PRICE IMPACT ESTIMATION OF BOND MARKET:

A MACHINE LEARNING APPROACH

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DECLARATION OF ORIGINALITY

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ABSTRACT

Price Impact Estimation of Bond Market:

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We conduct an empirical study to analyze the aggregate price impact behavior of Turkish government bonds over 17 years. Moreover, we want to find out the determinants of price impact for each trade. The primary motivation is to provide better guidance to high-frequency traders, fund managers, and institutional traders since generating alpha mostly depends on transaction costs when assets tend to perform similarly. We characterize the order and transaction records of Turkish government bonds in detail. We find that non-residents' positive portfolio flow and AUM in the Turkish private pension market are associated with lower aggregate price impact. In contrast, divergence from other emerging markets drives costs up. We present how price impact varies across trade size, market conditions, bond characteristics, and the state of the limit order book to compare our model with various liquidity measures proposed in the literature. Except for Kyle (1985)'s price impact lambda, our model subsumes the information that other liquidity measures provide. We confirm the square-root law by figuring a concave relationship between trade size and price impact. Finally, we examine how price impact forecasts can be improved via recent Machine Learning Techniques. We show that boosted trees with XGBoost outperforms other alternative models, i.e., random forest and elastic net methods, in out-of-sample estimations. We also find that the prevailing slope of the limit order book, maturity of bonds, and market volatility appear to be the top three factors affecting the slippage. Given the study's novel features, we aim to contribute price impact literature in employing machine learning techniques to long-term order book data.

ÖZET

Bono Piyasasında Fiyat Etki Analizi: Makine Öğrenmesi Yaklaşımı

Bu tezde, Türkiye devlet borçlanma senetlerinin tarihsel toplam fiyat etkisi davranışını analiz etmek için 17 yılı kapsayan ampirik bir çalışma yürüttük. Ek olarak, bir takas işleminin fiyat etkisini belirleyen faktörleri araştırdık. Çalışmanın arkasındaki temel motivasyon, yüksek frekanslı işlem yapan yatırımcılar, fon yöneticileri ve kurumsal yatırımcılar için daha iyi rehberlik sağlamaktır; çünkü, alfa üretimi, varlıklar benzer şekilde performans gösterme eğilimindeyken çoğunlukla işlem maliyetlerine bağlıdır. Türkiye bireysel emeklilik piyasasındaki borçlanma araçları fonlarında bulunan toplam yönetilen varlık miktarı ve yerleşik olmayanların yatırımcıların pozitif portföy akışının daha düşük toplam fiyat etkisi ile ilişkili olduğunu bulduk. Buna karşılık, diğer gelişmekte olan ülkelerden ayrışma, fiyat etkisi maliyetlerini artırıyor. Modelimizi literatürde önerilen çeşitli likidite ölçümleriyle karşılaştırmak için fiyat etkisinin işlem hacmi, piyasa koşulları, bono özellikleri ve limit emir defterinin durumuna göre nasıl değiştiğini gösterdik. Kyle (1985)'in fiyat etkisi lambdası dışında, fiyat etkisi modelimizin diğer likidite ölçümlerinin sağladığı bilgileri kapsadığını bulduk. İşlem hacmi ve fiyat etkisi arasında içbükey bir ilişki olduğunu göstererek yaygın olarak bilinen karekök yasasını onaylayıp, yeni geliştirilen makine öğrenmesi tekniklerini kullanarak fiyat etkisi tahminlerinin nasıl iyileştirilebileceğini de inceledik. XGBoost ile desteklenmiş ağaçların, örneklem dışı tahminlerde rassal orman ve elastik ağ yöntemleri gibi diğer alternatif modellerden daha iyi performans gösterdiğini bulduk. Ayrıca limit emir defterinin işlemden hemen önceki eğimi, tahvillerin vadesi ve piyasa oynaklığının fiyat etkisini etkileyen ilk üç faktör olduğunu gösterdik. Çalışmanın özgün özellikleri göz önüne alındığında, uzun bir tarihsel dönemi kapsayan emir defteri verilerine makine öğrenmesi tekniklerinin uygulanması konusunda fiyat etkisi literatürüne katkıda bulunmayı amaçlıyoruz.

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ABBREVIATIONS

AUM	Assets Under Management
BIST	Borsa Istanbul
CPI	Consumer Price Index
FED	Federal Reserve
ISIN	International Securities Identification Number
LOB	Limit Order Book
NYSE	The New York Stock Exchange
TAQ	Trade and Quote
TORQ	Trades, Orders, Reports, and Quotes
TRY	Turkish Lira
USD	United States Dollar
VWAP	Volume Weighted Average Price

CHAPTER 1

INTRODUCTION

Liquidity is an essential and elusive notion for financial markets; hence extensively investigated by researchers over decades (see Amihud & Mendelson, 1986; Hasbrouck, 2009; Vayanos, 1998). The widely accepted definition of liquidity corresponds to the ability to trade large volumes at low cost with little price impact (Liu, 2006). In addition to researchers, investors strive to measure liquidity, which directly influences portfolio performance since illiquidity incurs higher transaction costs. Although several measures are proposed to calculate the liquidity of a security, the one that is a change in price as a function of trade size, price impact, is of paramount importance to large traders. The historical calculation for price impact costs of each trade and employing its determinants requires high-frequency data, which induces higher computing costs, hence mostly done for U.S markets.

Academics and practitioners have been broadly studying determinants of price impact in both theoretical and empirical aspects. The central hypothesis is constructed around the relationship between price impact and trade size. While theories propose either a concave or linear relationship between price impact and trade size, most empirical research shows that the relationship is concave, i.e., subsequent price change increases with trade size at a decreasing rate. To this end, the existing studies agree that the price impact function is not precisely explored, and the concave relationship is not consistent with the theoretical findings (Bouchaud, Farmer, & Lillo, 2009).

In addition, how aggregate price impact costs behave over time is not thoroughly characterized, especially for emerging markets. The reason is that handling long-term, high-frequency data is a tedious task and requires high programming and computing power. Thus, the studies mostly use data sets spanning short time-horizons, i.e., one year, or containing only a specific institution's trades, which is not enough to define overall market liquidity.

The knowledge of what drives aggregate price impact over time enables regulators to be prepared for adverse market liquidity shocks since they will expect the shocks and their magnitude confidently. In addition, investors can revise their portfolios and trading activity accordingly. Moreover, understanding determinants of price impact incurred by a trade allows large investors to design their trading strategy to minimize the implicit transaction costs.

To this end, using voluminous intraday order and transaction data spanning from January 2001 to December 2017 across Turkish debt securities, we conduct an empirical study to provide a better understanding of aggregate price impact's behavior over time and determinants of price impact function. Our data and methodology include novel features to provide robust results. First, the data being used in this study covers 17 years and subsumes various events and their impacts on Turkey as an emerging market. Second, it contains order records time-stamped down to milliseconds; thus, we can identify whether a transaction is buyer- or seller-initiated to observe the exact sign of each price impact. Lastly, we employ machine learning models to examine what drives price impact function since machine learning models are able to figure non-linear relationships.

This study starts by characterizing the order and transaction book data to remove noises and prepare for the analysis. Then, by the knowledge of actual initiators of each transaction, we evaluate the performance for one of the trade classification algorithms. After constructing data, we measure realized price impact that trade incurs upon execution. We then further decompose the cost into temporary and permanent components. The permanent component indicates the remaining price effect a long time after the execution, while the temporary part reflects the impact that reverses back to its normal level. Using these measurements, we provide a thorough analysis of how aggregate price impact cost behaves over time in Turkey as an emerging market. Prior to examining the determinants of price impact function, we estimate the relationship between price impact and trade size. We then evaluate the price impact function using various explanatory variables in a full sample. Then we

assess a set of liquidity measures proposed in the literature in our price impact model. Lastly, we design a price impact model in rolling out-of-sample using two ensemble machine learning models, i.e., random forest and boosted trees with XGBoost, elastic net, and ordinary least squares regression.

The thesis proceeds as follows: Chapter 2 presents a literature review on price impact estimation. Chapter 3 describes and characterizes the data set on which the analysis is based. Chapter 4 presents the calculation of the realized price impact and its components. Chapter 5 describes explanatory variables and statistical models used in the study. Chapter 6 presents empirical results on the estimation of aggregate price impact and price impact function. Chapter 7 concludes.

CHAPTER 2

LITERATURE REVIEW

Illiquidity is often measured by transaction costs which are grouped into two: explicit cost and implicit costs. Explicit costs, e.g. commissions, market fees, and broker fees, are easily traceable and expected since they are directly processed to investors. However, implicit costs are calculated using execution price of a trade and some benchmark prices, e.g. arrival price and theoretical price (Perold, 1988). Price impact is an implicit cost and implies subsequent price change upon execution of a trade.

The main hypothesis that has been broadly tested in the literature is the relationship between price impact and trade size. Kyle (1985) states larger trades are associated with higher price impacts. Some theories and empirical results supports the concave relationship (Hasbrouck, 1991; Hausman, Lo, & MacKinlay, 1992; Keim & Madhavan, 1995; Almgren, Thum, Hauptmann, & Li, 2005), while some results propose linear correlation (Breen, Hodrick, & Korajczyk, 2002; Korajczyk & Sadka, 2004).

The reason why price impact is a concave function of trade size is discussed in Bouchaud et al. (2009) analyzing different theories. In addition to common rationale, i.e., small trades cause price changes as much as large trades due to reflecting as much information as large trades (Barclay & Warner, 1993), they comment on the consistency of selective liquidity taking, i.e., traders condition their trade sizes on best quotes, executing large trades when the market's liquidity is high (Doyne Farmer 5, Gillemot, Lillo, Mike, & Sen, 2004).

The determinants of price impact have been studied using various data sets, including mostly institutional proprietary data, e.g. Frazzini, Israel, and Moskowitz (2018). Findings mostly present concavity of the relationship and increasing costs with market volatility. In addition, steady decline in costs over time is a common outcome obtained in literature. Frazzini et al. (2018) state that this decline is associated with technological improvements, i.e., pre-decimalization.

Long-term transaction book data is hard to obtain and process; thus, how price impacts behave over time is not discussed enough, at least for emerging markets due to paucity of data. Chordia, Roll, and Subrahmanyam (2001) discuss the time series behavior of liquidity and trade activity and finds the strong day-of-the-week effect; Friday is associated with decrease in trading activity and liquidity. Lesmond (2005) studies emerging markets' liquidity and shows that political risks increase transaction costs by a 10 basis points.

For Turkey, there are very few studies on liquidity. Guloglu and Ekinci (2016) compare performances of low-frequency liquidity proxies for futures traded in BIST. Altay and Çalgıcı (2019) study on correlation between asset returns and illiquidity. Su and Tokmakcioglu (2020) provide a comparison of bid-ask spread measures and estimate bid-ask spreads using bond-level characteristics. Our study differs both in methodology and the time span of the data being used in the analysis.

Park, Lee, and Son (2016) conduct a study to estimate market impact cost using nonparametric machine learning models, i.e., neural networks, Bayesian neural network, Gaussian process, and support vector regression. They find that most nonparametric machine learning methods outperformed their benchmark models, e.g. I-star model proposed by Kissell, Glantz, and Malamut (2003) and Kissell (2013). We use tree-based ensemble models and elastic net to compare with the benchmark, ordinary least squares.

CHAPTER 3

DATA

This chapter describes and characterizes the data set on which the analysis is based and provides some descriptive statistics extracted from both low-frequency data and high-frequency data. First, we describe the transaction book and order book data, select bond universe, characterize trades and orders, i.e., assigning trade signs and ranking orders by aggressiveness; then, we estimate the limit order book.

3.1 Data

The sample for this study comes from Borsa Istanbul, and it consists of intraday transaction and order records of debt securities traded in the BIST Debt Securities Market (BIST-DSM). The BIST-DSM is a fully computerized market where all transactions are conducted via the automated multiple price-continuous auction system with price-time priority.

The secondary market trades of debt securities are effectuated in the Outright Purchases and Sales Market established within the BIST-DSM. A trading day is comprised of two sessions with a lunch break in the Outright Purchases and Sales Market; the first session from 9:30 am to 12:00 pm, and the second session from 1:00 pm to 2:00 pm. There is an additional session from 2:00 pm to 5:30 pm during which fund accounts are allowed to submit passive same-day orders while the continuous auction takes place only for forward settlement day orders. The minimum nominal order quantity is 100,000 in the normal Outright Purchases and Sales Market.

The data set spans from January 2001 to December 2017 and contains, prior to filtering, 6,118,349 trades across 3,519 debt securities, totaling 5,626.2 billion TRY in trades. Each transaction record includes the ISIN code of the security, unique order numbers of both sides, price, nominal quantity, time-stamp, and final status showing whether the trade is matched (M) or cancelled (C) by the market. As the transaction book does not have explicit information on whether each trade is

buyer-initiated or seller-initiated nor the prevailing quote and depth of each trade, we obtain historical order records from BIST. The order history enables us to determine the precise sign of each price impact and develop trade-level liquidity measures.

