Three Essays on the Microstructure of the BIST

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ABSTRACT

Three Essays on the Microstructure of the BIST

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This thesis consists of three essays. The first essay (chapter 2) examines the accuracy of five algorithms for classifying trades as buyer- or seller-initiated for BIST-30 index constituents over a period including the Lehman collapse. The highest classification accuracy rate (over 95%) is for the one-second lagged Lee & Ready (LR) algorithm. The LR's classification accuracy is highest (lowest) for trades representing mixed agency and principal (pure principal) relations between clients and executing brokers. Unlike for U.S. markets, almost all trades are classifiable with accuracy rates of 90-plus percent for both long and short trades. As for U.S. markets, higher misclassification rates occur for trades in the first versus last 30 minutes of the trading day, as the time between consecutive trades decreases, and for decreasing trade sizes.

The second essay (chapter 3) examines the trade price effects and their determinants for BIST-30 index constituents for a period that includes the Global Financial Crisis and the Lehman collapse. Consistent with theoretical predications, we find that informed trades in the BIST tend to be large. Our findings that price discovery appears to be fairly rapid on the BIST and that the average multi-sample stock trade price effect of less than 30 basis points is competitive with other markets have important implications for the purchase and execution decisions of investors. Our finding of positive mean price effects for short trades that are larger for seller-initiated trades and larger than for long trades has implications for the ongoing debate about the regulation of short sales since it suggest that the average short sales does not depress prices. Furthermore, the higher price effects of (especially buyer-initiated) trades in the last minutes of a trading session and the variation in price effects with whether the client-broker relationship is agency, principal or mixed have important implications for market regulators in

terms of refining their surveillance systems to better control any inappropriate stealth trading or end-of-session price manipulation.

The third essay (chapter 4) examines the price-limit hits for members of the BIST-50 index during the March 2008 through March 2009 period. The effects of price-limits are not homogeneous for upper and lower hits when they occur and if they continue in a subsequent trading session. Our results are supportive of the no-, dampening and spillover effects on volatility hypotheses, overreaction and no-effect price hypotheses, magnet price effect hypothesis, and greater informational asymmetric effect on market-quality hypothesis. They are not supportive of the price-delay hypothesis, and trading interference hypothesis. The results are robust using equi-distant and trade-by-trade returns and volatility measures ccounting for the autocorrelations in these return series. The results have implications for regulators contemplating the introduction of similar mechanisms or fine-tuning their current mechanisms.

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Table of Contents

CHAPTER ONE

1. INTRODUCTION

Despite the differences in their structures, regulations and functioning, security markets have important roles in price discovery, market efficiency, and the determination of the liquidity, risk, return and volatility of the assets traded therein. We empirically analyze some of these important roles in the three essays of this thesis.

Determining trade direction has become more important as intraday quote and trade data have become more available globally. Determining the initiator of each trade (buyer or seller) is used in assessing the role of information flow, order imbalances and liquidity providers when examining the efficiency of markets or the impact of corporate actions. Of the trade classification algorithms that are used to study various issues in finance, the one developed by Lee and Ready (1991) is most commonly used for stocks on various stock markets and the Ellis, Michaely and O`Hara (2000) or EMO algorithm is often used for NASDAQ stocks. In addition, the tick, quote and at-the-quote rule are also among the trade direction algorithms widely used in the market microstructure literature. In Essay 1, we examine the accuracy rates of five trade classification algorithms for a trade venue in a developing market, the Borsa Istanbul (BIST), for the seven months ending with December 2008 that is centered on the month of Lehman Brothers' collapse. Our propriety dataset from the BIST allows us to use the more accurate chronological approach (Odders-White, 2000) as a benchmark for assessing the accuracy rates of five trade classification algorithms since we have the order and trade IDs time stamped to the closest second. The traders are also classified in three main groups by the exchange (pure principal, pure agent, and mixed) which allows us to analyze each group separately.

We find that the one-second lagged version of the Lee-Ready (LR) algorithm outperforms the other four trade classification algorithms that we assess. To the best of our knowledge and despite the period examined, we document the highest accuracy rates for the LR algorithm (lagged one second) in the market microstructure literature of above 95%. We find significant differences in classification accuracy for buyer- versus seller-initiated trades among the five classification algorithms. For the four quote-based algorithms, the EMO algorithm exhibits the highest accuracy rate (over 95%) in classifying seller-initiated trades and lowest accuracy rate (<77%) in classifying buyer-initiated trades. In contrast, the LR algorithm places second in classification accuracy for seller-initiated trades and first for buyer-initiated trades (over 92% except for the use of contemporaneous quotes).

Using the three-way trader classification applied by the BIST, we document that the trade classification algorithms show significantly inferior accuracy in classifying trades that take place in the portfolios of the brokerage firms (pure principal) compared to the trades that take place in the accounts of the institutional and retail clients of the brokerage firms (pure agency), and the trades that take place at the investment funds managed by the brokerage firms (mixed).

In Essay 2, we examine the magnitude and duration of temporary and permanent price effects of trades of different sizes, which has important implications for price discovery, trade-price impact, market efficiency and the choice of trade-execution strategies. Various hypotheses have been proposed to explain the price effects associated with large trades, including that these trades are from informed traders. We examine the price effects associated with trade for the 38 companies during their tenure in the BIST-30 index during the twelve months from April 2008 through March 2009 which accounts for around 70% of the total trade volume on the BIST for our sample period and contains the global financial crisis and the Lehman collapse.

Most studies report differences in terms of market impacts of large trades between the buyer- and seller-initiated trades. A limitation of most of these studies is that their trade classifications depend on what proportion of the trades can be classified using the tick or Lee and Ready (1991) or Ellis et al. (2000) algorithms, and on the accuracy of the classifications for those trades that can be classified. Although a large portion of the trades remain unclassified in other studies, reported classification accuracies for the LR algorithm vary from 69.2% for long trades in Chakrabarty et al. (2012) to 93.0% in Lee and Radhakrishna (2000). Lee and Radhakrishna (2000) report a 93% accuracy rate for the Lee and Ready algorithm for a sub sample of 15 stocks from the TORQ dataset after eliminating approximately 40% of the trades in TORQ that could not be unambiguously classified as being either buyer- or seller-initiated.

In this second essay, we examine the price effects of a trade on a developing market where order arrival times are available to the closest second, short sale trades are identified and the IDs of each order and trade are available for matching purposes. We are able to successfully identify more than 99.5% of the trades for the selected sample as being buyer- or seller-initiated using the chronological method as in Odders-White (2000).

In this essay, we also provide a more precise assessment of the market impact of trades accounting for whether one or both sides of the trade(s) involve a short trade. Since short selling is not prohibited on the BIST during the crisis of 2008, it gives us an opportunity to compare the restriction of short sales as was the case for the financial companies during the same period in the U.S. and U.K.

We document that all mean permanent price effects are highly significant and positive for all short trade samples, and are substantially greater in magnitude for seller- versus buyer-initiated short trade seconds. These price effects are (highly) significantly more positive for the samples of short versus long trade seconds. Our evidence suggests that short trades are more informed than long trades (Battalio and Mendenhall, 2005; Hvidkjaer, 2006).

The second essay also fills a gap in the price effects literature by examining trade price impacts differentiated by whether large traders have a pure agency, pure principal and mixed relationship with the brokerage firms executing their trades based on the following trader classifications provided by the BIST: institutional and retail clients of the brokerage firms; portfolios of the brokerage firms; and investment funds managed by the brokerage firms. It is documented that the trades of retail investors move equity prices (Barber et al., 2009; Hvidkjaer, 2008). The trading dynamics of these two types of investors appear to be based on very different interpretations of information (Griffin et al., 2003). Furthermore, lottery-type stocks are over-weighted in the portfolios of retail but not institutional investors (Kumar, 2009).

We find that the smallest and largest negative mean total price effects are associated with the seller-initiated trades for the portfolios of the brokerage firms and trades for the institutional and retail accounts of the brokerage firms, respectively. This suggests that the former traders or their brokers are better in either trade execution or the timing of their trades. Furthermore, we find that the smallest (largest) permanent price effects are associated with the small buyer- (small and large seller-) initiated trades for the institutional and retail accounts of the brokerage firms.

End-of-session price effects may have important implications because stock exchanges and regulatory agencies around the world devote considerable human, technological and financial resources to curb market manipulation and to promote price discovery, market efficiency and market integrity. In the second essay, we find weak evidence for manipulators having incentives to realize high prices at the close as opposed to earlier in a trading session. When we examine price effects for a three-day announcement day (AD) period centered on the Lehman announcement compared to the three-day periods pre- and post-AD, we find that the mean total price effects are highest AD, and that the mean temporary and permanent price effects are highest for small-sized buyer- and seller-initiated trade seconds.

In Essay 3, we examine several hypotheses on the effects of price limits which are applied in order to prevent any consequences from high volatility in asset prices over a short period of time, especially in emerging markets. We re-examine the impact of price limits of the Borsa Istanbul using intra-day trades and quotes for all the firms that are included in the BIST-50 index during the thirteen-month examination period of March 2008 through March 2009. The hypotheses we examine are the volatility spillover and dampening hypotheses, the overreaction and delayed price-discovery hypotheses, magnet-effect hypothesis, trading interference hypothesis, and the market quality hypothesis. As a robustness test we use trade-by-trade returns adjusted for their associated serial correlations.

Among the hypotheses mentioned above, we find evidence to support the volatility no-effect, dampening and spillover hypotheses. We find that the impact of a price-limit hit on volatility depends on whether it is a lower or upper limit hit and on the time of the day when the price-limit hit begins and when it ends.

Our evidence supports the market overreaction hypothesis. We also find some support for the no-effect hypothesis since the returns in the post-hit windows are not significant for the other two samples of lower price-limit hits. Thus, our findings are supportive of the overreaction and no-effect hypotheses but not the price-delay hypothesis which can be interpreted as price-limit hits do not inhibit price discovery.

We document accelerating prices as they approach the price limit-hit. We report that the slope coefficients of the time-series trajectories of the mean returns up to the price-limit hits are highly significant and positive (negative) for the price-limit hits triggered at the upper (lower) limits using the equi-distant returns. This may be considered as an evidence for the magnet effect which may lead to the price overreaction behaviour prior to the price-limit hit.

Regarding the market quality hypothesis, we find that the lower price-limit hits significantly increase proportional quoted and effective spreads and significantly reduce share and TRY depth. We find that the median (not) mean composite measure of liquidity (i.e., proportional quoted spread divided by TRY depth) is generally significant (and higher) post-hit for both the lower and upper price-limit hits. Thus, price-limit hits generally have a significant adverse effect on spread and depth measures of market quality. We conclude that our findings are consistent with the greater informational asymmetry effect on market-quality hypothesis.

We test the robustness of some of our results using equi-distant returns and autoregressive integrated moving average (ARIMA) modeling, and trade-by-trade returns. The ARIMA model helps to alleviate some of the bias due to the autocorrelations in returns. Our findings show that our previous corresponding findings are robust to the use of these alternative tests.

CHAPTER TWO

TRADE CLASSIFICATION ACCURACY FOR THE BIST

2.1 INTRODUCTION

Much of the microstructure literature and applications thereof require a determination of whether a trade is initiated by the buyer or the seller (commonly referred to as trade signing or trade direction). Some early examples include the asymmetric-information and inventory-control theories of specialist behaviour (e.g., Hasbrouck, 1988), the effect of order imbalances and returns on NYSE stocks during the crash of October 1987 (Blume, MacKinlay and Terker, 1989), and the price impact of large trades (briefly reviewed in section two herein). Commonly used trade classification algorithms include the tick test, the Lee and Ready (1991) (hereafter LR) algorithm and the Ellis, Michaely and O`Hara (2000) or EMO algorithm (see Table 2.1 for a description of the ones used herein).

[**Please place Table 2.1 about here**]

Various papers illustrate the consequences of inaccurate trade classification in empirical finance. For example, Boehmer, Grammig and Theissen (2007) show analytically and empirically that inaccurate classification of trades leads to downward-biased PIN (probability of informed trade) estimates and that the magnitude of the bias is related to a security's trading intensity. Using two separate periods around the NYSE's change to a tick size of $1/16 in June 1997, Peterson and Sirri (2003) report that actual execution costs are overstated by up to 17% using effective spread estimates that incorporate errors in trade direction and benchmark quote assignments, and that the highest biases occur for small trades and for trades of larger firms.

To the best of our knowledge, the only study that examines trade classification accuracy for a developing market is by Lu and Wei (2009) for the Taiwan Stock Exchange. Thus, the primary purpose of this paper is to test the accuracy of five trade classification algorithms described in Table 2.1 for an important, active and representative market in a developing country, namely, the Borsa Istanbul (BIST). The BIST was the eighth most active market in equity trading out of 26 exchanges ranked in the category 'Europe /Africa /Middle East' by the World Federation of Exchanges for 2008.[1] We argue that a study of

[1] The BIST with 46.0 million equity trades in 2008 placed between the SIX Swiss Exchange and Saudi Stock Market (Tadawul) with 42.0 and 52.1 million trades, respectively. The BIST with 114,307.7 million shares traded in 2008 placed between the Johannesburg Stock Exchange and the BME Spanish Exchanges with 82,580.6 and

this market can provide some methodological support for the use of trade classification algorithms and the credibility of the resulting research for the BIST and other similar markets (i.e., fully-computerized markets with an order-driven mechanism via continuous auction, no official market maker and a small representation of short sales in total trading) when the data set available to the researcher requires that the order book be constructed or does not allow for the use of the more accurate chronological approach (defined later) to determine the true initiator of a trade.

We examine stocks in the BIST-30 because these stocks account for about 70% of total trades on the BIST during our chosen time period. This choice was also dictated by the extensive time need to clean the raw data provided by the BIST using 20-minute intervals for each company before constructing the limit order book in order to obtain the BBO (best bid and offer) for each second during each trading day for each of the 35 stocks in our sample due to quarterly index revisions. The accuracies of the trade classification algorithms are examined over the seven months of June through December 2008 which includes two quarterly index revisions. The test period is also centered on the month of the collapse of Lehman Brothers (namely, September 2008) to provide a first test of the accuracy of the five trade classification algorithms during a period including the effects of a financial crisis and the Great Recession.[2] Our choice of time period extends the work of Asquith, Oman and Safaya (2010) and Chakrabarty, Moulton and Shkilko (2012) who use two months in 2005 that the former authors (page 472) characterize as: "These two months also offer the advantage of capturing a recent, relatively "normal'' time in the markets — after decimalization, but before the financial crisis and the scrutiny of short sellers that followed …"

Since the times and IDs of each order and trade are available for our propriety dataset from the BIST, we use the more accurate chronological approach as the benchmark for the true initiator of a trade.[3] We find that the one-second lagged version of the LR algorithm outperforms the other four trade classification algorithms that we assess. To the best of our knowledge and despite the period examined, we document the highest accuracy rates for the LR algorithm (lagged one second) in the market

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119,701.2 million shares traded, respectively. For greater details, see: http://www.world-exchanges.org/statistics/annual/2009/equity-markets/total-number-trades-equity-shares-and-number-shares-traded

[2] Turkey and the following countries/territories went into economic recession in the third quarter of 2008: Euro-using nations in the European Union as a whole, Germany, Hong Kong, Japan, Italy, Singapore, Sweden, and the United Kingdom. They were followed into technical recession in the fourth quarter of 2008 by Spain, Switzerland, Taiwan and the United States. http://en.wikipedia.org/wiki/Great_Recession

[3] When trader IDs are not available (Lee and Ready, 1991), the immediacy approach defines the trade initiator as the trader who demands immediate execution (i.e., places a market order) and the non-initiator as the trader who is a liquidity provider but does not require immediate execution (i.e., places a limit order).

microstructure literature of above 95%.[4] Like Odders-White (2000), we find that the highest misclassification rates occur for trades that occur at the quote mid-spread. We find significant differences in classification accuracy for buyer- versus seller-initiated trades among the five classification algorithms. For the four quote-based algorithms, the EMO algorithm exhibits the highest accuracy rate (over 95%) in classifying seller-initiated trades and lowest accuracy rate (<77%) in classifying buyer-initiated trades. In contrast, the LR algorithm places second in classification accuracy for seller-initiated trades and first for buyer-initiated trades (over 92% except for the use of contemporaneous quotes).

To the best of our knowledge, this is the first paper to examine classification accuracy for trades differentiated by whether the trader has an agency or principal relationship with the brokerage firm executing the trade. To this end, we use the BIST's three-way trader classification that is included in our proprietary data set. We document that the trade classification algorithms show significantly inferior accuracy in classifying trades that take place in the portfolios of the brokerage firms (pure principal) compared to the trades that take place in the institutional and retail clients' accounts of the brokerage firms (pure agency), and the trades that take place at the investment funds managed by the brokerage firms (mixed). This has important implications for the use of trade classification algorithms for the determination of the probability of informed trading when the proportion of pure principal trades is material.

Our findings have implications for the ongoing debate on whether short trades are seller-initiated, and whether they consume liquidity more often than they provide it. We find significant differences in the accuracy rates of the trade classification algorithms that generally are higher for long versus short trades. Unlike Asquith, Oman and Safaya (2010) and Chakrabarty, Moulton and Shkilko (2012) who examine US data for June and December 2005 provided under the SEC's Reg SHO initiative,[5] we find accuracy rates of at least 90% using one-second lagged quotes for both long and short trades for the quote, at-the-quote and LR algorithms. Like these authors, we find that long sellers appear to consume liquidity more often than they provide it while short sellers appear to provide liquidity more often than they consume it. Like these studies, we find that short sales are predominantly buyer-initiated which is consistent with the expectation advanced by Chakrabarty, Moulton and Shkilko (2012) but not Asquith, Oman and Safaya (2010) whose prior is that short sales should be predominantly seller-initiated. This interpretation depends on the somewhat strong implicit assumption that any differential immediacy costs associated with the short-side of a trade are not material. To further illustrate the importance of this implicit assumption, we

[4] According to Asquith, Oman and Safaya (2010, p. 158), the degree of accuracy of the LR algorithm ranges from 72% to 93% depending on the study.
[5] Asquith, Oman and Safaya (2010) also examine data for March 2005.

note that Asquith, Oman and Safaya (2010) report that the proportion of buyer-initiated trades involving short sellers is significantly lower in the absence of short-selling restrictions like an uptick rule on the NYSE or a bid price test on NASDAQ.[6]

Our findings also have implications for tests of informed or manipulative trading at the close of a trading session. We find that a relationship exists between the misclassification of trade initiator and the time of the trade day. We find that misclassifications tend to be higher in the first 30 minutes compared to the last 30 minutes of the morning and afternoon trading sessions for our sample. As the time between the trades decreases, the misclassification rates increase with the exception of the tick algorithm.

The remainder of this paper is organized as follows. In the next section, we provide a brief review of the literature that examines the performance of trade classification algorithms. In the third section, some descriptive information on trade execution on the BIST is presented. In the fourth section, the sample and data are discussed. In the fifth section, we deal with the conceptual question of who is the trade initiator especially when the trade includes a short-sale side. In the sixth section, the hypotheses to be tested are specified and our results for the tests of these hypotheses are presented and discussed. We conclude with section seven.

2.2 BRIEF REVIEW OF THE RELEVANT LITERATURE

In this section, we discuss the studies summarized in Table 2.2 that test the accuracy of various trade classification (or signing) algorithms. Lee and Ready (1991) use the immediacy approach and the available BBO to obtain a benchmark for assessing trade classification accuracy of their individual trade classification or LR algorithm against the tick and the quote algorithms for 150 NYSE firms for 1988. They identify a delay between the reporting of quotes and their respective trades that should be reflected when classifying trades, and that classification performance deteriorates for trades inside the quoted spreads (i.e., when trade improvement occurs).

[**Please place Table 2.2 about here**]

Two studies use unique data sets with more complete data on quotes and trades (including some trader identities and/or trade direction indicators) for NASDAQ firms.[7] Ellis, Michaely and O'Hara (2000)

[6] Chakrabarty, Moulton and Shkilko (2012) could not provide a totally clean test of the effect of short selling restrictions on trade classification since they note that INET (their data source) did not enforce NASDAQ's bid price test.

document accuracy rates of 77%, 76% and 81% (lower for trades within the bid-ask quotes) for the tick, quote and LR algorithms, respectively, for a sample of 313 Nasdaq stocks over the 12 months starting with September 1996. Chakrabarty *et al.* (2007) present a new algorithm that first divides the spread into ten incremental deciles and then uses the quote rule when transaction prices are closer to the ask or bid and the tick rule when transaction prices are closer to the mid-spread. Their classification algorithm outperforms the tick, LR and EMO algorithms by 1.12%, 2.10% and 0.72%, respectively, for a sample of 750 NASDAQ firms over the three-month period of April-June 2005.

Various studies use the TORQ database. Since TORQ provides details on the parties to a trade, order submission times and the prior-to-execution handling of orders electronically routed (SuperDot) at the NYSE, information about the trader's identity (e.g., individuals versus institutional traders) and order characteristics (e.g., whether seller- or buyer-initiated) are directly observable for 144 NYSE stocks for the three months starting with November 1990. Lee and Radhakrishna (2000) report a 93% accuracy rate for the LR algorithm for a sub-sample of 15 stocks from the TORQ dataset after eliminating approximately 40% of the trades in TORQ that could not be unambiguously classified as being either buyer- or seller-initiated because they were market "crosses", stopped market orders, and pairings of market with executable limit orders. Odders-White (2000) reports an 85% classification success rate for the LR algorithm with systematic misclassifications of the transactions at the mid-spread, small transactions, and for large or frequently traded stocks. Based only on an analysis of signing accuracy for the LR algorithm by trade size, time between trades, number of transactions, and firm size, Odders-White (2000) finds that classification accuracy increases with the omission of trades at the mid-spread. She also reports overestimation of the number of buys and underestimation of the number of sells for small trades, and that the use of incorrectly signed trades leads to the overestimation of order processing costs. Including only those trades with a market order on one or both sides of the trade, Finucane (2000) reports a similar performance for the tick and LR algorithms that is superior to that for the reverse tick test. He also reports that the accuracy rate for the tick test is below that reported by Lee and Ready (1991) but better than that reported by Aitken and Frino (1996) and Ellis, Michaely and O'Hara (2000).

