOB does not convey any information to predict future price movements.

However, after more and more exchanges switched to electronic limit order markets without any designated market makers, this assumption is relaxed in the theoretical models, and informed traders are allowed to choose both limit and market orders in rational expectations equilibrium. In these models, it is also documented that informed traders may strategically choose to submit limit orders. In such a case, LOB is shown to be predictive about future price movements.

By modifying the model suggested by Glosten and Milgrom (1985), Kaniel and Liu (2006) studied whether informed traders use limit or market orders in the equilibrium and showed that informed traders might choose to use limit orders in place of market orders and the probability of choosing limit orders may be high enough that limit orders may convey more information then market orders do. However, the preference of informed traders' submission of limit orders depends, to a large extent, on the horizon of private information they have. If their private information is short-lived, they would not take the unexecution risk of limit orders and choose to enter market orders which are immediately executed. However, if the information they have is expected to be long-lived, then they prefer to enter limit orders which are executed with better prices as compared to market orders.

Using an experimental design that includes informed and liquidity traders, Bloomfield, O'Hara, and Saar (2005) showed that informed traders use limit orders and provide liquidity to the market more than liquidity traders do. However, their decision to use limit orders depends, to a large extent, on the value of the information they have. If the value of the information they have is high (low), they submit market (limit) orders and take (make) liquidity. The authors also showed that informed traders use market orders early in the day but choose to submit limit orders during the rest of the day, while the opposite is true for the liquidity traders.

Anand, Chakravarty, and Martell (2005) explored the question of whether informed traders choose to trade via limit or market orders during different stages of the trading day with an assumption that institutional investors are informed while individual investors are uninformed. Using data from New York Stock Exchange, the authors showed that informed traders use market orders during the earlier part of the trading day to take advantage of their private information. However, they used limit orders later in the trading session. Therefore, the authors confirmed the results that Bloomfield et al. (2005) reached using an experimental setting in an empirical study. They also showed that limit orders submitted by informed investors perform better than the ones submitted by uninformed investors.

Another strand of literature analyzes the information content of LOB by asking the question of whether LOB is predictive about future price changes. Harris and Panchapagesan (2005) used asymmetry in the bid and ask side as measured by both quantities and option values obtained from limit orders using Black-Scholes formulation as a measure of the information in the LOB. Their results showed that information in the LOB conveys information regarding future price changes.

Cont, Kukanov, and Stoikov (2011) explored the price impact of order book messages that can be classified as market orders, limit orders, and order cancellations by creating a single variable which is defined as order flow imbalance (OFI) and showed that OFI explained high-frequency price changes for a large sample of stocks with an adjusted R-squared of 65%. The authors also provided evidence that there is a negative relation between price impact coefficient and order book depth. Moreover, they also showed that trade price does have explanatory power about future price changes when OFI is taken into account.

Cao, Hansch, and Wang (2009) analyze the contribution of the information in the order book behind best prices to price discovery. To do so, using order book data for the month of March 2000 of most actively traded 100 stocks listed in the Australian Stock Exchange, the authors tested two hypotheses related to the information content of the order book. First of all, they calculated Hasbrouck Information Shares for midpoint price, last trade price, and weighted price of the orders resting in the order book between 2nd and 10th price levels. They found out that the contribution of the orders behind the best price levels is around 22%. Second, they analyzed the predictability of short-term returns from the information in the order book and found out a significant relationship between the two.

Hautsch and Huang (2012) analyzed the short-run and long-run price impact of limit orders using a cointegrated vector autoregressive (VAR) method by taking various characteristics of the order into account, including aggressiveness, volume, and conditions of the order book. Treating each limit order as a shock to the system, impulse response functions have been evaluated for 30 stocks listed on Euronext Amsterdam in 2008. Their results showed that limit orders, especially the first two levels of the book, have an impact on quote adjustments, and this effect increased with the size of the order. Limit orders narrow down the spread and market orders, while the opposite is true for market orders. These results implicitly imply that the order book contains private information of informed traders.

Similar to Cao et al. (2009), Arzandeh and Frank (2019) estimated the contribution of the information hidden in the limit order book beyond best bid and best ask prices to price discovery for agricultural commodity futures traded in

Chicago Mercantile Exchange (CME) Group. However, different from Cao et al. (2009), in addition to Hasbrouck Information Share, they used two other price discovery measures, which are Gonzalo and Granger Permanent-Transitory Effect (PT) and Modified Information Share (MIS). Their results suggest that orders beyond the best price levels contribute to price discovery for more than 27%, which is higher than the value found out for stock markets in the study of Cao et al. (2009). Furthermore, results for agricultural commodity futures show that order book steps that are closer to the best levels convey more information than the rest of the book.

Some studies approached the topic with a focus on the strategies of high-frequency traders. Brogaard, Hendershott, and Riordan (2019) analyzed the contribution of limit and market orders to price discovery by differentiating orders submitted through HFT and non-HFT channels. To do so, they used vector auto-regression (VAR) methodology suggested by Hasbrouck (1991a,1991b,1995) and showed that although market orders have a higher impact on price, the contribution of market orders submitted by HFT traders is very small while limit orders contribute a lot to price discovery. The contribution of HFT traders' limit orders to price discovery is found to be around 30%, while it is just 15% for non-HFT traders. However, this result changes under stressful market conditions under which HFTs trading behavior changes to further increase market volatility, and market orders start to contribute more to price discovery.

4.3 Literature on Measuring Price Discovery

In efficient financial markets, prices of the assets should reflect the fundamental value of the asset, and new information should immediately be reflected in prices. However, in the real world there are many market imperfections that move market prices away from the fundamental value, such as asymmetric information, government regulations, financial taxes, implicit or explicit transactions costs, and other microstructure frictions. Therefore, price discovery that means the process of the incorporation of new information into prices, is regarded as a key function of financial markets.

Understanding the mechanism underlying the price discovery process in financial markets has long been an interesting topic in market microstructure studies, and various methods have been suggested so far by researchers to further understand and measure how the price discovery process works in reality. Such studies generally explore different price series' contributions to price discovery either for assets cross-listed in different markets or for spots and derivatives of the same financial asset like stocks, commodities, or currencies. Moreover, as examples are provided in the literature review part, there are studies that investigate the contribution of order book or different stages of the trading day to the price discovery process.

Two widely used price discovery models are by Gonzalo and Granger (1995), which is known as permanent-transitory (PT), and Hasbrouck (1995), which is known as information shares (IS). Although both models are based on a vector error correction model (VECM), their definition of price discovery is not the same. IS model suggested by Hasbrouck (1995) considers variance of the innovations to the efficient price and calculates each price series' contributions to this variance. On the other hand, the PT model suggested by Gonzalo and Granger (1995) calculates each series' contribution to the efficient price, which is modeled as a linear function of VECM coefficients.

As pointed out by Baillie, Booth, Tse, and Zabotina (2002), IS and PT models provide similar results only if the residuals of VECM are not correlated.

Since the PT model does not take these correlations into account, it becomes flawed when there is a contemporaneous correlation between price series. IS model incorporates correlations through Cholesky decomposition, but it makes the results vulnerable to the ordering of prices. In other words, since different results are obtained with different orderings, IS measures are not unique. To overcome this problem, information shares are generally calculated for all the ordering combinations, and minimum and maximum values are obtained. However, the range of upper and lower bounds for information shares may be too high that interpreting the results would be very complicated.

Another model is suggested by Lien and Shrestha (2009), known as Modified Information Share (MIS). In this model, to model contemporaneous correlations of residuals, eigenvector factorization is used instead of Cholesky decomposition, which does not depend on the ordering of the variables. Therefore, the MIS model overcomes the shortcomings of IS model and provides a unique measure. Lien and Shrestha (2009) also empirically show that the MIS measure outperforms PT and IS models.

4.4 Methodology

4.4.1 Limit Order Book Variables

Following the methodology used in Cao et al. (2009), the shape of the order book is modeled by two summary measures known as length and height of each price step for bid and ask side.

The height of a particular price level and side is defined as follows:

$$H_j^b = P_j^b - P_{j-1}^b$$

$$H_j^a = P_j^a - P_{j-1}^a$$

where P_j^b is the bid price at step j on the buy-side and P_j^a is the ask price at step j on the sell side of the order book. The height of the best bid (ask) is defined as the difference between the price at the best bid (ask) and the mid-quote of the best bid and ask price. The height of each step will be normalized by the aggregate height (calculated as the difference between the price of the 10$^{\text{th}}$ price level and midpoint price).

The length of each price level L_j^b (L_j^a) is the aggregate number of shares for all orders at price P_j^b (P_j^a). The length of each step will be normalized by aggregate length as well (aggregate length is calculated as the sum of volumes available at price steps between 1 and 10).