For each order, the order book data includes the following information:

- ISIN code of the security, requested nominal quantity, price, and sign of the order, i.e, buy or sell.
- The date and time by which the order was submitted (OrderTime), withdrawn (AmendTime), and adjusted (AmendTime). All orders are time-stamped down to milliseconds. Adjusted orders are assigned a new order number after the update. The former order number of adjusted orders is specified as a linked order number after each update.
- The balance quantity that shows the remaining nominal quantity in case of order match or partial match otherwise equals to the requested nominal quantity. Some of the orders are partially filled.
- The security's CPI coefficient calculated by dividing the CPI index value at value date by the CPI index value at the issue date of the security.
- The final status showing whether the order is fully matched (M), adjusted (A), or withdrawn (W).

Table 1 and Table 2 present snapshots of the transaction records and the order records for the same bond, respectively. Trade numbers 784 and 785 illustrate the execution of order 14360 at prices 93.075 and 93.1. Table 2 indicates that order 14334 is updated at 11:16:58.788 to order 14360 before the execution. Furthermore, trade number 4383 shows the partial execution of order 14342 submitted at 11:15:11.627 and withdrawn at 13:47:39.949. Initiators of these trades are not explicitly stated; however, as order 14360 is placed last compared to its counterparts at both transactions, we can derive that order 14360 is the initiator at trades 784 and 785. This inference matches with initiator definition of Odders-White (2000). We elaborate on signing transactions in section 3.3.

Table 1. A Snapshot from the Transaction Records

TradeNo	Time	BuySell	OrderNo	Price	Quantity	CpiCoeff	Status
784	11:16:58	B	14360	93.075	500000	1	M
784	11:16:58	S	14061	93.075	500000	1	M
785	11:16:58	B	14360	93.1	1500000	1	M
785	11:16:58	S	14028	93.1	1500000	1	M
4383	13:42:44	B	14342	93.0	100000	1	M
4383	13:42:44	S	19469	93.0	100000	1	M

Table 2. A Snapshot from the Order Records

OrderNo	OrderTime	BuySell	Price	Quantity	Balance	AmendTime	LinkedOrderNo	Status
14300	11:13:19.726	S	93.325	5000000	5000000	11:55:15.860	0	W
14334	11:14:47.576	B	93.0	2000000	2000000	11:16:58.788	0	A
14342	11:15:11.627	B	93.0	2000000	1900000	13:47:39.949	0	W
14360	11:16:58.788	B	93.1	2000000	0	11:16:58.788	14334	M

3.2 Universe selection

In our study, in addition to intraday data, we utilize a database from Thomson Reuters-Eikon to obtain bond characteristics such as issuer, maturity date, denominated currency, amount outstanding, coupon type, and information on whether it is stripped or not. We exclude corporate bonds, indexed bonds, foreign currency-denominated bonds, floating-rate bonds, and stripped bonds, restricting the sample to TRY-denominated government bonds and treasury bills. After filtering securities by their characteristics, we take out canceled or corrected transactions additional to forward settlement day trades and trades executed in the extra session from 2:00 pm to 5:30 pm. We also require the bonds in our sample to have a trade history of at least 60% of their lifetime so that trade-level and daily liquidity measures can be developed from the data.

Table 3 reports the number of debt securities and the amounts traded (in billion TRY) each year from 2001 to 2017, for each maturity group separately. Our sample includes 255 government debt securities over a 17-year period. The amounts traded, within that period, have grown over time from 7 billion TRY to 57 billion TRY while a decreasing trend has been spotted since 2011. Treasury bills and government bonds, maturing in less than one year, account for every trade in the early

years. The trade volumes of long-term debt securities, maturing in three or more years, have grown over the years; however, amounts traded of long-term bonds plunged drastically in crisis periods such as 2008 and 2009. The fall can be attributed to the "flight to liquidity" phenomenon, suggesting traders shift to less risky and more liquid assets during recession periods. Lastly, on average, 51% of trade volumes take place in medium-term bonds.

Table 3. Descriptive Statistics of the Bond Universe by Year

		Amount Traded (Billion TRY)			
			By maturity		
Year	Number of Bonds	Total	Short-term	Medium-term	Long-term
2001	19	7.20	7.20	0.00	0.00
2002	31	31.62	31.62	0.00	0.00
2003	43	59.52	53.16	6.36	0.00
2004	52	86.25	32.67	53.58	0.00
2005	49	112.17	29.29	80.49	2.39
2006	39	113.10	32.37	75.08	5.65
2007	34	109.82	16.01	87.57	6.24
2008	28	92.70	23.33	66.62	2.75
2009	26	143.82	41.10	102.62	0.10
2010	21	127.75	35.72	86.43	5.60
2011	14	130.92	28.96	90.86	11.10
2012	16	120.58	42.73	54.82	23.03
2013	23	98.43	20.10	24.52	53.81
2014	28	67.13	7.45	15.03	44.65
2015	27	49.35	7.67	4.77	36.91
2016	25	77.91	16.68	5.14	56.09
2017	27	57.46	10.44	6.18	40.84
All	255	1485.73	436.50	760.07	289.16

3.3 Trades and orders

After setting up the bond universe, we characterize transactions and order flows in two steps; classifying trades (buyer- or seller-initiated) and ranking orders by aggressiveness.

The precise sign of each price impact hinges on the side of the trade initiator. Odders-White (2000) asserts that the initiator of a trade can be distinguished through order submission history; thus, the order placed last is the side that caused the transaction to occur. As the data being used in this study includes dates and times by

which each order was submitted, the trades are signed in line with the initiator definition of Odders-White (2000). Our sample, before filtering orders by aggressiveness, consists of 2,128,393 buyer-initiated and 1,775,743 seller-initiated trades.

The widespread use of TAQ data, which generally does not contain time-stamped order history, leads researchers to employ trade classification algorithms, mainly Lee and Ready (1991)'s algorithm (hereafter the Lee and Ready method), which combines quote test and tick test. We evaluate the Lee and Ready method to examine its performance on our sample. Following this, a transaction is classified as buyer-initiated (seller-initiated) if its execution price is closer to the prevailing ask (bid) quote than to the bid (ask). Any transaction effectuated exactly at the mid-quote is classified as buyer-initiated (seller-initiated) if there is an uptick (downtick). If the book is empty or there is no price change, zero-upticks are buys, and zero-downticks are sells. First transactions after the issue of bonds remain unclassified if prevailing mid-quote cannot be set (the book is empty) and there is no uptick or downtick. Note that there are only 200 unlabelled transaction records with 85 buys and 115 sells for the sample.

Panel A of Table 4 reports the comparison of the Lee and Ready method's classification with true buys and sells. We find a 95% accuracy rate of the Lee and Ready method, exceeding the 93% rate found in Lee and Radhakrishna (2000) from the TORQ database of NYSE and the accuracy reported by Aitken and Frino (1996) for the Australian Stock Exchange. The automated market system that updates transaction records without delay in time-stamps is the primary driver of the high accuracy rate, while the emptiness of limit order books before transactions is that of false classifications. Panel B of Table 4 documents a breakdown of the performance by amount outstanding (size). The debt securities are divided into three groups by their amount outstanding for each month, where group one is the top one-third of the bonds and group three is the bottom one-third. The percentage of misclassified transactions increases with size for both buys and sells, which may be caused by the

positive correlation between size and trading activity. This inference requires further investigation, which is out of the scope of this study.

Table 4. Trade Classification Performance of the Lee and Ready Method

		True Buy		True Sell	
		Total	Percentage	Total	Percentage
Panel A: Full sample classification					
	Lee and Ready method: Buy	2,033,199	52.08	102,138	2.62
	Lee and Ready method: Sell	95,109	2.44	1,673,490	42.87
Panel B: Full sample classification by size					
1	Lee and Ready method: Buy	1,117,055	28.61	53,418	1.37
	Lee and Ready method: Sell	47,967	1.23	863,476	22.12
2	Lee and Ready method: Buy	681,965	17.47	35,909	0.92
	Lee and Ready method: Sell	34,742	0.89	604,511	15.48
3	Lee and Ready method: Buy	234,179	6.00	12,811	0.33
	Lee and Ready method: Sell	12,400	0.32	205,503	5.26

In this study, the sample data, after filtering for selected bond universe, has 2,737,974 orders that initiated at least one transaction. As the data does not contain any information on the type of order submission, we employ the procedure proposed by Biais, Hillion, and Spatt (1995) to proxy market orders. Following this, orders are divided into six types where type one is the most aggressive, and type six is the least aggressive. Below we provide definitions of types for buy orders, where the sell-side orders are defined analogously.

- Type one orders walk up the limit order book above the best ask. That means these orders are submitted with a larger quantity than the depth at the best ask and at a price that is higher than the best ask. Note that the remaining part of the order can be converted to a limit buy order if it is a limit order and not fully executed.
- Type two orders are orders to buy a larger quantity than that available at the best ask but do not walk up the limit order book. It can be the case if the order is a limit buy order at the best ask.
- Type three orders are orders to buy a lower quantity than that available at the best ask, which results in complete execution.

- Type four orders represent orders whose price is better than the best bid but worse than the best ask. Type five orders are submitted at the best bid, while type six orders are remaining orders.

After labeling order types, we require orders in our sample to be type one or type three and fully and immediately executed. Table 5 reports time-series summary statistics on the trade level sample. A maximum number of 52 government debt securities are traded in a given year, while the minimum is 14. The number of orders submitted averages 101,644 per year, initiating 138,145 trades for an average trade size of 1,194,560 TRY. Note that the variation in the fraction of daily volume is too

Table 5. Summary Statistics on Trade Level Sample

	Mean	Median	Stdev	Min	Max
Number of bonds per year	29.53	27.00	10.84	14.00	52.00
Number of orders per year	101,644	93,811	33,785.24	33,562	153,540
Number of trades per year	138,145.5	132,400	48,486.87	43,360	215,251
Average trade size (x 1,000)	1,194.56	470.48	1,764.04	71.62	10,584.84
Fraction of daily volume (%)	3.67	0.67	13.91	0.03	815.59

wide with a standard deviation of 13.91%. Figure 1 plots the distribution of the fraction of daily volume in our sample. The distribution is too unbalanced to estimate price impact levels for a fraction of daily volume higher than 15% with certainty, as trade sizes are exogenous in price impact estimation. Therefore, we limit ranges of the fraction of daily volume from 0% to 15% in the analyses in which trade size is exogenous to price impact cost.

3.4 Limit order book estimation

A snapshot of LOB consists of limit orders submitted by traders to provide liquidity to those who demand immediate execution. To analyze quotes and depths at a point in time, estimation of the LOB is crucial. The order book data, which contains detailed records of order submission dates and times, enables us to construct the snapshots at each point in time. We estimate limit order books, following Kavajecz

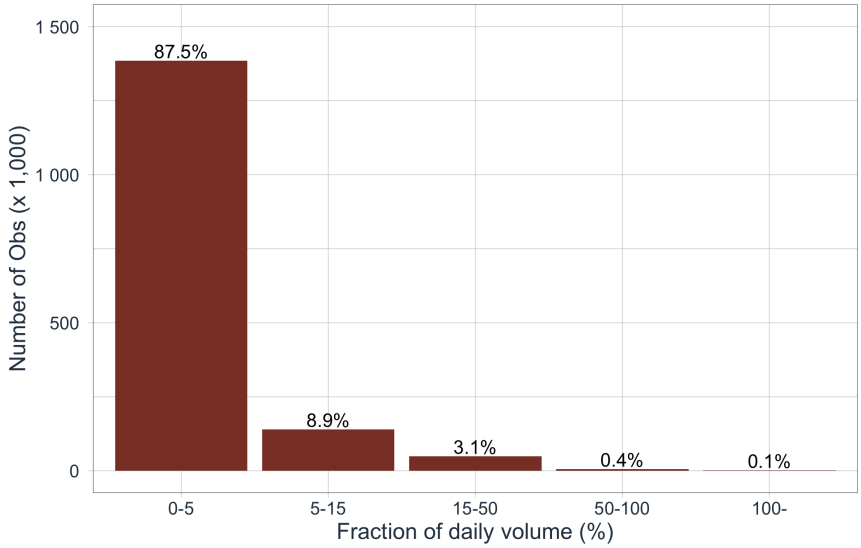


Figure 1. Observation numbers by fraction of daily volume

(1999), at one-minute intervals for the 255 debt securities in our sample, yielding 210 snapshots a day for one debt security. Additionally, to construct prevailing quotes, depths, and slopes of each transaction, we estimate snapshots 1:1000 seconds before each transaction's execution time. Figure 2 plots the snapshot for TRT070115T13 at 11:48:21.136 on May 10, 2013, estimated right before a seller-initiated transaction executed at price 102.425.