Based on the assumption that their algorithm correctly assigns trades, Blais and Protter (2012) report that the signing accuracy of the LR algorithm for trades is around 56% for both 30 liquid and 30 illiquid stocks drawn from the Morgan Stanley Order Book for stocks listed on the NYSE, AMEX, NASDAQ

[7] The data set used by Ellis, Michaely and O'Hara (2000) identifies whether a trade is by market makers, brokers and customers but only provides the names of market makers and brokers since this field is blank for customers. Chakrabarty *et al.* (2007) use data from the two largest ECNs, INET and ArcaEx, which provide buy and sell indicators. Using a proprietary dataset from the Chicago Board Options Exchange (CBOE) that reports trade direction, Savickas and Wilson (2003) report accuracy rates of 59%, 83%, 80% and 77% for the tick, quote, LR and EMO algorithms, respectively.

and LSE over the period of July 1 to December 19, 2003. Using a modeling approach that considers information strengths, microstructure effects and classification correlations for 2800 US stocks, Rosenthal (2012) reports 1 to 2% higher accuracy rates compared to other classification algorithms across dates, sectors and spreads for the ArcaTrade dataset that provides the non-initiating (first arriving) trade classification for all trades on the Archipelago ECN for December 2004. Using clean data unlike previous studies, he attributes the improvements in forecast accuracy to the use of information strengths (1 to 1.3%) and from estimating quotes (0.9% and 0.7% for Nasdaq and NYSE stocks, respectively).

Some studies test the accuracy of the trade classification methods for non-US, developed markets. Aitken and Frino (1996) report a 74% and 90% accuracy rate when using a tick algorithm to determine actual trade direction for about 1100 stocks in the Australian Stock Exchange when zero ticks are included and excluded, respectively. The tick algorithm outperforms the LR algorithm for their data sample except for seller–initiated and small buyer-initiated trades. Using the definition of true classification based on whether the Makler (the equivalent of the specialist on the Frankfurt Stock Exchange) bought or sold shares, Theissen (2001) documents accuracy rates of 72.2% and 72.8% for the tick and LR algorithms, respectively, for 15 stocks from 26 September to 25 October 1996.

For a developing market, Lu and Wei (2009) conclude that their adjusted version of the LR algorithm is the most appropriate algorithm examined for 684 stocks traded on the Taiwan Stock Exchange for the six-months ending June 30, 2006.[8] Due to the existing price limits and the absence of designated market makers on this exchange, Lu and Wei suggest that the lack of bid or ask quotes can be solved by first classifying trades using the quote and then the tick algorithm.

Findings on the trade classification accuracy of the LR algorithm are less supportive for short sales. Asquith, Oman and Safaya (2010) find that the tick, quote and LR algorithms often misclassify short sales as buyer-initiated based on a sample of 100 stocks from each of NASDAQ and NYSE during the three months of March, June and December 2005. The LR algorithm performs the best with a 33.4% accuracy rate for short sales when measured against a prior that short sales should be seller-initiated. In the absence of trader IDs, Chakrabarty, Moulton and Shkilko (2012) use a modified chronological approach for determining the true trade initiator that should be highly reliable. Using a prior that short sales should be buyer-initiated, Chakrabarty, Moulton and Shkilko (2012) report that the misclassification rate is higher than 30% for individual short sales and is reduced to 21% using one-second lagged instead of contemporaneous quotes for a sample of 100 Reg SHO pilot stocks from NASDAQ for June and December 2005. Since the misclassifications of buyer- and seller-initiated trades are almost evenly

[8] Their revised quote rule classifies a trade as a buy (sell) if there is only a bid-side (ask-side) quote available.

distributed, they report that the LR algorithm correctly identifies most short sales as buyer-initiated and most long sales as seller-initiated at the aggregate daily level. The generalizability of their results are based on how representative trades in the accounts of the electronic trading platform INET were of the wider market given that it only represented around one-quarter of total and total short-sale volume for the two months they studied, on the effect of INET not enforcing NASDAQ's bid price test for short sales during their sample period (Diether *et al.*, 2009b), and of the acquisition of Instinet by NASDAQ which was announced in April 2005 and closed in December 2005 (Morcroft, 2005).

2.3 THE BORSA ISTANBUL (BIST)[9]

National Market firms require daily average trading volumes (number of trades) of >1% (≥ 4%) of the total for all National Market listings.[10] National Market listings have increased from 325 (December 31, 2008) to 397 (November 14, 2012). Other markets on the BIST during our studied time period include: the Second National Market for small- and medium-sized firms that are temporarily or permanently delisted from the National Market; the New Economy Market for telecommunication, electronic, internet and computer manufacturing firms considered as fast growing and in need of financing; the Exchange Traded Funds Market for ETF transactions; and the Watchlist Market for companies under special surveillance and investigation due to extraordinary stock transactions.

Trading for BIST-30 (and BIST-100) constituents is fully computerized and order-driven with buy and sell order matching based on price and time priority.[11] The opening of a session for BIST-30 (and BIST-100) constituents is designed as a call market. During the opening of a session, trades in the limit-order book are executed at the price that provides the maximum executable amount of trade for each stock. However, this opening price is not used to generate a new base price and price limits in the continuous auction market phase. If an opening price for a particular stock is not obtained, all the orders entered into the system are carried over to the continuous auction session where market makers have no role.[12]

Up to October 13, 2008, the time period for order collection, order matching and continuous trading are 9:30 to 9:40, 9:40 to 9:45 and 9:45 to 12:00, respectively, for the first daily trading session. Thereafter, the time periods for each of the three functions are 9:30 to 9:45, 9:45 to 9:50 and 9:50 to 12:30, respectively. The second daily session for our sample time period is from 14:00 to 17:00 where the

[9] A more extensive description of the BIST listing categories and trading mechanics is available from the authors.
[10] The listing requirements are given in detail in the BIST Operations Manual 2008 and 2009 available at www.ise.org The daily average trading volume and number of trades of all companies are reviewed quarterly. If a company fails to meet the minimum circulation criteria during one of these reviews, it is transferred to the Second National Market.
[11] The exchange was founded on December 26, 1985 and became fully automated from October 21, 1994.
[12] Based on communications with the BIST.

first five-minute period consists of electronic order transmission. All of these changes are reflected in our subsequently reported results.

2.4 SAMPLE AND DATA

2.4.1 Sample

Our sample consists of all the firms in the BIST-30 Index which in the aggregate accounts for about 70% of the total trading volume on the BIST for the seven-month period ending in December 2008 and centered on September 2008 (the month of Lehman's collapse). The BIST-30 index is updated quarterly and consists of the 30 most frequently traded firms on the BIST chosen from National Market listings and the stocks of real estate investment trusts and venture capital investment trusts listed on the Collective Products Market. Since the sample period covers two (at the end of June and September) of these quarterly index revisions when five firms were replaced, our sample consists of 35 firms. The aggregate market capitalization and total value of shares traded for the BIST-30 Index in 2008 was $11 billion and $248 billion US, respectively. Figure 2.1 plots the monthly closing levels and aggregate number of shares traded for the BIST-30 Index for our seven-month sample period. This is a period of generally increasing trade activity and decreasing index levels.

[Please place Figure 2.1 about here.]

2.4.2 Data Manipulation

The raw data provided by the BIST consists of incoming order and trade files that provide the date, time (up to the closest second), order number, order type, quantity, and price information. The uncleaned order file contains some entry errors due to, for example, the inclusion of orders cancelled by phone, altered orders (by order type or quantity) and multiple order entries. Using a search over 20-minute increments for each stock (i.e., 2499 20-minute intervals for the seven-month period examined herein), we identify order file errors as those orders that appear in the order but not trade book and cause the spread to be non-positive. We eliminate any identified order errors, and then recheck each 20-minute time interval until no additional errors are identified.

We construct the limit order book consisting of the ten best different bids and ten best different offers and their corresponding volumes for each second of the trading day based on price and then time priority by using the order flow and trade data. Our second-by-second limit order book for each stock is updated when new orders are added, existing orders are canceled or existing or new orders are executed. A new buy (sell) order is placed in the buy queue after (before) all orders to buy (sell) at the same price or after (before) all orders to buy (sell) at a higher (lower) price if the queue does not already include an order to buy (sell) at the same price. A trade removes an order from the inside of the book (oldest buy order at the highest buying price or the oldest sell order at the lowest selling price). The unique 15 or 16-digit ID number and timestamp up to the closest second attached to each order allows us to perfectly match orders between the order-flow and trade data sets. This makes it possible to obtain the chronological ranking of the orders and trades and the trade initiator using the chronological method as in Odders-White (2000).

Our initial "cleaned" sample consists of 8,375,672 trades of which we can classify 99.5% or 8,332,218 trades using the chronological method since the chronological method cannot classify executed orders that arrive at the same time (i.e., have the same time stamp). The sample of trades is further reduced to 7,894,420 trades with the deletion of the first five minutes of continuous trading of the trading day,[13] and to 7,889,985 trades after deleting trades that could not be classified using the five classification algorithms used herein. A total of 46.1 billion shares were traded for our final sample of trades over the seven months examined herein.

Thus, our final sample of the number of trades represents 94.2% of all the trades in the original sample. This elimination rate of 5.8% is much lower than that reported in the literature for other markets. Some elimination rates for studies using TORQ trades are 25% in Finucane (2000), 25.1% in Odders-White (2000) and about 40% in Lee and Radhakrishna (2000). Elimination rates using other datasets include 24.6% in Ellis, Michaely and O'Hara (2000).

2.5 WHO IS THE TRADE INITIATOR?

Before proceeding to our examination of the performance of the various trade classification algorithms for the BIST, we need to discuss how the identity of the actual initiator of each trade or comparison benchmark is determined. In the absence of short sales and given full information on trades and quotes (such as time and trader identification), the actual trade initiator is the party to the trade that pays the largest "immediacy premium'' that reflects both a time and cost dimension.

The two common approaches for determining the trade initiator are based on the implicit assumption that all trades are long-long. When trade IDs are not available, a trade is assumed to be initiated by the trader whose market order has been executed against a standing limit order. The advantage of this immediacy approach is that it considers both dimensions of liquidity for trades that match a market with a limit order that are on opposite sides of the market. However, as noted by Odders-White (2000), this

[13] Continuous trades began at 9:45 am for trades up to October 13, 2008, and from 9:50 thereafter. Thus, we use trades from 9:50am and 9:55am, respectively.

approach cannot identify the actual trade initiator for crossed market orders, limit-limit order matches and stopped market orders. Odders-White reports that crossed market orders and limit-limit order matches account for about 12% and 17%, respectively, of the transactions in the TORQ data set. When trade IDs are available, the chronological approach is used where the trade initiator is identified as being the trader who places an order last chronologically. The two-part rationale behind this approach is that: (i) the first-in party to the trade acts as the liquidity provider at its chosen price; and (ii) the last-in party pays the "immediacy premium" for the rapid execution of the trade. The advantage of this approach is that it considers both dimensions of liquidity for a wider set of order type pairings.

There is a divergence of opinion in the literature on who is the trade initiator when one side of the trade includes a short sale. While Asquith, Oman and Safaya (2010) argue conceptually that short sales should be predominantly seller-initiated, Chakrabarty, Moulton and Shkilko (2012) argue that by using INET order data they can correctly identify the true trade initiator for short sales as being predominantly buyer-initiated. Given different conceptual benchmarks, it is not surprising that they arrive at different conclusions about the reliability of using the LR algorithm for classifying trades when the LR algorithm classifies most (majority of) trades involving short sales as being buyer-initiated for stocks (not) subject to either the uptick or inside bid rule depending upon the trading venue examined.

We argue that it is not possible to obtain an unambiguous determination of the true trade initiator for trades that involve short sales even if the researcher has access to trader IDs. We argue that it is not reasonable to assume that other trade immediacy costs are symmetrical for both trade sides for a trade that involves a short sale, since the short side incurs various additional immediacy-related trade costs (Lesmond, Schill and Zhou, 2004) that are not incurred by the long side even in the absence of an uptick rule. As noted by Asquith, Oman and Safaya (2010), these include at a minimum the need to locate a security to borrow and to accept a below-market rebate rate (i.e., the equivalent of the overnight repo rate minus the lending fee on a daily basis).[14] The existence of these additional trade costs only for the short seller means that both parties pay an "immediacy premium" for rapid execution of the trade. Thus, the competing actual trade initiator benchmarks differ based on the assumption made in terms of the relative importance of these additional trade costs. If they are not material, one arrives at a benchmark that trades involving short sales should be predominantly buyer-initiated as advocated by Chakrabarty, Moulton and Shkilko (2012). If they are material and sufficiently large, one arrives at a benchmark that trades involving short sales should be predominantly seller-initiated as advocated by Asquith, Oman and Safaya (2010).

[14] Other indirect costs associated with the short side are recall risk, and the short term adverse consequence of the marking to market of collateral when the price moves against the borrower (short seller).

The empirical evidence finds that lending fees (rebate rates) are material but not sufficiently large for most stocks to either conclude that the actual initiator of a trade involving a short sale should be predominantly buyer- or predominantly seller-initiated. Two examples are the studies by D'Avolio (2002) and Cohen, Diether and Malloy (2007) both of which use proprietary databases of stock lending activity from a large (different) institutional investor. For the period of April 2000 through September 2001, D'Avolio (2002) reports that for the 91% of the firms not "on special" (defined as a loan fee greater than 1% per annum), the typical loan fees are around 20 basis points per annum. For the period of September 1999 to August 2003, Cohen, Diether and Malloy (2007) report mean (median) annual loan fees of 0.39% (0.13%) and 3.94% (3.93%) for firms above and below the median value of market equity of firms listed on the NYSE. They also note that the loan fee for retail borrowers is typically equal to the interest rate on cash funds since retail investors typically receive no interest on their proceeds from the short sale. For the rebate rates based on the small proportion of short sales collected by Takasbank,[15] we observe that almost all rebate rates exceed one percent annually.

Thus, given that lending fees are firm-specific and time-varying and not available for most traded stocks (especially over the longer time periods examined in many microstructure studies), no unambiguous benchmark of the identities of the actual trade initiators is possible for trades involving short sales. However, if such data became available, a researcher could adjust the mid-spreads used in the LR algorithm upwards to account for estimates of these differentials.

2.6 HYPOTHESES AND FINDINGS

Before proceeding to a presentation of the hypotheses to be tested and the test results, our primary test for goodness-of-fit is the chi-square test, χ^2. We also use the G-test, which is also known as a (log-) likelihood ratio test, as an alternative test since the chi-square test is simply an approximation to the G-test for convenient manual computation and the G-test is based on the multinomial distribution without using the normal distribution approximation. The chi-square and G- test statistics are computed as:[16]

$$\chi^2_{(r-1)(c-1)} = \sum_{i,j} \frac{\left(O_{ij}-E_{ij}\right)^2}{E_{ij}}, \text{ and } G = 2\sum_{i,j} O_{ij}\,.\ln\left(O_{ij}/E_{ij}\right),$$

[15] The major purpose and activity of the Takasbank is to provide clearing, settlement and custody services within the capital market and related exchange regulations of Turkey as well as rendering investment banking services within the scope of the Banking Law and other banking regulations. As the central clearing and settlement institution to Borsa Istanbul, Takasbank is authorized to provide cash and securities settlements for transactions for equities, debt securities, foreign securities, derivatives and precious metals.

[16] The two statistics will converge for large sample size *n* since the two measures differ by terms of the order of $1/\sqrt{n}$. For greater details, see: http://www.statsref.com/HTML/index.html?g_contingency_table_test.html

where O_{ij} and E_{ij} are the observed and expected frequencies for cell i, j, respectively, in the contingency table; ln is the natural logarithm; and the sum is taken over all non-empty cells.

2.6.1 Total Sample (not) Differentiated by Time of the Trading Day

2.6.1.1 Hypotheses

Since many studies that were reviewed earlier find that the LR algorithm tends to have the highest accuracy rate for markets in developed countries, we expect that such will also be the case for the BIST even though it is situated in a developing country. Therefore, our first hypothesis in its alternate form is:

H_A^1: The LR algorithm has a better rate of accuracy for the total sample not differentiated by time-of-day than the tick, quote, at-the-quote and EMO algorithms for trade classification.

Researchers generally exclude trades for short periods after the opening and near the closing of a trading day. For example, Odders-White (2000) excludes the first fifteen minutes of trading from her analysis based on the argument that the concept of an initiator is not applicable for this period of time due to the opening auction. Petersen and Fialkowski (1994) exclude the orders entered prior to the market opening when they document a significant difference between the posted and effective spreads paid by investors. In the spirit of Odders-White while minimizing the loss of trades, we only exclude the first five minutes of continuous trading for the first trading session of each trading day when examining the rates of accuracy of the five classification algorithms for the first and last 30 minutes of both the morning and afternoon trading sessions. We also account for the change of trading times on October 13, 2008 that was discussed earlier. Therefore, our second hypothesis in its alternate form is:

H_0^2: The accuracies of the trade classification algorithms differ during the first and last 30 minutes of each trading session.

The first potential determinant of trade misclassifications examined in the literature is the lag length of the quote used in some of the trade classification algorithms. According to Lee and Ready (1991), misclassifications are reduced significantly by comparing a trade to the quote in effect five seconds earlier. Although her highest misclassification rate of 20.1% occurs for trades that are less than five seconds apart, Odders-White (2000) finds that the five-second rule only affects 4% of her data sample and that the rule changes the classification for only 1,218 out of 318,364 transactions. Since the elimination of the five-second rule causes more misclassifications, she concludes that the increased misclassification of trades that are less than five seconds apart is not due to the failure of the five-second rule. Chakrabarty, Moulton and Shkilko (2012) report that the misclassification rate drops by one third when one-second lagged quotes are used in the LR algorithm instead of contemporaneous quotes. We also expect to have better results using one- versus five-second lagged quotes given the fully computerized nature of the order-driven market on the BIST. Therefore, our third null hypothesis is:

H_0^3: The classification accuracy of the various trade classification algorithms for trades on the BIST is the same for quote lag lengths of zero, one and five seconds that are commonly used in the microstructure literature.

2.6.1.2 Results

We report the average accuracy rates for the full trading day and for the first and last 30 minutes of the morning and afternoon trading sessions in panels A and B of Table 2.3, respectively. The results are based on 7,889,985 transactions for the whole sample over the full seven months examined herein. For the undifferentiated sample, we find that the one-second version of each of the four trade classification algorithms that use quotes have the highest classification accuracies, and that this version of the LR algorithm has the best performance with an average accuracy rate of 96.38%.[17] The use of zero-second lagged quotes results in the lowest classification accuracies for all quote-based algorithms. For one-second lagged quotes, the average trade classification accuracy rate for the LR algorithm is followed by the quote, at-the-quote, tick and EMO algorithms with average accuracy rates of 95.00%, 93.05%, 90.38%, and 86.93%, respectively. These results support the findings of Chakrabarty, Moulton and Shkilko (2012) that the use of quotes lagged one second lead to higher classification accuracies than the use of contemporaneous quotes.

[**Please place Table 2.3 about here**]

As for the undifferentiated sample, we find that the one-second version of each of the four trade classification algorithms that use quotes have the highest trade classification accuracies for the differentiated samples. Furthermore, this version of the LR algorithm has the best performance with an average accuracy rate of 96.52% and 96.32% for the first and last 30 minutes of the morning trading session, respectively, and 95.89% and 96.99% for the first and last 30 minutes of the afternoon trading session, respectively. As for the undifferentiated sample, this average trade accuracy rate for the LR algorithm is followed by the quote and at-the-quote algorithms. The tick (EMO) followed by the EMO (tick) algorithm come next for the morning (afternoon) session.[18] Based on the chi-square and G- tests and one-second lagged BBO, the accuracy rates are significantly higher (lower) for the last 30 versus the first 30 minutes for the at-the-quote and EMO (quote and LR) algorithms in the morning session and for all

[17] Since the tick algorithm does not use quotes, its classification accuracy is invariant to whether a zero, one or five second lagged quote is used.

[18] Based on untabulated results, the average classification accuracies are materially inferior for the reverse tick classification algorithm.

four classification algorithms in the afternoon session. They are also significantly higher using the tick algorithm for both sessions. Thus, we reject our third null hypothesis at the 0.001% level that classification accuracy is independent of whether trades occur near the beginning or end of the morning or afternoon sessions for all trade classification algorithms and all lag lengths.

2.6.2 Total Sample Differentiated by Trade Positioning within the BBO

2.6.2.1 Hypothesis

It is well documented that trade classification algorithms perform significantly better for the trades at the BBO quotes. Since the LR algorithm compares the transaction price to the posted quotes, Chakrabarty *et al*. (2007) find that its accuracy is higher for the trades that occur at either BBO quote. Odders-White (2000) documents an 89.6% accuracy rate for the trades at or outside the quotes using the LR algorithm. However, the LR algorithm for her sample only correctly classifies 78.23% and 62.63% of the trades that are inside the spread but not at the spread midpoint and at the spread midpoint, respectively. Similarly, Rosenthal (2012) documents that the LR algorithm using one second lagged quotes has the best classification accuracy of 79% of the trades that take place at the ask quote for his sample of Nasdaq and NYSE stocks for December 1 and 2, 2004. Thus, our fourth hypothesis in its alternate form is:

$\mathrm{H}_{\mathrm{A}}^{4}$: The accuracy rate for classifying trades using the LR algorithm is higher when trades take place at the BBO quotes compared to when they occur at the mid-spread or inside the quotes but not at the mid-spread.

2.6.2.2 Results

The accuracy rates of the trade classification algorithms based on the trade price positioning against the BBO quotes and their mid-spreads are reported in Table 2.4. Once again, the LR algorithm with one-second lagged quotes exhibits the best performance with accuracy rates of 96.18%, 93.30% and 95.42% for the trades that occur at or outside the BBO spread, at the BBO mid-spread, and within the BBO spread but not at the mid-spread, respectively.[19] Interestingly, the other three classification algorithms that use quotes have the highest accuracies for trades at the mid-spread when their lag length is five seconds. Among the three trade positions relative to the BBO, the tick algorithm performs best with an accuracy rate of 90.17% when the trades occur at or outside the BBO spread. Our results for lagged versions of the LR algorithm are consistent with those of Odders-White (2000) in that the highest rates of misclassifications occur for the trades that take place at the quote mid-spread. Furthermore, based on the

[19] The results are similar when locked trades are removed from the sample. One difference is that the quote algorithm using a one-second lagged BBO has the highest accuracy rate of 95.40% versus 94.60% for its LR algorithm counterpart for trades within the BBO spread but not at the mid-spread. Not surprisingly, the accuracy rates increase substantially for all classification algorithms and BBO lag lengths for trades at the mid-spread.

chi-square and G-test statistics and their associated p-values, we reject our fourth null hypothesis at the 0.001% level that classification accuracy is independent of the positioning of the trade relative to the BBO for all trade classification algorithms and all lag lengths.