Price and the quantity aspect of the order book is combined as a single value defined as a weighted price metric that is calculated as follows:

$$WP^{k_1-k_2} = \frac{\sum_{j=k_1}^{k_2}(L_j^b P_j^b + L_j^a P_j^a)}{\sum_{j=k_1}^{k_2}(L_j^b + L_j^a)}, k_1 \leq k_2$$

For the first step of the order book, WP^1, the weighted average mid-quote is calculated as follows:

$$WP^1 = \frac{L_1^b P_1^b + L_1^a P_1^a}{L_1^b + L_1^a}$$

The weighted price measure summarizes all the information contained in the order book for the selected steps k_1 and k_2. It reflects changes in supply and demand conditions as its value changes whenever bid or ask price or volume change in one of the steps.

4.4.2 Error Correction Model and Information Shares

Similar to the methodology used in Arzandeh and Frank (2019), three different methods are used to analyze the contribution of LOB on the price discovery process. In addition to the permanent-transitory (PT) model suggested by Gonzalo and Granger (1995) and information shares model suggested by Hasbrouck (1995), commonly used in the price discovery literature, modified information shares (MIS) method suggested by Lien and Shrestha (2009) is also used.

All these models are based on a VECM that is based on the idea that different price series may be non-stationary, but because they depend on the same underlying asset, they are cointegrated and move together in the long run. Therefore, VECM is an appropriate model to analyze cointegrating relations of price series, and it captures short-term deviations from the efficient price. VECM also enables the researcher to measure the contribution of different prices to the changes of the efficient price by means of a variance decomposition.

In the following part, details of VECM and each information share methodology will be specified. Information in this part is based on Lien and Shrestha (2009) and Arzandeh and Frank (2019).

Let X_t be an $n \times 1$ vector of n price series with $n-1$ cointegrating vectors and a single common stochastic trend. In this study, X_t is composed of either four variables ($P_t, WP^1, WP^{2-5}, WP^{6-10}$) or three variables ($P_t, WP^1, WP^{2-10}$). VECM is represented as follows:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k} A_i X_{t-i} + \varepsilon_t \text{ where } \Pi = \alpha\beta' \quad (1)$$

where α and β are $n \times (n-1)$ matrices with a rank of $(n-1)$. α is a matrix of adjustment coefficients showing how fast prices turn back to their equilibrium prices. β is a matrix of $(n-1)$ cointegrating vectors.

Covariance matrix of the error term ε_t is denoted as $\Omega = E(\varepsilon_t \varepsilon_t')$.

Vector moving average (VMA) representation of equation (1) becomes (Stock and Watson (1988)):

$$X_t = X_0 + \psi(1) \sum_{i=1}^{t} \varepsilon_i + \psi^*(L)\varepsilon_t$$

For cointegrated series, Engle and Granger representation theorem shows that

$$\beta'\psi(1) = 0 \text{ and } \psi(1)\alpha = 0$$

Therefore, as suggested by De Jong (2002), equation (2) becomes

$$X_t = X_0 + \beta_\perp \alpha_\perp' \sum_{i=1}^{t} \varepsilon_i + \psi^*(L)\varepsilon_t$$

where $\beta_\perp$ and $\alpha_\perp$ are orthogonal vectors to α and β. $\alpha_\perp' \sum_{i=1}^{t} \varepsilon_i$ component represents non-stationary common stochastic trend that follows a random walk process and $\psi^1(L)\varepsilon_t$ represents innovations' effect on long-run prices.

4.4.2.1 Gonzalo-Granger Permanent-Temporary Measure (PT)

Permanent-Temporary measure suggested by Gonzalo-Granger (1995) is based on the idea that the vector of non-stationary price series X_t consists of two components. The first one is the permanent component known as the common factor f_t and it represented the fundamental price or equilibrium price. The second component is the stationary component, also known as the transitory component $\tilde{X}_t$.

There are two identification conditions. The common factor f_t is a linear function of price series X_t and the stationary component $\tilde{X}_t$ does not Granger cause common factor f_t. When these conditions hold, X_t can be defined as follows

$$X_t = Af_t + \tilde{X}_t \text{ and } f_t = \theta' X_t$$

where θ is common factor coefficient vector such that each component i shows the contribution of price series i to price discovery. As suggested by Harris, McInish, and Wood (2002), θs are used as measures of price discovery after they are normalized i.e., they add up to 1.

Finally, Gonzalo and Granger (1995) also showed that $\theta = \alpha_{\perp}$ where $\alpha_{\perp}$ is orthogonal to adjustment coefficient vector α as defined in equation (1) above.

4.4.2.2 Hasbrouck Information Share (IS)

Using common factor representation in equation (2) suggested by Stock and Watson (1988), Hasbrouck (1995) measures the contribution of different price series to price discovery. Different from the PT approach, in this model, variance decomposition is applied to permanent component, and contribution of each price series' variance to the variance of fundamental price is measured.

Variance of the innovations of the permanent component is represented as

$$var(\Psi\varepsilon_t) = \psi\Omega\psi'$$

where ψ is a row vector in $\psi(1)$ matrix defined in equation (2).

When there is a contemporaneous correlation between price series i.e., when the variance covariance matrix Ω is not diagonal, information share for price series i is calculated with the following formula

$$IS_j = \frac{([\psi F]_j)^2}{\psi\Omega\Psi'}$$

where F is the lower triangular matrix of the Cholesky factorization of matrix Ω represented as $\Omega = FF'$.

Due to Cholesky factorization that is applied as a result of contemporaneous correlations between price series, calculated information measures are not unique i.e., they depend on the ordering of prices. Therefore, as suggested by Hasbrouck (2002), all the combinations of different orderings are tried, and upper and lower bounds of information shares are stored.

4.4.2.3 Modified Information Shares (MIS)

To overcome the shortcomings of the previous two models, a new method is suggested by Lien and Shrestha (2009), known as Modified Information Share (MIS). In this model, different from the PT model, the correlation between price series is taken into consideration. Moreover, instead of covariance matrix, the correlation matrix of innovations is used that does not depend on the ordering of the price series.

Let Φ be the correlation matrix of the innovations, Λ be the diagonal matrix consisting of the eigenvalues of the correlation matrix, and G be the vector of the corresponding eigenvectors.

Given that V is a diagonal matrix that contains standard deviation of innovations, then Lien and Shrestha (2009) show that we have the following relationship:

$$\varepsilon_t = \hat{F} z_t$$

where $\hat{F} = [G\Lambda^{-1/2}G'V^{-1}]^{-1}$, $\Omega = FF'$ and z_t is innovation matrix with $E[z_t] = 0$ and $cov(z_t z_t') = I$.

Modified Information Share (MIS) is given by

$$MIS_i = \frac{[\psi F]_i^2}{[\psi F]\Omega[\psi F]'}$$

4.5 Data

Two separate samples are specified in this study. The first sample includes 30 most liquid stocks, which are constituents of the BIST30 Index for the months of January and February in 2016, and the second sample includes constituents of the BIST30 Index for the months of May and June in 2019. Half-days (03/06/2019) are excluded from both samples if any. The first period is selected to include a month before and a month after the pre-trade transparency rule change that was implemented starting from February 01, 2016. After this rule change, information for the order book depth has started to be disseminated in real-time for ten price levels instead of five. The second sample is selected to be able to analyze the information content of LOB in downward and upward trending market conditions. Table 15 and Table 16 show summary statistics for trading activity in both samples (volume statistics are shown in million TRY). Order statistics are calculated during the continuous trading session, but trade statistics are calculated for the whole session.

Statistics from Table 15 show that the average daily trading volume for a stock is 109 million TRY and average daily volume of orders is 309 million TRY. Share of Fill and Kill orders that are either executed immediately or canceled without resting in the book among all the order volume is around 13,6%. The share of marketable orders among all order volume is around 39%.

Table 15. Summary Statistics for the First Sample

VARIABLES	Mean	StDev	Min	Max	Median
TRADE VOLUME (TL)	109	179	5	1.139	38
NUM OF TRADES	4.609	3.668	824	25.305	3.310
AVG TRADE SIZE	3.042	3.685	39	25.605	1.615
ORDER VOLUME (TL)	309	456	14	3.054	131
FILL&KILL ORDER VOLUME (TL)	42	63	0	639	19
MARKETABLE ORDER VOLUME (TL)	122	194	5	1.304	45
NUM OF ORDERS	6.812	4.456	1.752	33.557	5.362
NUM OF FILL&KILL ORDERS	1.026	787	24	4.734	798
NUM OF MARKETABLE ORDERS	2.302	1.736	412	12.656	1.724

Table 16 shows summary statistics for the trading activity of 30 sample stocks between May and June in 2019. Average daily trading volume for a stock is 161 million TRY, and the average daily order volume is 480 million TL. The share of Fill and Kill orders among all order volume is around 17%, and the share of marketable orders is around 38%.