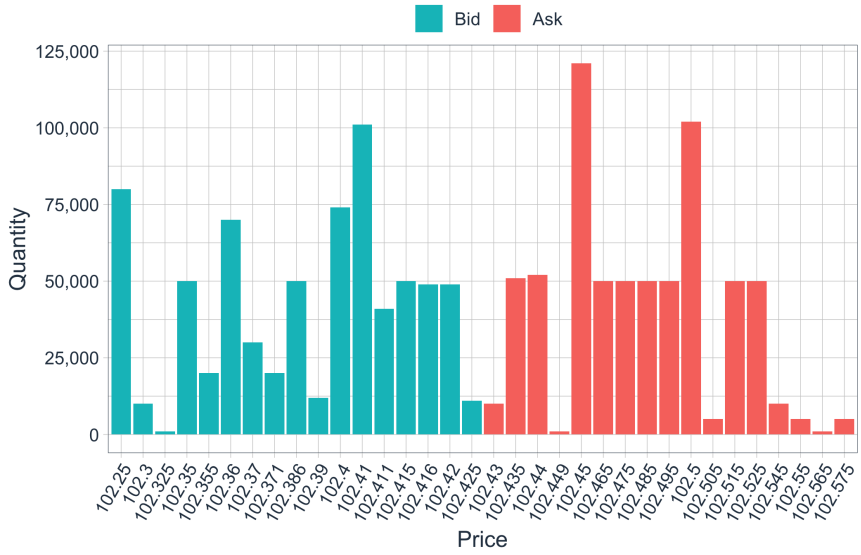


Figure 2. Snapshot of the limit order book for TRT070115T13 at 11:48:21.136 on May 10, 2013

CHAPTER 4

PRICE IMPACT

In this chapter, we calculate our realized impact cost used in the analysis and its components and provide descriptive statistics of the price impact, aggregated monthly across debt securities.

Each order placed in the limit order book faces two primary costs: explicit costs and implicit costs. Explicit costs include market fees and commissions and are easy to account for as they are charged directly to traders. Implicit costs vary regarding the aggressiveness of the order. Aggressively implemented orders experience execution cost to demand immediate liquidity from those supply liquidity on the counter side. In contrast, passive orders face the cost of delay in execution, i.e., opportunity cost. Delay or partial execution cost may increase if associated with adverse market price movement.

In this study, we measure price impact, which is an implicit cost that gauges the correlation between an order, generally a meta-order, and resulting adverse market price movement. Our study includes only immediately and fully executed orders, directing our focus on the cost of execution rather than the opportunity cost. The realized execution cost experienced on an order is measured by the gap between the execution price and a benchmark price. The benchmark price is set depending on the study and selected from the set of pre-trade prices, i.e., theoretical price, arrival price, close price, and open price, and intra-trade price, i.e., VWAP (Kissell & Malamut, 2005).

For each trade, we calculate the realized cost in terms of returns as defined below:

$$PI = \frac{d_i(P_{ex} - P_0)}{P_0} \tag{1}$$

with P_{ex} and P_0 representing the volume-weighted average execution price and the arrival price (the mid-quote right before the execution begins) and d_i representing the direction-of-trade (1 for buys and -1 for sells).

Order flow is the way to convey new information to the market. Any improvement on fundamentals perceived through order flow leads liquidity suppliers to revise their expectations, which results in higher mid-quotes. However, the same result may be achieved through uninformed traders' order flow seen as the arrival of new information. In the former case, the impact of orders lasts a long-time as the price is adjusted to a new fair value, while in the latter case, the impact is dissipated over time. This motive requires us to further decompose our price impact measure into temporary and permanent components.

We calculate the permanent impact as the remaining effect one and a half-hour after the last execution. The defined time interval should be taken long enough that any temporary effects in the price have reversed to the fair value. The remaining part between the execution of the trade and one and a half-hour later the execution expresses the temporary effect. Below, we define the temporary and permanent components formally:

$$PI^{perm} = \frac{d_i(P_0^{t+\varepsilon} - P_0^t)}{P_0^t} \tag{2}$$

$$PI^{temp} = PI - PI^{perm} \tag{3}$$

where $P_0^{t+\varepsilon}$ and P_0^t are the mid-quote following the one and a half-hour after the last execution and the prevailing mid-quote of the trade, and d_i represents the direction-of-trade (1 for buys and -1 for sells).

Table 6 depicts the descriptive statistics of the price impact estimates, which we calculated through equations (1) to (3) over 17 years for each maturity group separately. The cross-sectional mean estimates are calculated each month, and the time-series average of these estimates are reported in the first three-row of each panel, where each month is weighted by the number of debt securities traded in that month. The following three rows contain the time-series average of the cross-sectional mean, where each trade is weighted by its trade size (value-weighted mean, as "vw mean"). The final two rows of each panel report a median and standard error of monthly

Table 6. Descriptive Statistics of Realized Price Impact and Its Components

		By maturity		
	All	Short-term	Medium-term	Long-term
Panel A: Full sample				
Realized PI mean	3.29	1.74	2.99	7.31
Temporary PI mean	0.53	0.26	0.59	1.11
Permanent PI mean	2.76	1.48	2.40	6.20
Realized PI vw mean	3.42	1.87	3.25	7.47
Temporary PI vw mean	0.01	0.03	0.20	0.30
Permanent PI vw mean	3.41	1.84	3.05	7.17
Realized PI median	2.41	1.43	2.67	6.32
Realized PI sd	0.30	0.22	0.18	0.49
Panel B: 2001-2012 period				
Realized PI mean	2.23	1.73	2.48	6.90
Temporary PI mean	0.37	0.22	0.55	1.71
Permanent PI mean	1.86	1.51	1.93	5.19
Realized PI vw mean	2.53	1.88	2.76	7.22
Temporary PI vw mean	0.01	-0.07	0.33	0.46
Permanent PI vw mean	2.52	1.95	2.43	6.76
Realized PI median	2.04	1.36	2.56	5.89
Realized PI sd	0.27	0.30	0.17	0.68
Panel C: 2013-2017 period				
Realized PI mean	5.33	1.80	3.85	7.46
Temporary PI mean	0.83	0.47	0.75	1.00
Permanent PI mean	4.50	1.33	3.10	6.46
Realized PI vw mean	5.54	1.83	4.26	7.83
Temporary PI vw mean	0.05	0.27	-0.03	0.06
Permanent PI vw mean	5.49	1.56	4.29	7.77
Realized PI median	5.39	1.61	3.84	7.07
Realized PI sd	0.34	0.14	0.24	0.65
Panel D: 2007-2009 period				
Realized PI mean	2.17	1.19	3.00	7.32
Temporary PI mean	0.41	0.28	0.47	1.35
Permanent PI mean	1.76	0.91	2.53	5.97
Realized PI vw mean	2.22	1.24	3.32	7.60
Temporary PI vw mean	0.15	0.08	0.45	-0.44
Permanent PI vw mean	2.06	1.16	2.87	8.04
Realized PI median	2.01	1.13	2.56	6.31
Realized PI sd	0.22	0.08	0.36	1.11
Panel E: 2010-2012 period				
Realized PI mean	1.89	0.88	1.85	5.30
Temporary PI mean	0.55	0.21	0.52	1.74
Permanent PI mean	1.34	0.67	1.33	3.56
Realized PI vw mean	2.05	1.01	1.93	6.44
Temporary PI vw mean	0.12	-0.01	0.11	1.26
Permanent PI vw mean	1.93	1.02	1.82	5.18
Realized PI median	1.92	0.84	1.77	5.03
Realized PI sd	0.13	0.11	0.11	0.71

estimates calculated in line with Fama and MacBeth (1973). Panel A of Table 6 reports summary statistics over the entire sample. The mean realized cost is 3.29 basis points while the value-weighted mean is 3.42 basis points, which is consistent with the argument that transaction costs increase with trade size. The permanent impact accounts for about 85% of the realized impacts, which is similar across maturity groups. On average, 0.53 basis points of the 3.29 basis point of realized impact are dissipated over one and a half-hour interval after a trade, which corresponds to the temporary component of the price impact. Long-term debt securities, maturing in three or more years, generates higher price impact, i.e., 7.31 basis points, compared to debt securities with shorter maturities. Other panels of Table 6 report the same summary statistics for sub-periods. The lowest mean and standard error of monthly estimates occur from 2010 to 2012, while the highest is from 2013 to 2017. In addition to higher price impacts, in crisis periods such as 2007-2009, the standard error increases substantially for long-term debt securities. From 2007 to 2009, short-term debt securities generate lower price impacts with lower standard errors than other periods. These results can be attributed to the fact that market risk and illiquidity play key roles in price impact costs. Figure 3 shows time-series behavior of price impact.

Figure 3 plots the time-series average of monthly cross-sectional mean of realized impact with 90% and 10% quantiles. According to the literature, aggregate transaction costs decline over time due to technological improvements. Frazzini et al. (2018) find, using a trade execution database from a large institutional money manager, that the decline in aggregate trading costs comes from technological events such as moving to decimalization at traded prices. The steady decline is not exhibited in our aggregate price impact costs, as seen in Figure 3. Rather than a steady decline, there are substantial upside movements in recession periods such as 2001-2002, 2008-2009, and 2013-2014. We further analyze what drives these movements over time using macroeconomic factors in section 6.1.

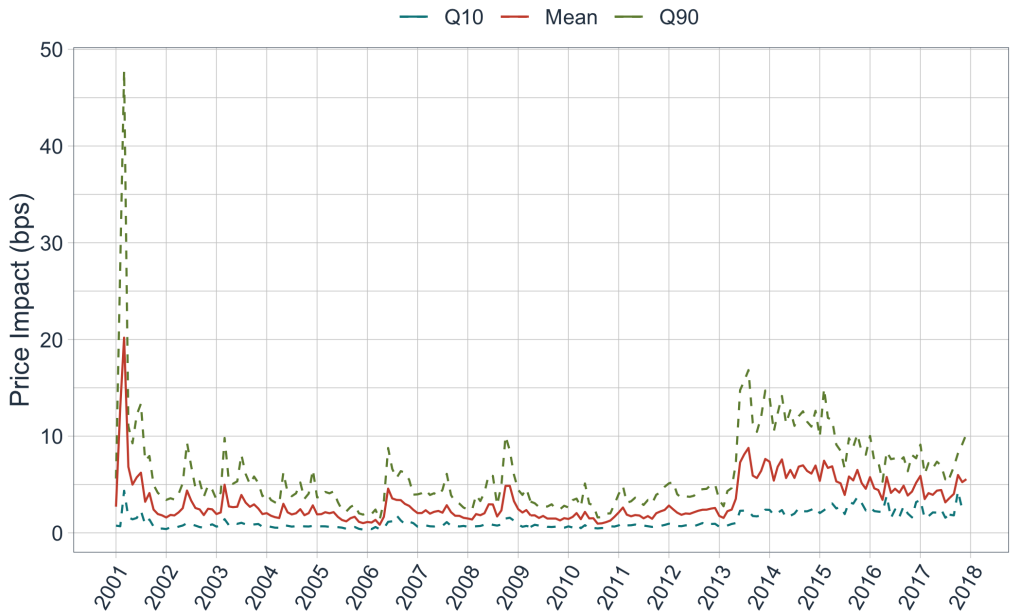


Figure 3. Monthly time series average of realized price impact

CHAPTER 5

METHODOLOGY

This thesis aims to examine how aggregate price impact costs behave over time and what drives price impact function for each trade. Doing that, we first obtain macroeconomic variables such as non-residents' portfolio flow, 2-year interest rates of emerging market countries, and AUM of fixed income funds operated in the Turkish private pension market. In the first section of Chapter 6, we estimate the determinants of aggregate price impact over time by running monthly ordinary least squares (OLS) regressions. We then present the relationship between price impact and trade size calculated as a fraction of daily volume. Moreover, we model price impact function both in full-sample and in rolling out-of-sample. We examine a set of market-, bond-, and trade-level variables to capture the variation in price impact. First section of this chapter introduces explanatory variables and their calculations. The second section explains models used in rolling out-of-sample estimation of price impact.

5.1 Variables

5.1.1 Trade size

Many studies in the literature have investigated the relation between trade size and subsequent expected price change, which is defined as price impact. The theories propose either linear (Breen et al., 2002; Korajczyk & Sadka, 2004) or, mostly, concave relationship (Kyle, 1985) between the amount traded and price impact. More formally, the relation is defined as follows:

$$\mathbb{E}\left[\mathrm{r}|\mathrm{v}\right] \propto \mathrm{v}^{\alpha}$$

where r and v stand for subsequent price change and trade size, respectively. Therefore we test whether $\alpha = 1$ or $\alpha < 1$ in which the former implies a linear relationship and the latter implies a concave one, where $\alpha > 0$.