[Please place Table 2.4 about here]

2.6.3 Total Sample Differentiated by Time between Trades

2.6.3.1 Hypothesis

Easley and O'Hara (1992) show that the time between trades plays a role in price behavior in that trade provides a signal of the direction of any new information and the lack of trade indicates the absence of any news and provides an indicator of event uncertainty. Since the time between trades cannot be isolated from the information content and the price process, we analyze the effect of the time difference between trades when assessing the performances of the trade classification algorithms. In other words, we investigate if a relationship exists between the misclassification of trades and trade frequency. This will provide an indirect test of whether trade classification accuracy has a relationship with the frequency of informed trading. Odders-White (2000) investigates this hypothesis by applying two different measures: time between trades and the total number of transactions during her sample period. Therefore, in order to provide further evidence on the effect of this trade characteristic for our market, our fifth hypothesis in its alternate form is:

H_A^5: Trade classification accuracy is inversely related with the time between trades.

2.6.3.2 Results

To conduct this test, we divide our sample into three categories: trades occurring less than or equal to five seconds apart (76.2% of the total), trades occurring more than five and less than or equal to 30 seconds apart (15.8% of the total), and trades occurring more than 30 seconds apart (8.0% of the total). The accuracy rates of the trade classification algorithms based on the time between trades are reported in Table 2.5. Based on the chi-square and G-test statistics, the rates of trade classification accuracy are significantly different for each classification algorithm for each lag quote length. Thus, our results do not support our fifth null hypothesis at the 0.001% level that classification accuracy is independent of the elapsed time between trades for all trade classification algorithms and all lag lengths.

[Please place Table 2.5 about here]

The one-second lagged version of the LR algorithm continues to have the best performance for three time-between-trades categories with a classification accuracy range of 96.19% to 97.50%. Holding the lag to one-second, the accuracy rates in descending order are the quote, at-the-quote, and the EMO algorithms for all three categories. The tick algorithm consistently outperforms the EMO algorithm for all BBO lag lengths and time-between-trades categories. The rate of trade accuracy tends to deteriorate as the time between trades decreases for all but the EMO trade classification algorithm. Except for the tick algorithm and the one- and five-second lagged quote versions of the EMO algorithm, all trade direction algorithms exhibit the lowest performances for successive trades occurring within five seconds or less. This result is consistent with the findings of Odders-White (2000) although she finds that 20.07% of the transactions occurring within five seconds or less of each other are misclassified using the LR algorithm. We find that the accuracy rate for the LR algorithm changes marginally when moving from five to one-second lagged quotes, except for a five-second or less period between trades where it increases from 93.77% to 96.29%. This result is also consistent with the finding of Oders-White (2000) for developed markets who notes that the increased misclassification for consecutive trades occurring within five seconds or less is not caused by the failure of the use of five-second lagged quotes. As further support, we find that the LR algorithm only successfully classifies 81.20% of the trades in this trade-time category using contemporaneous quotes. The misclassification rate increases from 6.23% to 18.80% when we move from five- to zero-second quotes, where the latter percentage represents the highest misclassification rate for the LR algorithm for all categories and for all lag lengths. These results are consistent with the conjecture that frequently traded stocks exhibit higher trade misclassification rates which may be attributed to the increased number of informed trades taking place when the time between consecutive trades is shorter.

2.6.4 Total Sample Differentiated by Trade Size

2.6.4.1 Hypothesis

There is reason to expect that trade classification accuracy may be lower for larger-sized trades. Various studies use either trade size categorization in dollars traded or shares traded to identify trades by retail investors (e.g., Brandt *et al.*, 2010) or informed traders (e.g., Kryzanowski and Zhang, 1996; Schultz, 2000). Petersen and Fialkowski (1994) document greater price improvement for smaller trades, which may be caused by a greater proportion of small trades taking place inside the bid-ask spread. Odders-White (2000) reports that 16.85% of the transactions with 300 or fewer shares that she examined are misclassified by the LR algorithm, whereas 13.65% of the transactions consisting of more than 300 shares are misclassified. Aitken and Frino (1996) document similar results for the Australian market using the tick algorithm. In contrast, Chakrabarty, Moulton and Shkilko (2012) document higher misclassification rates for trades larger than their mean trade size of 300 shares and median of 100 shares. Given these mixed results, the sixth hypothesis in its alternate form is:

H_0^6: Smaller trades are more likely to be misclassified compared to larger trades, since they occur more frequently inside the bid ask spread.

2.6.4.2 Results

There are three main metrics used in the microstructure literature to determine trade sizes: number of shares transacted, dollar value of shares transacted, or number of board lots transacted. Kryzanowski and Zhang (1996) use the dollar value of shares transacted in the Canadian Market and designate four categories: odd lot,[20] small board lot (value of less than $10,000), middle board lot (value equal to or greater than $10,000 and less than $100,000), and large board lot (value equal to or greater than $100,000) in their analysis of the trading patterns of small and large trades around stock split ex-dates using intraday data for the Toronto Stock Exchange between 1983 and 1989. In exploring the competition between ECNs and NASDAQ market makers, Barclay, Hendershott and McCormick (2003) use the number of shares transacted on these trade venues when grouped into three categories: one to 1000 shares; 1001 to 9999 shares; and ≥ 10000 shares. Using the board lots size (considered as the generally accepted unit of trading), Ahn and Cheung (1999) analyze the behavior of bid and ask spreads and depths for 471 stocks listed on the Hong Kong Stock Exchange.

To be consistent with Odders-White (2000), we divide our trades into six categories based on the number of shares traded. The resulting trade size groupings are: fewer than or equal to 500 shares, between 501 and 1,000 shares, between 1001 and 5000 shares, between 5001 and 15,000 shares, between 15,001 and 45,000 shares, and more than 45,000 shares. Based on the accuracy rates for these trade size groupings reported in Table 2.6, we observe that almost half of the trades (41.6%) are in the smallest trade size category of 500 or fewer shares, whereas the largest trade size grouping with trades of more than 45,000 shares represent only 3.1% of all trades. The LR algorithm once gain outperforms the other four trade classification algorithms for each trade-size grouping using one-second lagged quotes with accuracy rates of 96.77% and 96.79% for the smallest (fewer than or equal to 500 shares) and largest (more than 45,000 shares) trade size groupings, respectively. Based on the chi-square and G-test statistics and their associated p-values, we reject our sixth null hypothesis at the 0.001% level that classification accuracy is independent of trade size for all trade classification algorithms and all lag lengths.

[Please place Table 2.6 about here]

Our findings are consistent with Chakrabarty, Moulton and Shkilko (2012) but not Odders-White (2000) and Aitken and Frino (1996). The misclassification rates for our smallest trade size category

[20] A board lot is defined as 100 shares for a stock with a price of $1 or higher (definition Canadian Securities Institute). An Odd Lot corresponds to the number of shares that are less than a board lot.

(between 501 and 1,000 shares) are (significantly) higher than that for the largest trade size category (greater than 45,000 shares) for the tick algorithm and the other four classification algorithms using zero and five-second lagged BBO. In contrast, they are smaller for the four classification algorithms that use a one-second lagged BBO, and significantly so for all but the LR algorithm. The misclassification rates for the second smallest trade size category (greater than 1000 shares but less than or equal to 5000 shares) are generally significantly larger than those for the second largest trade size category (greater than 15,000 shares but less than or equal to 45,000 shares). The rates are significantly higher for the second largest versus second smallest trade size category for the at-the-quote and EMO algorithms using one-second lagged BBO. Based on our results, our evidence supports the hypothesis that the smallest trades are more frequently misclassified than the largest trades.

2.6.5 Total Sample Differentiated by Long versus Short Trades

Short sales are allowed on the BIST using a conventional uptick rule after the opening price is determined by the system or against the previous session's closing trade price in cases where the system does not determine an opening price.

2.6.5.1 Hypothesis

Examining differences between short and long trades has attracted increasing research interest as more sophisticated data has become available. As discussed in section two, researchers report lower accuracy rates for trade classification algorithms for short versus long trades although they differ on whether short sales are expected to be buyer-initiated (Chakrabarty, Moulton and Shkilko, 2012) or seller-initiated (Asquith, Oman and Safaya, 2010). We also expect the classification accuracy of the LR algorithm for short sales to be best using one-second lagged quotes when benchmarked against the actual trade classification from the chronological approach. However, as we discussed in section five, the reliability of using the chronological approach for identifying the actual trade initiator is dependent upon the relative importance of the additional trade (immediacy) costs associated with the short and not the long side of a trade involving a short sale. We invoke the assumption in this section of the paper that these additional costs are not material so that our benchmark is that trades involving short sales are predominantly buyer-initiated.[21] We do this for presentation purposes and because the tick rule on the BIST may be a constraint for short sales. Therefore, our seventh hypothesis in its alternative form is:

$\mathrm{H}_{\mathrm{A}}^{7}$: The LR algorithm using one second lagged quotes performs better than the other classification algorithms for both long and short trades.

[21] When we classify our samples of long and short trades using the chronological method, we find that 92.2% and only 51.2% of the short and long trades, respectively, are classified as being buyer-initiated.

2.6.5.2 Results

The results for trade classification accuracy differentiated by long versus short trades are reported in Table 2.7. For the four trade classification algorithms that use quotes (quote, at the quote, LR and EMO), the rate of "misclassification" is higher for the short trades than for the long trades using one second lagged quotes, consistent with the results reported by Asquith, Oman and Safaya (2010) and Chakrabarty, Moulton and Shkilko (2012).[22] While the differences in classification accuracies for the same algorithm are statistical significant based on the chi-square and G-test statistics, the magnitudes are not that different. For instance, the "misclassification" rates for the LR algorithm for short and long trades are respectively 16.18% and 16.12% using contemporaneous quotes, 5.07% and 3.57% using one-second lagged quotes, and 8.05% and 3.57% using five-second lagged quotes. Although the corresponding "misclassification" rate magnitudes are higher in Chakrabarty, Moulton and Shkilko (2012), they report a similar ordering based on the quote lag length for the LR algorithm. Specifically, they report for short and long trades respective "misclassification" rates of 32% and 31% using contemporaneous quotes, 21.4% and 21.8% using one-second lagged quotes, and 23.7% and 23.4% using five-second lagged quotes. For the four trade classification algorithms that use quotes, the rate of "misclassification" is lowest (highest) when one second (contemporaneous) quotes are used for both the short and long trades. Thus, our results support the seventh hypothesis that the LR algorithm using one-second lagged quotes outperforms the other trade direction algorithms for both long and short trades.

[Please place Table 2.7 about here]

2.6.6 Total Sample Differentiated by Seller-or-Buyer-Initiated Trades

2.6.6.1 Hypothesis

While informed traders buy upon good information and sell upon bad information, uninformed (liquidity) traders are considered, on average, to buy or sell at similar levels. This distinction between informed and uninformed traders has been analyzed by many researchers for various purposes, such as the PIN of Easley *et al.* (1996) and the spread decomposition models of Madhavan, Richardson and Roomans (1997) and Glosten and Harris (1988). Since the PIN estimate depends on the probability of information events and on the arrival rates of both informed and uninformed traders, where the LR algorithm is generally used to determine the number of buys and sells for each period of time (such as a day).

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[22] This is the case even though the participation rate of short sales in our sample is lower than that reported in the U.S. For example, short sales account for 3.7% and 5.3% of the total number of trades and total number of shares traded, respectively, in our sample based on the last seven months of 2008. In contrast, Asquith *et al.* (2010, table 1, page 162) report respective corresponding average values of 29.7% and 27.9% for their sample for the three months examined in 2005.

Similarly, the trade indicator variables in these spread decomposition models generally rely on the LR algorithm to determine if a trade is buyer- or seller-initiated. Thus, we now examine whether the accuracy rates of the five trade classification algorithms differ for buyer- and seller-initiated trades. Therefore, our eighth hypothesis is:

H_0^8: There is no significant difference in the accuracies of the trade classification algorithms between buyer- and seller-initiated trades.

2.6.6.2 Results

The trade classification accuracy results differentiated by buyer- or seller-initiated trades are reported in panel A of Table 2.8. Based on the chi-square and G-test values, the null hypothesis that trade classification accuracy is independent of whether the trade is buyer or seller-initiated is rejected at greater than the 0.01 level for all but the quote classification algorithm for a zero lag (p-value = 0.06). For the buyer-initiated trades which represent 52.8% of all trades, the LR algorithm using one-second lagged quotes has the best accuracy rate at 94.81%. In contrast, for the seller-initiated trades which represent 47.2% of all the trades, the EMO algorithm with a one-second lag has the best accuracy rate at 99.07%, followed by the LR algorithm with a one-second lag at 98.12%. While the EMO algorithm is also best for the other two lag lengths for seller-initiated trades, its performance is far inferior to the tick and other three quote-based trade classification algorithms for the buyer-initiated trades.[23]

[Please place Table 2.8 about here]

2.6.7 Total Sample Differentiated by BIST`s trader classifications

2.6.7.1 Hypothesis

To the best of our knowledge, we are the first to conduct a more complete test of the classification accuracy of trades differentiated by whether the trader has an agency or principal relationship with the brokerage firm executing the trade.[24] To this end, we use the following three-way trader classification that is included in our proprietary dataset from the BIST: institutional and retail clients of the brokerage firms [M(Ins. & Retail)], portfolios of the brokerage firms [P(portfolio)], and the investment funds managed by the brokerage firms [F(fund)]. For testing purposes, we consider these three categories as representing pure agency, pure principal and most likely mixed agency and principal relations between client and

[23] Consistent with the findings of Funicane (2000) and untabulated results, the reverse tick rule displays the poorest classification accuracy for buyer- and seller-initiated trades.
[24] Since they could not determine who initiated trades between market makers and between brokers, Ellis, Michaely and O`Hara (2000) examine the 75.4% of their sample that involves trades between market makers or brokers and customers.

executing broker, respectively. Thus, our ninth null hypothesis, which examines whether the accuracy of the trade classification algorithms is independent of the BIST's trader classifications, is:

H_0^9: The accuracy of the trade classification algorithms is independent of the BIST`s classification of traders.

2.6.7.2 Results

The average trade classification accuracies in percent for each of the five trade classification algorithms based on the BIST`s classification of traders are reported in panel B of Table 2.8. Based on the chi-squares and G-test statistics, the null hypothesis that trade classification accuracy is independent of the BIST's trader classification is rejected at greater than the 0.01 level. Consistent with previously reported results, the LR algorithm using one-second lagged quotes has the best classification accuracy at 96.38%, 95.72% and 96.89% for the M, P and F trader classifications, respectively. Trades for the investment funds managed by the brokerage firms (mixed agency and principal relations) exhibit the highest accuracy rates with the exception of the LR algorithm using contemporaneous quotes. Trades for the portfolios of the brokerage firms (pure principal relations) exhibit the lowest accuracy rates. When compared to the undifferentiated results reported earlier in Table 2.3, we find lower accuracy rates for this grouping for all classification algorithms and lag lengths. Therefore, our results do not support our null hypothesis that the accuracies of the trade classification algorithms are independent of the BIST`s three-way classification of traders.

2.7 CONCLUSION

We examine the accuracy rates of five trade classification algorithms for a trade venue in a developing market for the seven months ending with December 2008 that is centered on the month of Lehman Brothers' collapse. The order book data from the BIST is extensively cleaned to remove human errors prior to determining the BBO for each second for each trading day for each stock in the primary BIST index (the BIST-30).

We find that the one-second lagged version of the LR algorithm with over 95% classification accuracy not only outperforms the other four trade classification algorithms analyzed herein but is also higher than that previously reported for other markets including the U.S. This is consistent with the guidance that the five-second rule needs to be replaced by its one-second counterpart for trade classifications for US markets (Chakrabarty, Moulton and Shkilko, 2012). It is also consistent with the observation of Peterson and Sirri (2003) that trade misclassifications for the LR algorithm based on the NBBO trade-contemporaneous instead of the order-submission NBBO depend on how long an order takes to execute.

We find that the LR algorithm using one-second lagged quotes is generally the best for seven differentiated samples, and that the highest rates of misclassifications occur for trades at the quote mid-spread and as the time between consecutive trades decreases (Odders-White, 2000). Misclassifications also tend to be lowest for agency trades and higher in the first versus the last 30 minutes of both daily trading sessions which may be due to more informed trading during these periods. Unlike Odders-White (2000) and Aitken and Frino (1996), we find that larger transactions generally are more frequently misclassified but only for the classification algorithms using one-second lagged BBO.

Unlike Asquith, Oman and Safaya (2010) and Chakrabarty, Moulton and Shkilko (2012), we find accuracy rates of at least 90% using one-second lagged quotes for both long and short trades for the quote, at-the-quote and LR (but not EMO) algorithms. While the EMO algorithm is best for correctly classifying seller-initiated trades with over 95% accuracy rates and worst for correctly classifying buyer-initiated trades, the LR algorithm using a one-second lagged BBO is second best for correctly classifying seller-initiated trades and best for correctly classifying buyer-initiated trades.

CHAPTER THREE

MARKET IMPACTS OF TRADES FOR STOCKS LISTED ON THE BORSA ISTANBUL

3.1. INTRODUCTION

Due to the effect (drag) of spread and price impacts of trade on investment performance; market participants implement various trading strategies in order to minimize their impact on net returns. With the increasing rate of participation of financial institutions in equity markets worldwide, large trades have substantially increased and become of increasing concern to market participants and regulators due to the perception that institutional traders are, on average, more informed. Due to their effect on the operational efficiency and transparency of markets, trading venues and regulators consider these impacts as some of the most important indicators of market quality. To illustrate using a 2012 example, the SIX Swiss Exchange extended its free Market Quality Metrics (MQM) service to ensure greater comparability and increased pre-trade transparency for its bond listings by providing investors with the ability to observe the historical availability of BBO (best bid and offer) quotes, the daily average spreads and the average depths on both sides of the order book.[25]

As reviewed more extensively in the next section of the paper, most studies that examine the market impacts of large trades for various international markets report that these effects differ for buyer- and seller-initiated trades. A limitation of most of these studies is that their trade classifications depend on what proportion of the trades can be classified using the tick or Lee and Ready (1991) or Ellis, Michaely and O'Hara (2000) algorithms and the accuracy of the classifications for those trades that can be classified.[26] Although a large portion of the trades remain unclassified in other studies, reported classification accuracies for the LR algorithm varies from 69.2% for long trades in Chakrabarty, Moulton and Shkilko (2012) to 93.0% in Lee and Radhakrishna (2000). As an illustration of the extent of trades that cannot be classified in many studies, Lee and Radhakrishna (2000) report a 93% accuracy rate for the Lee and Ready algorithm for a sub-sample of 15 stocks from the TORQ dataset after eliminating approximately 40% of the trades in TORQ that could not be unambiguously classified as being either buyer- or seller-initiated because they were market “crosses”, stopped market orders, and pairings of market with executable limit orders.

[25]As reported at: http://www.world-exchanges.org/focus/2012-11/m-4-8.php. Further details on the MQM are found at: http://www.six-swiss-exchange.com/statistics/mqm/overview_en.html

[26] Other methods for classifying trades as buys and sells that are not necessarily buyer- or seller-initiated include Keim and Madhavan (1996) who use the trading history of a passive investment management firm containing all upstairs-negotiated trades between July 1985 and December 1992.

Thus, a first motivation for this study is to examine the price effects of a trade on a developing (emerging) market (BIST or Borsa Istanbul) where order arrival times to the closest second, short sale trades are identified and the IDs of each order and trade are available for matching purposes. For our chosen market, this enables us to successfully identify more than 99.5% of the trades for the selected sample as being buyer-or seller-initiated using the chronological method as in Odders-White (2000).[27] To illustrate the BIST's growing importance, we note that on December 31, 2013, NASDAQ OMX concluded an agreement with the BIST to deliver market-leading technologies and advisory services, to take an equity stake in BIST, and to closely work together to further BIST's "position and brand as the capital markets hub for the Eurasia region".[28]

We examine trade price effects for various (not) differentiated samples of aggregated trades of relatively large and small sizes and trading frequencies that occur during the same trade second of the trading day for stocks included in the BIST-30 index. Since stocks in this index account for about 70% of the total trade volume on the BIST for our sample period of April 2008 through March 2009, they represent the investment opportunity set of greatest interest to (particularly foreign) investors. While the findings should not be generalized to the less heavily traded securities on the BIST, they do cover a period of considerable market turbulence associated with the Lehman collapse and the Global Financial Crisis (GFC). As such, they should be of interest to market overseers engaged in preventing possible stealth trading activity or market manipulation,[29] and to practitioners when formulating and executing their investment decisions.

Consistent with the literature, we find that mean price effects are less than 30 basis points, and are (somewhat) counter-intuitive using the day's closing (subsequent fifth trade second) price instead of the price for the first post trade second. Since an informed trader needs to cover the cost and risk of making the trade and thin trading is associated with larger inside bid-ask spreads, lower liquidity and higher volatility due to the addition of microstructure noise to the variance of the unobservable efficient returns that would prevail in a frictionless economy, we find, as expected, more positive and more negative total and permanent price effects for buyer- and seller-initiated trade seconds for the relatively less frequently traded stocks.

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[27] The chronological approach identifies the trade initiator as being the trader who placed her order closest to the trade being signed as buyer-or seller-initiated.

[28] NASDAQ OMX and Borsa Istanbul sign landmark deal, *NASDAQ OMX Press Release*, December 31, 2013. Available at: http://ir.nasdaqomx.com/releasedetail.cfm?ReleaseID=816529. The newly incorporated BIST became Turkey's sole exchange entity by combining the former Istanbul Stock Exchange (ISE), the Istanbul Gold Exchange and the Derivatives Exchange of Turkey under the same umbrella from April 5, 2013.

[29] Stealth trading is the practice of breaking up trades by informed investors into sequences of smaller trades and trading during periods of increased market activity in order to conceal their private information about the fundamental value of a stock.

The second motivation for this paper is to provide a more precise assessment of the market impacts of trades accounting for whether one or both sides of the trade(s) involve a short trade given that our data set from the BIST identifies short sales. Examining differences between short and long trades has attracted increasing research interest as more sophisticated data has become available. Several authors (e.g., Asquith, Oman and Safaya, 2010; Chakrabarty, Moulton and Shkilko, 2012) find short sellers are generally not the trade initiators and that the accuracy rates are lower for short versus long trades using the three trade classification algorithms that are commonly used to examine the differentiated price effects of large trades. The price effects of short selling on the BIST is of further interest since the BIST did not restrict short sales during the crisis of 2008 as was the case in some other markets (e.g., prohibition of short selling in financial companies in the U.S. and U.K. in late September 2008). The theory of Miller (1977) and extensions by others states that, under heterogeneous expectations, short-sales constraints will inflate an asset's price above its intrinsic value. Thus, an examination of the price effects associated with short sales provides evidence on whether short sellers contribute to price discovery and market efficiency in a developing market. Such findings are important from a policy perspective given the negative public image of short sellers among the public and policy-makers and the ongoing debate on whether short-sales restrictions should or should not be imposed.

We find that all mean permanent price effects are highly significant and positive for all short trade samples, and are substantially greater in magnitude for seller- versus buyer-initiated short trade seconds. We also find that these price effects are (highly) significantly more positive for the samples of short versus long trade seconds. This suggests that short trades are more informed than long trades (Battalio and Mendenhall, 2005; Hvidkjaer, 2006).