Table 16. Summary Statistics for the Second Sample

VARIABLES	Mean	StDev	Min	Max	Median
TRADE VOLUME (TL)	161	229	3	1.721	84
NUM OF TRADES	10.677	8.841	656	64.212	7.808
AVG TRADE SIZE	2.453	3.203	69	18.634	1.147
ORDER VOLUME (TL)	480	638	10	4.581	283
FILL&KILL ORDER VOLUME (TL)	84	112	0	908	47
MARKETABLE ORDER VOLUME (TL)	180	260	3	2.013	95
NUM OF ORDERS	16.090	11.806	843	83.502	13.094
NUM OF FILL&KILL ORDERS	1.742	1.761	24	49.063	1.533
NUM OF MARKETABLE ORDERS	5.320	4.170	395	27.121	4.094

Data includes price and volume information for the best ten price levels of the bid and ask sides of the order book taken at every 5 seconds. At the time period of the first (second) sample, continuous trading starts at 09:35 (10:00) and continues until midday call auction that starts at 12:30 (13:00) ends at 13:25 (13:55). No trades are executed during midday call-auction, but new orders can be entered into the system, and existing orders can be modified or canceled. Continuous trading resumes again at 13:30 (14:00) and ends at 17:30 (18:00). Because there is no trading during midday call-auction, it is assumed that there are two trading sessions each day, the morning session before midday call-auction and the afternoon session afterward. For the first sample, the number of observations is around 6.1 million, and for the second sample, it is around 5.8 million.

Table 17 reports summary statistics related to the shape of the order book averaged across all stocks for the first sample. Length (%) shows bid or ask order volume available at each step as a percent of the total volume available at the first ten price steps. Height (%) shows the price difference between each step as a percentage of the difference between the 10th step and midprice. For both bid and ask sides, steps become shorter when it moves away from the best level. Consistent with the findings of Cao et al. (2009), the relative length for each of the first five levels are more than 10%, and the first step is shorter than the second step. The last step accounts for 6,78% of the bid length and %7,54 of the ask length. The height of the book is stable between steps of the book, showing that there is no gap between price levels.

Table 17. Order Book Statistics for the First Sample

	Length (%)		Heigth (%)	
Level	**Bid**	**Ask**	**Bid**	**Ask**
1	13.16	12.02	6.79	6.74
2	13.2	12.11	10.32	10.41
3	12.04	11.4	10.31	10.39
4	11.21	10.97	10.27	10.35
5	10.36	10.4	10.26	10.32
6	9.52	9.87	10.28	10.31
7	8.56	9.18	10.33	10.33
8	7.85	8.55	10.39	10.35
9	7.32	7.96	10.49	10.37
10	6.78	7.54	10.58	10.42

Table 18 reports summary statistics of the order book for the second sample. For the bid side, the length of the first four steps is greater than 10%, and the length of the first five steps is greater than 10% for the ask side. The length of the second and third steps is greater than the first step for both bid and ask sides.

Table 18. Order Book Statistics for the Second Sample

	Length (%)		Heigth (%)	
Level	**Bid**	**Ask**	**Bid**	**Ask**
1	11.76	11.16	5.87	5.85
2	13.31	12.38	10.39	10.39
3	12.13	11.33	10.41	10.40
4	11.04	10.68	10.42	10.42
5	9.92	10.07	10.45	10.45
6	9.12	9.61	10.45	10.46
7	8.74	9.13	10.45	10.47
8	8.54	8.97	10.46	10.47
9	7.97	8.50	10.51	10.52
10	7.46	8.18	10.57	10.56

Length of the first five steps accounts for around 55% to 60% of the total length for both samples in bid and ask sides. Height variable does not vary between different steps meaning that there is no gap in the book between price levels in the first ten steps, possibly because of relatively high tick sizes.

4.6 Results

To analyze the information share of the limit order book, first VECM is estimated with three different price series (P_t, WP^1, WP^{2-10}). Then, in order to analyze whether the results differ with respect to different price steps, the model is estimated with four price series ($P_t, WP^1, WP^{2-5}, WP^{6-10}$) using order book data sampled every 5 seconds. Three different price discovery methods are used to estimate the information share of each price series. Minimum, maximum, and average values are reported for Hasbrouck information share. This analysis is repeated for both samples.

4.6.1 Results for the First Sample (January-February 2016)

Table 19 reports results for three variable case of the first sample (January-February 2016). Estimates for each month are reported separately to be able to observe the impact of the pre-trade transparency rule change that was implemented in February 2016. Estimation results show that information share of the weighted average price of the order book between levels 2-10 has the highest contribution if measured with MIS and PT methods. However, if estimated with IS, the average of information shares is highest for weighted average mid-quote.

Table 19. Price Discovery Measures of First Sample for Three Price Series

	January 2016			February 2016		
	Mean	StDev	Median	Mean	StDev	Median
Hasbrouck Inf. Share						
P_High	0.412	0.195	0.425	0.407	0.191	0.419
P_Low	0.173	0.122	0.168	0.163	0.121	0.149
P_Mid	0.292	0.153	0.297	0.285	0.151	0.284
WP1_High	0.565	0.201	0.581	0.575	0.205	0.595
WP1_Low	0.251	0.212	0.205	0.242	0.202	0.208
WP1_Mid	0.408	0.181	0.395	0.408	0.178	0.404
WP210_High	0.438	0.260	0.406	0.459	0.258	0.439
WP210_Low	0.208	0.210	0.149	0.205	0.209	0.137
WP210_Mid	0.323	0.216	0.291	0.332	0.216	0.305
Permanent-Transitory						
Price	0.230	0.159	0.221	0.231	0.153	0.228
WP1	0.281	0.188	0.265	0.290	0.188	0.281
WP210	0.489	0.292	0.487	0.479	0.285	0.476
Modified Inf. Share						
Price	0.249	0.154	0.244	0.240	0.153	0.227
WP1	0.371	0.185	0.352	0.369	0.179	0.364
WP210	0.381	0.237	0.349	0.392	0.237	0.387

Table 20. Price Discovery Measures of First Sample for Four Price Series

	January 2016			February 2016		
	Mean	StDev	Median	Mean	StDev	Median
Hasbrouck Inf. Share						
P_High	0.409	0.211	0.414	0.405	0.208	0.420
P_Low	0.120	0.107	0.100	0.113	0.104	0.086
P_Mid	0.264	0.152	0.260	0.259	0.148	0.256
WP1_High	0.567	0.227	0.572	0.564	0.214	0.568
WP1_Low	0.179	0.155	0.144	0.164	0.144	0.137
WP1_Mid	0.373	0.167	0.363	0.364	0.152	0.358
WP25_High	0.357	0.215	0.328	0.372	0.215	0.355
WP25_Low	0.112	0.121	0.073	0.123	0.125	0.085
WP25_Mid	0.235	0.149	0.212	0.247	0.153	0.226
WP610_High	0.241	0.222	0.183	0.245	0.219	0.184
WP610_Low	0.130	0.170	0.059	0.129	0.170	0.060
WP610_Mid	0.185	0.171	0.131	0.187	0.170	0.136
Permanent-Transitory						
Price	0.194	0.148	0.178	0.191	0.140	0.179
WP1	0.240	0.157	0.216	0.232	0.148	0.211
WP25	0.360	0.218	0.337	0.369	0.212	0.351
WP610	0.206	0.166	0.168	0.208	0.167	0.172
Modified Inf. Share						
Price	0.199	0.150	0.181	0.188	0.143	0.162
WP1	0.317	0.153	0.312	0.307	0.140	0.306
WP25	0.314	0.189	0.296	0.326	0.189	0.319
WP610	0.169	0.186	0.100	0.178	0.187	0.115

Table 20 reports results for four variable case of the first sample. When VECM is estimated with four variables, WP^1 has the highest contribution for IS and

MIS methods, but WP^{2-5} has the highest contribution if PT is used. Information share is lowest for WP^{6-10} if estimated with IS and MIS. Results show that contribution of both WP^{2-5} and WP^{6-10} increased in February after the pre-trade transparency rule change.

4.6.2 Results for the Second Sample (May-June 2019)

Table 21 and Table 22 show information share measures for the second sample, which is divided into two periods based on changes in the closing values of the BIST30 Index. The first period covers trading days between May 02 and May 27 in which the BIST30 index decreased by around 10%, while the second period covers trading days between May 28 and June 28 in which the index appreciates by around 13%.