We define trade size as a fraction of daily volume, which equals the trade volume divided by the bond's average 20-days volume. In line with the discussion in Chapter 3, we allow the fraction of daily volume to range from 0% to 15%.

5.1.2 Market characteristics

Furthermore, we include market-wide proxies to capture the effects resulting from both global and local market conditions. We include the variable "TR2Y_Difference*BuySell", which is a daily difference of Turkey's 2-year interest rate times a variable "BuySell" which equals 1 for buys and -1 for sells. This variable is used to account for the effect of being a momentum trader or contrarian. Also, this variable does not affect the estimation of expected price impact from in-sample results as the expected daily difference of the 2-year interest rate is unpredictable. However, we use a 20-day moving average of the daily difference in out-of-sample estimation as the best expectation. Kyle (1985) finds that volatility increases the transaction costs as a result of increasing inventory costs; however, information on bonds' duration is not available in our sample. Thus, we also include "Sd TR2Y_Difference", which is the volatility of daily differences in a 20-day window. We consider "Market Liquidity" to capture the overall liquidity condition of the bond market, which is the deviation of average market trading volume from its L1 trend (with lambda = 3000) proposed by Kim, Koh, Boyd, and Gorinevsky (2009). We calculate average market volume as a logarithm of its 20-day moving average. Note that this variable should not be included in out-of-sample estimation as the trend comes from the entire sample; otherwise, it constitutes an in-sample bias. Hence, in out-of-sample estimation, we fit the trend in the rolling 20-day window and take the last residual available before the trade. Lastly, to account for global market risks, we include "VIX", which stands for Chicago Board Options Exchange Volatility Index and measures market expectations for volatility over the next 30 days.

5.1.3 Bond characteristics

In addition to market characteristics, we include bond-specific variables to capture variation in the price impact, which results from cross-sectional differences. We include maturity dummies to capture the effect of term differences where we divide the securities into three groups:

- "Maturity Group (= 1)" for bonds maturing in less than or equal to one year.
- "Maturity Group (= 2)" for bonds maturing in between one and three years.
- "Maturity Group (= 3)" for bonds maturing in more than three years.

We also calculate a liquidity score (LiqScore) each day to capture the liquidity variation across bonds, which is a 20-day moving average of a bond's volume share in its maturity group. As a result, having a high volume share in its maturity group defines a bond with a higher liquidity score.

5.1.4 State of the limit order book

State of limit order book before each transaction is worth analyzing as a trader conditions his/her order quantity and price on it, leading to the price impact cost to vary. Doyne Farmer 5 et al. (2004) states that significant price impacts are mainly driven by the market's ability to absorb new orders and are independent from the volume of orders. Moreover, Weber and Rosenow (2006) show that density of limit orders prior to a trade, in addition to order volume, is necessary to investigate large price impacts.

We include "Slope" to account for the price sensitivity of each side, which is the change in price relative to the cumulative quantity available from level 1 to level 20, i.e., price elasticity. We define the slopes of both sides as the natural logarithm of absolute slope since the slope of the bid side is always negative. For buy-side initiators, we define the prevailing slope as the ask-side slope, and for sell-side initiators, it is the buy-side slope. We also include order book imbalance ("OB Imbalance") which captures order flow imbalance offered at the best bid and best ask.

Formal definitions of prevailing slope and order book imbalance for a buyer-initiated trade are as follows:

$$\text{Slope}^{\text{A}} = \log\left|\frac{\text{P}^{\text{A}}_{20} - \text{P}^{\text{A}}_{1}}{\text{Q}^{\text{A}}_{1,20}}\right|$$

$$\text{OB Imbalance} = 100 * \frac{\text{Q}^{\text{Bid}}_{1} - \text{Q}^{\text{Ask}}_{1}}{\text{Q}^{\text{Bid}}_{1} + \text{Q}^{\text{Ask}}_{1}}$$

where P^{A}_{20} and P^{A}_{1} represent the prevailing ask price at level 20 and level 1, and $\text{Q}^{\text{A}}_{1,20}$ is the prevailing cumulative total quantity from level 1 to level 20. $\text{Q}^{\text{Bid}}_{1}$ and $\text{Q}^{\text{Ask}}_{1}$ stand for the prevailing quantities supplied at the best bid and best ask.

Finally, we analyze order imbalance in the limit order book, and we define "Imbalance_Coef" to capture the order flow with respect to maturity (in years). For each day, we regress the cross-sectional average of order book imbalance on maturities (in years) and extract the slope coefficient as a variable. Figure 4 plots an example for two dates from our sample. The slope coefficient from 2017-10-11 is assigned to trades executed in 2017-10-12 as "Imbalance_Coef". Furthermore, we define "Diff_Imbalance_Coef" to capture the change in order flow, equaling to the difference of two slope coefficients from the previous two days.

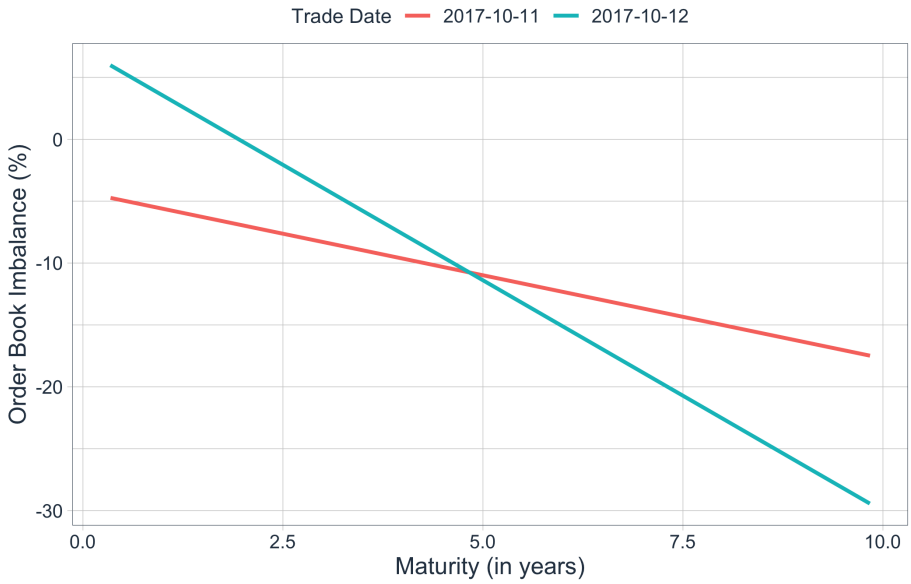


Figure 4. Order book imbalance with respect to maturity

5.1.5 Other liquidity measures

We examine and compare our price impact estimates with liquidity measures proposed in the literature. We use four liquidity measure, i.e., modified measure of Roll (1984), "Zeros" measure of Lesmond, Ogden, and Trzcinka (1999), illiquidity measure of Amihud (2002), and price impact λ of Kyle (1985).

5.1.5.1 Roll

Roll (1984) introduces an implicit measure to estimate effective bid-ask spread using low-frequency data, i.e., daily asset prices. The paper assumes an efficient market and develops the idea that the negative co-variance of two consecutive price changes results in higher bid-ask spreads. Roll (1984) shows that this serial co-variance equals:

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

where ΔP_t is the log price change on day t. Note that when the serial co-variance is positive, the measure is undefined. Thus Goyenko, Holden, and Trzcinka (2009) modify this measure as follows:

$$\text{Modified Roll} = \begin{cases} 2\sqrt{-\text{cov}(\Delta P_t, \Delta P_{t-1})} & \text{if } \text{cov}(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0 & \text{if } \text{cov}(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases}$$

We calculate "Modified Roll", following Hasbrouck (2009), in a rolling 20-days window for each debt security, and use daily prices constructed from the transaction book.

5.1.5.2 Amihud

Amihud (2002) introduces a low-frequency price impact measure that calculates "daily price response associated with one dollar of trading volume." We define "Amihud MI" in a rolling 20-days window using daily prices for each debt security as follows:

$$\text{Illiquidity}_t = \frac{1}{N}\sum_{t=1}^{t=N}\frac{|r_t|}{\text{Volume}_t}$$

$$\text{Amihud MI}_t = \text{Illiquidity}_t * \frac{1}{N}\sum_{t=1}^{t=N}\text{Volume}_t$$

with r_t and Volume_t representing the bond's return and total trade volume on day t. N is the number of all positive-volume days in a 20-days window.

5.1.5.3 Zeros

Lesmond et al. (1999) introduce the proportion of days with zero returns. They state that conveying information to stocks with higher transaction costs is difficult; thus, even on positive volume days, they experience zero returns. Below the formulation of "Zeros" that we calculate in a rolling 20-days window using daily prices for each debt security:

$$\text{Zeros} = \frac{\text{Number of days with zero returns}}{N}$$

where N equals the number of available trading days in a 20-days window.

5.1.5.4 Kyle

Kyle (1985) develops a square root relation between trade size and subsequent market impact. We follow Hasbrouck (2009) to calculate high-frequency price impact measure (known as the Kyle (1985) lambda) over five-minute intervals. More formally:

$$\Delta P_\tau = \lambda \text{sign}(V_\tau)\sqrt{|V_\tau|} + u_\tau$$

where ΔP_τ is the log price change in basis points over τth 5 minutes time interval, and V_τ is the signed total trade volume over the interval. λ corresponds to the market impact resulting from V_τ traded.

5.2 Models

5.2.1 Elastic net

Elastic net, proposed by Zou and Hastie (2005), is a type of linear regression, which combines two penalties, i.e., L1 regularization and L2 regularization. Note that ordinary least squares (OLS) regression aims to minimize the sum of squared errors. When the assumptions of OLS are met, the coefficients estimated are unbiased and have the lowest variance. However, with advances in technology and the start of the big-data era, large amounts of explanatory variables are employed to capture the variation in the dependent variable. In OLS, increasing independent variables results in overfitting, which causes high errors in the testing sample. Thus, regularization models offer to control coefficients to avoid overfitting. Specifically, regularization models employ a penalty/shrinkage to coefficients, and constantly penalize them towards zero. The only way for a coefficient to increase is experiencing a decrease in the sum of squared errors. Formally, elastic net combines L1 penalty, proposed by Hoerl and Kennard (1970), and L2 penalty, proposed by Tibshirani (1996), as follows:

$$\min\left\{ \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 + \lambda_1 \sum_{j=1}^{p}\beta_j^2 + \lambda_2 \sum_{j=1}^{p}|\beta_j| \right\}$$

where λ is a tuning parameter which controls penalty terms. Note that, in elastic net, λ ranges from 0 to 1 inclusive.

5.2.2 Random forest

Random Forest, proposed by Breiman (2001), is an ensemble machine learning algorithm that consists of large number of decision trees (see Quinlan (1986)), called estimators. The algorithm repeatedly and randomly construct sample subsets from training data with replacement, which is called bootstrapping. To train each estimator, decision tree, the algorithm assigns a subset of independent variables; thus, no decision tree captures all data at once, avoiding decision trees to memorize all

training samples. This method limits the overfitting problem of the decision tree algorithm. The final outcome is produced by averaging results of all decision trees, called aggregation. The primary hyperparameters of random forest are the number of trees in the forest and the number of random features included at each node to be split. With the higher number of trees included in the forest, the model can reach more robust results with a lower variance; however, training time increases with the size of the forest. Tuning the number of random features is essential for a robust model since small values are associated with lower variance and higher bias while large values vice versa.

5.2.3 Boosted trees with XGBoost

Gradient boosting, introduced by Friedman (2001), aims to minimize a loss function, e.g. root mean square error for regression, using weak learners to make predictions. Decision trees are generally the weak learners. The weak learners work in a sequential manner while bagging methods, e.g. random forest, run in a parallel manner using sub-sampling. Each weak learner tries to minimize the biggest error that comes from the previous learner, which is boosting. The gradient implies residuals when the loss function defined as sum of squared errors. Namely, given a set of independent variables, gradient boosting algorithm tries to find local gradient of the loss function at the end.

XGBoost, introduced by Chen and Guestrin (2016), stands for extreme gradient boosting, an optimized gradient boosting library that offers improvements in selecting different weak learners and loss functions. In addition, as the gradient boosting algorithm works sequentially, it is hard to execute it with parallel processing. However, XGBoost offers procedures to support GPU and Spark compatibility to fit the model using distributed processing engines.

CHAPTER 6

EMPIRICAL RESULTS

Using voluminous intraday data spanning 17 years from the Turkish debt securities market, we examine how aggregate price impact costs behave over time and what drives the price impact function for each trade. First, the chapter presents the role of macroeconomic factors on the time-series behavior of price impacts. Then, the price impact function is modelled as a function of trade size, market-, bond-, and trade-level characteristics, both in full-sample and rolling out-of-sample, respectively.