A third motivation for our study is to fill a gap in the price effects literature by being the first to the best of our knowledge to examine trade price impacts differentiated by whether large traders have a pure agency, pure principal and mixed relationship with the brokerage firms executing their trades based on the following trader classifications provided by the BIST: institutional and retail clients of the brokerage firms; portfolios of the brokerage firms; and investment funds managed by the brokerage firms. Previous studies examine trade behavior and performance of retail and/or institutional investors. Selected results include that retail investor trades move equity prices (Hvidkjaer, 2008; Barber, Odean and Zhu, 2009); that the trading dynamics of these two types of investors appear to be based on very different interpretations of information (Griffin, Harris and Topaloglu, 2003); and that lottery-type stocks are over-weighted in the portfolios of retail but not institutional investors (Kumar, 2009). Whether or not and how the price effects differ on whether the trade is a principal or agent trade has important implications for the effect of agency issues on trade execution, and on the equity or fairness objective of security regulation.

We find that the smallest and largest negative mean total price effects using prior to trade prices are associated with seller-initiated trades for the portfolios of the brokerage firms and trades for the institutional and retail accounts of the brokerage firms, respectively. This suggests that the former traders or their brokers are better in either trade execution or the timing of their trades. Furthermore, we find that the smallest (largest) permanent price effects are associated with the small buyer- (small and large seller-) initiated trades for the institutional and retail accounts of the brokerage firms.

A fourth motivation for our study is to estimate end-of-session price effects. This may have important implications because stock exchanges and regulatory agencies around the world devote considerable human, technological and financial resources to curb market manipulation and to promote price discovery, market efficiency and market integrity.

We find some (weak) evidence that is consistent with the conjecture that manipulators have incentives to realize high prices at the close as opposed to earlier in a trading session since all three types of mean price effects are considerably higher positive (smaller negative) magnitudes in the last minute of the afternoon versus morning session for buyer- (seller-) initiated trade seconds. When we examine price effects for a three-day announcement day (AD) period centered on the Lehman announcement compared to the three-day periods pre- and post-AD, we find that the mean total price effects are highest AD, and that the mean temporary and permanent price effects are highest for small-sized buyer-and seller-initiated trade seconds.

The fifth and final motivation for this paper is to identify the determinants of the three types of price effects for buyer- and seller-initiated trade seconds (not) differentiated by trade size using our richer data set. We observe that most of the expected relations between the three-types of price effects and various potential determinants are significant and have their expected signs. For example, we find that increased buyer- and seller-initiated trades in the last one minute of trading and the last five to one minute of trading are associated with an increase and decrease, respectively, of the total price effects of trade.

The remainder of the paper is organized as follows. Section two provides a brief and focused review of the literature on the impact of large trades. Section three presents the hypotheses and the methodology to test the hypotheses. Section four describes the sample and data. Section five reports and discusses the trade price effects for various delineations of the trades (such as long vs. short; trader type; and near the end of the trading session). Section six conducts panel regressions to identify the determinants of the price effects associated with various trade samples. Section seven concludes the paper.

3.2. BRIEF REVIEW OF THE LITERATURE ON THE IMPACT OF LARGE TRADES

In this section, we refer to a number of papers that examine price effects in various markets. Non-US markets are identified in this section of the paper, and some summary details (e.g., sample and time period examined) for some of the studies that examine the price effects of large trades are presented in Table 3.1.

[Please place Table 3.1 about here.]

Using a rational expectations model, Kyle (1985) shows that informed traders hide their trades among noise traders and maximize their returns by limiting trade size so that trade information is incorporated into prices gradually. Easley and O'Hara (1987) provide a theoretical explanation for the impact of large trades in which an adverse selection trading problem occurs because informed traders are willing to trade larger amounts at any given price. This is consistent with prior evidence by Copeland and Galai (1983) and Glosten and Milgrom (1985) that informed traders have an effect on bid and ask prices, and, for example, the findings by Alzahrani, Gregoriou and Hudson (2013) for the Saudi Stock Exchange (SSE).

Four hypotheses are advanced in the literature to explain the price effects of large trades. The empirical evidence often supports more than one of these hypotheses. The substitution hypotheses asserts that large trades only have small price impacts due to their minimal impact on the average demand and supply for stocks based on the assumption that all stocks are close substitutes for each other (Scholes, 1972; Ball and Finn, 1989; Aitken, Frino and Sayers, 1994). Supportive evidence include Holthausen, Leftwich and Mayers (1987), and Ball and Finn (1989) for the Australian Stock Exchange (ASE).

The information-effects hypothesis asserts that permanent price effects are expected with large trades. The underlying argument is that seller- (buyer-) initiated large trades indicate the arrival of "bad" ("good") news based on the party's perception that a security is over- (under-) valued. Supportive evidence includes Fan, Hu and Jiang (2012) for the Shanghai Stock Exchange for seller-initiated large trades only. The permanent price effects are generally found to be greater for buyer- versus seller-initiated large trades (Gemmil, 1996, for the UK market; Aitken and Frino, 1996, for the ASE; Alzahrani, Gregoriou and Hudson, 2013, for the SSE). Together with the finding that buys (sells) exhibit price continuation (reversals), this suggests that only buyers pay a liquidity premium. One explanation for these asymmetric price effects is that buyer-initiated trades occur when firm-specific information arrives whereas seller-initiated trades are more liquidity than information based (e.g., Chan and Lakonishok, 1993; Keim and Madhavan, 1996).

The price pressure or segmented market hypothesis states that large trades cause temporary changes in short-run demand (supply) for buys (sells), which in turn causes temporary changes in stock prices. Studies supporting this hypothesis include Holthausen, Leftwich and Mayers (1987); Chan and Lakonishok (1993) for sells only; Keim and Madhavan (1996) for trades in the upstairs markets. Some studies find that the temporary effects are greater for buys than sells (Holthausen, Leftwich and Mayers, 1990; Frino, Mollica and Romano, 2012).[30] Other studies identify partial or full price reversals subsequent to a large trade (e.g., Frino, Jarnecic and Lepone 2009, for the ASE;[31] Alzahrani, Gregoriou and Hudson, 2013, for the SSE) and price reversals for large sales and price continuations for large purchases (Holthausen, Leftwich and Mayers, 1990).

The short-run liquidity-cost hypothesis, which is grounded in the models used by Kraus and Stoll (1972), Stoll (1978) and Ho and Stoll (1981), asserts that the market effects of any liquidity (immediacy) costs associated with large trades are temporary. When the trades involve an intermediary, the trades compensate the intermediary for inventory costs and any additional size-related risks associated with the trade. Ball and Finn (1989) provide several theoretical arguments against this hypothesis. They argue that brokers do not have to trade at off-equilibrium prices because their cost of holding stock is already reflected in the equilibrium expected return and pre-large-trade transaction price, and brokerage commissions cover the intermediary's cost of locating buyers and sellers. Studies supporting this hypothesis include Kraus and Stoll (1972), Holthausen, Leftwich and Mayers (1987), and Chan and Lakonishok (1993) for buys only.

We now provide a brief discussion of six methodological issues that the literature addresses when examining the price effects of large trades. The first issue is what constitutes a large trade. Some studies define a large (or block) trade as involving more than 10,000 shares (Kraus and Stoll, 1972; Ball and Finn, 1989, for the ASE). Other studies define a large trade as having a monetary value of at least 100,000 in local currency (Ball and Finn, 1989, for the ASE) or as being in the largest 1 per cent of on-market transactions for each stock in each calendar year (Frino, Jarnecic and Lepone, 2007, for the ASE).

The second issue involves the choice of pre- and post-trade prices when calculating temporary, permanent and total price effects. Some studies use the immediately prior trade to the large trade when calculating the temporary and total price effects (Kraus and Stoll, 1972; Holthausen, Leftwich and Mayers 1987, 1990), others use the day's opening price (Chan and Lakonishok, 1993) or the previous day's

[30] The proportion of the total price effect represented by the permanent effect changes from 25% in Holthausen, Leftwich and Mayers (1987) to 85% in Holthausen, Leftwich and Mayers (1990).
[31] In contrast, Frino, Jarnecic and Lepone (2009) find positive (negative) continuations following positive (negative) initial impacts of large purchases (sales) using quote data for the ASE.

closing price (Keim and Madhavan, 1996; Frino, Mollica and Romano, 2012), and still others use the first (Holthausen, Leftwich and Mayers, 1990) or the fifth trade before the large trade (Frino, Jarnecic and Lepone, 2007, for the ASE; Hwang and Qian, 2011; Alzahrani, Gregoriou and Hudson, 2013, for the SSE). Similarly for the post-trade price, some studies use the same-day closing price (Kraus and Stoll, 1972; Holthausen, Leftwich and Mayers, 1987; Chan and Lakonishok, 1993; Aitken and Frino, 1996, for the ASE; Frino *et al.,* 2005, for the ASE; Frino, Mollica and Romano, 2012) or the next-day's closing price (Keim and Madhavan, 1996), and still others use the first, third, fifth, or sixth trade after the large trade (Holthausen, Leftwich and Mayers, 1990; Frino, Jarnecic and Lepone, 2007, for the ASE; Hwang and Qian, 2011; Alzahrani, Gregoriou and Hudson, 2013, for the SSE).

The third issue is the choice of method used to distinguish buys or buyer-initiated trades from sells or seller-initiated trades. Trades are classified as buyer- or seller-initiated using a tick algorithm (e.g., Kraus and Stoll, 1972; Ball and Fin, 1989, as modified for the ASE; Keim and Madhavan, 1996; Hwang and Qian, 2011; Fan, Hu and Jiang, 2012, for the Shanghai Stock Exchange), the Ellis, Michaely and O'Hara (2000) classification algorithm (e.g., Frino, Mollica and Romano, 2012, for the ASE), and the Lee and Ready (1991) classification algorithm (e.g., Chan and Lakonishok, 1993; Alzahrani, Gregoriou and Hudson, 2012 & 2013, for the SSE). No study could be found that uses the better performing chronological classification algorithm to assess trade direction as is done in our paper.

The fourth issue is whether the price effects for trades differentiated by trader type should be examined, as in, e.g., Keim and Madhavan (1995) who find that trade duration increases with order size and market liquidity, and trades are spread over longer periods for buys versus sells. No study could be found that examines the price effects of large trades transacted on an agency versus principal basis. The fifth issue is whether the examination of trade price effects is in the downstairs or upstairs market, where the latter is an off-the-exchange venue used to transact large trades. Exceptions to the examination of price effects in the downstairs market include Keim and Madhavan (1996). Consistent with most of the literature, we also examine price effects in the downstairs market on the BIST.

The sixth issue is whether to identify the determinants of the price effects of large trades. For the ASE, Ball and Finn (1989) document no relation between trade size and stock returns, while Frino, Jarnecic and Lepone (2007) find that proxies for block size, liquidity, volatility, market returns and broker execution abilities exhibit limited explanatory power. For the SSE, Alzahrani, Gregoriou and Hudson (2013) interpret their panel regression results as providing some evidence that permanent price effects increase with larger trades, higher volatilities and positive market returns, and that permanent price impacts decrease for stocks exhibiting more active trading, higher relative spreads and return momentum.

3.3. HYPOTHESES AND METHODOLOGY

As discussed earlier, many studies report permanent but asymmetric price impacts from large sales and purchases.[32] We test the same hypothesis for our emerging market during a period that covers the financial crisis (2008). As discussed in section two, past studies examine the temporary, permanent and total effects of trades of various sizes (usually large) that are (not) differentiated by buyer- or seller-initiated trades. Therefore, our first null hypothesis is:

> H_0^1: There are no temporary, permanent or total price effects of trades (not) differentiated by buyer- and seller-initiated trades.

To be consistent with the previous literature (e.g., Holthausen, Leftwich and Mayers, 1987), we test the temporary, permanent and total price effects of a trade as $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{prior} is the market price prior to the trade that does not include any information conveyed by the trade, P_{trade} is the price of the trade whose effect is being assessed, and P_{post} is the equilibrium price after the temporary effect of the trade has dissipated. For P_{prior}, we use the price of the immediately prior trade second in the spirit of Holthausen, Leftwich and Mayers (1987) and Frino, Mollica and Romano (2012).

We first use that day's market closing price for P_{post} as in Holthausen, Leftwich and Mayers (1987) to test the conjecture by Holthausen, Leftwich and Mayers (1990) that calculating the temporary and permanent effects using closing prices may cause systematic biases due to observed large positive returns in the last five minutes of trading (see Harris, 1986) or much quicker price discovery. If their conjecture is valid for the BIST, temporary (permanent) effects will be biased upward (downward) for seller-initiated transactions and vice versa for buyer-initiated transactions. We test the robustness of using that day's market close by comparing the price effects associated with the first and fifth trade second after the trade second being examined. However, unlike most studies, we have the trade IDs so we do not have to use any trade classification algorithm (such as that of Lee and Ready, 1991) to separate trades as being buyer- or seller-initiated.

We also conjecture that the three types of price effects from trade differ when trades are delineated by various characteristics such as long/short trades, trade frequency, and trader type. Therefore, our second hypothesis in its null form is:

[32] These include Holthausen, Leftwich and Mayers (1987, 1990), Chan and Lakonishok (1993), Aitken and Frino (1996), Frino, Jarnecic and Lepone (2009) and Alzahrani, Gregoriou and Hudson (2013).

H_0^2: The price effects of a trade on the BIST do not differ for various types of trades (short versus long; less versus more frequently traded; near the end of a trading session) and trader types (specifically, institutional and retail accounts of brokerage firms, portfolios of brokerage firms, and the investment funds of the brokerage firms).

In traditional hypothesis testing, researchers test if the test statistic is, for example, significantly different from the null hypothesis value at say the 1% level. Since the confidence intervals become smaller with larger sample sizes, a researcher is increasingly more likely (almost certain) to reject the null hypothesis for an increasingly large (infinite) sample size for a given level of significance (Leamer, 1978, Ch. 4; Shanken, 1987; Connolly, 1989). However, the posterior level of belief in the prescribed value (under the null hypothesis) would be close to certainty since the estimated value would be very close to the actual value as the sample size approaches infinity. Various approaches are implicitly or explicitly used in the literature to address this paradox by setting a more appropriate (lower) critical level of significance for the test.[33] They include the use of (i) a 0.001 level of significance (e.g., Aitken and Frino, 1996), (ii) a large-sample posterior odds ratio which can be approximated by $\sqrt{\pi(d.f.)/2} * exp[-(t^2/2)]$ drawn from Zellner (1984) and used by, e.g., Griffiths and White (1993) and Kryzanowski and Zhang (2002) to find the t-statistic needed to generate a posterior odds ratio of 20:1, and where d.f. is the degrees of freedom and t is the traditional t-statistic, and (iii) sample size-adjusted critical t-values of $\left[(n-k)\left(\sqrt[n]{n}-1\right)\right]^{0.5}$ drawn from Leamer (1978) and used by, e.g., Connolly (1989), Davidson and Faff, 1999, and Frino, Jarnecic and Lepone (2007), where n is the number of observations and k is the number of parameters estimated under the null or alternative hypothesis. In this paper, we use the third approach as a further test of the significance of our estimates. As subsequently reported, our Bayesian critical t-values using this approach straddle the critical t-value of 3.30 or 3.29 that corresponds to the use of a 0.001 level of significance when n is 1,000 or approaches infinity, respectively.

3.4. SAMPLE AND DATA

Our sample consists of all the firms that are included in the BIST-30 index of the Borsa Istanbul during our twelve-month examination period of April 2008 through March 2009. Due to quarterly updating of the index, our sample consists of 38 companies. Since the BIST-30 index consists of stocks with the greatest trading frequency, this index represents around 70% of the total trade volume on the BIST for our sample period. We observe increasing trading activity and significantly decreasing index

[33] This is often referred to as Lindley's paradox.

levels over the studied time period due to the global crisis of 2008 that included the declaration of bankruptcy by Lehman brothers in September 2008.

Our data, which was provided by Borsa Istanbul, include all incoming orders and executed trades over this one-year period for our sample firms. Availability of a unique trade ID number and a timestamp up to the closest second enable us to identify almost all the trades as being either buyer- or seller-initiated using the chronological method as in Odders-White (2000). Since the chronological method cannot classify the 64,911 orders that arrive and are executed during the same second, all subsequent results are based on our examination of the remaining 13,895,277 trades that can be classified using the chronological method. Thus, we are able to classify more than 99.5% of the trades correctly as being either buyer- or seller-initiated according to the chronological method.

We examine the price effects of trades using various definitions of what constitutes a "large" trade. Some empirical studies measure the market impacts of large trades using individual trades even if they have the same time stamps in their data sets because they do not have access to trade or trader IDs. Our trade-"second" aggregation partially accounts for the concern of Bertsimas and Lo (1998) that best execution cannot be defined as a single number or often cannot be assessed based on a single trade if, for example, a trade from the same trader is transacted against multiple counterparties or the same trader enters separate orders in an attempt to conceal the trades. [34] Since our dataset includes trade but not trader IDs, our trade-"second" aggregation addresses the first concern since most single trades executed against multiple counterparties are executed in the same trade-"second" but does not address the second concern.

The aggregated trade-"second" method begins by aggregating all the trades that occur for each of the 5,839,261 seconds in our sample that include one or more trades for the version where the first trade second after the trade second being examined is used as the post-trade price.[35] We have 7345 firm days during our sample period. We delete the first and the last trade seconds for each firm each day, since it would not be possible to assess the price impact of these trade seconds. Therefore, the number of trade seconds decreases by 14,690 (7345 times 2) and becomes 5,824,571, which is used in Table 3.2. After excluding the 2.7% or 158,275 aggregated trade seconds that are not completely buyer- or -seller-initiated, we are left with 3,245,494 and 2,420,802 aggregated trade "seconds" that are solely buyer- and seller-initiated, respectively. Since an aggregated trade-"second" could be of large size even when it does not contain any individual large trades, we also examine aggregated trade "seconds" that contain at least one non-aggregated large trade.

[34] This is documented by Keim and Madhavan (1995), Barclay and Warner (1993), Chakravarty (2001), and Frino, Johnstone and Hui (2010).
[35] Thus, as in Engle and Russell (1998) and Spierdijk (2004), we treat multiple transactions during the same second as a single transaction with aggregated trade volume and an averaged price. Similarly, Alzahrani, Gregoriou and Hudson (2013) use aggregated data for every minute in their multivariate analysis of block trades on the Saudi Stock Market.

The numbers of trades subsequently reported in Tables 2 to 8 can vary for two reasons. First, the numbers of trades for the ALL cases can differ because of different post-trade prices used for P_{post}. For example, the 5,824,571 trade seconds reported for ALL in Table 3.2 using the first post-trade second becomes 5,795,171 trades in untabulated results when we use the fifth post-trade second price as P_{post}because we lose the last five trade seconds of each trading day for each firm or 154,933 trade seconds in total. Second, the number of trades is reduced when we delete the trade seconds where buyer- and seller-initiated trades occur within the same trade seconds in order to have solely buyer- and seller-initiated trade seconds. For example, 158,275 trade seconds are so removed in Table 3.2.

3.5. TRADE PRICE EFFECTS FOR VARIOUS TRADE-SECONDS SAMPLES

3.5.1 Trade price effects for aggregated trade seconds differentiated by trade initiator and size

As discussed previously, prices measured at different times post-trade are used in the literature to calculate the price effects of a trade. We start with analyzing the three types of price effects based on the use of the closing daily price as the post-trade price (Kraus and Stoll, 1972; Ball and Finn, 1989; Holthausen, Leftwich and Mayers, 1987) to illustrate how this choice adversely affects inferences because the price effects of a trade are most likely fully incorporated into prices prior to the daily closing price.

Based on untabulated results, we find that all three types of mean trade price effects are generally statistically significant and no absolute value exceeds 30 basis points (bps). While all of the single sorted mean price effects are significant, mean price effects do not have the expected positive sign for one buyer-initiated trade and negative sign for one seller-initiated trade. All double-sorted mean total price effects [ln(P_{trade}/P_{prior})] are significantly positive and negative for buyer- and seller-initiated trades as expected. While many of the double-sorted mean temporary price effects [ln(P_{trade}/P_{post})] are significant, they are not consistent in sign for buyer- or seller-initiated trades. All of the double-sorted mean permanent price effects [ln(P_{post}/P_{prior})] are significant. However, they display a counter-intuitive pattern in that they are negative for buyer-initiated trades and positive for seller-initiated trades for all small trade classifications.

Next, we examine how our initial results change using the first post-trade second price. Based on the results reported in Table 3.2, no absolute mean price effect exceeds 30 basis points (bps). All of the mean price effects for the double-sorted samples are highly significant and positive (negative) for buyer-initiated (seller-initiated) trade seconds. Trade seconds with aggregated share volumes of less than 15,000 shares have the most positive and most negative mean total price effects [$\ln(P_{trade}/P_{prior})$] of 19.03 bps and -25.62 bps for buyer- and seller-initiated trade seconds, respectively, and the most positive and most negative mean temporary price effects [$\ln(P_{trade}/P_{post})$] of 18.06 bps and -24.16 bps for buyer- and seller-initiated trade seconds, respectively. In contrast and as expected, the most positive and most negative mean permanent price effects [$\ln(P_{post}/P_{prior})$] of 10.14 bps and -11.99 bps occur for trade seconds with aggregated share values of at least 150,000 TRY that are buyer- and seller-initiated, respectively. In comparison for the ASE, Frino *et al.* (2005) report mean total, temporary and permanent price effects of 61.86 bps (-38.19 bps), 05.10 bps (4.89 bps) and 56.76 bps (-43.08 bps), respectively, for buyer- (seller-) initiated trades.[36] Since the mean permanent price effects capture the information content of the trades, these results suggest that informed traders in the BIST tend to trade in larger values which is consistent with the findings of Alzahrani, Gregoriou and Hudson (2013) for the SSM.

[Please place Table 3.2 about here]

We then examine the untabulated mean temporary, permanent and total price effects based on using the price for the fifth post-trade second for the various samples. Compared to the first post-trade second results, we now observe three negative mean temporary price effects for the double-sorted buyer-initiated trade seconds. Specifically, they are for buyer-initiated trade seconds with aggregated share volumes of at least 25,000 (-0.65 bps) and with aggregated trade values of at least 100,000 TYL (-0.66 bps) and 150,000 TYL (-1.49 bps). These results are consistent with the hypothesis that the price effects of a trade are fully incorporated into prices quite quickly and definitely prior to the daily close.