Table 21. Price Discovery Measures of Second Sample for Three Price Series

	First Period (2nd to 27th May)			**Second Period (28th May to 28th June)**		
VARIABLES	Mean	StDev	Median	Mean	StDev	Median
Hasbrouck Information Share						
P_High	0.421	0.175	0.430	0.413	0.181	0.427
P_Low	0.131	0.090	0.119	0.118	0.083	0.106
P_Mid	0.276	0.125	0.274	0.265	0.125	0.271
WP1_High	0.645	0.163	0.666	0.669	0.159	0.692
WP1_Low	0.255	0.161	0.223	0.265	0.163	0.231
WP1_Mid	0.450	0.141	0.448	0.467	0.131	0.462
WP210_High	0.465	0.172	0.468	0.466	0.166	0.447
WP210_Low	0.158	0.147	0.118	0.150	0.154	0.102
WP210_Mid	0.311	0.141	0.293	0.308	0.134	0.283
Permanent-Transitory						
Price	0.203	0.125	0.202	0.198	0.126	0.197
WP1	0.345	0.161	0.338	0.345	0.154	0.343
WP210	0.452	0.236	0.431	0.457	0.238	0.436
Modified Information Share						
Price	0.217	0.119	0.209	0.203	0.117	0.201
WP1	0.410	0.132	0.411	0.420	0.126	0.420
WP210	0.374	0.161	0.372	0.377	0.158	0.376

Estimation results for three-variable model in Table 21 show that WP^1 has the highest contribution if measured with IS and MIS in both periods, and its contribution has increased or not changed in the second period. P has the lowest contribution irrespective of the model, and its contribution has declined in the second period. WP^{2-10} has the highest contribution in the PT model and the second highest contribution in the IS and MIS models. Contribution of WP^{2-10} is higher in the second period when measured with PT or MIS models, and it is lower under IS model.

Table 22. Price Discovery Measures of Second Sample for Four Price Series

	First Period (2nd to 27th May)			**Second Period (28th May to 28th June)**		
VARIABLES	Mean	StDev	Median	Mean	StDev	Median
Hasbrouck Information Share						
P_High	0.433	0.188	0.453	0.429	0.188	0.453
P_Low	0.086	0.065	0.077	0.078	0.061	0.066
P_Mid	0.260	0.120	0.273	0.254	0.119	0.258
WP1_High	0.631	0.154	0.640	0.645	0.155	0.655
WP1_Low	0.172	0.119	0.146	0.174	0.136	0.140
WP1_Mid	0.402	0.113	0.397	0.410	0.111	0.399
WP25_High	0.359	0.150	0.347	0.399	0.158	0.386
WP25_Low	0.085	0.071	0.068	0.093	0.075	0.079
WP25_Mid	0.222	0.099	0.211	0.246	0.106	0.235
WP610_High	0.281	0.157	0.262	0.266	0.155	0.259
WP610_Low	0.111	0.118	0.068	0.095	0.104	0.062
WP610_Mid	0.196	0.116	0.178	0.180	0.106	0.166
Permanent-Transitory						
Price	0.168	0.112	0.157	0.161	0.116	0.148
WP1	0.273	0.135	0.263	0.259	0.130	0.242
WP25	0.353	0.177	0.336	0.380	0.178	0.376
WP610	0.207	0.126	0.183	0.201	0.124	0.177
Modified Information Share						
Price	0.171	0.106	0.163	0.159	0.105	0.145
WP1	0.335	0.098	0.332	0.333	0.099	0.330
WP25	0.303	0.131	0.297	0.331	0.136	0.329
WP610	0.192	0.127	0.164	0.177	0.116	0.155

Table 22 presents the results of the model that includes four price series. According to estimates of the IS model, WP^1, P, WP^{2-5} and WP^{6-10} have provided the highest contribution in both periods respectively. With PT model, P has the lowest and WP^{2-5} has the highest contribution and with MIS model, P has the lowest and WP^1 has the highest contribution. Comparing estimation results between the first and second period, it is observed that information share of WP^{2-5} is higher for the second period in which the market moves upward and information share of WP^{6-10} is higher in the first period in which there is a downward movement in the market.

Apart from the analyzes summarized above, in order to better understand the impact of market and stock level movements on the information share of the order book, the second sample is divided into five different groups based either on index returns, stock returns, and trading volume of the market. Table 23 and Table 24 report the estimation results with this classification for three variable and four variable models. Boundary values that define these quintiles are summarized in Appendix D.

According to Table 23, which presents estimates of 3 variable model, information share of WP^{2-10} reaches its minimum level when there is no remarkable change in the index value, when there is a positive return of the single stock, or when the trading volume of the market is close to its average value. Similarly, when an analysis is made about the market conditions in which this value reaches its maximum, it is observed that contribution of the orders beyond best bid and best ask prices become higher when the market moves in a positive direction moderately, or when stock returns are moderately negative, or when trading volume of the market is in the second lowest range.

Estimation results of the four-variable model presented in Table 24 show that the orders that are away from the top of the book (WP^{6-10}) become less informative in positive market conditions and more informative when the market moves downwards or when there is a moderate change in the price of the single stocks.

Table 23. Price Discovery Measures for the Second Sample with Three Price Series Based on Index Return, Stock Return and Volume Quintiles

	Hasbrouck Inf. Share			**Modified Inf. Share**			**Permanent-Transitory**		
Panel A Information Shares for Different Index Return Classes									
Index Return	**P**	**WP1**	**WP2-10**	**P**	**WP1**	**WP2-10**	**P**	**WP1**	**WP2-10**
Quintile 1 (Lowest)	0.271	0.467	0.301	0.211	0.424	0.364	0.200	0.361	0.439
Quintile 2	0.285	0.447	0.305	0.224	0.404	0.372	0.212	0.342	0.447
Quintile 3	0.271	0.472	0.295	0.212	0.426	0.362	0.205	0.360	0.435
Quintile 4	0.255	0.456	0.332	0.190	0.410	0.399	0.183	0.330	0.487
Quintile 5 (Highest)	0.270	0.455	0.313	0.210	0.411	0.379	0.199	0.334	0.466
Panel B Information Shares for Different Daily Stock Return Classes									
Stock Return	**P**	**WP1**	**WP2-10**	**P**	**WP1**	**WP2-10**	**P**	**WP1**	**WP2-10**
Quintile 1 (Lowest)	0.282	0.457	0.300	0.220	0.418	0.361	0.209	0.355	0.437
Quintile 2	0.265	0.452	0.320	0.206	0.406	0.388	0.197	0.336	0.467
Quintile 3	0.269	0.452	0.316	0.209	0.403	0.387	0.198	0.330	0.472
Quintile 4	0.263	0.464	0.314	0.200	0.415	0.384	0.194	0.343	0.463
Quintile 5 (Highest)	0.273	0.470	0.298	0.211	0.432	0.357	0.202	0.362	0.437
Panel C Information Shares for Different Daily Trading Volumes (for all stocks)									
Volume	**P**	**WP1**	**WP2-10**	**P**	**WP1**	**WP2-10**	**P**	**WP1**	**WP2-10**
Quintile 1 (Lowest)	0.281	0.448	0.307	0.223	0.407	0.370	0.207	0.340	0.453
Quintile 2	0.247	0.466	0.329	0.184	0.422	0.395	0.175	0.342	0.483
Quintile 3	0.279	0.467	0.291	0.218	0.418	0.364	0.214	0.354	0.432
Quintile 4	0.274	0.456	0.310	0.214	0.414	0.372	0.205	0.349	0.446
Quintile 5 (Highest)	0.273	0.459	0.309	0.209	0.414	0.377	0.201	0.341	0.458

Table 24. Price Discovery Measures for the Second Sample with Four Price Series Based on Index Return, Stock Return and Volume Quintiles

	Hasbrouck Inf. Share				Modified Inf. Share				Permanent-Transitory			
Index Return	**P**	**WP1**	**WP2-5**	**WP6-10**	**P**	**WP1**	**WP2-5**	**WP6-10**	**P**	**WP1**	**WP2-5**	**WP6-10**
Quintile 1 (Lowest)	0.259	0.404	0.221	0.199	0.168	0.334	0.303	0.195	0.169	0.268	0.351	0.212
Quintile 2	0.265	0.395	0.238	0.187	0.175	0.329	0.315	0.181	0.175	0.267	0.363	0.195
Quintile 3	0.257	0.406	0.235	0.188	0.165	0.332	0.319	0.184	0.167	0.267	0.363	0.204
Quintile 4	0.246	0.405	0.249	0.188	0.151	0.333	0.333	0.183	0.151	0.257	0.383	0.209
Quintile 5 (Highest)	0.255	0.420	0.230	0.176	0.163	0.341	0.319	0.177	0.160	0.268	0.376	0.197
Stock Return	**P**	**WP1**	**WP2-5**	**WP6-10**	**P**	**WP1**	**WP2-5**	**WP6-10**	**P**	**WP1**	**WP2-5**	**WP6-10**
Quintile 1 (Lowest)	0.268	0.401	0.226	0.193	0.173	0.332	0.308	0.187	0.170	0.266	0.360	0.204
Quintile 2	0.242	0.399	0.246	0.195	0.152	0.318	0.336	0.194	0.153	0.250	0.394	0.204
Quintile 3	0.252	0.405	0.238	0.188	0.164	0.330	0.322	0.185	0.164	0.254	0.371	0.211
Quintile 4	0.253	0.409	0.237	0.187	0.161	0.337	0.317	0.186	0.163	0.268	0.359	0.209
Quintile 5 (Highest)	0.267	0.415	0.227	0.175	0.174	0.351	0.306	0.169	0.171	0.289	0.351	0.189
Trade Volume	**P**	**WP1**	**WP2-5**	**WP6-10**	**P**	**WP1**	**WP2-5**	**WP6-10**	**P**	**WP1**	**WP2-5**	**WP6-10**
Quintile 1 (Lowest)	0.259	0.398	0.235	0.188	0.172	0.331	0.318	0.179	0.168	0.264	0.371	0.197
Quintile 2	0.241	0.408	0.234	0.199	0.150	0.334	0.318	0.199	0.148	0.265	0.367	0.221
Quintile 3	0.265	0.404	0.235	0.182	0.169	0.331	0.320	0.179	0.173	0.262	0.370	0.196
Quintile 4	0.258	0.411	0.232	0.187	0.166	0.336	0.313	0.185	0.166	0.272	0.365	0.197
Quintile 5 (Highest)	0.260	0.409	0.237	0.182	0.168	0.336	0.320	0.177	0.169	0.262	0.363	0.206