6.1 Macroeconomic determinants

In this section, the relation between macroeconomic factors and the time-series evolution of market impact is explored. Changes in the macroeconomic environment direct investors to revise both their wealth allocation and trading activity. For example, a realization of an increase in bond yields may stimulate traders to reallocate their portfolios to devote a more significant portion for debt securities. In addition, an increase in either country-specific or global risks results in higher inventory costs on which liquidity is based (Demsetz, 1968; Ho & Stoll, 1981; Stoll, 1978). To account for these points, we include two years bond yield difference of Turkey and other emerging market countries consisting of Brazil, China, Czech Republic, India, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, and Thailand. The spread captures the effect of any divergence from emerging markets due to country-specific risks.

As order flow triggers investors to revise their expectations, any information on initiators of the order flow does too. Therefore, figuring if any incumbent-entrant game occurs in the market requires further investigation; however, we consider the net flow of the debt securities portfolio of non-residents in Turkey as a starting point for further studies.

Another variable associated with liquidity is volume. Therefore, we include the monthly change in total assets under management of fixed income funds operated in the private pension market of Turkey. The market was established in 2003, and investors are responsible for the amount and allocation of monthly contributions. Therefore, there is a constant inflow to funds which obliges fund managers to re-balance the funds accordingly.

Seasonality is crucial to investigate for any time-series model. In this design, seasonality captures the changes in investors' sentiments towards trading activity over the week or year. Foster and Viswanathan (1990) indicate that the transaction costs are higher on Monday, and the informed trader has more information on Monday. Chordia et al. (2001) find liquidity and trading activity decline on Friday while Tuesday is the day of the week with the highest liquidity. Thus, in line with the frequency of macroeconomic variables, we consider calendar month dummy variables in our model.

Table 7 shows the in-sample regression results estimated from January 2006 to December 2017. We use a monthly difference of cross-sectional average of market impact, in basis points, as the dependent variable. Net debt securities portfolio flow of non-residents (Net Foreign Flow, in a million USD), the change in AUM of fixed income funds (FI Funds' AUM, in %), two years bond yield difference of Turkey and other emerging markets (TR-EM 2Y Spread, in %) and the calendar month dummies as proxies. Note that the proxies are observable ex-ante except for the change in AUM of fixed-income funds. The adjusted R^2 ranges from 6.1% to 17.8%, indicating the model captures a significant part of the time-series variation in the market impact costs.

The net flow of non-residents has a significantly negative but relatively small impact; nevertheless, it is a clear signal that the market liquidity follows the non-resident's portfolio flow, which decreases the transaction costs. The liquidity generated through the private pension market decreases the market impact cost by 0.065 basis points for a one percentage point increase in the AUM of the funds.

Table 7. In-Sample Regression Results with Macroeconomic Proxies

	Dependent variable:			
	ΔMarket Impact (bps)			
	(1)	(2)	(3)	(4)
Constant	–0.249	–0.180	–0.035	–0.005
	(–0.818)	(–0.605)	(–0.117)	(–0.017)
Net Foreing Flow		–0.0002***	–0.0001**	–0.0001**
		(–2.662)	(–2.356)	(–2.405)
FI Funds AUM			–0.067**	–0.065**
			(–2.415)	(–2.376)
TR-EM 2Y Interest Rate Spread				0.137*
				(1.716)
Feb	0.090	0.049	0.089	0.076
	(0.219)	(0.122)	(0.225)	(0.195)
Mar	0.313	0.314	0.303	0.274
	(0.758)	(0.782)	(0.769)	(0.701)
Apr	0.076	0.156	0.162	0.109
	(0.183)	(0.386)	(0.409)	(0.276)
May	0.687*	0.598	0.564	0.576
	(1.666)	(1.481)	(1.426)	(1.468)
Jun	0.538	0.495	0.486	0.415
	(1.306)	(1.229)	(1.232)	(1.054)
Jul	0.311	0.421	0.430	0.343
	(0.754)	(1.043)	(1.084)	(0.867)
Aug	0.158	0.123	0.147	0.194
	(0.375)	(0.300)	(0.366)	(0.486)
Sep	0.412	0.328	0.349	0.360
	(0.956)	(0.780)	(0.846)	(0.878)
Oct	0.656	0.547	0.620	0.529
	(1.435)	(1.222)	(1.410)	(1.204)
Nov	0.076	–0.082	–0.059	–0.118
	(0.172)	(–0.189)	(–0.137)	(–0.277)
Dec	0.585	0.610	0.674	0.606
	(1.357)	(1.452)	(1.633)	(1.476)
Observations	144	144	144	144
R^2	0.061	0.114	0.157	0.178
Adjusted R^2	–0.027	0.024	0.062	0.078

Note: *p<0.1; **p<0.05; ***p<0.01, and t-statistics in parentheses.

As the Turkish private pension market has very low capitalization relative to its GDP (around 3%), a growth of the market will stimulate trading activity and decrease market impact cost. In terms of bond yields, a divergence from the emerging markets significantly affects the market impact costs since investors perceive the divergence as a risk. These results serve as some intuitions to comment on the spike in the 2013-2014 period. Fueled with the FED's announcement on the possible tapering of its bond purchases in 2013, the short-term bond yields started to rise while long-term bond yields hit record lows. However, the emerging market bond yields increased less than the corresponding U.S bond yield, resulting in the outflows from the emerging economies in search for yield. From May 2013 to December 2013 inclusive, the net portfolio flow of non-residents in Turkish government debt securities is -3,877 million USD, which drives the market impact up.

Appendix A reports the robustness check of the model, mainly for column (4) of Table 7. We include market variables such as the 20-days rolling standard deviation and average of Turkish 2-year bond yield's daily differences. The idea is to check if the macroeconomic factors are still significant after we account for a primary market condition, i.e., volatility. The results suggest that the recent market volatility and high-level upside or downside movements are associated with an increase in the price impact. We conclude that the model represented in column (4) of Table 7 are robust and proxy the time-series evolution of the price impact.

6.2 Trade size

This section presents our results on modeling the price impact with respect to trade size. The theories on the dependency of price impact on trade size discuss the either linear or concave relationship. Our unique data set spanning 17 years of trade and order history of the Turkish debt securities market provides valuable results to investigate this correlation. Note that our sample includes the most aggressive orders, i.e., market orders, totaling 1,458,773 observations after characterizing the data set.

Figure 5 plots the average market impact as a function of the fraction of daily volume. First, we divide all trade sizes into 20 bins depending on the fraction of daily volume across the order sizes considered. Then we compute the average realized impact faced in each bucket. The plot shows that the impact grows with the fraction of daily volume at a decreasing rate; thus, we confirm that the concave relationship describes our data better, in line with most of the studies. For example, Loeb (1983) and Torre (1997) model square-root relationship between price impact and trade size, and Almgren et al. (2005) empirically describe the power-law relation, using Citigroup Equity Trading's stock trade data, in favor of 0.6. We plot the log-log regression of price impact on the fraction of daily volume in Appendix B, resulting with slope 0.193 and R^2 of 94.8%. Our coefficient is smaller than square root law, i.e., 0.5; however, still confirms the concavity of the power-law relation.

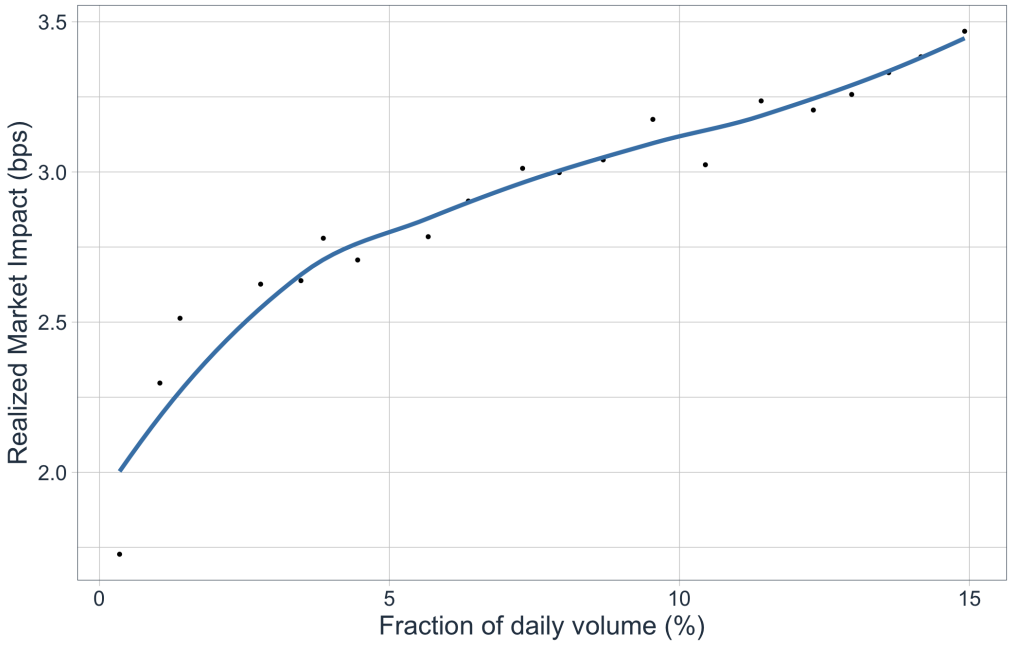


Figure 5. Realized market impact by fraction of daily volume

Figure 6 shows the concave power-law relation is persistent across maturity groups, except short-term debt securities, maturing in less than one year. This result stems from the high liquidity of the short-term bonds, concluding the price impact being independent of trade size for this maturity group.

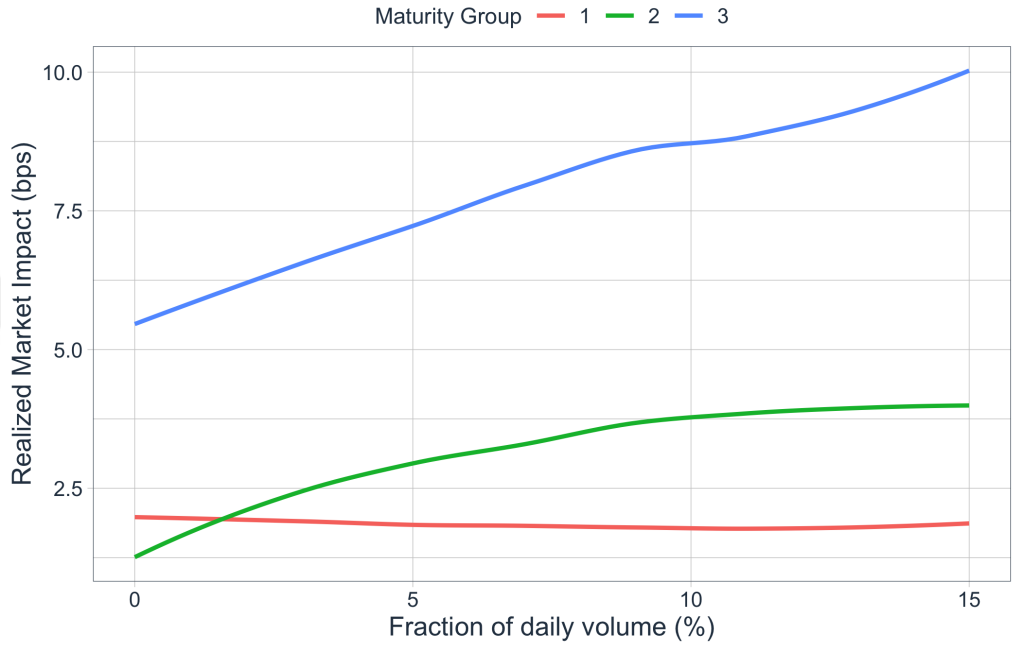


Figure 6. Realized market impact by fraction of daily volume across maturity groups

6.3 Full sample estimation

This section presents a thorough analysis of what drives the price impact function. First, we employ the set of market-, bond-, and trade-level characteristics explained in Section 5.1 to estimate the realized price impact, in basis points, by running pooled regressions. Then, using in-sample estimations, we model the expected price impact across maturity groups with observable variables and a choice variable, i.e., trade size. Finally, we compare our price impact model with other liquidity measures proposed in the literature.