Table 3.2 also presents the p-values for the Kruskal and Wallis (K-W p-val.) test of whether the distributions of price effects are significantly different when the day's closing price (not tabulated), or the first (Table 3.2) or the fifth post-trade second (not tabulated) are used when we do not adjust for the smaller number of trades when the fifth trade second is used as the post-trade price. We observe that the temporary [$\ln(P_{trade}/P_{post})$] and permanent [$\ln(P_{post}/P_{prior})$] price effects are highly significantly different between the three choices for post-trade second price.[37] However, they are small in magnitude (no more than a few basis points) for all double-sorted buyer-initiated samples.

[36] Based on cross sectional regressions, Holthausen, Leftwich and Mayers (1987) document higher mean total price effects between -2.48% and 1.68%, mean temporary price effects between -1.30% and 0.06% and mean permanent price effects between -1.18% and 0.78%.

[37] As expected, the K-W p-values for the total price effects are all one when we use an identical sample of trades; namely, the sample based on the fifth post-trade second. The inferences remain qualitatively unchanged when we use this same sample for all three types of post-trade second prices.

For large and small trade sizes using the first post-trade second price, the mean differences tend to be more and less positive for the temporary price effects and less and more positive for the permanent price effects, respectively. The price effects are significantly different but small in magnitude (no more than one-half of a basis point) for the temporary and permanent price effects for all double-sorted seller-initiated common samples with smaller trade sizes. The significant differences tend to be more negative and less negative for the temporary and permanent price effects, respectively, for the double-sorted seller-initiated samples using the first post-trade second price.

3.5.2 Further Delineations of the Trades

To conserve valuable journal space and given their similarity to the undifferentiated sample, we do not report the single-sorted results by trade size and some of the sample delineations that are referred to as untabulated results in this section of the paper. To illustrate, the untabulated mean price effects for the long trades are consistent with those reported earlier in Table 3.2 for the full sample.

3.5.2.1 Trade price effects for less frequently traded stocks

To examine if the three types of price effects associated with trade depend upon relative trade frequency, we categorize the stocks into two groups based on whether their relative monthly number of trades is above or below the median of all the stocks in our sample for that month. We observe that all the price effects for the double-sorted samples of trades of the relatively less frequently traded stocks reported in Table 3.3 are highly significant and positive for buyer-initiated trades and negative for seller-initiated trades. With only two exceptions, the price effects are highly significantly different for the three types of price effects between the corresponding double-sorted samples differentiated by their relative trade frequency. As expected, both the total price effects [$\ln(P_{trade}/P_{prior})$] and the permanent price effects [$\ln(P_{post}/P_{prior})$] are consistently more positive and more negative for buyer- and seller-initiated trades for the relatively less frequently traded stocks. Furthermore, as expected, the differences are substantially higher for the double-sorted samples of larger-sized trades. For example, the mean permanent price effects for the relatively less frequently traded sample of buyer-initiated trades with share values above and below 100,000 TRY are 8.23 and 1.75 bps higher than the corresponding untabulated samples of relatively more frequently traded counterparts. For the temporary price effects [$\ln(P_{trade}/P_{post})$] for the double-sorted samples, the means are consistently more negative for seller-initiated trades but mixed for buyer-initiated trades.

[Please place Table 3.3 about here.]

3.5.2.2 Trade price effects for short trades

In this section, we examine if the various types of trade price effects differ for short trades since some of our previous aggregated trade seconds included both long and short trades. Clearly indicated covered and naked short-sale orders are allowed for firms classified as Group A by the BIST, which covers the majority of the listed securities based on liquidity and capitalization.[38] The BIST applies the up-tick rule so that short sales should be executed at a price higher than the previous traded price. In this section, the double-sorted samples of buyer- and seller-initiated trade seconds exclude trade seconds where both long and short trades appear together in the same trade second in order to obtain "clean" or unambiguous samples to aid in inference. Our major finding is that short sales are associated with positive permanent price effects and that knowing whether a short sale is buyer- or-seller-initiated is of value for researchers and practitioners in assessing the price effects of a short sale.

Table 3.4 presents the mean price effects for the short trades. Possible aided by the up-tick rule, all mean total price effects [ln(P_{trade}/P_{prior})] are positive. They are highly significantly different between all long and short samples, and more positive and less positive for long versus short buyer-initiated trades for double-sorted samples of large and small trade sizes, respectively. In contrast, they are more negative for long versus short seller-initiated trade seconds for all double-sorted samples. All mean temporary price effects [ln(P_{trade}/P_{post})] are highly significant and positive for buyer-initiated short trades and highly significant and negative for seller-initiated short trades. They are also highly significantly different between all long and short double-sorted buyer-initiated trade samples and six out of eight double-sorted seller-initiated trade samples. All mean permanent price effects [ln(P_{post}/P_{prior})] are highly significant and positive for all samples of short trades, and are highly significantly more positive for the samples of short trade seconds than their corresponding samples of long trades.

[Please place Table 3.4 about here.]

3.5.2.3 Trade price effects for the BIST trader-type classifications

To assess whether the three types of price effects associated with trades differ for different trader-type classifications, we use the three main trader type classifications used by the BIST. They are based on trades taking place in the: (i) institutional and retail brokerage firm accounts (M), (ii) brokerage firm portfolios (P), and (iii) brokerage firm investment funds (F). The mean price effects and tests of their individual significance are reported in Table 3.5 for M accounts and in Table 3.6 for P and F accounts, and tests of whether at least one distribution (median) differs from the others is also presented in Table

[38] The securities, transaction prices and volumes involved in short-sale transactions are announced at the end of the day on the BIST's website.

3.5. We observe that the double-sorted buyer- (seller-) initiated trade seconds always have highly significant and positive (negative) mean total price effects [ln(P_{trade}/P_{prior})]. At least one distribution differs significantly from the others for a comparison of the M, P and F accounts, with the exception of one seller-initiated trade-second sample where the Kruskal and Wallis statistic is not significant at the 0.10 level. If that sample is not considered, the ordering of the mean total price effects associated with seller-initiated, double-sorted trade-second samples takes on negative values of greater magnitude as we move from the P to F to M trader types for all the corresponding samples. In contrast, the orderings of the means across the three trader types for buyer-initiated trades are mixed for the various double-sorted samples.

[Please place Tables 5 and 6 about here.]

Not only are all the mean temporary price effects [ln(P_{trade}/P_{post})] for the double-sorted trade-second samples highly significant but they are positive for buyer-initiated trades and negative for seller-initiated trades. Based on the Kruskal and Wallis tests, at least one distribution (median) differs significantly from the others for a comparison of the M, P and F trader types for each of the samples. The orderings of the means in ascending magnitudes are M, P and then F trader types for the relatively large trade sizes for the double-sorted samples of buyer- and seller-initiated trades, and are in the reverse order for the relatively small trade sizes for buyer-initiated trades. They are P, F and then M trader types for the double-sorted sample of seller-initiated trades with relatively small trade sizes. Thus, the temporary price effect following a trade for the institutional and retail accounts of the brokerage firms is smallest for relatively large trades and largest for relatively small trades.

We observe quite different results for the mean permanent price effects [ln(P_{post}/P_{prior})] for the double-sorted trade-second samples. While the means are highly significant for all buyer-initiated trade-second samples for the three trader types, they are only highly significant for the seller-initiated trade-second samples for trader type M. For the other two trader types, significance is only achieved with relatively large trade sizes in terms of value. Based on the Kruskal and Wallis tests, at least one distribution (median) differs significantly from the others for a comparison of the M, P and F trader types for most of the samples. For the double-sorted samples, the orderings of the means in ascending magnitudes are M, F and then P trader types for all seller-initiated trades and only for the relatively small trade sizes for buyer-initiated trades. Thus, buyer-initiated trades for the institutional and retail brokerage firm accounts (M) have the smallest permanent price effects for relatively small trades and their seller-initiated trades have the largest permanent price effects regardless of the relative trade size. This suggests an increased information content of the trade seconds for trader type M for larger trade sizes. This is consistent with the notion of Glosten and Milgrom (1985) and Easley and O'Hara (1987) that informed trading is higher with larger trade sizes.

3.5.2.4 Trade price effects for last minutes of the two trading sessions

In this section, we examine the three types of price effects associated with trade seconds during the last minute of trading for the BIST, which has daily morning and afternoon trading sessions. A common belief on the street is that manipulators have incentives to realize high prices at the close as opposed to earlier in a trading session, and that it is easier to maintain a liquidity imbalance just prior to the close than earlier in the trading session. The empirical evidence (e.g., Carhart *et al.*, 2002) finds that the price distortions caused by closing price manipulation are short-lived as they are reversed in the following morning. Based on intraday returns over 15-minute intervals, Kucukkocaoglu (2008) concludes that close-end price manipulation through big buyers and big sellers is possible in the BIST.

Since we want to examine the permanent price effects without including next day trades, we exclude the last trade second for both sessions. The means for each of the three types of price effects for the first and second session of a trading day and tests of their individual significance are presented in Panels A and B of Table 3.7, respectively, and tests of whether their distributions (medians) differ are also presented in Panel A. The mean total [$\ln(P_{trade}/P_{prior})$] and temporary [$\ln(P_{trade}/P_{post})$] price effects are highly significant and positive (negative) for buyer- (seller-) initiated trades for the double-sorted samples in both sessions. Based on the Mann-Whitney-Wilcoxon test, their distributions (medians) are highly significantly different for the buyer-initiated trade seconds and for the seller-initiated trade seconds of relatively smaller sizes. For both of these price effects, the means are of considerably higher positive magnitudes in the last minute of the afternoon session for buyer-initiated trade seconds, and of a smaller negative magnitude for seller-initiated trade seconds of relatively small sizes. While most of the mean permanent price effects [$\ln(P_{post}/P_{prior})$] are not significant for the various double-sorted samples in the first session, all are positive and highly significant for the buyer- and seller-initiated samples of small sizes in the second session. Based on the Mann-Whitney-Wilcoxon test, their distributions (medians) are highly significantly different for the buyer- and seller-initiated trades of relatively smaller sizes. For these permanent price effects, the means are of a considerable higher positive magnitude in the last minute of the afternoon session for buyer-initiated trade seconds, and of a smaller negative (or larger positive) magnitude for seller-initiated trade seconds of relatively small sizes.

[Please place Table 3.7 about here.]

3.5.2.5 Trade price effects around Lehman Brothers' announcement

After intense but unsuccessful efforts over the week-end to arrange for an acquisition of Lehman by Barclays or the Bank of America, Lehman filed for bankruptcy protection just before the opening of Asian markets at 1:45AM Eastern Standard Time on Monday, September 15, 2008 to become the biggest victim of the credit and sub-prime crises. The collapse of Lehman Brothers had a ripple effect on the Monday across international financial markets starting in Asia, then Europe (including the BIST) and ending up in North America.[39]

We analyze the three price effects for a three-day announcement day (AD) period centered on the Lehman announcement on September 15, 2008 to allow for anticipation, lags and ripple effects of the announcement. We benchmark these price effects against the trade-second price effects for the three days before (pre-AD) and after (post-AD) this three-day announcement period. Based on untabulated results, we find that all of the double-sorted mean total price effects [$\ln(P_{trade}/P_{prior})$] are highly significant for all three windows, and are positive and negative for buyer- and seller-initiated trade seconds. Based on the Kruskal and Wallis test, we find that the distributions (medians) of the total price effects are significantly different between the three windows for both buyer- and seller-initiated trade seconds with relatively small trade sizes where the mean effects are smallest pre-AD and highest AD. They are also significantly different for all samples of seller-initiated trade seconds with relatively large trade sizes where the magnitudes of the mean effects are smallest post-AD and highest AD. Thus, the immediate price effects of trade spiked during the Lehman announcement.

When we examine the untabulated results for the temporary price effects, we find that most of the double-sorted mean temporary price effects [$\ln(P_{trade}/P_{post})$] are significant for all three windows, and are positive and negative for buyer- and seller-initiated trade seconds when significant. Based on the Kruskal and Wallis test, we find that the distributions (medians) of the temporary price effects are significantly different between the three windows for all the double-sorted samples of buyer-initiated trade seconds, and for the samples of seller-initiated trade seconds with relatively small trade sizes. The least and most positive means for the samples of buyer-initiated trades are AD and pre-AD for relatively small trade sizes and their reverse for relatively large trade sizes. The least and more negative mean values for the seller-initiated trades of relatively small trade sizes are post-AD and AD. Thus, the mean temporary price effects are elevated for the Lehman announcement period for small-sized buyer- and seller-initiated trades.

[39] Emek Kaplangil, Lehman's bankruptcy filing shatters Turkish lira, shares on Monday, Hurriyet DailyNews.com. Available at: http://www.hurriyet.com.tr/english/finance/9900493.asp

Based on the untabulated results, we find that all double-sorted mean permanent price effects [$\ln(P_{post}/P_{prior})$] are significant for all three windows, and are positive and negative for buyer- and seller-initiated trade seconds. Based on the Kruskal and Wallis test, we find that the distributions (medians) of the permanent price effects are significantly different between the three windows for all the double-sorted samples with one exception (i.e., seller-initiated with values of at least 150,000 TRY). The least and most positive means for the samples of buyer-initiated trades are pre-AD and AD for relatively small trade sizes and pre-AD and post-AD for relatively large trade sizes. The least and more negative mean values for the samples of seller-initiated trade seconds are pre-AD and AD for trades of relatively small trade sizes, and mixed for relatively large trade sizes but are elevated for the AD window.

3.6. DETERMINANTS OF THE PRICE EFFECTS

3.6.1 Methodology

To identify the determinants of the price effects (k = temporary, permanent and total, respectively) for trade second i for firm j, we run the following regression for various samples:[40]

$$\begin{aligned} Effect_{i,j}^{k} &= \beta_0 + \beta_1 \ln(MktCap_{i-1,j}) + \beta_2 RelSpd_{i-1,j} + \beta_3 \ln(TradeValue_{i,j}) \\ &+\beta_4 Mom[-5:-1]_{i,j} + \beta_5 SD_{d-1,j} + \beta_6 Tleft_{i,j,d} + \beta_7 R_{M,d} \\ &+\beta_8 OFI_{i-1,j} + \beta_9 D1_{i,j} \times Tleft_{i,j,d} + \beta_{10} D2_{i,j} \times Tleft_{i,j,d} + \varepsilon_i \end{aligned} \tag{3.1}$$

Where $ln(MktCap_{i-1,j})$ is the natural log of the market cap of firm j for the trade second immediately prior to trade second i for firm j. Since market cap is perceived as being positively related to firm liquidity (e.g., Hasbrouck, 2009), we expect market cap to be negatively related to price impact as reflected in negative and positive coefficients for buyer- and seller-initiated trades (especially if they are larger-sized) for this variable.

$RelSpd_{i-1,j}$ is the relative half-spread (i.e., the ratio between the bid-ask spread and the quote-midpoint) that occurs immediately prior to trade second i for firm j , which is used as a proxy for the prevailing immediacy costs (Frino, Jarnecic and Lepone, 2007; Alzahrani, Gregoriou and Hudson, 2013). Unlike Frino, Jarnecic and Lepone (2007), researchers such as Aitken and Frino (1996) and Gemmill (1996) find that this variable has little explanatory power for the price effects of packages of transactions executed by a broker and large transactions executed off-market on the London Stock Exchange, respectively. Since the price effect should be higher with higher relative spreads (higher prevailing

[40] We also ran equation (1) including the relative trade aggressive proxy, $Aggress_{i-1,j}$, which is the relative size of trade second i in number of shares divided by the corresponding depth at the bid or ask if it is a seller- or buyer-initiated trade, respectively, that prevails for the trade second immediately prior to trade second i for firm j.This regressor generally was not significant.

immediacy costs), we expect the relationship between the relative inside spread and the price effect to be positive. This should be reflected in positive and negative coefficients for buyer- and seller-initiated trade seconds for this variable.

$ln(TradeVal_{i,j})$ is the natural log of the dollar value of shares traded in second *i* for firm *j* in TRY (Turkish Lira) divided by 1,000,000 (used in Holthausen, Leftwich and Mayers, 1987; Frino, Jarnecic and Lepone, 2007; Alzahrani, Gregoriou and Hudson, 2013, use the number of shares). Based on the premise that trade size and the probability that the trade initiator holds private information are positively correlated, information asymmetry models imply that larger-sized trades are associated with greater price impacts (Easley and O'Hara, 1987). However, while large trade sizes may consume market liquidity, smaller trade sizes may provide market liquidity. This implies that positive and negative coefficients should exist for buyer- and seller-initiated trades of large size for this variable.

$Mom[-5:-1]_{i,j}$ is the lagged cummulative (compounded) daily return for firm *j* over the five trading days prior to trade second *i* for firm *j* (Frino, Jarnecic and Lepone, 2007; Alzahrani, Gregoriou and Hudson, 2013). Saar (2001) finds that past price performance plays an important role in the asymmetry of the permanent price impact between buyer- and seller-initiated block trades. There is support in the literature for both herding (Alzahrani, Gregoriou and Hudson, 2013) and contrarian trade behaviour relative to a stock's returns during the previous week or day (e.g., Kaniel, Saar and Titman, 2008, for individuals; Boehmer and Wu, 2008, for institutions and individuals). If contrarian trade behavior dominates, then we expect a positive (negative) relationship to exist between the cumulative stock return and the price impact for buyer- and seller-initiated trade seconds so that their coefficients should both be positive. If herding trade behavior dominates, then we expect the reverse relationships so that all coefficients should be negative.

$SD_{d-1,j}$ is our risk proxy given by the standard deviation of trade-to-trade prices on the trading day prior to the trading day *d* of the trade second *i* for firm *j* (Frino, Jarnecic and Lepone, 2007; Alzahrani, Gregoriou and Hudson, 2013). Since investors require higher compensations for bearing higher risks (Domowitz, Glen and Madhavan, 2001) and variance is found to vary proportionate to the change of information flow (Ross, 1989), we expect a positive relation with this variable (i.e., positive and negative coefficients respectively for buyer- and seller-initiated trade seconds).

$Tleft_{i,j,d}$ is the number of hours of trading time left until the end of trading after trade second *i* for firm *j* for that trading day *d* (Holthausen, Leftwich and Mayers, 1987). We exclude the lunch break, which is between 12:00 and 14:00 pm for the dates before October 13, 2008 and between 12:30 pm and 14:00

pm for the dates thereafter. Several studies show that proxies for liquidity exhibit U-shaped intraday patterns (e.g., McInish and Wood, 1992) and that quoted depths are associated with wider spreads and increased volume, particularly near the close of trading. Thus, the price impact of a trade may depend upon when it occurs during the trading day. Furthermore, a trade later in the trade day may cause a greater temporary market effect if an unofficial liquidity provider is the purchaser since this individual may be exposed to overnight risk (Holthausen, Leftwich and Mayers, 1987). Thus, prior to the period near the close of trading when spreads may increase, we expect a negative (positive) relationship to exist between Tleft and the price impact for buyer- and seller-initiated trade seconds so that their coefficients should both be negative.

$R_{M,d}$ is the market return for the ISE-100 Index (now BIST-100) for day *d*. This main index for the BIST consists of 100 stocks which are selected among the stocks of companies traded on the National Market and the stocks of real estate investment trusts and venture capital investment trusts traded on the Collective Products Market. BIST 100 Index automatically covers BIST 30 and BIST 50 stocks. Based on the findings of Aitken and Frino (1996a), Frino, Jarnecic and Lepone (2007) and Bonser-Neal, Linnan and Neal (1999), we expect a positive (negative) relationship to exist between market return and the price impact for buyer- and seller-initiated trade seconds so that their coefficients should both be positive. In other words, a positive market return leads to larger (smaller) price effects for buyer- (seller-) initiated trade seconds.

$OFI_{i-1,j}$ is the Order Flow Imbalance which is the difference between the volume at the best ask and the volume at best bid for the trade second immediately prior to trade second *i* for firm *j*. If the trading imbalance reflects information-based trading, then we would expect a positive (negative) relationship to exist between OFI and the total price impact for buyer- and seller-initiated trade seconds so that their coefficients should both be positive. If the price impact is only a temporary response to uninformed OFI, then we would expect a quick reversal in the price effects so that a negative (positive) relationship would be expected between OFI and the temporary price effect for buyer- and seller-initiated trade seconds so that their coefficients should both be negative. Boehmer and Wu (2008) find positive coefficients for this relationship and no evidence of any reversal.

$D1_{i,j} \times Tleft_{i,j,d}$ and $D2_{i,j} \times Tleft_{i,j,d}$ are interactive variables that are the product of dummy variables and *Tleft*. *D1* and *D2* are equal to one if trade second *i* is in the last minute and the second through fifth last minutes of the afternoon trading session, respectively, and zero otherwise. If there is any trade price manipulation as the trading day nears the close, we expect the price effects to be positively related with the both of these interactive variables so that the coefficients will be positive and negative for buyer- and seller-initiated trade seconds, respectively.

Summary statistics for the regressors in equation (1) for the total sample of trade seconds undifferentiated by trade size and samples of clean trade seconds differentiated by buyer- and seller-initiated trades are presented in Table 3.8. A clean trade second is one where all the trades contained therein are initiated by the same side of the market (e.g., all buyer-initiated). The values are quite similar for many of the regressors. Some notable differences are that the means and medians for trade values are higher for clean seller- versus buyer-initiated trade seconds, and that the means and medians OFI for trade values are higher for clean seller- versus buyer-initiated trade seconds. Interestingly, the mean proportions of seller-initiated trades in the last one and five minutes of the afternoon session (1.59% and 4.90%, respectively) exceed the corresponding proportions of 1.15% and 3.58%, respectively, for buyer-initiated trades. Based on untabulated correlation matrices for the full sample and the clean samples of buyer- and seller-initiated trade seconds, only one correlation exceeds absolute 0.2, and that is a correlation between $ln\left(MktCap_{i-1,j}\right)$ and $SD_{d-1,j}$ which is between 0.54 and 0.57 for these three samples. However, all of the VIF values including those for the two dummy variables are below 1.6 for these three samples, which strongly suggests that multicollinearity is not a problem.[41]

[Please place Table 3.8 about here.]

Since the number of potential trade-seconds is in the millions, we adopt a pooling regression approach for estimating equation (1) using only the trade seconds for which we have full data for all the variables included in equation (1).[42] For drawing inferences about the estimated coefficients, we use firm and day clustered standard errors as per Petersen (2009).

3.6.2 Regression Results for Buyer- and Seller-initiated Trade Seconds

The summary results from estimating equation (1) for the three price effects for clean samples of buyer- and seller-initiated trades are reported in Table 3.9. We also report the summary results for trade seconds with a value of at least 100,000 TRY for the buyer- and seller-initiated samples. This trade size is chosen because it corresponds with previous studies (e.g., Ball and Finn, 1989, for the ASE) and this trade size generally has the highest and lowest mean permanent price effects (i.e., highest information

[41] A rule of thumb is that a variable whose VIF values are greater than 10 may merit further investigation. Thus, the tolerance, defined as the inverse of the variance inflation factor (1/VIF), of at least 0.625 (i.e., 1/1.6) is considerably higher than 0.1 for all the regressors.