4.6.3 Robustness of Results

As emphasized in Arzandeh and Frank (2019), the choice of the optimal time difference between snapshots is important. If it is too long, then useful information may be lost between two data points. If it is too short, then repetitive data may cause the problem of heteroscedasticity. In this study, order book data taken at each 5 seconds interval is used, and data taken at every 30 seconds interval is used as a robustness check. This analysis shows that results are robust to a large extent.

CHAPTER 5

CONCLUSION

This thesis is composed of two separate studies and aims to offer an explanation for three important topics in the field of market microstructure for Borsa İstanbul: market transparency, liquidity, and informativeness of the limit order book as measured by its contribution to the price discovery process.

In the first study, the effect of post-trade transparency i.e., real-time public disclosure of broker identifiers in trade feeds on liquidity, is analyzed. Liquidity is quantified using complex order book data-based measures like Xetra Liquidity Measure (XLM) and Marginal Cost of Immediacy (MCI) as well as more classical measures like effective spreads, depth weighted spread, and orders waiting the best price level. Two different samples are constructed based on different setttings utilized in the post-trade transparency reform, and each sample is analyzed individually.

Results of univariate analysis and estimates of panel data regressions performed for the first sample that includes 70 stocks from the BIST100 index document an improvement in liquidity after the switch to post-trade transparency. This result is consistent with Waisburd (2003), Pham et al. (2016), and Poskitt et al. (2011). Furthermore, based on Linnainmaa and Saar (2012) and Meling (2021), who suggest that only institutional investors shift their trading behavior as a response to a change in the anonymity regime, this sample is divided into two groups depending on the institutional ownership levels of individual stocks. Although an improvement in liquidity is observed for both samples, the significance and magnitude of the change are relatively small for stocks with lower institutional ownership.

The experiment-like setting of the second sample that includes 29 stocks from the BIST30 index allows forming a control and treatment group whose members change each month. Due to this experimental setting, a diff-and-diff approach is used in addition to multivariate regressions. Diff-and-diff results show that trading volume increased significantly for the first two months while no significant change is observed in liquidity measures until the fourth month. Moreover, this analysis provides mixed results in terms of the direction of the change. Estimations of panel data regression with stock fixed effects showed a modest decline in liquidity, and it is not significant for XLM_500, XLM_1m, XLM_1pc, DWS, ESPR_V, and Best. This result is in line with Dennis and Sandas (2020), who found out that spreads widened for large stocks while it is not statistically significant for small to mid-sized stocks after switchback to transparency regime in Nasdaq Nordic.

In the second study, using two different samples, the informativeness of the order book is analyzed by estimating the information share of orders resting in the order book steps between 2-10 in addition to mid-quote prices and last trade price. Price discovery is estimated with three different measures, information shares (IS) as suggested by Hasbrouck (1995), permanent-transitory (PT) components as suggested by Gonzalo-Granger (1995), and modified information shares (MIS) as suggested by Lien and Shrestha (2009). The MIS model overcomes the limitation of IS, which depends on the ordering of the variables and thus not providing a unique measure. Results showed that order book beyond best bid and ask prices contributes to price discovery with around 32% to 49% for different sample periods and different price discovery measures. This figure is much higher than the one documented in Cao et al. (2009), who studied the most active 100 stocks in the Australian Stock Exchange.

Furthermore, to be able to analyze the contribution of orders that are away from the top of the book, information share of price steps between 2-5 and 6-10 are estimated separately. Results showed that the contribution of orders that are close to the top of the book is higher, while the contribution of steps between 6-10 is between 17% to 21%.

Analysis for the first sample that includes the period between January-February 2016 allowed us to make inferences for the effect of disclosing the order book steps between 6-10 that took place at the beginning of February. Comparing information shares of January 2016 with February 2016 shows that information share of steps 6-10 slightly increased after the rule change.

Similarly, the second sample that includes the period between May-June 2019 allowed to make an analysis for periods of increasing and decreasing market trends, and it is found out that the information content of the limit order book between steps 2-5 is higher and steps 6-10 is lower when there is an increasing trend in the market.

APPENDIX A

EMPIRICAL LITERATURE REVIEW ON TRANSPARENCY AND LIQIDITY RELATION

Table A1. Empirical Literature Review on Transparency and Liquidity Relation

Authors (Year)	**Dataset**	**Liquidity Measure**	**Rule Change**	**Findings**
Foucault, Moinas, and Theissen (2007)	39 stocks of CAC40 Index between 26 March 2001 and 20 May 2001 in Euronext Paris	Quoted spread, quoted percentage spread and effective spread	On 23 April 2001, brokers' identifier had been removed from the orders standing in the order book in Euronext Paris.	Spreads and its informativeness became smaller after switch to anonymity.
Comerton-Forde and Tang (2009)	463 stocks between 25 July 2005 and 6 April 2006 in Australian Stock Exchange	Time weighted proportional quoted spread, Effective half spread (Decomposed into Price impact and Realized Spread)	Real time display of broker identifiers were removed from trading screens on 28 November 2005.	Positive effect on liquidity (tightened spreads, increased order book depth) Reduced order aggressiveness as limit orders become more attractive Liquidity improvement is more significant for large shares Order flow goes to anonymous market
Hachmeister and Schiereck (2010)	30 instruments between 3 February 2003 and 30 May 2003 in Xetra	Exchange Liquidity Measure (XLM)	Post-trade anonymity was introduced for first set of instruments on 27 March 2003 and for second set of instruments on 10 April 2003.	After post-trade anonymity, liquidity increased so they found a positive relation between liquidity and post-trade anonymity. Post-trade anonymity did not cause an increase in informed trading.
Comerton-Forde, Putnins, and Tang (2011)	141 stocks, 59 trading days between 1 May-31 July 2004 in Toronto Stock Exchange	Bid-ask spread	Disclosure of Broker IDs in trading screens became voluntary on 2002.	Ratio of anonymous orders' volume to total volume is relatively small and anonymity is generally preferred by specialists. Anonymous orders are generally large and informed and they increase when spreads are wider as informational advantage of informed trades increase with uncertainty. Traders strategically choose to trade with anonymous orders to reduce their execution costs.

Authors (Year)	Dataset	Liquidity Measure	Rule Change	Findings
Friederich and Payne (2011)	134 shares that were components of either FTSE 100 or FTSE 250 indices from the end of July 2000 till the end of January 2001, and from 1 March until 30 August 2001 respectively	Daily time-weighted inside spread, effective spreads	Introduction of a central-counter-party (CCP) in London in February 2001 which led to anonymous trading (counterparty information was no longer disclosed to traders)	Liquidity increased, order submission strategies changed, and execution costs of single trades decreased after anonymity. Positive changes stem from the decrease in predatory trading while no reduction was not observed in asymmetric information problem
Dennis and Sandas (2020)	556 stocks in Nasdaq Nordic Exchanges (Helsinki, Copenhagen and Stockholm) between 3 March 2008 to 10 July 2009.	Quoted bid-ask spread	Equity-related markets in Helsinki, Reykjavik, and the five most traded stocks in Stockholm applied post-trade anonymous reporting in June 2008 while other stocks in Stockholm and Copenhagen remained transparent. The change reversed in April 2009.	Spreads tightened for stocks that switched to post-trade anonymity in 2008 as compared to other stocks that did not switch When the change reversed to post-trade transparency in 2009, spreads widened for large stocks while the change is not statistically significant for small to mid-sized stocks.
Swan and Westerholm (2019)	Largest 33 exchanges from March 2000 to October 2001	Effective spread Trade volume weighted relative effective spread	Broker ID Disclosure used as an independent variable Brussels and Paris Exchanges changed their transparency regimes from transparency to opacity	In general, transparency improves market quality. For small and medium stocks, displaying a large part of the order book is beneficial while large orders perform better under opacity. It is better for the exchanges to set different market rules for stocks with different sizes.
Waisburd (2003)	Paris Bourse	Bid-Ask Spreads	Concealment of broker identifiers in trade information i.e., post-trade anonymity implemented by Paris Bourse	Bid-ask spreads increased by around 25% after anonymity
Pham, Swam and Westerholm (2016)	South Korea Exchange	Effective spreads, realized spreads	Trades of top five brokers disclosed to all participants at the end of each session (morning and afternoon)	After post-trade transparency, trading volume have increased and spreads have narrowed down. They concluded that post-trade transparency improved market quality in South Korea Exchange.