Table 8 reports pooled regression results of realized market impact (in basis points) on market-, bond- and trade-level characteristics. Note that standard errors are

clustered by calendar months. The first column reports that price impact declines by cross-sectional liquidity score, indicating traders experience lower costs while trading a bond with higher liquidity than its peers (in its maturity group). Bonds with longer maturities face higher price impact cost, which is intuitive as long-term bonds have greater duration than short-term bonds; thus, they carry higher interest rate risks. In

Table 8. In-Sample Price Impact Model

	Dependent variable:							
	Market Impact (bps)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.692***	2.495***	2.347***	0.448***	0.361**	2.122***	2.123***	2.123***
	(17.422)	(15.947)	(14.329)	(2.948)	(2.008)	(6.519)	(6.522)	(6.529)
Time Trend (Jan 2001 = 1)	–0.009***	–0.009***	–0.009***	–0.005***	–0.005***	0.001	0.001	0.001
	(–7.404)	(–7.799)	(–7.808)	(–6.134)	(–6.084)	(1.159)	(1.147)	(1.154)
TR2Y_Difference*BuySell	–0.065***	–0.063***	–0.063***	–0.049***	–0.049***	–0.046***	–0.046***	–0.046***
	(–6.765)	(–6.619)	(–6.553)	(–6.582)	(–6.531)	(–6.125)	(–6.118)	(–6.136)
LiqScore	–1.732***	–1.516***	–1.438***	–1.250***	–1.257***	–1.157***	–1.159***	–1.158***
	(–12.649)	(–11.493)	(–9.965)	(–10.551)	(–10.730)	(–9.519)	(–9.524)	(–9.519)
Market Liquidity	–0.643**	–0.584*	–0.566*	–0.719***	–0.698***	–0.619***	–0.620***	–0.619***
	(–1.985)	(–1.805)	(–1.751)	(–3.084)	(–2.944)	(–2.661)	(–2.663)	(–2.661)
Maturity Group (= 2)	0.491***	0.540***	0.555***	0.866***	0.872***	1.023***	1.023***	1.023***
	(4.984)	(5.391)	(5.522)	(10.440)	(10.500)	(12.279)	(12.281)	(12.314)
Maturity Group (= 3)	4.426***	4.480***	4.479***	4.400***	4.432***	4.050***	4.051***	4.051***
	(19.945)	(20.305)	(20.286)	(22.705)	(22.252)	(19.879)	(19.878)	(19.878)
Fraction of daily volume		0.081***	0.019	0.015	0.015	0.024	0.024	0.024
		(10.066)	(1.132)	(1.015)	(1.031)	(1.615)	(1.622)	(1.628)
sqrt(Fraction of daily volume)			0.223***	0.293***	0.295***	0.296***	0.296***	0.296***
			(3.092)	(4.847)	(4.828)	(4.813)	(4.807)	(4.813)
Sd TR2Y_Difference				0.845***	0.837***	0.722***	0.723***	0.723***
				(10.582)	(10.321)	(8.197)	(8.201)	(8.177)
VIX					0.005	0.004	0.004	0.004
					(0.970)	(0.839)	(0.835)	(0.835)
Slope						0.130***	0.130***	0.130***
						(8.523)	(8.517)	(8.534)
OB Imbalance							0.026***	0.026***
							(2.581)	(2.581)
Imbalance_Coeff								0.014
								(0.090)
Observations	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773
Adjusted R^2	0.197	0.200	0.201	0.246	0.246	0.254	0.254	0.254

Note: *p<0.1; **p<0.05; ***p<0.01, and t-statistics in parentheses.

addition, being contrarian in the market decreases the price impact cost that an order experiences as the coefficient of "TR2Y_Difference*BuySell" is significantly

negative. That is, while two-year interest rates are declining in the market, being a buyer is less costly compared to being a seller. Moreover, in line with the literature, price impacts have declined over time. Frazzini et al. (2018) shows that technological events drive the decline; however, in our sample, the time-series evolution of the Turkish debt securities is primarily driven by either AUM growth of fixed income funds traded in the pension market or net foreign flow to the bonds as is seen in Section 6.1. We add fraction of daily volume to the regression in column two. It shows that larger trades experience higher price impact (Kyle, 1985). Column three adds the square root of the fraction of daily volume. The square root term significantly tracks the variation in price impact, matching the results reported in Section 6.2. Note that we use the square root term rather than the power of 0.193 to avoid over-fitting. Column four and column five add controls for the level of both global and local market volatility, i.e., "Sd TR2Y_Difference" and "VIX." More volatile market conditions result in higher price impact costs, in line with that liquidity suppliers, mainly market makers, require compensation in volatile markets.

Finally, we add high-frequency variables derived prior to each trade to extract any information embedded in the limit order book. Note that market-wide and bond-level variables are in daily frequency. Column six reports that higher slopes in absolute terms are associated with higher price impacts. For example, a one-unit increase in slope implies that buyers request a lower price to buy one more quantity while sellers request a higher price to sell. Column eight adds order book imbalance and imbalance coefficient, indicating an increase in order book imbalance is associated with an increase in price impact. Given that the overall market data is quite noisy and provides us with only the ability to proxy the average investor, it is remarkable that the lowest R^2 in our regressions is 19.7%. We conclude that price impacts are concave function of trade size, decline with both cross-sectional and market-wide liquidity, and increase with market volatility. Also, being a contrarian trader and trading bonds with shorter maturities decrease costs. Finally, we find that prevailing slope and order book imbalance are associated with higher costs.

6.3.1 Expected price impact

Assuming the relations obtained in Table 8 are stable over time, one can easily construct out-of-sample price impact curves with a choice variable, i.e., trade size. Furthermore, all variables are observable prior to trade except daily change in interest rates; thus, we fix the expected change in the Turkish 2-year interest rate to zero in our expected price impact model. Finally, we calibrate our expected price impact model using the estimates from column seven of Table 8. Formally, we define the model as follows:

$$\begin{aligned} MI_t = \alpha + \beta_1 TimeTrend + \beta_2 r_t^{TR2Y} BuySell + \beta_3 LiqScore_{t-1} + \beta_4 MarketLiq_{t-1} + \\ \beta_5 Maturity2 + \beta_6 Maturity3 + \beta_7 Volume_{t-1} + \beta_8 sign(Volume_{t-1})\sqrt{|Volume_{t-1}|} + \\ \beta_9 \sigma_{t-1}^{TR2Y} + \beta_{10} VIX_{t-1} + \beta_{11} Slope_{t-1} + \beta_{12} OBimb_{t-1} + \varepsilon_t \end{aligned}$$

where $\mathbb{E}\left(r^{TR2Y}\right) = 0$ and $Volume_{t-1}$ represents signed fraction of daily volume (%). To compute the price impact curves across maturity groups with a choice of trade size, we evaluate all exogenous variables at their sample means.

Figure 7 plots the expected price impact curves for each maturity group across the choice of fraction of daily volume. The figure gives a reflection from the overall sample spanning 2001 to 2017.

To check the robustness of the model, we divide our sample into four sub-periods and rerun the regressions. Appendix C presents the regression results, indicating that in crisis periods, bonds with longer-term maturities are associated with higher price impacts and the importance of cross-sectional liquidity score increases.

Figure 8 shows the expected price impact across different market volatility scenarios for each maturity group. An order experiences, on average, a price impact of 18 basis points with a trade size equals a 5% fraction of daily volume in a market that had 20% volatility in the last 20 days.

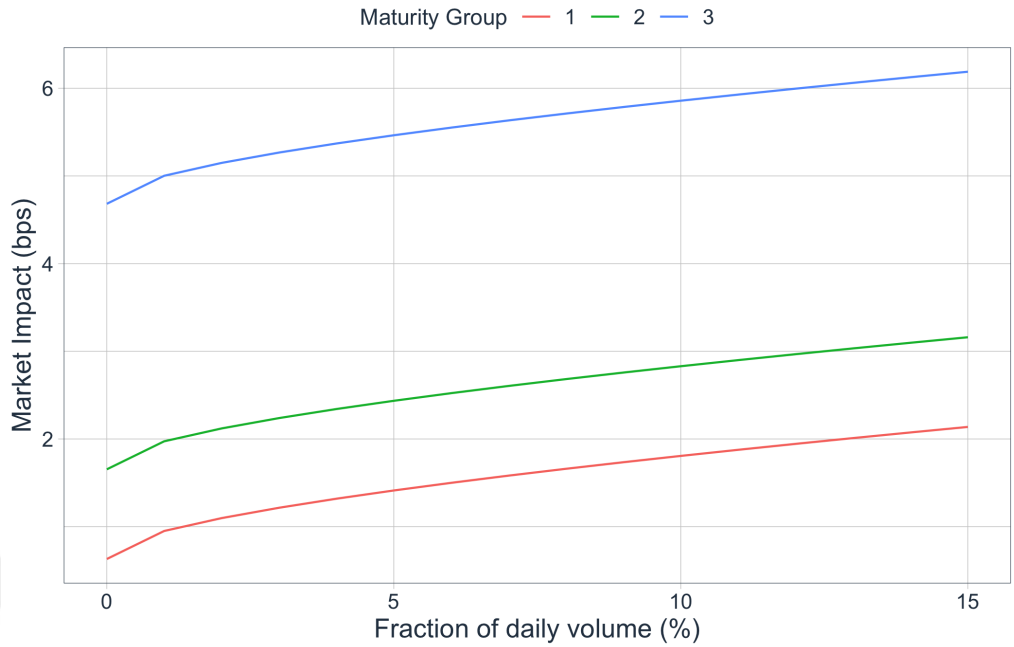


Figure 7. Expected price impact across maturity groups

6.3.2 Comparison with other liquidity measures

We examine the performance of liquidity measures proposed in the literature; precisely, modified measure of Roll (1984), "Zeros" measure of Lesmond et al. (1999), illiquidity measure of Amihud (2002), and price impact lambda of Kyle (1985). We rerun the regressions in columns (1) and (8) of Table 8 where the independent variable is the realized price impact (in basis points), and proxies cover market-wide, bond- and trade-level variables. Results are presented in Table 9.

The first column of Table 9 shows that higher effective spreads estimated by modified Roll are positively and significantly correlated with our price impact measure. However, as column (2) indicates, trade size and other market- and trade-level variables subsume modified Roll's explanatory power. Columns (3) and (4) report the Amihud market impact measure, with a coefficient of 0.003, which exhibits a minimal effect on our price impact measure. Columns (5) and (6) examine proportional of zero return days, which shows a significantly positive effect with a coefficient of 9.924; however, the measure capture relatively lower variation in the price impact. Lastly, columns (7) and (8) report Kyle lambda, with a coefficient of

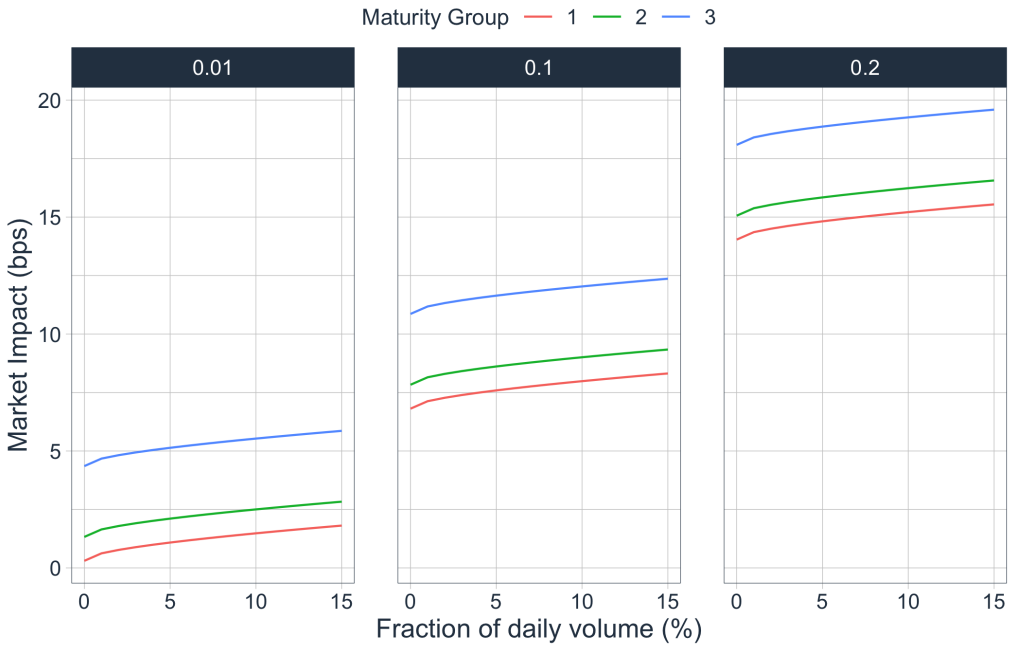


Figure 8. Expected price impact by market volatility

0.089, indicating a significantly positive correlation between our price impact measure.

The results of the comparison exhibit that the high-frequency liquidity measure, Kyle lambda, has a significant ability to explain our price impact costs even once we add our variables from Table 8, while low-frequency measures underperform. Moreover, the outperformance of Kyle lambda is intuitive since it is designed to estimate price impact, whereas others to proxy liquidity.