[42] We lose a very small percentage of trade seconds for the eight stocks that enter the ISE 30 during the quarterly updates after the beginning of our sample period primarily because five prior days are required to calculate the momentum variable in equation (1).

content). The highly significant mean price effects are almost identical to those reported earlier in Table 3.2 for the samples of buyer- and seller-initiated trades not differentiated by trade size. The much lower adjusted R^2 values for the regressions for the permanent versus other price effects probably reflects the relative smallness of the mean permanent effects compared to their temporary and total price effect counterparts. Also, the adjusted R^2 values for the seller-initiated trades are almost double those for the buyer-initiated trades.

[Please place Table 3.9 about here.]

The market capitalization [$ln\left(MktCap_{i-1,j}\right)$] coefficients are significant and of the correct sign of negative and positive for the permanent price effects for respectively buyer- and seller-initiated trade seconds for all and large trades. The coefficients for the other two price effects are highly significant and positive for buyer-initiated trade seconds and significant for seller-initiated trade seconds for large but not all trades.

The relative spread [$RelSpd_{i-1,j}$] coefficients are highly significant for the three types of price effects for all but not large buyer- initiated trade seconds and highly significant for all and large seller-initiated trade second with the exception of the temporary price effect for large trades. However, the coefficient signs are counter to expectations when significant since they are negative for buyer-initiated trades and positive for seller-initiated trades. Thus, our results differ from Aitken and Frino (1996) and Gemmill (1996) who find that relative spreads are not a significant determinant of trade price effects.

The trade size [$ln\left(TradeVal_{i,j}\right)$] coefficients are highly significant for the three types of price effects for both buyer- and seller-initiated trade seconds for all and large trades. Their coefficient signs are consistent with their positive and negative expectations for the permanent price effects for all and large trades but not for the temporary price effects for buyer- and seller-initiated trade seconds where they are reversed for all and large trades. They are similarly reversed for the total price effects for buyer- and seller-initiated trade seconds for all trades but consistent with expectations for large trades.

The momentum [$Mom[-5:-1]_{i,j}$] coefficients are highly significant with one exception and positive for the three types of price effects for both buyer- and seller-initiated trade seconds. This is consistent with contrarian trade behavior by the consensus market participants for the stocks and time period examined herein.

The standard deviation [$SD_{d-1,j}$] coefficients are highly significant and positive (negative) for the three types of price effects for both buyer- (seller-) initiated trade seconds for all and large trades. Thus, increased volatility leads to greater price effects for both buyer- and seller-initiated trade seconds. This is consistent with our prior expectations and previous studies (e.g. Chan and Lakonishok, 1997; Chiyachantana *et al.*, 2004; Frino, Jarnecic and Lepone, 2007).

The coefficients for the time left in the trading day prior to the closing five minutes [$Tleft_{i,j,d}$] are with one exception for all trades and two exceptions for large trades (highly) significant for the three types of price effects for both buyer- (seller-) initiated trade seconds. All of the significant coefficients have their expected negative signs.

The market return [$R_{M,d}$] coefficients are positive and significant for the permanent price effects for all trades only and for the temporary and total prices effects for large trades only for buyer-initiated trade seconds. In contrast, they are positive and highly significant for the three types of price effects for the seller-initiated trade seconds with the exception of the weakly significant negative coefficient for the temporary price effect for large trades. Thus, according to expectations, positive market returns generally lead to larger but not necessary significant price effects for buyer-initiated trade seconds and smaller temporary, permanent and total price impacts for seller-initiated trade seconds. This is consistent with the findings of Aitken and Frino (1996a), Frino, Jarnecic and Lepone (2007) and Bonser-Neal, Linnan and Neal (1999) that the coefficients of this variable for buyer- and seller-initiated trade seconds should both be positive. In other words, a positive market return generally leads to larger (smaller) price effects for buyer- (seller-) initiated trade seconds.

The order flow imbalance [$OFI_{i-1,j}$] coefficients are all highly significant and positive with the exception of large trades for the temporary price effects for buyer- and seller-initiated trades. This is consistent with the expectations of a positive (negative) relationship between OFI and the three types of price effects for buyer- and seller-initiated trade seconds. Thus, a positive OFI (i.e., larger positive difference between the volume at the best ask and the volume at best bid) leads to larger (smaller) price effects for buyer- (seller-) initiated trade seconds.

The coefficients for last minute and last fifth to last minute of a trading day [$D1_{i,j} \times Tleft_{i,j,d}$ and $D2_{i,j} \times Tleft_{i,j,d}$] are highly significant with the exception of permanent price effect for large buyer-initiated trades. They have the expected signs for the last minute with the exception of the positive sign for the permanent price effect for all and large trades for seller-initiated trade seconds, and for the last fifth to last minute with the exception of the sign for the permanent price effect for large buyer-initiated trade seconds.

3.7. CONCLUSION

The magnitude and duration of temporary and permanent price effects of trades of different sizes for an important emerging market, which has important implications for price discovery and market efficiency, was analyzed in this study. Various hypotheses have been proposed to explain the price effects associated with large trades, including that these trades are from informed traders.

We examined the price effects associated with trade for the 38 companies during their tenure in the BIST-30 index during the twelve months from April 2008 through March 2009 which accounts for around 70% of the total trade volume on the BIST for our sample period and contains the GFC and the Lehman collapse. We find that mean price effects are less than 30 basis points, are competitive with those found for other markets, and are (somewhat) counter-intuitive using the price at the (subsequent fifth trade second) day's close instead of the subsequent first trade second as the post-trade price. These findings imply that price discovery in fairly rapid on the BIST.

Except for the trades of less frequently traded stocks and short sales, we found that large trade seconds have the most positive and most negative mean permanent price effects for buyer- and seller-initiated trade seconds, respectively. This suggests that generally informed traders in the BIST have the tendency to focus on large trades. This is consistent with the prediction of Glosten and Milgrom (1985) and Easley and O'Hara (1987) that informed trading is more predominant for larger trades.

One of the striking results is that the permanent price effects are highly significant and positive for all samples of short trades, are substantially greater in magnitude for seller- versus buyer-initiated short-trades, and are highly significantly more positive than their corresponding samples of long-trades. This suggests that short trades do not unduly depress prices, and is consistent with movements towards eliminating short-sale constraints in many markets such as the U.S. Furthermore, the significantly higher price effects of trades in the last minutes of a trading session that we uncover have important implications for market regulators in terms of refining their surveillance systems to eliminate or minimize any inappropriate stealth trading or end-of-session price manipulation if it exists in the BIST.

Our findings have important implications for the purchase and execution decisions of investors since we document that the price effects of trade differ by how they are measured (especially for the post-trade price), trade type (long or short), trader aggressiveness (buyer- or seller-initiated), trade size (smaller or larger), share liquidity, when the trade is executed (e.g., near the close), the client-broker relationship (agency, principal or mixed), and market volatility (e.g., around the Lehman announcement). Such activities by investors will also benefit from a knowledge of what are the significant determinants of the price effects of trade, which we have identified for the BIST as including five-day return momentum, standard deviation of returns, order-flow imbalance, and the one and five-to-one minute prior to the close of trading for the day.

CHAPTER FOUR

EFFECTS OF PRICE LIMITS ON THE BIST

4.1. INTRODUCTION

For the past 20 years the market microstructure literature has examined the effects of price limits on volatility, price overreactions, delayed price discovery, trading interference and information asymmetry. Price limits are based on predetermined maximum and minimum price boundaries for an asset during a trading day or session based on the close for the previous trading day or session or volume-weighted average prices thereof. Price limits are applied by exchange regulators in order to prevent any (potentially detrimental) consequences from high fluctuations in asset prices over a short period of time, especially in emerging markets.

As a response to unusually volatile trading on May 6, 2010, where the Dow Jones Industrial average lost more than 600 points in about five minutes, U.S. exchanges and the Financial Industry Regulatory Authority (FINRA) in June 2010 approved pilot basis procedures for single-stock circuit breaker trading pauses for five minutes if the price of an asset moves up or down sharply in a five-minute window.[43] On May 31, 2012, the single circuit breaker rule was replaced by a "limit up-limit down" mechanism which brings price bands of 5%, 10%, and 20%, or the lesser of $0.15 or 75% depending on price and is intended to prevent trades of assets from occurring outside of these price bands. Various other markets (e.g., in Italy, Greece, France, Japan, Switzerland, Spain, Taiwan, and Turkey) also apply a version of price limits to shield their markets and traders from the negative effects of large price fluctuations.

The empirical evidence on the effects of price limits is mixed. Advocates argue that price limits moderate stock price volatility, correct short-term overreaction by providing a cooling off period by

[43] For further information, see http://www.sec.gov/investor/alerts/circuitbreakersbulletin.htm

providing time for investors to digest new information. They also argue that after the observance of a price-limit hit, there is likely to be a price reversal, lower price volatility and thinner trading volume. On the other hand, critics argue that price limits may only delay the price discovery process by inefficiently stopping the order flow and causing volatility spillover.

Most of the empirical evidence supports the predictions of the critics although most studies do not compare periods with and without price limits. This includes studies by George and Hwang (1995) for the Japanese stock market, Chen (1998) for U.S. futures markets, Phylatkis, Kavussanos, and Manalis (1999) for the Greek stock market, Kim and Limpaphayom (2000) for the Taiwan and Thailand stock markets, Chan, Kim, and Rhee (2005) for the Malaysian stock market, Chen, Rui, and Wang (2005) for the Chinese stock markets, Henke and Voronkova (2005) for the Polish stock market, and Bildik and Gülay (2006) for the Turkish stock market. Studies that similarly do not examine periods with and without price limits that support the predictions of the price-limit advocates include Ma, Rao, and Sears (1989a, 1989b) who examine the effects of price limits on Treasury bond futures in the Chicago Board of Trade (CBOT). Kim, Liu and Yang (2013) find that price limits can facilitate price discovery, moderate transitory volatility, and mitigate abnormal trading activity when they compare a period with price limits (1997-2001) with one without such limits (1992-1996) for the two Chinese markets. Deb, Kalev, and Marisetty (2010) find that for a cross section of 43 equity markets that the likelihood that price-limit rules exist is greater in markets with higher monitoring costs due to poorer business disclosure, more corruption and less efficiency in legal, regulatory and technological environments.[44]

This paper re-examines the impact of price limits of the Borsa Istanbul using intra-day trades and quotes. To this end, we examine the following hypothesis for price-limit hits that occurred for all the firms that are included in the BIST-50 index during the thirteen-month examination period of March 2008 through March 2009. These include the volatility spillover and dampening hypotheses, the overreaction and delayed price-discovery hypotheses, magnet-effect hypothesis, trading interference hypothesis, and

[44] 40 of the 58 countries that they list in their Table 1 have price limits as of December 2004.

the market quality hypothesis. We also test if our results based on equi-distant returns are robust when we use trade-by-trade returns adjusted for their associated serial correlations.

We find evidence to support the volatility no-effect, dampening and spillover hypotheses since the impact of a price-limit hit on volatility depends on whether it is a lower or upper limit hit and on the time of the day when the price-limit hit begins and when it ends. Post-hit volatilities tend to be lower for limit hits near the beginning of the first trading session, unchanged for limit hits that transcend a trading session and for upper price-limit hits near the end of either trading session, and higher for lower price-limit hits near the end of either trading session.

We find support for the market overreaction hypothesis since we observe partial and significant return reversals in the post-hit windows for the four samples of upper price-limit hits and for two of the four samples of lower price-limit hits. We also find support for the no-effect hypothesis since the returns in the post-hit windows are not significant for the other two samples of lower price-limit hits. Thus, our findings are supportive of the overreaction and no-effect hypotheses but not the price-delay hypothesis. These results can be interpreted as price-limit hits do not inhibit price discovery.

Our results provide support for our third alternative hypothesis that the prices prior to a limit hit accelerate as they approach the price-limit hit. Using the equi-distant returns, we always find that the slope coefficients of the time-series trajectories of the mean returns up to the price-limit hits are highly significant and positive (negative) for the price-limit hits triggered at the upper (lower) limit. Thus, there appears to be magnet behavior that may contribute to the price overreaction behavior during the period prior to the price-limit hits.

We observe that buyer-initiated trading activity is always higher after the lower price-limit hits and lower after the upper price-limit hits, although the change is not significant for some of the measures and samples of upper price-limit hits. We interpret these finding as supporting our overreaction trading hypothesis that buyer-initiated trade activity increases after lower price-limit hits and decreases after upper price-limit hits.

We find that the lower price-limit hits significantly increase proportional quoted and effective spreads (except for hits occurring in the first 30 minutes of the first session) and significantly reduce share and TRY depth. These two spread measures for the upper price-limit hits are significantly higher for hits near the end of a trading session and insignificantly lower for hits during the first 30 minutes of the first trading session. Share and TRY depths are significantly lower for upper price-limit hits, unless they occur during the first 30 minutes of the first trading session where they are insignificantly higher. We find that the median (not) mean composite measure of liquidity (i.e., proportional quoted spread divided by TRY depth) is generally significant (and higher) post-hit for both the lower and upper price-limit hits. Thus, price-limit hits generally significantly reduce or have no effect on spreads and depth measures of market quality. In turn, this can leave the composite measure of liquidity generally unchanged. We conclude that these market-quality findings are consistent with the greater informational asymmetry effect on market-quality hypothesis.

We test the robustness of some of our results using equi-distant returns and ARIMA modeling, and trade-by-trade returns and ARIMA modeling. The ARIMA model helps to alleviate some of the bias due to the autocorrelations in returns. Our findings show that our previous corresponding findings are robust.

By examining hits at the upper and lower limits separately, we are able to address the question of whether upper limits are necessary (Lee and Chou, 2004). The effects of limit hits may be asymmetric since investors are likely to be averse to downside deviations but open to upside potential. Hits at the downside limits may partially protect investors who have limited short-selling or option trading possibilities (Wong, Liu and Zeng, 2009). While we do find that the effects for upper and lower price-limit hits differ, we find as noted above that the time hits occur is of at least equal importance.

The remainder for the paper is organized as follows. The next section presents the price limit procedures on the BIST. Section 3 discusses the sample and data manipulation. Section 4 presents tests of various hypotheses dealing with price limits. Section 5 concludes the paper and provides some policy implications of our findings.

4.2. THE BIST AND ITS PRICE LIMIT PROCEDURES

Borsa Istanbul (BIST), formerly known as the Istanbul Stock Exchange (ISE), is a fully computerized order-driven market that employs various trading mechanisms that match buy and sell orders using price and time priority. Trading takes place Monday through Friday in two separate sessions from 09:30 a.m. to 12:30 p.m. and from 14:00 p.m. to 17:30 p.m. According to the price limit rule in the BIST, each stock price can fluctuate to a maximum of 10% in each session from the “base price”, which is the volume-weighted average price (VWAP) of the previous session. Due to rounding to the nearest tick for both the upper and lower limits, the maximum or minimum price may fall slightly outside the bounds of the 10% threshold. These limits are set and directed by the system automatically and they can be seen easily in the intraday data. In the case of a limit hit, trading is not interrupted and it continues until the end of the session within the same minimum and maximum price limit brackets. However, in the case of an excessive number of buy (sell) orders at the up-limit (down-limit) price with no corresponding sell (buy) orders, trading is either interrupted or continues at the limit price. This situation is referred to as a “limit lock” by Bildik and Gulay (2006). The interruption continues until there is a seller (buyer) willing to trade at a price not greater than the up–limit (not lower than the down-limit) price for that session. Trading may continue in the following session when the price limits are reset.

As in Kim and Yang (2008), our data set includes single limit hits, consecutive limit hits and closing limit hits. For our purposes, each limit hit is preceded and followed by 30-minute windows with no limit hit transacted price.

4.3. SAMPLE AND RESEARCH DESIGN

Our sample of firms consists of all the firms that are included in the BIST-50 index during the thirteen-month examination period of March 2008 through March 2009. Due to quarterly updating of the index, our sample consists of 59 companies. Our cleaned data include all transactions and incoming orders and the limit-order book reconstructed by us for all the companies in our sample. During our sample period, 10 and 14 companies are either added or delisted from the up- and down-limit samples, respectively, due to index revisions. The 18,989,498 trades in the BIST-50 companies during our sample period are reduced to 8,070,537 trade-second observations after the trade-second aggregations. There are 44,037 and 52,816 trade-seconds occurring within the 30 minutes prior and after the down-limit observations, respectively. In a similar vein, there are 42,957 and 58,769 trade-seconds within the 30-minute pre- and post-periods for the up-limit hit observations, respectively. We also used a daily dataset which includes the closing, minimum, maximum, and volume-weighted average price data for each stock and each session in order to double-check the minimum and maximum values during the trading day to determine if there was a limit hit on a particular day for a particular stock.

To aid in the identification of price-limit hits (time period during which prices hit and/or remain at either their upward or lower limits), we first compute the upper and lower price limits using the following equations in Bildik and Gulay (2006) that are modified to reflect any rounding to the nearest tick:

Upper limit or bound on trade price: $H_s \approx VWAP_{s-1}(1 + 0.10)$ (4.1)

Lower limit or bound on trade price: $L_s \approx VWAP_{s-1}(1 - 0.10)$ (4.2)

where H_s is the maximum price permitted in session s, L_s is the minimum price permitted in session s, $VWAP_{s-1}$ is the volume-weighted average price in session *s-1* and the 0.10 is the deviation in price that is permitted in session s from the volume-weighted average price in the previous session *s-1*. Thus, the limit hit is in force when trading is either interrupted or continues at one of the limit prices.

Since our research design involves various comparisons of the values of various metrics for the 30 minutes after a price-limit hit to their values in the 30 minutes prior to the price-limit hit (Kim and Yang 2008), we identify a limit hit as being unique for testing purposes if 60-minutes of trading at non-limit-prices is centered on that limit hit (i.e., 30 minutes before and after). In this study, a price-limit hit also refers to a series of price-limit hits that are consecutive or whose initial and final hits are not preceded and followed, respectively, by 30 minutes of trading at non-limit-prices. It also refers to a closing limit hit that occurs when no other non-limit transaction prices occur after a limit hit price is reached during the same trading session.

Table 4.1 reports the total number of downward and upward limit locks for our sample of firms and subsamples thereof that have at least 7 trades in the 30 minutes before and after each price-limit hit. The choice of at least 7 trades allows us to satisfy the minimum number of observations of five for an ARIMA (p, d, q) based on Jarrett and Kyper (2011) and six for the SAS proc ARIMA procedure. Of the 328 hits at the lower price limit,[45] 133 and 16 occur in the first 30 minutes of the first and second trading session of the trade day. Of the 267 hits at the upper price limit, 77 and 9 occur in the first 30 minutes of the first and second trading session of the trade day. No more than 39 hits occur in the last 30 minutes of a session for hits at either the upper or lower price limits. Interestingly, 79 and 127 of the price hits at the lower and upper price limits, respectively, are in place at the close of a trading session. To ensure reasonable sample sizes, we examine the following separately for upper and lower price-limit hits: all price-limit hits; price-limit hits triggered during the first 30 minutes of the first session; price-limit hits triggered during the last 30 minutes of the first and second sessions; and price-limit hits still in place at the end of the same session.

[Please place Table 4.1 here.]

Table 4.2 reports the number of trade seconds for various buckets for the sample of limit hits on the BIST. A paucity of trade seconds in either the pre- or post-windows for the price-limit hits of 30 minutes should not be a concern since over 94% of those windows have at least 30 seconds with trades. Furthermore, the percentages of those windows with at least 60 seconds with trades range from 69.8% to 85.4% (respectively, pre-window for lower price-limit hits and post- window for upper price-limit hits).

[Please place Table 4.2 here.]

[45] This reflects the elimination of one limit lock with less than five trade seconds in the pre-limit-hit period. This is consistent with previous studies. For example, Goyal and Santa-Clara (2003) exclude stocks with less than five trading days in a month from the computation of this measure for that month.

4.4. TESTS OF THE VOLATILITY SPILLOVER AND DAMPENING HYPOTHESES

4.4.1 Hypothesis

The volatility spillover hypothesis argues that price volatility after a limit hit or lock is expected to be higher than that before (e.g., Kim and Rhee, 1997) if price limits or locks cause greater uncertainty and delay the price discovery process by adversely affecting trading (Fama 1989; Lehmann, 1989). However, if this type of market intervention provides traders with a reflection period during which they can obtain information to reduce informational asymmetry,[46] reassess the market price, and avoid or correct overreaction, then it follows from the volatility dampening hypothesis that the price volatility may be lower after a limit hit or lock (Kim and Yang 2008). Another possible outcome is that these two opposing effects neutralize each other so that there is no change in price volatility after a limit hit or lock. Thus, the first null and alternative hypotheses to be tested are:

H_0^1: The volatility of a stock after a price-limit hit is unchanged from what it was before the price-limit hit (volatility no-effect hypothesis).

H_{a1}^1: The volatility of a stock after a price-limit hit is lower from what it was before the price-limit hit (volatility dampening hypothesis).

H_{a2}^1: The volatility of a stock after a price-limit hit is higher from what it was before the price-limit hit (volatility spillover hypothesis).

4.4.2 Methodology

The first methodological consideration is the choice of benchmark as there are three types of benchmarks used in the literature to test the volatility spillover hypothesis. The first type of benchmark uses a control group composed of stocks that did not reach their limit prices but had stock price movements approaching the price limits (e.g., between 90% to almost 100% of the price limit, and between 80 to 90% of the price limit). Using this type of benchmark, Kim and Rhee (1997) and Bildik

[46] Spiegel and Subrahmanyam (2000) argue that excessive price volatility is associated with informational asymmetry.

and Gulay (2006) report support for the volatility spillover hypothesis for the Tokyo and Istanbul Stock Exchanges, respectively, using the squared close-to-close (not demeaned) returns for the 21-days centered on the limit locks that occurred during a trading day (session for the latter study). The second type of benchmark uses the period prior to the introduction of price limits or a change in the price limits. Bildik and Gulay (2006) report lower (GARCH-estimated) volatilities based on daily closing prices for a 30-stock sample following a structural change on July 14, 1994 on the Istanbul Stock Exchange that doubled the daily cumulative price limit due to a transition from a one-to-two session trading day. They attribute this change in volatility to the two-hour break between the two daily sessions and not to the change in price limits. Kim, Liu and Yang (2013) compare a period with price limits to one without price limits in China, and report that price limits can moderate volatility calculated as the natural log of the ratio of daily high and low prices (Grossman 1988). The third type of benchmark uses the period prior to a price lock. Henke and Voronkova(2005) provide empirical evidence that price limits result in excess next-day volatility for the call auction segment of the Warsaw Stock Exchange over the period from January 1996 to November 2000. Kim and Yang (2008) report lower intraday volatilities after limit hits on the Taiwan Stock Exchange for periods of 15 (and of 30 minutes) before and after a limit hit. In this paper, we use the third type of benchmark where we measure volatility or variation in the 30 minutes before and after a limit hit or lock on the BIST.