Authors (Year)	Dataset	Liquidity Measure	Rule Change	Findings
Poskitt, Marsden and Nguyen (2011)	41 stocks that are constituents of NZX 50 Index, divided into 3 subsamples based on market cap with 3 sample periods with 20, 60, and 120 days before and after the switch date	Volume-weighted percentage effective spread	New Zealand Stock Exchange (NZX) introduced post trade anonymity on 30 July 2017 and broker identity of trader entering the order had not been disclosed until two trading days after the trade	Anonymity led to a decrease in market liquidity and an increase in adverse selection costs for all the subsamples Anonymity led to an increase in the NZX's share on markrt volume for cross-listed stocks
Meling (2021)	Constituents of OBX list between 2008 and 2010	Final spread before the closing auction, relative bid-ask spread, effective spread	Oslo Stock Exchange introduced post-trade anonymity regime on June 2, 2008 and turned back to transparency on April 12, 2010. Rule change was implemented only for 25 stocks included in the OBX list while all the other stocks remained post trade transparent.	Post trade anonymous trading increased trading volume by more than 50% and increased stock liquidity as measured by bid-ask spreads by more than 40%. Increased in stock liquidity was due to increased trading of institutional investors while no such change was observed for retail investors.

APPENDIX B

SAMPLE STOCKS

Table B1. BIST30 Sample

Instrument	Title	Sector
AKBNK.E	Akbank T.A.Ş.	Banks
ARCLK.E	Arçelik A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
ASELS.E	Aselsan Elektronik Sanayi ve Ticaret A.Ş.	Defense
BIMAS.E	Bim Birleşik Mağazalar A.Ş.	Consumer Trade
EKGYO.E	Emlak Konut Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
ENKAI.E	Enka İnşaat ve Sanayi A.Ş.	Construction and Public Works
EREGL.E	Ereğli Demir ve Çelik Fabrikaları T.A.Ş.	Basic Metal
FROTO.E	Ford Otomotiv Sanayi A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
GARAN.E	Türkiye Garanti Bankası A.Ş.	Banks
HALKB.E	Türkiye Halk Bankası A.Ş.	Banks
ISCTR.E	Türkiye İş Bankası A.Ş.	Banks
KCHOL.E	Koç Holding A.Ş.	Holding and Investment Companies
KOZAL.E	Koza Altın İşletmeleri A.Ş.	Mining of Coal and Lignite
KRDMD.E	Kardemir Karabük Demir Çelik Sanayi ve Ticaret A.Ş.	Basic Metal
OTKAR.E	Otokar Otomotiv ve Savunma Sanayi A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
PETKM.E	Petkim Petrokimya Holding A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
SAHOL.E	Hacı Ömer Sabancı Holding A.Ş.	Holding and Investment Companies
SISE.E	Türkiye Şişe ve Cam Fabrikaları A.Ş.	Holding and Investment Companies
SODA.E	Soda Sanayii A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
TAVHL.E	Tav Havalimanları Holding A.Ş.	Holding and Investment Companies
TCELL.E	Turkcell İletişim Hizmetleri A.Ş.	Telecommunication
THYAO.E	Türk Hava Yolları A.O.	Transportation and Storage
TKFEN.E	Tekfen Holding A.Ş.	Holding and Investment Companies
TOASO.E	Tofaş Türk Otomobil Fabrikası A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
TTKOM.E	Türk Telekomünikasyon A.Ş.	Telecommunication
TUPRS.E	Tüpraş-Türkiye Petrol Rafinerileri A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
ULKER.E	Ülker Bisküvi Sanayi A.Ş.	Food, Beverage and Tobacco
VAKBN.E	Türkiye Vakıflar Bankası T.A.O.	Banks
YKBNK.E	Yapı ve Kredi Bankası A.Ş.	Banks

Table B2. BIST100 Sample

Instrument	Title	Sector
AEFES	Anadolu Efes Biracılık Ve Malt Sanayii A.Ş.	Food, Beverage and Tobacco
AFYON	Afyon Çimento Sanayi T.A.Ş.	Non-Metallic Mineral Products
AKENR	Akenerji Elektrik Üretim A.Ş.	Electricity Gas and Steam
AKSA	Aksa Akrilik Kimya Sanayii A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
AKSEN	Aksa Enerji Üretim A.Ş.	Electricity Gas and Steam
ALARK	Alarko Holding A.Ş.	Holding and Investment Companies
ALBRK	Albaraka Türk Katılım Bankası A.Ş.	Banks
ALGYO	Alarko Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
ALKIM	Alkim Alkali Kimya A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
ANACM	Anadolu Cam Sanayii A.Ş.	Non-Metallic Mineral Products
AYEN	Ayen Enerji A.Ş.	Electricity Gas and Steam
AYGAZ	Aygaz A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
BAGFS	Bagfaş Bandırma Gübre Fabrikaları A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
BIZIM	Bizim Toptan Satış Mağazaları A.Ş.	Wholesale and Retail Trade, Restaurants and Hotels
BJKAS	Beşiktaş Futbol Yatırımları Sanayi Ve Ticaret A.Ş.	Sports Activities, Amusement and Recreation Activities
BRISA	Brisa Brıdgestone Sabancı Lastik Sanayi Ve Ticaret A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
BRSAN	Borusan Mannesmann Boru Sanayi Ve Ticaret A.Ş.	Basic Metal
CCOLA	Coca-Cola İçecek A.Ş.	Food, Beverage and Tobacco
CEMTS	Çemtaş Çelik Makina Sanayi Ve Ticaret A.Ş.	Basic Metal
CIMSA	Çimsa Çimento Sanayi Ve Ticaret A.Ş.	Non-Metallic Mineral Products
CLEBI	Çelebi Hava Servisi A.Ş.	Transportation Storage and Telecommunication
CRFSA	Carrefoursa Carrefour Sabancı Ticaret Merkezi A.Ş.	Consumer Trade
DEVA	Deva Holding A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
DOAS	Doğuş Otomotiv Servis Ve Ticaret A.Ş.	Wholesale Trade
DOCO	Do & Co Aktıengesellschaft	Transportation and Storage
DOHOL	Doğan Şirketler Grubu Holding A.Ş.	Holding and Investment Companies
ECILC	Eis Eczacıbaşı İlaç, Sınai Ve Finansal Yatırımlar Sanayi Ve Ticaret	Holding and Investment Companies
ECZYT	Eczacıbaşı Yatırım Holding Ortaklığı A.Ş.	Holding and Investment Companies
EGEEN	Ege Endüstri Ve Ticaret A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
FENER	Fenerbahçe Futbol A.Ş.	Sports Activities, Amusement and Recreation Activities
GOLTS	Göltaş Göller Bölgesi Çimento Sanayi Ve Ticaret A.Ş.	Non-Metallic Mineral Products
GOODY	Goodyear Lastikleri T.A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
GOZDE	Gözde Girişim Sermayesi Yatırım Ortaklığı A.Ş.	Venture Capital Investment Trusts
GSDHO	Gsd Holding A.Ş.	Holding and Investment Companies
GSRAY	Galatasaray Sportif Sınai Ve Ticari Yatırımlar A.Ş.	Sports Activities, Amusement and Recreation Activities