6.4 Rolling out-of-sample estimation

In previous sections, we construct a price impact model using all data points available in the sample, called in-sample estimation. However, in-sample estimation entails the risk of overfitting, which paves the way to face substantial errors while testing the model in new data points. To this end, this section aims at designing a price impact model with a higher predictive ability to facilitate further usage of the model in real-life trading. Thus, this section models price impact function using two ensemble machine learning models, i.e., random forest and boosted trees with XGBoost,

Table 9. Comparison with Other Liquidity Measures

	Dependent variable:							
	Market Impact (bps)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.426***	2.142***	2.328***	2.008***	2.669***	2.079***	2.271***	3.533***
	(16.727)	(6.665)	(14.892)	(6.355)	(17.199)	(6.426)	(13.070)	(11.328)
Modified Roll	0.011***	0.004*						
	(5.235)	(1.811)						
Amihud MI			0.003***	0.002***				
			(4.026)	(3.346)				
Zeros					9.924***	8.450***		
					(10.152)	(9.005)		
Kyle Lambda							0.089***	0.088***
							(11.023)	(11.759)
Time Trend (Jan 2001 = 1)	–0.007***	0.001	–0.008***	0.001	–0.010***	–0.0002	–0.009***	0.004***
	(–6.441)	(1.520)	(–6.814)	(0.997)	(–8.324)	(–0.220)	(–7.600)	(5.041)
TR2Y_Difference*BuySell	–0.063***	–0.045***	–0.061***	–0.045***	–0.065***	–0.046***	–0.059***	–0.042***
	(–7.096)	(–6.157)	(–6.962)	(–6.188)	(–6.705)	(–6.149)	(–6.115)	(–5.305)
LiqScore	–1.831***	–1.190***	–1.491***	–1.039***	–1.626***	–1.126***	–0.988***	–0.545***
	(–13.466)	(–9.917)	(–11.829)	(–8.759)	(–12.030)	(–9.439)	(–8.413)	(–5.415)
Market Liquidity	–0.650**	–0.607***	–0.486	–0.519**	–0.557*	–0.562**	0.100	0.121
	(–2.046)	(–2.634)	(–1.629)	(–2.271)	(–1.743)	(–2.486)	(0.363)	(0.662)
Maturity Group (= 2)	0.463***	0.998***	0.431***	0.926***	0.490***	1.003***	–0.109	0.405***
	(4.893)	(11.707)	(5.006)	(11.611)	(4.994)	(11.949)	(–1.129)	(6.130)
Maturity Group (= 3)	4.096***	3.949***	3.937***	3.750***	4.370***	4.014***	2.226***	1.586***
	(18.626)	(19.233)	(18.941)	(19.191)	(20.136)	(20.092)	(10.940)	(8.933)
Fraction of daily volume		0.020		0.018		0.021		0.034***
		(1.374)		(1.266)		(1.408)		(2.647)
sqrt(Fraction of daily volume)		0.313***		0.287***		0.254***		0.131**
		(5.060)		(4.841)		(4.213)		(2.554)
Sd TR2Y_Difference		0.668***		0.636***		0.727***		0.476***
		(7.047)		(7.230)		(8.306)		(5.298)
VIX		0.005		0.002		0.005		–0.005
		(0.930)		(0.375)		(0.910)		(–0.959)
Slope		0.131***		0.118***		0.124***		0.207***
		(8.814)		(8.070)		(8.157)		(13.444)
OB Imbalance		0.025**		0.020**		0.025**		0.012
		(2.496)		(2.017)		(2.472)		(1.437)
Observations	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773	1,458,773
R^2	0.208	0.255	0.222	0.265	0.204	0.259	0.252	0.301
Adjusted R^2	0.208	0.255	0.222	0.265	0.204	0.259	0.252	0.301

Note: *p<0.1; **p<0.05; ***p<0.01, and t-statistics in parentheses.

elastic net, and OLS. Finally, the training and testing performance comparisons of the models are presented.

We use our market-, bond-, and trade-level variables while employing the models to estimate realized price impact (in basis points). To construct models, we split our sample into 12 periods where each contains five years of training and one year testing period. Then we tuned our models on the training sample in the walk-forward framework, with 260 days rolling window and 130 days testing horizon. For each training set, the models are tuned with respect to the performance metric of Root Mean Squared Error (RMSE). Furthermore, we optimized the hyperparameters for each model as follows:

- Elastic Net: We define an alpha grid specifying the model, i.e., 1 for Lasso, 0.5 for Elastic Net, and 0 for Ridge, and a lambda grid ranging from e^{-12} to 1 with 20 elements. Hence the dimension of our grid matrix is 60x2.
- Boosted Trees: We tuned the number of trees, maximum tree depth, column and row sampling parameters with a grid search with a dimension of 96x4 for each training set.
- Random Forest: We define a grid for the number of variable that is randomly selected to be sampled at each split time, and fixed the number of trees to 500. The grid contains 1, 3, 5, and 7.

Table 10 presents the descriptive statistics of statistically prominent performance metrics: root mean squared error (RMSE), mean absolute error (MAE), and r-squared (R^2) evaluated over 12-period training and testing estimation for each model. We find that random forest provides, on average, a relatively better fit with a lower standard deviation in the training dataset; however, boosted trees outperform the others in testing with an average R^2 of 0.10. Moreover, we observe the goodness of fit performance of linear models deviates across periods more than ensemble models, induced by non-linear relationships between price impact and explanatory variables. Finally, note that the square root of the fraction of daily volume is provided to linear models as an explanatory variable, which comes with in-sample bias

problem; however, ensemble models are left to observe the relationship on the fraction of daily volume.

Table 10. Training and Test Performance Results of Elastic Net, Random Forest, OLS, and Boosted Trees

Model		Training Dataset			Test Dataset		
		RMSE	MAE	R^2	RMSE	MAE	R^2
OLS	Max	4.94	3.13	0.28	5.68	3.32	0.29
	Min	1.78	0.94	0.05	1.42	0.74	-0.35
	Mean	2.85	1.62	0.17	3.08	1.86	0.04
	Sd	1.07	0.75	0.07	1.44	0.92	0.17
Elastic Net	Max	4.91	3.06	0.28	5.87	3.32	0.32
	Min	1.73	0.84	0.05	1.33	0.62	-0.15
	Mean	2.78	1.51	0.17	3.07	1.77	0.07
	Sd	1.08	0.78	0.07	1.50	0.98	0.12
Random Forest	Max	4.60	2.92	0.29	6.00	3.70	0.13
	Min	1.66	0.92	0.10	1.33	0.69	-0.05
	Mean	2.79	1.59	0.21	3.08	1.83	0.07
	Sd	0.99	0.73	0.06	1.51	1.02	0.06
Boosted Trees	Max	4.69	2.92	0.25	6.15	3.22	0.20
	Min	1.77	0.80	0.08	1.18	0.55	-0.04
	Mean	2.75	1.43	0.19	3.08	1.62	0.10
	Sd	1.02	0.75	0.06	1.62	0.98	0.07

Figure 9 plots the average feature importance for each model, suggesting that the prevailing slope of the limit order book is among the most critical factors determining the price impact for all four algorithms. We also see that the top three factors by feature importance prove the algorithms capture market-, bond-, and trade-level diversification in modeling price impact function.

We exhibit a correlation matrix of average feature importance in Table 11. We sum the importance of the fraction of daily volume and the square root of the fraction of daily volume for linear models prior to constructing a correlation matrix. The correlations are high, suggesting the algorithms mostly derive similar effects for each explanatory variable. The lowest correlations are between elastic net and tree-based ensemble models.Suppose lasso regression is selected as optimal to minimize RMSE in a period. Then, it may shrink the coefficient of the fraction of daily volume to zero, which affects the average feature importance substantially.

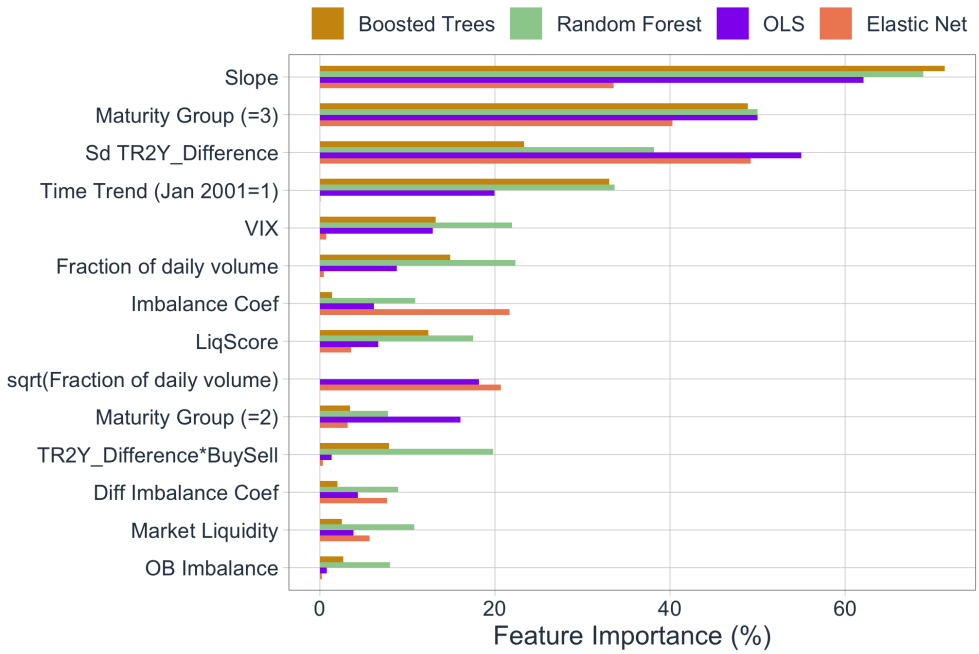


Figure 9. Feature importance for elastic net, random forest, OLS, and boosted trees

To check similarity and consistency across algorithms we employ, we derive partial dependence curves estimated in the last training period (2012-2016) for a fraction of daily volume, cross-sectional liquidity score, recent market volatility, and prevailing slope of the limit order book. As shown in Figure 10, at least in the last period, two ensemble models differ from estimating the functional relationship between price impact and the fraction of daily volume where random forest's estimation is close to linear relationship whereas boosted trees indicate a concave curve. We also show that tree-based models estimate greater price impacts for trades with a very high prevailing slope than linear models. More liquid bonds than their peers in the maturity group induce a decrease in price impact at an increasing rate.

Table 11. Correlation Matrix of Feature Importance

	Boosted Trees	Random Forest	OLS	Elastic Net
Boosted Trees	1			
Random Forest	0.98	1		
OLS	0.85	0.89	1	
Elastic Net	0.58	0.67	0.86	1

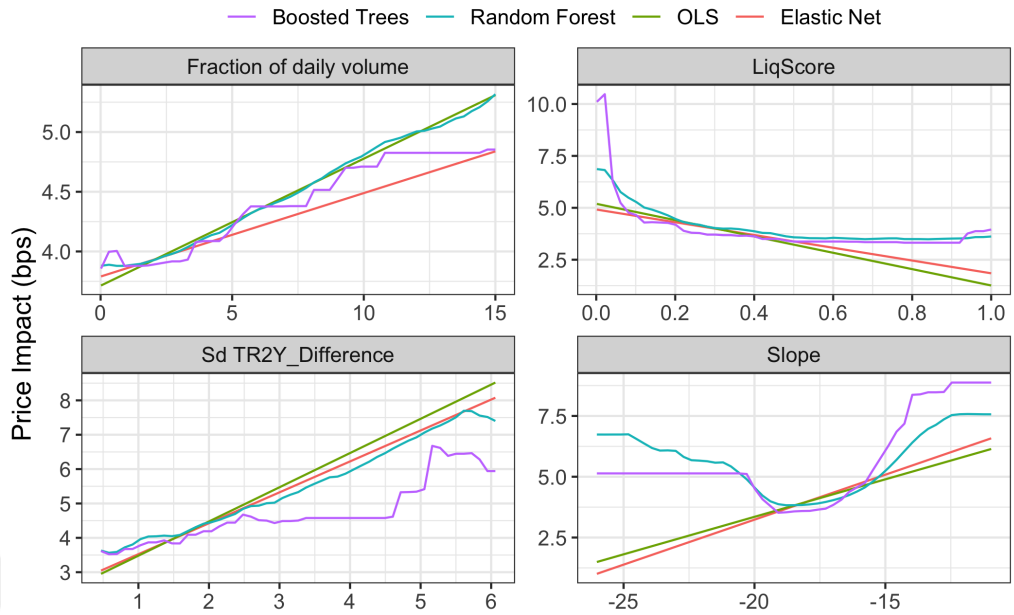


Figure 10. Partial dependence for elastic net, random forest, OLS, and boosted trees

Finally, we present the out-of-sample aggregated price impact estimation of boosted trees over time for trades with fraction of daily volume between 1% and 2%. As shown in Figure 11, the predictions of the algorithm are consistent with the insights examined in Section 6.1. After 2013, given the shock of non-resident's portfolio flow and divergence from other emerging markets, average price impact starts to increase substantially. This period also indicates high volatility in price impacts as unstable policy decisions and institutional changes experienced in Turkey.