The next methodological consideration is whether the data should remain unequally spaced in time or should be aggregated up to fixed (discrete) intervals. While most studies choose a discrete sampling scheme when examining the effect of limit hits to control for microstructure noise, the severity of any bias introduced with this choice is unclear. First, the value of the metric being examined seldom coincides with the end of each equi-distant interval due to trade randomness. Thus, the calculation of evenly spaced high-frequency returns necessarily relies on some form of interpolation among prices recorded around the endpoints of the given sampling intervals that results in a nonsynchronous trading or quotation effect that may induce negative autocorrelation and heteroscedasticity in the interpolated return series. These biases may be exacerbated in a multivariate context since varying degrees of interpolation are employed in the calculation of the returns for different securities. Second, the impact on the metric being examined (e.g., price and volume behavior) of intra-interval events with informational content are imperfectly captured by the choice of equi-distant intervals. As a result, the equi-distant intervals may discard valuable information. Thus, the choice of measurement interval involves a tradeoff between statistical measurement error that decreases and untreated microstructure-induced bias (e.g., significant autocorrelation caused by bid-ask bounce as described by Roll, 1984) that increases as the sampling frequency increases (e.g., from trade-by-trade intervals to twenty-minute equi-distant intervals).

To make our choice of interval frequency for our base results, we estimate ARIMA (1,0,0) models using trade-by-trade returns for the price-limit hits that the Dickey-Fuller test does not find evidence of a unit root in both the paired pre- and post-windows which is not the case for only seven lower price-limit hits and only two upper price-limit hits. Based on untabulated results, we find price reversals or bid-ask bounce is likely to be a problem when using trade-by-trade returns. For example, the mean and median rho estimates for the full sample without a unit root that range between -0.34 and -0.40 for the pre-and post-windows for the lower price-limit hits are highly significant (all p-values <0.0001). We obtain similar magnitudes and significances for the other three samples of lower price-limit hits and for all four samples of upper price-limit hits. Thus, our base results use intra-day equi-distant intervals. Nevertheless, we do provide some results in various sections of this paper using unequally spaced intervals to emphasize the impact of this high level of negative autocorrelation in our trade-by-trade returns on inferences.

When we use equally spaced returns, we use ten 3-minute returns for the pre- and post-limit hit windows. Our choice of ten 3-minute intervals allows us to satisfy the minimum number of observations of five for an ARIMA (p, d, q) based on Jarrett and Kyper (2011) and six for the SAS proc ARIMA procedure. We use the following model-free but definition dependent metrics to measure volatility or variation in each 30-minute window:

$$Vol_{1ij} = \sqrt{(n-1)^{-1} \sum_{t=1}^{n_l} \left(R_{ijt} - \bar{R}_{ij}\right)^2}; \qquad (4.3)$$

$$Vol_{2ij} = \sum_{t=1}^{n_l} \left|R_{ijt}^*\right|/n; \tag{4.4}$$

$$Vol_{3ij} = \sqrt{\sum_{t=1}^{n_l} R_{ijt}^{*2} + 2\sum_{t=1}^{n_l-1} R_{ilt}^* R_{ilt-1}^*}. \tag{4.5}$$

$$Vol_{4ij} = \frac{1}{\sqrt{2/\pi}} \sum_{t=1}^{n_l-1} \left|R_{ijt}^*\right|^r \left|R_{ijt-1}^*\right|^s. \tag{4.6}$$

For the above measures, R_{ijt} and R_{ijt}^* are the $n = 10$ not demeaned and demeaned 3-minute returns, respectively, for limit hit *i* in window *j* (pre- or post-limit hit) for a window of length l (= 30 minutes herein). The measure given by (6) is the (l, l)-order realized bipower variation for the special case where r=s=1 (Barndorff-Nielsen and Shephard, 2004). The second term under the square root sign in (5) includes an autocorrelation (ρ) adjustment. This adjustment was used by French, Schwert and Stambaugh (1987) to deal with the autocorrelation in returns due to non-synchronous trading and subsequently used by Goyal and Santa Clara (2003), Wei and Zhang (2005), amongst others. Goyal and Santa Clara (2003, ftn. 6, p. 769) state that, although the volatility estimate is negative when $\rho < -0.5$ because the second term dominates the first, that the average occurrence of negative estimates is 5% for their sample of individual stocks.[47]

We also use the Grossman (1988) measure of volatility for each window given by:

$$Vol_{5ij} = ln(HP_{ijl}/LP_{ijl}); \tag{4.7}$$

where HP_{ijl} and LP_{ijl} are the highest and lowest price, respectively, for limit hit *i* in window *j* of length l.

4.4.3 Results

We report summary statistics for the estimates for each of the five volatility measures for hits at the lower-price limit for the full sample and three differentiated subsamples in Table 4.3. We observe that all of the means and medians for all five volatility measures are significantly lower after the lower-price limit hits for the full sample (panel A)[48] and for lower-price limit hits that were triggered during the first 30

[47] We get no negative estimates using the demeaned three-minute returns but do using the non-demeaned three-minute returns.

[48] Not unexpectedly, the differences either become insignificant or change sign for the full sample but not the sample of lower price-limit hits triggered during the first 30 minutes of the first session when we use trade-by-trade

minutes of the first session (panel B). In contrast, we observe that the means and medians for all five volatility measures are higher and significant (with one exception) after the lower-price limit hit that are triggered during the last 30 minutes of the first or second session (panel C), and none of the means and medians for all five volatility measures are significantly different after the lower-price limit hits for those that remain in place at the end of the trading session (panel D). Thus, the average effect of a lower-price limit hit depends upon when during the day the limit hit is first triggered and also on whether it is still in place at the end of a trading session.

[Please place Table 4.3 here]

We report summary statistics for the estimates for each of the five volatility measures for the upper-price limit hits for the full sample and the same three differentiated subsamples in Table 4.4. As was the case for the lower-price limit hits, we observe that all of the means and medians for all five volatility measures are significantly lower after the upper-price limit hits for the full sample (panel A) and for upper-price limit hits that occur during the first 30 minutes of the first session (panel B),[49] and for most of the means and medians for all five volatility measures for upper-price limit hits that persist through the close of a trading session (panel D).[50] Unlike the lower-price limit hits, none of the means and medians for all five volatility measures are significantly different after the upper-price limit hits that are triggered during the last 30 minutes of the first or second session (panel C). Thus, the average effect of an upper-limit hit depends upon when during the day the limit hit is first triggered and also on whether it is still in place at the end of a trading session.

[Please place Table 4.4 here.]

Thus, we draw a number of initial inferences from these results. First, our results provide support for both our null and two alternative first hypotheses (i.e., volatility no-effect, volatility dampening and

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returns in the calculation of the two volatility measures that captures the effect of bid-ask bounce; namely, Vol_3 and Vol_4.

[49] Not unexpectedly, the differences either become insignificant or change sign for the full sample and become insignificant for the sample of lower price-limit hits triggered during the first 30 minutes of the first session when we use trade-by-trade returns in the calculation of the two volatility measures that captures the effect of bid-ask bounce; namely, Vol_3 and Vol_4.

[50] The two exceptions are the significantly lower mean Vol_4 and median Vol_4after the upper limit hits.

volatility spillover, respectively) since the post-window impact of a price-limit hit depends on the time of the day when the price-limit hit begins and when it ends. While volatilities associated with limit-price limit hits near the beginning of the first trading session tend to be lower post-limit hit, those near the end of either trading session tend to be higher post-hit for lower-price limit hits and unchanged for upper-price limit hits, and those that are still in place at the end of a session tend to be unchanged after the price limit hit. Second, the differences in some of the inferences across volatility measures may be partially misleading when considered in isolation if the price-limit hits facilitate price discovery. We examine this issue in the next section of the paper.

4.5. TESTS OF THE OVERREACTION AND DELAYED PRICE-DISCOVERY HYPOTHESES

4.5.1 Hypotheses

Price-limit opponents argue that short-term overreactions are not prevented by price limits without delaying the price discovery process due to their adverse effect on trade and the provision of market liquidity (Lehmann 1989). As a result, prices will continue in the same direction after a price-limit hit until equilibrium is re-established (Kim and Rhee, 1997). In contrast, price-limit advocates argue that price limits aid in the price-discovery process by providing investors with a cooling-off period during which they can reassess prices, and thus, correct short-term market overreactions. If the overreaction hypothesis holds, a price reversal is expected after a price-limit hit. If the price-limit hit persists through the close of a trading session, the delayed price discovery hypothesis predicts that prices will be higher when trading resumes in the next session with its new price limits. We test the following null and alternative hypotheses to determine if short-term overreactions or delayed price-discovery is associated with price-limit hits:

H_0^2: There are no significant mean return continuations or reversals in the post- versus pre-window for price-limit hits (no-effect price hypothesis).

H_{a1}^2: There are significant mean return continuations in the post- versus pre-window for price-limit hits (price-delay hypothesis).

H_{a2}^2: There are no significant mean return reversals in the post- versus pre-window for price-limit hits (market overreaction price hypothesis).

The empirical evidence is mixed in its support of the overreaction hypothesis. This includes the studies by Ma, Rao, and Sears (1989a, 1989b) for Treasury bond future prices; Huang (1998) and Huang, Fu and Ke (2001) for the Taiwan stock market; and Diacogiannis *et al.* (2005) for the Athens Stock Exchange. In contrast, Phylaktis, Kavussanos, and Manalis (1999) for the Athens Stock Exchange and Chen (1998) for U.S. futures markets find no and little evidence for the overreaction hypothesis, respectively.

Similarly, the empirical evidence is mixed in its support of the delay price-discovery hypothesis. Supportive evidence includes Kuhn, Kurserk, and Locke (1991) for the S&P stock and stock index futures, Chen (1993) for the Taiwan Stock Exchange, Bildik and Gulay (2006) for the Istanbul Stock Exchange, Kuserk and Locke (1996) for the Chicago Merchantile Exchange, Kim and Rhee (1997) for the Tokyo Stock Exchange, Arak and Cook (1997) for U.S. Treasury bond futures, Chen (1998) for U.S. futures contracts, and Henke and Voronkova (2005) for the Warsaw Stock Exchange. Contradictory evidence includes Huang, Fu and Ke (2001) for the Taiwan Stock Exchange, Kim, Liu and Yang (2013) for the Chinese Stock Markets and Ma, Rao and Sears (1989a, 1989b) for the Chicago Mercantile Exchange and U.S. treasury bonds.

4.5.2 Methodology and Results

To test hypotheses (H_2), we examine if the mean and median returns for the 30-minutes after the price-limit hits are significant and carry a different sign from their counterparts for the 30-minutes before the price-limit hits for the four samples of price-limit hits. Specifically, we find the mean return for the ten 3-minute intervals in the pre- and the post- windows for each price-limit hit. We then test the cross-sectional mean and median of these mean returns for the pre- and post-windows and for the paired differences in the returns between the post- and pre-windows. The implicit assumption is that either no material news is disseminated from the 30 minutes prior through the 30 minutes after the price-limit hits or that the cross-section effect on prices of such disclosures in event time averages out over a series of such price-limit hits. The latter is a common assumption invoked in most event studies.

Panels A and B of Table 4.5 report various summary statistics for estimates of the mean returns in the pre- and post-30 minute windows for the four samples for those price-limit hits triggered by hitting lower and upper price limits, respectively. As expected, all of the means and medians are significantly negative and significantly positive prior to the price-limit hits for those triggered by hitting a lower and an upper price limit, respectively. For the price-limit hits triggered by hitting the lower price limit, the mean and median returns are significant (and positive) in the post-window for the full sample and for those triggered during the first 30 minutes of the first session. The mean and median returns are insignificantly different from zero (with three out of four negative signs) for those triggered during the last 30 minutes of the first and second sessions and for those triggered during the trading session that were still in place at the close of that session. In contrast, for the price-limit hits triggered by hitting the upper price limit, the mean and median returns are significant and negative post-price-limit hit for all four samples. For the four samples, the mean and median returns in the pre-limit hit window are significantly larger in absolute magnitude that their counterparts in the post-limit hit window.

[Please place Table 4.5 here.]

To summarize, we find support for H_{a2}^2(the market overreaction price hypothesis) since we observe partial and significant return reversals in the post-hit windows except for two samples of lower price-limit hits. The results for these two samples support H_0^2 (no-effect price hypothesis) since the post-hit window returns are insignificant. These two samples are for the lower price-limit hits that occur in the last 30 minutes of a trading session or are still in place at the end of a trading session. Thus, our findings are supportive of the overreaction and no-effect price hypotheses but not the price-delay hypothesis.

4.6. TESTS OF THE HYPOTHESIS THAT PRICE LIMITS ACT AS MAGNETS

4.6.1 Hypothesis

The magnet-effect hypothesis argues that the price accelerates towards a price limit as the price gets closer to the limit. Rationale provided by proponents of the magnet effect of price limits are based on investors becoming less willing to wait to trade either due to the fear of the loss of liquidity and trading imbalances (Lehmann 1989) or due to their fear of missing out on a trend (Arak and Cook 1997) or the transactional risk associated with asymmetric information (Kodres and O'Brien, 1994). Phylaktis, Kavussanos and Manalis (1999) conjecture that investor overreaction to new information drives the share price to reach the limit. The hypothesis also is theoretically motivated as Subrahmanyam (1994) shows that a price limit can increase ex ante price variability and the probability of the price hitting the limit in an intertemporal one-market model when the price is close to the limit. The cooling-off effect of price limits, which was discussed earlier, is a counter argument to the magnet effect. We test the following null hypotheses for the magnet-effect:

H_0^3: The prices prior to a limit hit do not accelerate as they approach the price-limit hit (no magnet effect hypothesis).

$H_{a:}^3$ The prices prior to a limit hit accelerate as they approach the price-limit hit (magnet effect hypothesis).

The evidence for magnet-effect is also mixed. Some studies document statistically and economically significant (weak) tendency for stock prices to accelerate toward the upper (lower) bound as the price approaches the bound (Cho, Russell, Tiao and Tsay, 2003) and others find supporting evidence in an experimental setting (Ackert, Church and Jayaraman, 2001) or alternative empirical setting (Hsieh, Kim and Yang, 2009, for the Taiwan Stock Exchange; Tooma, 2011, with price-limit imposition on the Egyptian Stock Exchange). Other studies examine runs and reversals and other measures such as trading behavior around trading limits and find little evidence to support a magnet effect (e.g., Kuserk, Moriarty, Kuhn and Gordon, 1989, for T-Bond, soybean and corn contracts; Arak and Cook, 1997, for Treasury bond futures; Abad and Pascual, 2007, for rule-based halts on the Spanish Stock Exchange; Huang, Fu and Ke, 2001, for closing limit halts on the Taiwan Stock Exchange).

4.6.2 Methodology and Results

We begin by assessing the existence of a magnet effect graphically. To do this, we first calculate the cumulative returns for each price-limit hit starting with the most distant 3-minute interval prior to the price-limit hit (i.e., [-10]) and then continue to add another 3-minute interval ending with the closest 3-minute interval prior to the price-limit hit (i.e., [-10: -1]). We then calculate the cross-sectional mean and median for each of these cumulative returns. We use a similar procedure for the ten 3-minute intervals after the price-limit hits except that we first calculate the cumulative returns for each price-limit hit starting with the most recent 3-minute interval after the price-limit hit (i.e., [+1]) and then continue to add another 3-minute interval ending with the most distant 3-minute interval after the price-limit hit (i.e., [+1: +10]).

Figure 4.1 provides the plots based on the cumulative cross-sectional mean returns for the price-limit hits that were triggered by the upper and lower price limits for the four samples. It is visually obvious that the change in the cumulative cross-sectional mean returns accelerates as it approaches the price-limit hit. To further examine this statistically, we run simple regressions of the changes in the cumulative cross-sectional mean returns against time for the windows prior to the price-limit hits for the up and down hits for the four samples. Based on untabulated results, we always find that the slope coefficients are highly significant and positive (negative) for the price-limit hits triggered at the upper (lower) limit. To illustrate, the estimated coefficients for the all case (Figure 1, Panel A) are 0.1012 (t-value = 4.86) and -0.1074 (t-value = -5.24) for the upper- and lower-limit hits, respectively.

Thus, these results provide at least preliminary support for our third alternative (magnet effect) hypothesis that the prices prior to a limit hit accelerate as they approach the price-limit hit. However, it would appear that this magnet effect behavior may not be rationale given the overreaction price behavior identified in the previous section of the paper.

[Please place Figure 4.1 here.]

4.7. TESTS OF THE TRADING-INTERFERENCE HYPOTHESIS

4.7.1 Hypothesis

According to Lauterbach and Ben-Zion (1993, p. 1909), amongst others, price limits (and coordinated trading halts) are "obviously cost-interfering with market liquidity." Greenwald and Stein (1991) associate unwarranted trading uncertainty with asymmetric information. The trading-interference hypothesis asserts that price limits induce pre-limit order imbalances that limit trading in this window which spills-over into an increase in trading volume after the price-limit hit (Lehmann 1989). If price-limit hits impede the movement towards a higher (lower) equilibrium price for upward (downward) price limits, it is not obvious why patient buyers (sellers) would wait for prices to reach equilibrium. Furthermore, if the marginal investor perceives that the price-limit hit was due to market reaction, then we would expect that buyer-initiated trade activity would increase after a lower price-limit hit and decrease for an upper price-limit hit. Thus, to address the trading interference hypothesis, we test the following null and alternate hypotheses:

H_0^4: Trading activity remains unchanged after a price-limit hit (no trading-inference hypothesis).

H_{a1}^4: Trading activity increases after a price-limit hit (trading-inference hypothesis).

H_{a2}^4: Buyer-initiated trade activity increases after a lower price-limit hit and decreases after an upper price-limit hit (overreaction trading hypothesis).

The empirical evidence for the trading-interference hypothesis is mixed. Studies using daily data find that trading activity after a price-limit hit increases (e.g. Kim and Rhee, 1997; Bildik and Gulay, 2006), increases only for upper price-limit hits (e.g., Li, Zheng and Chen, 2014), or decreases (Chen, Rui and Wang, 2005).[51] Studies using intra-day data find similar contradictory results that trading activity after a

[51] The periods examined vary from [-3, 5] in Chen, Rui and Wang (2005) to [-4, 5] in Kim and Rhee (1997) and Chen, Rui and Wang (2005) to [-11, 11] in Bildik and Gulay (2006).

price-limit hit increases only for upper limit hits (e.g., Wong, Liu and Zeng, 2009), or remains unchanged (e.g., Kim, Liu and Yang, 2013).

4.7.2 Methodology and Results

To test this hypothesis we examine the change in trading activity from the pre- to post-window for price-limit hits. For this purpose, we use the total number of transactions and total shares in number and value traded, undifferentiated and buyer-initiated. Since the times and IDs of each order and trade are available for our propriety dataset from the BIST, we use the more accurate chronological approach to identify the true initiator of a trade (Aktas and Kryzanowski, 2014). The authors use the available timestamp to the closest second for each order in order to identify the most recent one as the trade-initiator according to the chronological method first used by Odders-White (2000).

Since few mean and median changes are significant at conventional levels,[52] the results remain untabulated for the three trading activity measures undifferentiated by trade direction for the four samples to conserve valuable journal space. Taken at face value, this could lead to the incorrect conclusion that these results support our null hypothesis that trading activity remains unchanged after a price-limit hit. However, as we next learn examining trading activity undifferentiated by trade initiator masks an interesting new observation.

The four panels of Table 4.6 report various summary statistics for buyer-initiated trading activity for the three measures in the pre- and post-30 minute windows and their differences for the four samples of lower price-limit hits. We observe that all of the mean and median trading activity values are significantly higher after these lower price-limit hits. This most likely helps to explain the significant mean and median returns (all positive) found earlier for the post-hit windows for the full sample and the sample of lower price-limit hits during the first 30 minutes of the first session.

[52] There is only two cases where both the mean and median paired differences are significant. This is for the increase in the number of transactions after a price-limit hit for price-limit hits triggered by hitting either lower or upper price limits that were in place at a session's close.

The four panels of Table 4.7 report similar information for the four samples of upper price-limit hits. We observe that the mean and median trading activity measures for buyer-initiated trades are always lower after the upper price-limit hits. Furthermore, both the means and medians of the three trading activity measures are always significant for the total sample of upper price-limit hits and for the sample of upper price-limit hits triggered during the last 30 minutes of the first and second sessions. For the other two samples, none of the means are significant and all but the median for the number of trades for the upper price-limit hits that remain at session close. This most likely helps to explain the significantly negative mean and median returns found earlier after the upper price-limit hits for all four samples. Thus, we interpret these finding as supporting the second of our fourth alternative hypothesis (H_{a2}^{4}); namely, that buyer-initiated trade activity increases after lower price-limit hits and decreases after upper price-limit hits (overreaction hypothesis).

[Please place Tables 4.6 and 4.7 here.]

In summary, we observe that buyer-initiated trading activity is always higher after the lower price-limit hits and lower after the upper price-limit hits. These finding are supportive of our overreaction trading hypothesis that buyer-initiated trade activity increases after lower price-limit hits and decreases after upper price-limit hits. Our results do not support the trading interference hypothesis.

4.8. MARKET QUALITY HYPOTHESIS

4.8.1 Hypothesis

If price limit hits provide time for information dissemination and revelation and provide investors with time to better assess such information, then market quality should improve after price-limit hits (e.g., Chan, Kim and Rhee, 2005; Chen, Kim and Rui, 2005). Furthermore, if price limits mitigate information asymmetry, then providers of liquidity will narrow bid-ask spreads and/or widen spread depths because they will face fewer adverse selection risks from informed traders after limit hits. However, market quality should deteriorate after price-limit hits if price-limit hits interfere with information-based trading (i.e., trading-inference hypothesis). Thus, to address the effect, if any, of price-limit hits on market quality, we test the following null and alternate hypotheses:

H_0^5: Market quality remains unchanged after a price-limit hit (no informational asymmetry effect on market-quality effect hypothesis).

H_{a1}^5: Market quality decreases after a price-limit hit (greater informational asymmetry effect on market-quality hypothesis).

H_{a2}^5: Market quality increases after a price-limit hit (lower informational asymmetry effect on market-quality hypothesis).