Instrument	Title	Sector
GUBRF	Gübre Fabrikaları T.A.Ş.	Chemicals, Petroleum Rubber and Plastic Products
HLGYO	Halk Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
IHLAS	İhlas Holding A.Ş.	Holding and Investment Companies
IPEKE	İpek Doğal Enerji Kaynakları Araştırma Ve Üretim A.Ş.	Mining and Quarrying
ISGYO	İş Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
IZMDC	İzmir Demir Çelik Sanayi A.Ş.	Basic Metal
KARSN	Karsan Otomotiv Sanayii Ve Ticaret A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
KARTN	Kartonsan Karton Sanayi Ve Ticaret A.Ş.	Paper and Paper Products, Printing and Publishing
KIPA	Kipa Ticaret A.Ş.	Consumer Trade
KONYA	Konya Çimento Sanayii A.Ş.	Non-Metallic Mineral Products
KORDS	Kordsa Teknik Tekstil A.Ş.	Textile, Wearing Apparel and Leather
KOZAA	Koza Anadolu Metal Madencilik İşletmeleri A.Ş.	Mining and Quarrying
LOGO	Logo Yazılım Sanayi Ve Ticaret A.Ş.	Information Technology
METRO	Metro Ticari Ve Mali Yatırımlar Holding A.Ş.	Holding and Investment Companies
MGROS	Migros Ticaret A.Ş.	Consumer Trade
NETAS	Netaş Telekomünikasyon A.Ş.	Information Technology
NTTUR	Net Turizm Ticaret Ve Sanayi A.Ş.	Restaurants and Hotels
NUGYO	Nurol Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
ODAS	Odaş Elektrik Üretim Sanayi Ticaret A.Ş.	Electricity Gas and Steam
PGSUS	Pegasus Hava Taşımacılığı A.Ş.	Transportation and Storage
POLHO	Polisan Holding A.Ş.	Holding and Investment Companies
PRKME	Park Elektrik Üretim Madencilik Sanayi Ve Ticaret A.Ş.	Mining of Coal and Lignite
SELEC	Selçuk Ecza Deposu Ticaret Ve Sanayi A.Ş.	Wholesale Trade
TATGD	Tat Gıda Sanayi A.Ş.	Food, Beverage and Tobacco
TMSN	Tümosan Motor Ve Traktör Sanayi A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
TRGYO	Torunlar Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
TRKCM	Trakya Cam Sanayii A.Ş.	Non-Metallic Mineral Products
TSKB	Türkiye Sınai Kalkınma Bankası A.Ş.	Banks
TSPOR	Trabzonspor Sportif Yatırım Ve Futbol İşletmeciliği Ticaret A.Ş.	Sports Activities, Amusement and Recreation Activities
TTRAK	Türk Traktör Ve Ziraat Makineleri A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
VERUS	Verusa Holding A.Ş.	Holding and Investment Companies
VESBE	Vestel Beyaz Eşya Sanayi Ve Ticaret A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
VESTL	Vestel Elektronik Sanayi Ve Ticaret A.Ş.	Fabricated Metal Products Machinery Electrical Equipment and Transportation Vehicles
VKGYO	Vakıf Gayrimenkul Yatırım Ortaklığı A.Ş.	Real Estate Investment Trusts
ZOREN	Zorlu Enerji Elektrik Üretim A.Ş.	Electricity Gas and Steam

Source: Public Disclosure Platform

APPENDIX C

UNIVARIATE ANALYSIS FOR BIST30 SAMPLE

Table C1. Univariate Analysis for BIST30 Sample

Security	Month	Volume (TRY)	Volume (Shares)	XLM_50	XLM_100	XLM_500	XLM_1000	XLM_1PC	MCI	DWS	Depth	BestVal	ESPR_TL	VOL _MINMAX
EREGL	March	64.5	10.7	0.174	0.177	0.271	0.451	0.580	0.041	1.497	12.9	1.0	1.028	0.561
	April	186.3	31.4	0.174	0.175	0.198	0.254	0.300	0.018	1.463	30.5	2.7	1.014	0.564
	Diff	*121.8****	*20.7****	*0.000*	*-0.002*	*-0.074****	*-0.196****	*-0.280****	*-0.023****	*-0.034*	*17.6****	*1.6****	*-0.014****	*0.003*
TOASO	March	14.1	0.5	0.190	0.283	1.300	2.370	0.474	0.223	0.753	1.6	0.1	2.890	0.433
	April	20.0	0.7	0.180	0.273	1.231	2.235	0.466	0.217	0.735	1.7	0.1	3.072	0.492
	Diff	*6.0****	*0.2***	*-0.009*	*-0.010*	*-0.069*	*-0.136*	*-0.008*	*-0.006*	*-0.017*	*0.1*	*0.0*	*0.182*	*0.059**
ULKER	March	22.1	1.2	0.140	0.228	1.057	1.636	0.342	0.204	0.524	1.4	0.1	1.364	0.487
	April	20.4	1.1	0.154	0.247	0.963	1.473	0.365	0.203	0.569	1.7	0.1	1.538	0.440
	Diff	*-1.7*	*-0.1*	*0.014*	*0.019*	*-0.093*	*-0.164**	*0.023*	*-0.001*	*0.045***	*0.3**	*0.0*	*0.174***	*-0.047*
VAKBN	March	109.2	20.2	0.189	0.190	0.218	0.291	0.300	0.019	1.626	23.5	1.9	1.013	0.531
	April	141.2	23.8	0.175	0.177	0.206	0.277	0.286	0.018	1.513	25.0	1.7	1.021	0.579
	Diff	*32.0***	*3.7*	*-0.013****	*-0.013****	*-0.012***	*-0.014*	*-0.014*	*-0.001*	*-0.112****	*1.4*	*-0.2*	*0.008*	*0.048*
YKBNK	March	107.1	27.6	0.261	0.262	0.271	0.291	0.293	0.013	2.108	42.5	4.0	1.007	0.537
	April	145.8	35.3	0.247	0.248	0.262	0.299	0.304	0.015	2.034	37.0	3.3	1.007	0.639
	Diff	*38.6***	*7.7**	*-0.014****	*-0.014****	*-0.010***	*0.009*	*0.011*	*0.002**	*-0.075*	*-5.5***	*-0.7***	*0.001*	*0.102***
AKBNK	April	228.5	24.9	0.112	0.113	0.131	0.171	0.249	0.010	0.971	30.0	2.1	1.061	0.487
	May	234.1	24.9	0.108	0.109	0.123	0.159	0.232	0.010	0.949	32.0	2.1	1.031	0.445
	Diff	*5.7*	*0.0*	*-0.003****	*-0.004****	*-0.007***	*-0.012*	*-0.018*	*0.000*	*-0.022*	*2.0*	*0.0*	*-0.030*	*-0.042*
ASELS	April	104.8	5.8	0.081	0.100	0.243	0.392	0.560	0.033	0.616	10.4	0.3	1.209	0.439
	May	275.4	12.9	0.102	0.108	0.175	0.270	0.383	0.018	0.966	25.0	0.9	2.179	0.665
	Diff	*170.5****	*7.2****	*0.021****	*0.007***	*-0.068****	*-0.122****	*-0.176****	*-0.015****	*0.350****	*14.6****	*0.6****	*0.970****	*0.227****
KCHOL	April	52.8	3.3	0.102	0.124	0.349	0.659	0.563	0.063	0.634	4.5	0.3	1.253	0.443
	May	161.4	10.0	0.090	0.105	0.257	0.498	0.415	0.046	0.571	14.8	1.2	1.272	0.400
	Diff	*108.6**	*6.7**	*-0.012**	*-0.019***	*-0.093***	*-0.162***	*-0.148***	*-0.018***	*-0.063****	*10.3***	*0.9**	*0.019*	*-0.043*