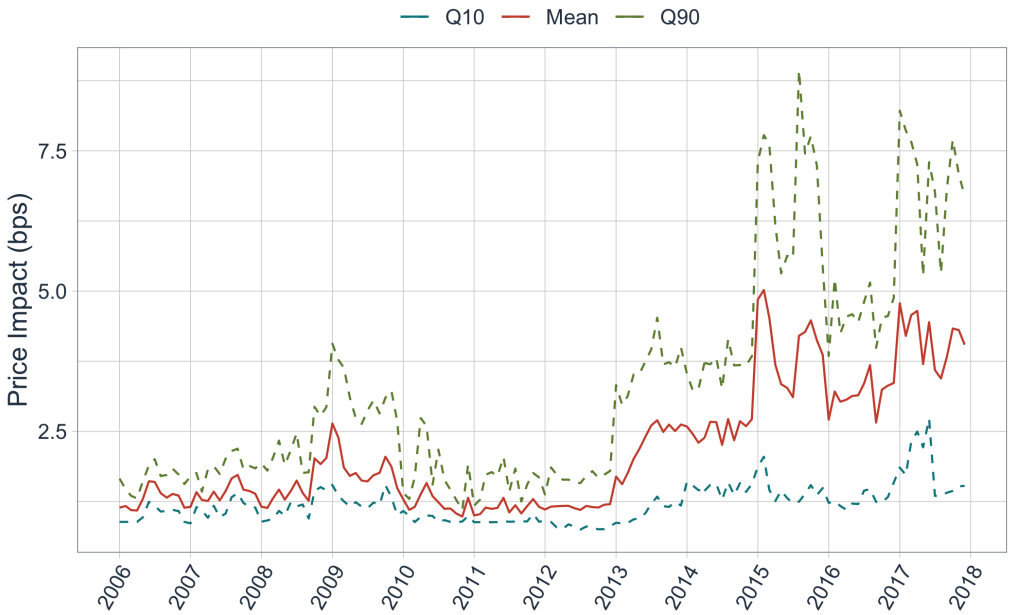


Figure 11. Time series of boosted trees' out-of-sample price impact estimations for trades with 1-2% fraction of daily volume

CHAPTER 7

CONCLUSION

We conduct an empirical study to analyze the aggregate price impact behavior of Turkish government debt securities over 17 years. In addition, we want to find out the determinants of price impact for each trade. We start by characterizing the order and transaction book data containing, prior to filtering, 6,118,349 trades across 3,519 debt securities. As overall market data is noisy, we select a subset of the Turkish government debt securities and treasury bills, totaling 1,485.73 billion TRY in trades. After identifying the accurate sign of each transaction, we present the performance of Lee and Ready (1991)'s algorithm in our sample, with a 95% accuracy rate. We find that the percentage of misclassified transactions increases with the amount outstanding for both buys and sells.

We calculate the realized price impacts using prevailing mid-quote as a benchmark price for various trade sizes ranging from 0% to 15% of a fraction of daily volume. The variation in the fraction of daily volume paves the way to estimate price impact as a function of trade size. However, one caveat of our sample stems from a lack of investor identifiers, resulting the estimate proxies average investor in the market. We further examine time-series behavior and the temporary and permanent components of the price impact across maturity groups over time. We find that permanent impact accounts for around 85% of price impact and increases with trade size.

Using these descriptive insights, we first provide a thorough analysis of how aggregate price impact costs behave overtime in Turkey as an emerging market. We find a decrease in transaction costs when the market liquidity follows the non-resident's portfolio. In addition, the liquidity generated through the Turkish private pension market induces a decline in the price impact by 0.056 basis points for a one percentage point increase in the AUM of fixed-income funds.

Second, we examine the correlation between price impact and trade size calculated as fraction of daily volume and find a power-law function with a coefficient of 0.193, confirming concave relationship in line with Kyle (1985) and Almgren et al. (2005). We also show that the concave relationship does not exist for bonds maturing in less than one year, which is a result of high liquidity in short-term debt securities.

Third, we estimate the price impact model using characteristics grouped into: market-wide, bond-level, and trade level. As a result of in-sample pooled regressions, we find that price impact increases with trade size, maturity, and market volatility and is negatively correlated with cross-sectional and market-wide liquidity. Also, being a contrarian trader is associated with a decrease in price impact. Furthermore, we find that the prevailing slope of the limit order book captures a high variation in price impact.

Fourth, we examine a set of liquidity measures proposed in the literature in our price impact model. The results exhibit that Kyle (1985)' price impact lambda has a significant ability to explain our price impact costs; however, our variable set subsumes the information that other liquidity measures provides.

Finally, we examine how price impact forecasts can be improved via recent Machine Learning Techniques. We show that boosted trees with XGBoost outperforms other alternative models such as random forest and elastic net methods in rolling out-of-sample estimations. We also find that the prevailing slope of the limit order book, maturity of bonds, and market volatility appears to be the top three factors affecting the slippage.

Advances in technology and statistical models enable researchers to test relationships between a target variable and a large amount of explanatory variables using big data. Of course, it comes with a cost and requires high programming and computing power, which is attainable as there are lots of open-source programming tools, e.g. R and Python, and cloud computing services offering high computing engines. This study aims to fill the gap in the literature in a way that employing

machine learning algorithms to long-term order and transaction book to estimate price impact function. In addition, the primary motivation behind the study is to provide better guidance to high-frequency traders, fund managers, and institutional traders since generating alpha mostly depends on transaction costs when assets tend to perform similarly.

APPENDIX A

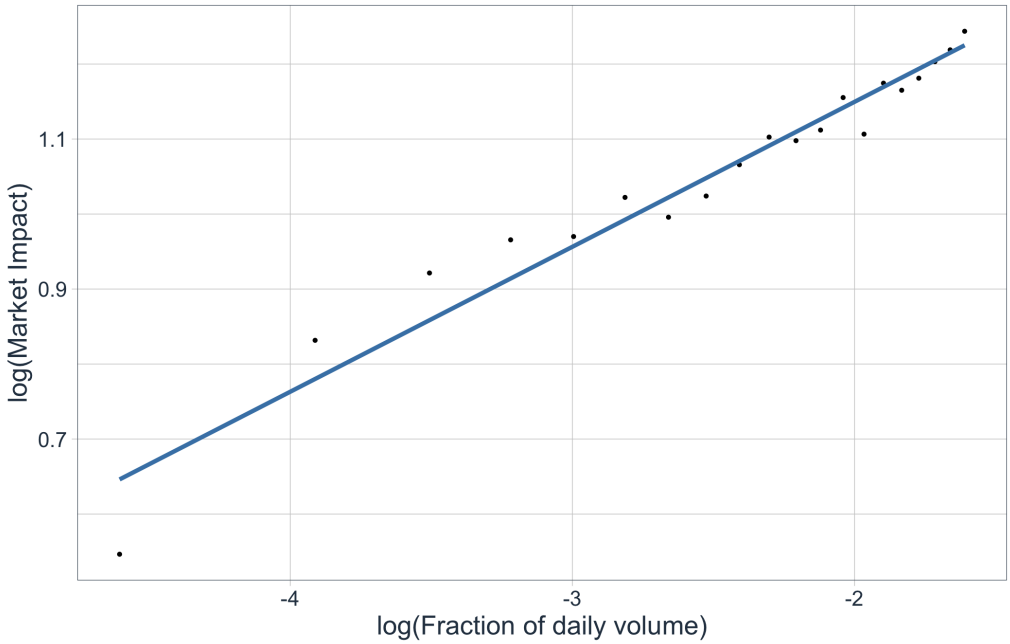
ROBUSTNESS CHECK FOR MACROECONOMIC FACTORS

	Dependent variable:		
	Market Impact (bps)		
	(1)	(2)	(3)
Constant	–0.916***	–0.484	–0.905***
	(–2.866)	(–1.631)	(–2.843)
SD RET	0.577***		0.440***
	(5.205)		(3.049)
ABS RET		1.163***	0.494
		(4.338)	(1.457)
Net Foreing Flow	–0.0001	–0.0001**	–0.0001
	(–1.605)	(–2.054)	(–1.629)
FI Bonds AUM	–0.046*	–0.045*	–0.042*
	(–1.861)	(–1.740)	(–1.694)
TR-EM 2Y Interest Rate Spread	0.070	0.116	0.077
	(0.952)	(1.562)	(1.052)
Feb	0.318	0.229	0.326
	(0.893)	(0.626)	(0.919)
Mar	0.524	0.437	0.534
	(1.470)	(1.196)	(1.507)
Apr	0.349	0.063	0.273
	(0.976)	(0.172)	(0.759)
May	0.688*	0.701*	0.714**
	(1.938)	(1.913)	(2.020)
Jun	0.329	0.431	0.356
	(0.925)	(1.177)	(1.005)
Jul	0.393	0.377	0.396
	(1.100)	(1.023)	(1.112)
Aug	0.353	0.369	0.390
	(0.973)	(0.986)	(1.078)
Sep	0.546	0.487	0.556
	(1.470)	(1.275)	(1.505)
Oct	0.531	0.450	0.497
	(1.341)	(1.101)	(1.259)
Nov	0.033	–0.274	–0.069
	(0.087)	(–0.690)	(–0.176)
Dec	0.704*	0.650*	0.700*
	(1.896)	(1.700)	(1.893)
Observations	144	144	144
R^2	0.336	0.294	0.348
Adjusted R^2	0.248	0.201	0.256

Note: *p<0.1; **p<0.05; ***p<0.01, and t-statistics in parentheses.

APPENDIX B

LOG PRICE IMPACT ON LOG FRACTION OF DAILY VOLUME



APPENDIX C

IN-SAMPLE PRICE IMPACT ESTIMATION OVER SUB-PERIODS

	Dependent variable:							
	Market Impact (bps)							
	2001-2012		2013-2017		2007-2009		2007-2017	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.814***	2.507***	10.728***	9.400***	0.362	6.407***	1.613***	5.280***
	(17.372)	(7.282)	(4.607)	(5.480)	(0.759)	(10.928)	(7.962)	(12.740)
Time Trend (Jan 2001=1)	–0.014***	0.0004	–0.045***	–0.018**	0.011**	–0.008*	–0.001	–0.003**
	(–9.237)	(0.345)	(–3.487)	(–2.378)	(1.961)	(–1.951)	(–0.912)	(–2.368)
TR2Y_Difference*BuySell	–0.041***	–0.025***	–0.136***	–0.106***	–0.037***	–0.016*	–0.099***	–0.066***
	(–4.316)	(–3.386)	(–7.299)	(–5.118)	(–3.724)	(–1.781)	(–9.812)	(–7.061)
LiqScore	–1.283***	–1.014***	–6.259***	–4.770***	–1.823***	–1.159***	–2.021***	–1.024***
	(–11.074)	(–9.807)	(–10.937)	(–8.761)	(–15.126)	(–9.543)	(–10.347)	(–6.484)
Market Liquidity	–0.393	–0.160	–1.809**	–2.144***	–0.844**	–0.317**	–0.779**	–0.829***
	(–1.373)	(–1.074)	(–2.473)	(–4.118)	(–2.302)	(–2.050)	(–2.067)	(–3.083)
Maturity Group (=2)	0.381***	0.814***	2.131***	1.903***	0.916***	0.821***	1.003***	0.901***
	(3.865)	(10.271)	(9.997)	(9.481)	(10.081)	(10.504)	(11.331)	(12.213)
Maturity Group (=3)	4.350***	4.209***	3.824***	3.510***	5.978***	4.789***	4.371***	3.675***
	(15.109)	(15.183)	(14.130)	(13.616)	(9.253)	(8.958)	(19.064)	(20.091)
Fraction of daily volume		–0.005		0.133***		0.036**		0.081***
		(–0.459)		(6.132)		(2.378)		(5.050)
sqrt(Fraction of daily volume)		0.269***		–0.022		0.132*		0.162**
		(5.597)		(–0.249)		(1.945)		(2.334)
Sd TR2Y_Difference		0.536***		1.119***		0.262***		1.063***
		(5.539)		(14.723)		(2.599)		(15.658)
VIX		0.010*		–0.022		0.020***		–0.006
		(1.802)		(–1.186)		(2.905)		(–1.030)
Slope		0.135***		0.277***		0.294***		0.271***
		(8.288)		(7.017)		(8.878)		(11.904)
OB Imbalance		0.015*		0.039		–0.001		0.019
		(1.830)		(1.223)		(–0.194)		(1.637)
Observations	1,171,282	1,171,282	287,491	287,491	358,143	358,143	893,389	893,389
R^2	0.132	0.195	0.159	0.205	0.192	0.238	0.259	0.311
Adjusted R^2	0.132	0.195	0.159	0.205	0.192	0.238	0.259	0.311

Note: *p<0.1; **p<0.05; ***p<0.01, and t-statistics in parentheses.

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