Security	Month	Volume (TRY)	Volume (Shares)	XLM_50	XLM_100	XLM_500	XLM_1000	XLM_1PC	MCI	DWS	Depth	BestVal	ESPR_TL	VOL _MINMAX
KRDMD	April	54.7	44.1	0.815	0.815	0.815	0.815	0.816	0.017	4.442	56.1	12.0	1.000	1.038
	May	131.5	87.9	0.686	0.686	0.687	0.691	0.697	0.016	4.710	67.1	9.9	1.000	1.172
	Diff	*76.7****	*43.8****	*-0.129****	*-0.129****	*-0.128****	*-0.124****	*-0.119****	*-0.001*	*0.268***	*11.0****	*-2.1****	*0.000*	*0.134***
TAVHL	April	30.1	2.0	0.143	0.206	0.707	1.249	0.450	0.134	0.710	3.5	0.1	1.287	0.449
	May	45.0	2.8	0.120	0.173	0.620	1.112	0.389	0.113	0.655	3.5	0.2	1.339	0.555
	Diff	*14.9*	*0.8*	*-0.023***	*-0.033**	*-0.087*	*-0.137*	*-0.061*	*-0.020*	*-0.055****	*0.1*	*0.0*	*0.052*	*0.105***
BIMAS	May	43.5	0.7	0.119	0.140	0.363	0.682	0.286	0.064	0.812	5.5	0.4	6.526	0.480
	June	30.7	0.5	0.128	0.154	0.406	0.756	0.320	0.071	0.786	5.4	0.3	6.690	0.431
	Diff	*-12.7*	*-0.2**	*0.009**	*0.014***	*0.043**	*0.075*	*0.034**	*0.008*	*-0.026*	*-0.1*	*-0.1**	*0.164*	*-0.049*
FROTO	May	14.0	0.4	0.212	0.351	1.489	2.241	0.465	0.295	0.655	1.3	0.1	3.887	0.557
	June	14.4	0.3	0.207	0.352	1.487	2.120	0.463	0.301	0.593	1.2	0.1	3.807	0.514
	Diff	*0.4*	*0.0*	*-0.005*	*0.000*	*-0.002*	*-0.121*	*-0.001*	*0.006*	*-0.062***	*-0.1*	*0.0*	*-0.080*	*-0.043*
ISCTR	May	141.7	20.2	0.146	0.148	0.172	0.229	0.245	0.014	1.305	29.2	1.9	1.025	0.460
	June	92.3	12.9	0.146	0.147	0.177	0.244	0.263	0.016	1.262	23.1	1.6	1.029	0.393
	Diff	*-49.4****	*-7.3****	*0.000*	*0.000*	*0.005*	*0.016**	*0.018**	*0.002**	*-0.042*	*-6.1****	*-0.3***	*0.004*	*-0.066****
PETKM	May	173.2	32.2	0.189	0.190	0.199	0.221	0.251	0.009	1.631	49.9	3.4	1.008	0.522
	June	150.8	25.5	0.175	0.176	0.189	0.220	0.256	0.010	1.594	49.0	3.1	1.026	0.495
	Diff	*-22.4*	*-6.6*	*-0.014****	*-0.013****	*-0.010***	*-0.002*	*0.005*	*0.001***	*-0.037*	*-0.9*	*-0.3*	*0.018****	*-0.027*
SISE	May	22.3	4.8	0.231	0.246	0.605	1.534	0.295	0.112	1.770	4.9	0.5	1.023	0.559
	June	16.9	3.6	0.225	0.237	0.486	1.019	0.273	0.092	1.709	5.6	0.6	1.025	0.465
	Diff	*-5.4***	*-1.2***	*-0.006*	*-0.009**	*-0.119***	*-0.515**	*-0.022**	*-0.020**	*-0.061*	*0.7*	*0.0*	*0.001*	*-0.095****
EKGYO	June	117.74	39.7	0.337	0.337	0.338	0.339	0.340	0.006	2.395	87.4	11.1	1.001	0.527
	July	147.26	47.3	0.325	0.325	0.326	0.329	0.333	0.006	2.358	83.8	10.8	1.001	0.550
	Diff	*29.52*	*7.6*	*-0.013****	*-0.013****	*-0.012****	*-0.010****	*-0.008***	*0.000*	*-0.036*	*-3.6*	*-0.4*	*0.000*	*0.023*
HALKB	June	185.03	14.3	0.088	0.091	0.131	0.193	0.376	0.013	0.765	25.5	1.1	1.073	0.406
	July	182.51	12.9	0.083	0.087	0.132	0.198	0.386	0.013	0.707	21.0	1.0	1.130	0.425
	Diff	*-2.52*	*-1.4*	*-0.005***	*-0.004*	*0.002*	*0.005*	*0.010*	*0.000*	*-0.058****	*-4.5****	*-0.2**	*0.057****	*0.019*
THYAO	June	485.97	64.8	0.134	0.135	0.138	0.145	0.350	0.005	1.294	106.7	5.0	1.031	0.547
	July	600.55	69.5	0.117	0.117	0.120	0.126	0.284	0.004	1.144	114.7	5.2	1.026	0.525
	Diff	*114.58**	*4.7*	*-0.018****	*-0.018****	*-0.018****	*-0.020***	*-0.066****	*-0.001****	*-0.150****	*8.0*	*0.3*	*-0.005*	*-0.022*
ENKAI	July	23.7	4.4	0.196	0.205	0.354	0.588	0.229	0.049	1.570	10.7	0.8	1.048	0.409
	August	17.7	3.3	0.203	0.215	0.408	0.717	0.249	0.063	1.576	7.5	0.7	1.029	0.417

Security	Month	Volume (TRY)	Volume (Shares)	XLM_50	XLM_100	XLM_500	XLM_1000	XLM_1PC	MCI	DWS	Depth	BestVal	ESPR_TL	VOL _MINMAX
	Diff	-6.0*	-1.0	0.007**	0.010**	0.054*	0.129*	0.020**	0.014**	0.006	-3.3***	-0.2*	-0.019	0.008
GARAN	July	349.1	34.0	0.099	0.100	0.106	0.122	0.303	0.006	0.896	54.1	3.3	1.021	0.409
	August	304.4	28.5	0.096	0.097	0.108	0.132	0.368	0.007	0.884	42.9	2.5	1.035	0.420
	Diff	-44.7	-5.4*	-0.003***	-0.002***	0.002	0.010*	0.064**	0.002***	-0.012	-11.2***	-0.7***	0.014***	0.011
OTKAR	July	41.3	0.3	0.154	0.202	0.501	0.814	0.336	0.074	0.930	6.6	0.2	13.534	0.523
	August	14.8	0.1	0.220	0.303	0.884	1.508	0.552	0.162	0.949	3.2	0.1	15.554	0.483
	Diff	-26.5***	-0.2***	0.066***	0.101***	0.383***	0.694***	0.217***	0.088***	0.019	-3.4***	-0.1***	2.020*	-0.040
SAHOL	July	67.3	6.2	0.107	0.116	0.218	0.370	0.259	0.033	0.849	14.3	0.9	1.103	0.357
	August	75.3	7.1	0.107	0.111	0.169	0.258	0.193	0.020	0.865	16.7	1.0	1.063	0.338
	Diff	8.0	0.9	0.000	-0.005	-0.049**	-0.112**	-0.065**	-0.013***	0.016	2.4	0.2	-0.040**	-0.019
TUPRS	July	76.6	0.7	0.110	0.119	0.225	0.376	0.368	0.031	0.909	12.1	0.7	11.015	0.465
	August	143.3	1.2	0.098	0.102	0.165	0.262	0.257	0.021	0.859	16.6	0.9	11.303	0.502
	Diff	66.7***	0.5***	-0.013***	-0.017***	-0.060***	-0.114***	-0.111***	-0.010***	-0.050*	4.4***	0.2***	0.289	0.037
ARCLK	August	34.8	1.4	0.134	0.176	0.618	1.145	0.468	0.113	0.783	3.4	0.2	2.667	0.498
	September	46.9	2.0	0.125	0.155	0.482	0.944	0.369	0.090	0.824	4.3	0.3	2.382	0.516
	Diff	12.0**	0.6***	-0.009	-0.020	-0.136*	-0.201	-0.099	-0.023	0.041*	0.9**	0.1**	-0.285**	0.018
KOZAL	August	117.6	3.5	0.164	0.219	0.594	0.991	0.740	0.110	0.726	4.5	0.1	3.773	1.166
	September	55.5	1.8	0.206	0.291	0.884	1.478	1.111	0.186	0.757	2.5	0.1	3.611	0.986
	Diff	-62.1***	-1.8***	0.041*	0.072**	0.290***	0.487***	0.371***	0.076***	0.031	-2.0***	0.0***	-0.162	-0.181
SODA	August	14.2	2.6	0.231	0.289	0.953	2.018	0.395	0.161	1.628	4.0	0.3	1.066	0.571
	September	21.7	4.2	0.215	0.249	0.696	1.408	0.318	0.124	1.744	5.0	0.4	1.021	0.572
	Diff	7.4**	1.5**	-0.016	-0.040*	-0.257*	-0.610**	-0.077*	-0.037	0.117***	1.0*	0.1	-0.044***	0.002
TCELL	August	93.5	7.3	0.094	0.100	0.189	0.336	0.486	0.031	0.734	9.9	0.8	1.145	0.460
	September	142.7	11.5	0.097	0.103	0.186	0.324	0.466	0.030	0.738	10.8	0.8	1.225	0.509
	Diff	49.2	4.2*	0.003	0.003	-0.003	-0.012	-0.020	-0.001	0.003	0.9	0.0	0.080	0.048
TKFEN	August	25.4	2.1	0.213	0.301	1.483	2.752	0.691	0.196	0.935	3.2	0.1	1.695	0.614
	September	15.5	1.3	0.285	0.454	2.090	3.432	1.084	0.376	0.994	1.4	0.1	1.900	0.836
	Diff	-9.9**	-0.8**	0.072***	0.153***	0.606**	0.679	0.393***	0.180***	0.059**	-1.8***	0.0***	0.205*	0.222***
TTKOM	August	15.2	2.1	0.212	0.292	1.201	2.719	0.468	0.206	1.280	2.8	0.3	1.146	0.514
	September	19.4	2.9	0.220	0.306	1.432	2.866	0.529	0.246	1.262	2.4	0.3	1.148	0.604
	Diff	4.2*	0.7**	0.007	0.014	0.231	0.147	0.061	0.040	-0.018	-0.4	0.0	0.002	0.090

APPENDIX D

BOUNDARY VALUES FOR MARKET VARIABLE QUINTILES

Table D1. Boundary Values for Market Variable Quintiles

Quintiles	**Index Return**	**Stock Return**	**Trading Volume**
Quintile 1	-2.45% and -1.41%	-22.55% and -1.71%	2.96 to 4.36 billion TL
Quintile 2	-1.37% and -0.23%	-1.71% and -0.53%	4.46 to 4.64 billion TL
Quintile 3	-0.22% and 0.13%	-0.53% and 0.55%	4.65 to 4.95 billion TL
Quintile 4	0.20% and 1.32%	0.56% and 1.86%	5.02 to 5.74 billion TL
Quintile 5	1.39% and 4.13%	1.86% and 8.43%	5.75 to 7.99 billion TL

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