The empirical evidence for the effect of price-limit hits on market quality in general is that price-limit hits either lessen market quality or have no effect. Kim, Yague and Yang (2008) find that proportional quoted and effective spreads are wider and depths are lower, especially after lower price-limit hits. Kim and Yang (2008) find that proportional quoted spreads are unchanged after single limit hits, and are higher for lower price-limit closing hits and upper price-limit consecutive hits. Wong, Liu and Zeng (2009) find wider depth-weighted quoted spreads only as stock prices approach floor limits.

4.8.2 Methodology and Results

As in Chordia, Roll and Subrahmanyam (2001), we measure market quality using the following metrics:[53]

$$PropQS_{it} = (A_{it} - B_{it})/M_{it} \text{ where } M_{it} = (A_{it} + B_{it})/2 \tag{4.8}$$

$$PropES_{it} = (2|R_{it} - M_{it}|)/M_{it} \tag{4.9}$$

$$Depth_{it} = (BidDepth_{it} + AskDepth_{it})/2 \tag{4.10}$$

$$\$Depth_{it} = \left((B_{it} \times BidDepth_{it}) + (A_{it} \times AskDepth_{it})\right)/2 \tag{4.11}$$

$$CompositeLiq_{it} = \%QS_{it}/\$Depth \tag{4.12}$$

[53] We also calculate and discuss when appropriate but do not tabulate the following additional measures: $QS_{it} = A_{it} - B_{it}$, $ES_{it} = 2|P_{it} - M_{it}|$, $ShrDepthImbal_{it} = BidShrDepth_{it} - AskShrDepth_{it}$, and $\$DepthImbal_{it} = (B_{it} \times BidShrDepth_{it}) - (A_{it} \times AskShrDepth_{it})$, where the last two measures are for imbalance of share and dollar depth, respectively.

Where $PropQS_{it}$ is the proportional quoted spread; *i* and *t* refer to price-limit hit *i* and time t, respectively; A_{it} and B_{it} are the inside bid and ask quotes; M_{it} is the mid-spread; $PropES_{it}$ is the proportional effective spread; $BidDepth_{it}$ is the number of shares bid for at the inside bid; and $AskDepth_{it}$ is the number of share offered at the inside ask. $CompositeLiq_{it}$ is designed to measure the average slope of the liquidity function in percent per dollar traded.

We examine changes in these market quality measures by comparing their paired differences found by subtracting the value 30 minutes before a price-limit hit from its value for the 30 minutes after the price-limit hit. The results for the four samples of lower price-limit hits are summarized in Table 4.8. For the full sample of lower-price limit hits, we observe that both the proportional quoted and effective spreads are higher post-hit, and the share and dollar depths are lower post-hit. We observe that the composite liquidity measure is significantly higher post-hit based on the median but not the mean. For the sample of lower-price limit hits that occurred during the first 30 minutes of the first session, we observe no significant differences in the proportional quoted and effective spreads and composite liquidity measure between the post- and pre-hit 30 minutes. However, the share and dollar depths are significantly lower post-hit.

[Please place Table 4.8 here.]

For the sample of lower price-limit hits that occurred during the last 30 minutes of either session, we observe significantly higher proportional quoted and effective spreads and significantly lower share and dollar depths post-hit. As for the full sample, the composite liquidity measure is significantly higher post-hit based on the median but not the mean. For the sample of lower-price limit hits that are not resolved within either session, we observe significantly higher proportional quoted and effective spreads and significantly lower share and dollar depths post-hit.[54]

The results for the four samples of upper price-limit hits are summarized in Table 4.9. For the full sample of upper-price limit hits, we observe that proportional quoted and effective spreads are lower and

[54] The mean quoted spread post-hit is higher but not significantly different from its counterpart pre-hit.

higher post-hit, respectively,[55] and the share and dollar depths are lower post-hit. We observe that the composite liquidity measure is significantly higher post-hit. For the sample of upper-price limit hits that occurred during the first 30 minutes of the first session, we observe no significant mean and median paired differences in the proportional quoted spread and the mean proportional effective spread. The median paired difference (post minus pre value) is significantly negative for the proportional quoted spread and the composite liquidity measure. Although all the depths are higher post-hit, the only significant difference is for the dollar depth based on the median.

[Please place Table 4.9 here.]

For the sample of upper price-limit hits that occurred during the last 30 minutes of either session, we observe significantly higher proportional quoted and effective spreads and significantly lower share and dollar depths post-hit. For the sample of upper price-limit hits that are not resolved within either session, we observe significantly higher proportional effective but not quoted spreads and significantly lower share and dollar depths post-hit. As for the full sample, the composite liquidity measure for these two samples is significantly higher post-hit based on the median but not the mean.

To summarize, we find that the lower price-limit hits significantly increase proportional quoted and effective spreads (except for those in the first 30 minutes of the first session) and significantly reduce share and TRY depth. These two spread measures for the upper price-limit hits are significantly higher for hits near the end of a trading session and insignificantly lower for hits during the first 30 minutes of the first trading session. Share and TRY depths are significantly lower for upper price-limit hits, unless they occur during the first 30 minutes of the first trading session where they are insignificantly higher. The median (but not mean) composite measure of liquidity (i.e., proportional quoted spread divided by TRY depth) is generally significant (and higher) post-hit for both the lower and upper price-limit hits. Thus, price limit hits generally significantly reduce or have no effect on spreads and depth measures of market quality. In turn, this leaves the composite measure of liquidity generally unchanged. We conclude that

[55] The mean proportional quoted spread is not significantly lower post-hit.

these market-quality findings are consistent with the greater informational asymmetry effect on market-quality hypothesis (H_{a1}^{5}).

4.9. FURTHER TESTS OF ROBUSTNESS

4.9.1 Trade-by-Trade Returns and ARIMA Models

In this section, we conduct a number of tests of robustness using trade-by-trade returns and AIRMA models. Various papers suggest that the bias due to the autocorrelations caused by using trade-by trade returns can be alleviated somewhat by using ARIMA(1,0,0) or ARIMA(0,0,1) models which are commonly referred to as AR(1) and MA(1) models, respectively. Since there is no consensus on which modeling approach is better, our robustness tests use both models.[56] Furthermore, they provides us with the opportunity to examine how our previous results are affected by increasing sampling randomness and decreasing sampling discreteness given the finding of Aït -Sahaila and Mykland (2003) that the effect of sampling randomness is greater than the effect of sampling discreteness in many situations.

The AR(1) and MA(1) models estimated herein are given by:

$$\text{AR(1)}: r_{it} = \alpha_i + \rho_i r_{it-1} + \varepsilon_{it} \tag{4.13}$$

$$\text{MA(1)}: r_{it} = \mu_i + \epsilon_{it} + \theta_i \epsilon_{it-1} \tag{4.14}$$

where $\rho_i$is the correlation between successive return observations in the AR(1); and ε_{it} and ϵ_{it} are assumed to be IID normal. It is well known that the theoretical mean and variance from the AR(1) model are given by $\alpha_i/(1-\rho_i)$ and $\sigma^2(\varepsilon_{it})/(1-\rho_1^2)$, respectively. Similarly, the theoretical mean and variance from the MA(1) model are given by μ_i and $\sigma^2(\varepsilon_{it})(1+\theta_1^2)$, respectively. The first-order $\rho_i$for

[56] Corsi, Zumbach, Muller and Dacorogna (2001) demonstrate that using a MA(1) representation permits a highly efficient treatment of inhomogeneous time series (i.e., not equally spaced in time). Bollen and Inder (2002) use an AR(K) representation in calculating their VARHAC estimator, which appears to apply the same variance adjustment as we use when the lag length operator K is equal to 1. Den Haan and Levin (1996) provide the step-by-step description of the procedure for estimating the VARHAC estimator of Den Haan and Levin (1994).

the MA(1) is given by $\theta_1/(1+\theta_1^2)$.[57] We estimate these equations for the pre- and post-windows for each price-limit hit but only for the price-limit hits where the Dickey-Fuller test indicates that the series for both the pre-and post-windows for the same price-limit hit are stationary (i.e., $\rho_i < 1$).

The summary results for the four samples using both time-series models with trade-by-trade returns for the lower and upper price-limit hits are summarized in Tables 10 and 11, respectively. We note that the first-order autocorrelations for the pre- and post-windows in both tables are highly significant but are negative for the AR(1) model and positive for the MA(1) model. For the pre-windows, the mean and median mean returns (Mean) for both ARIMA models are always highly significant and negative for lower price-limit hits (Table 4.10) and positive for upper price-limit hits (Table 4.11). These results are consistent with what was reported earlier in both panels of Table 4.5. For the post-windows, the mean and median mean returns (Mean) for both ARIMA models are always of the same sign and statistical inference based on conventional levels of significance. Furthermore, the mean and median mean returns (Mean) for both ARIMA models in Table 4.10 are generally consistent with what was reported earlier in panel A of Table 4.5. They are significantly positive for all lower price-limit hits and for those during the first 30 minutes of the first session, insignificantly different for those during the last 30-minutes of both sessions, and still negative but now significant for those in place at sessions' closes. They are significantly negative for the four samples of upper price-limit hits in Table 4.11 as they were previously in panel B of Table 4.5. Thus, our initial mean results based on 3-minute intervals are robust. This reinforces our previous inference that our test results support our two second alternative hypotheses that either market overreactions or price delays are associated with price-limit hits depending on the timing and duration of the price-limit hits.

[Please place Tables 4.10 and 4.11 here.]

We now do similar comparisons of the mean and median return variances for the paired differences (i.e., Adj. σ) reported in each table for each AIRMA model, and with their counterparts reported earlier in

[57] For user friendly sources, see respectively: https://onlinecourses.science.psu.edu/stat510/node/60 and https://onlinecourses.science.psu.edu/stat510/node/48

Tables 3 and 4 for the variances that account for serial autocorrelation (i.e., Vol_3 and Vol_4). With only a few exceptions, the mean and median return variances (Adj. σ) for both ARIMA models are always of the same sign and statistical inference based on conventional levels of significance. The exceptions are positive means and medians for lower price-limit hits during the last 30 minutes of both sessions that are nearly significant and are significant for the AR(1) and MA(1) models, respectively. When we compare the Table 4.10 and 11 estimates against those reported earlier for Vol_3 and Vol_4 for the paired post- and pre-window differences, we observe the following consistencies for the lower price-limit hits: significantly lower variances post-window for the full sample of price-limit hits, significantly lower variances post-window for price-limit hits during the first 30 minutes of the first session, higher (either significant or nearly so) variances post-window for price-limit hits during the last 30 minutes of both sessions, and not significantly different variances post-window for price-limit hits that transcend the end of sessions. Similarly, we observe the following consistencies for the upper price-limit hits: significantly lower variances post-window for the full sample of price-limit hits, significantly lower variances post-window for price-limit hits during the first 30 minutes of the first session, and not significantly different variances post-window for price-limit hits during the last 30 minutes of both sessions. The only inconsistencies are that the changes in the variances post-window differ in sign and significance for price-limit hits that transcend the end of sessions.[58] Thus, these new results support our previous variance results based on 3-minute intervals. Thus, our previous variance results based on 3-minute intervals are robust. This reinforces our previous inference that our test results support our second null and our two second alternative hypotheses since the post-window impact on return variances of a price-limit hit depends on the time of the day when the price-limit hit begins (e.g. beginning or end of a trade session) and when it ends (e.g., in the same or subsequent session).

4.9.2 3-minute Returns and ARIMA Models

[58] The mean and median variances post-window are higher based on the AR(1) and MA(1) models but only the medians are significant. In contrast, the mean and median variances post-window are lower and higher based on the Vol_3 and Vol_4 metrics but only the mean for Vol_4 is significant.

In this section, we conduct tests of robustness using the ten 3-minute returns for each of the pre- and post-windows for each price-limit hit using the two ARIMA models.[59] However, due to the low power and distorted size of unit-root tests (e.g., Mahadeva and Robinson, 2004)[60] when combined with the moderate increase in the critical t-values as the sample size decreases (e.g., Rinat and Kumar, 2013), we expect that the null hypothesis that the 3-minute return series have a unit root will be rejected less often using the Dickey-Fuller test for the various time-series each consisting of only ten observations. This is what we find as we are unable to reject the null of a unit root for about 67% of the pre- and post-windows for the full samples of lower and upper price-limit hits. Nevertheless, using the remaining samples does provide additional evidence on the robustness of our previously reported results. However, to conserve valuable journal space these results remain available but untabulated.

For the pre-windows, the mean and median mean returns for both ARIMA models are always highly significant and negative for lower price-limit hits and positive for upper price-limit hits. These results are consistent with what was reported earlier in both panels of Table 4.5. For the post-windows, the mean and median mean returns for both ARIMA models carry the same sign as reported earlier in both panels of Table 4.5 but now they are no longer significant for both ARIMA models for the lower price-limit hits during the first 30 minutes of the first session and the last 30 minutes of both sessions. The mean post- minus pre-window differences in average returns continue to be always positive and significant for the four samples of lower price-limit hits and negative and significant for the four samples of upper price-limit hits. Thus, our previous mean results based on 3-minute intervals are robust. This reinforces our previous inference that our test results support our two second alternative hypotheses that either market overreactions or price delays are associated with price-limit hits depending on the timing and duration of the price-limit hits.

[59] Andersen, Bollerslev, Diebold and Ebens (2001) estimate an MA(1) model for each of the 5-minute return series using a five-year sample in order to purge the high-frequency returns of the negative serial correlation induced by the uneven spacing of the observed prices .
[60] These terms are respectively an incorrect probability of rejecting a true null and a high probability of accepting a false null.

We now compare the mean and median variances of returns for the paired differences (i.e., Adj. σ) for each ARIMA model (untabulated), and with their counterparts reported earlier in Tables 3 and 4 that account for serial autocorrelation (i.e., Vol_3 and Vol_4). A positive (negative) difference indicates that the post-window variance is larger (smaller) than its pre-window counterpart. We begin with a discussion of the results for the lower price-limit hits. While both the mean and median differences for Vol_3 and Vol_4 for the full sample are significantly negative, the median for the MA(1) is no longer significant. Both the mean and median differences for Vol_3 and Vol_4 for the lower price-limit hits during the first 30 minutes of the first session continue to be significantly negative, those during the last 30 minutes of both sessions continue to be positive and generally significant, and those that transcend the close of a session continue to be insignificant. We continue with a discussion of the results for the upper price-limit hits.

While both the mean and median differences for Vol_3 and Vol_4 for the full sample are significantly negative, the median difference from the AR(1) model becomes insignificant for the MA(1) model. While both the mean and median differences for Vol_3 and Vol_4 for the upper price-limit hits during the first 30 minutes of the first session are significantly negative, both difference average are insignificant for the AR(1) model. While both the mean and median differences for Vol_3 and Vol_4 for the upper price-limit hits during the last 30 minutes of both sessions are not significant, they remain insignificant for the MA(1) model but become significantly negative for the AR(1) model. The variance differences for the upper price-limit hits that transcend a session close continue to be generally insignificant. Thus, our previous variance results based on 3-minute and trade-by-trade intervals are robust. This reinforces our previous inference that our test results support our second null and our two second alternative hypotheses since the post-window impact on return variances of a price-limit hit depends on the time of the day when the price-limit hit begins (e.g. beginning or end of a trade session) and when it ends (e.g., in the same or subsequent session).

4.10. CONCLUSION

This study provides evidence that the effects of price-limits are not homogeneous as they differ between upper and lower hits but also when they occur during a trading session or trading day and whether they continue in a subsequent trading session at least for the BIST. Our results are based on the price-limit hits for members of the BIST-50 index during the thirteen-month examination period of March 2008 through March 2009. Thus, whether they can be generalized to non-members of this index remains to be tested. Our results are robust to a number of further tests such as using trade-by-trade returns instead of equi-distant returns, and accounting for the effect of autocorrelation in both series.

Our major findings can be summarized as follows:

- They are supportive of the volatility no-effect, volatility dampening and volatility spillover hypotheses depending on the time of the day when the price-limit hit begins and/or ends, and whether it is a lower or upper price-limit hit.
- They are supportive of the overreaction and no-effect price hypotheses but not the price-delay hypothesis.
- They are supportive of the magnet effect hypothesis that the prices prior to a limit hit accelerate as they approach the price-limit hit.
- They are not supportive of the trading interference hypothesis but are supportive of the overreaction trading hypothesis that buyer-initiated trade activity increases after lower price-limit hits and decreases after upper price-limit hits.
- They are supportive of a greater informational asymmetry effect on market-quality hypothesis.

Our findings have implications for the BIST and for emerging markets that plan to impose similar mechanisms or to fine-tune their current mechanisms. Regulators may want to experiment with more flexible (somewhat discretionary) price limits especially for price-limit hits that appear that they will continue into the next trading session. Given the evidence supporting the overreaction and magnet-effect hypothesis, regulators may want to closely monitor pre- and-post-limit periods to ensure that these are not periods that are being exploited by market manipulators or insiders. We believe that all regulatory actions that facilitate market quality, integrity and fairness are especially important for an emerging market such as the BIST.

CHAPTER FIVE

5. CONCLUSION

Researchers are interested in trade direction algorithms because they help to better analyze the market for immediacy. Therefore, the main motivation of the first essay was to empirically investigate the accuracy rates of five trade classification algorithms for a trade venue (the BIST) in a developing market for the seven months ending with December 2008 that is centered on the month of the collapse of Lehman Brothers.

In this essay, we documented that the one-second lagged version of the Lee and Ready (LR, 1991) algorithm with a greater than 95% classification accuracy rate outperformed the other four trade classification algorithms examined therein. Our accuracy result for the LR algorithm was also higher than that previously reported for other markets including the U.S. Our results also supported the finding that the five-second rule needs to be replaced by its one-second counterpart, as found by others for US markets (e.g., Chakrabarty *et al.*, 2012). This result may imply that fully computerized order driven markets such as the BIST provide for a better sequencing of the actual entrance of trades and orders.

In addition to the superior performance of the LR algorithm using one-second lagged quotes, we found that the highest rates of misclassifications occurred for trades at the quote mid-spread and as the time between consecutive trades decreased (Odders-White, 2000). We documented the lowest misclassification rates for agency trades and that misclassification rates were higher in the first versus the last 30 minutes of both daily trading sessions of the BIST. This may be the result of informed trading during these periods although these periods are closely monitored by exchanges such as the BIST to minimize possible manipulative actions.

Unlike Odders-White (2000) and Aitken and Frino (1996), we found that larger transactions generally are more frequently misclassified but only for the classification algorithms using one-second lagged BBO (Best Bid and Offer). A special trade or cross, especially for large transactions, where buyers and sellers agree prior to the trade on the terms of the trades may be a factor in these situations. Unlike

Asquith *et al.* (2010) and Chakrabarty *et al.* (2012), we found accuracy rates of at least 90% using one-second lagged quotes for both long and short trades for the quote, at-the-quote and LR (but not EMO) algorithms. While the EMO algorithm was best for correctly classifying seller-initiated trades with an over 95% accuracy rates and worst for correctly classifying buyer-initiated trades, the LR algorithm using a one-second lagged BBO was second best for correctly classifying seller-initiated trades and best for correctly classifying buyer-initiated trades.

The firms examined in the first essay were the thirty most frequently traded firms in the BIST, and the time period examined included the impact of the global financial crisis. In future work, we plan to add relatively smaller firms to our sample and to examine other time periods with less volatility to determine if the high accuracy rate of the LR algorithm remains during such periods.

In Essay 2 we examined the magnitudes and durations of the temporary and permanent price effects of trades with various characteristics, such as being large or small. To this end, we examined the price effects associated with trades for the 38 companies during their tenure in the BIST-30 index during the twelve months from April 2008 through March 2009. Our findings support the conclusion that price discovery is fairly rapid on the BIST. To illustrate, we found that the mean price effects are less than 30 basis points, are competitive with those found for other markets, and are (somewhat) counter-intuitive using the price at the (subsequent fifth trade second) day's close instead of the subsequent first trade second as the post-trade price. We also found that large trade seconds generally have the most positive and most negative mean permanent price effects for buyer- and seller-initiated trade seconds, respectively. This is consistent with the prediction of Glosten and Milgrom (1985) and Easley and O'Hara (1987) that informed trading is larger for larger trades.

Another major finding of the second essay is that the permanent price effects are highly significant and positive for all samples of short trades. They are substantially greater in magnitude for seller- versus buyer-initiated short trades, and are significantly (highly) more positive than their corresponding samples of long trades. This suggests that short trades do not unduly depress prices, and is consistent with the elimination of short trades or movements towards doing such in many markets such as in the U.S.

Another major finding of the second essay is that the price effects of trades in the last minutes of a trading session are significantly higher. This result may have important implications for market regulators in terms of refining their surveillance systems to eliminate or minimize any inappropriate stealth trading or end-of-session price manipulation.

In Essay 3, we examined price-limit hits for members of the BIST-50 index during the March 2008 through March 2009 period. We found that the effects of price-limit hits are not homogeneous as they differ between upper- and lower-limit hits, according to when they occur during a trading session or trading day, and whether they continue in a subsequent trading session. In this third essay, we document supporting evidence for the volatility no-effect, volatility dampening and volatility spillover hypotheses depending on the time of the day when the price-limit hit begins or ends. This implies that exchanges such as the BIST may consider paying extra attention to the timing of a price-limit hit and may consider adjusting their enforcement of such hits based on the timing of the price-limit hits.

Another major finding of this third essay is that we provided support for the magnet effect hypothesis that stipulates that the prices prior to a price-limit hit accelerate as they approach the price-limit hit price. While the reported evidence did not support the trading interference hypothesis, it did provide some support for the overreaction hypothesis since buyer-initiated trade activity increased after lower price-limit hits and decreased after upper price-limit hits.

On a broader perspective, the findings reported in the third essay may be very useful for regulators of emerging markets in terms of price-limit hit enforcement. Basically, more flexible rules in terms of price-limit enforcements may be more effective in terms of promoting improved price discovery and liquidity. Moreover, more scrutiny may be required during the periods prior to and after price-limit hit periods in order to alleviate any stealth trading activity. Such regulatory actions could improve market quality and enable exchanges (particularly emerging-markets such as the BIST) to provide a fairer trading environment.

In future work, we plan to examine the impact of price-limit hits for relatively smaller firms and other time periods. We also plan to examine how the order book and its slope changes around price-limit hits using our ability to construct the limit order book consisting of the ten best different bids and ten best different offers and their corresponding volumes for each second of the trading day based on price and then time priority by using the order flow and trade data. Given the richness of our dataset, we also plan to use a new specification of an existing vector autoregressive (VAR) model used by Al-Suhaibani and Kryzanowski (2000) to assess the information content of a newly submitted order around price-limit hits and in periods without such hits.

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Figure 2.1. Plot of the level and monthly share volume of the BIST-30 Index

This figure plots the month-end level of the BIST-30 Index and its monthly share volume over the period from month-end January 2005 through month-end October 2012. The "♦"and "▲" delineate the beginning and end of the sample time period examined in this study.

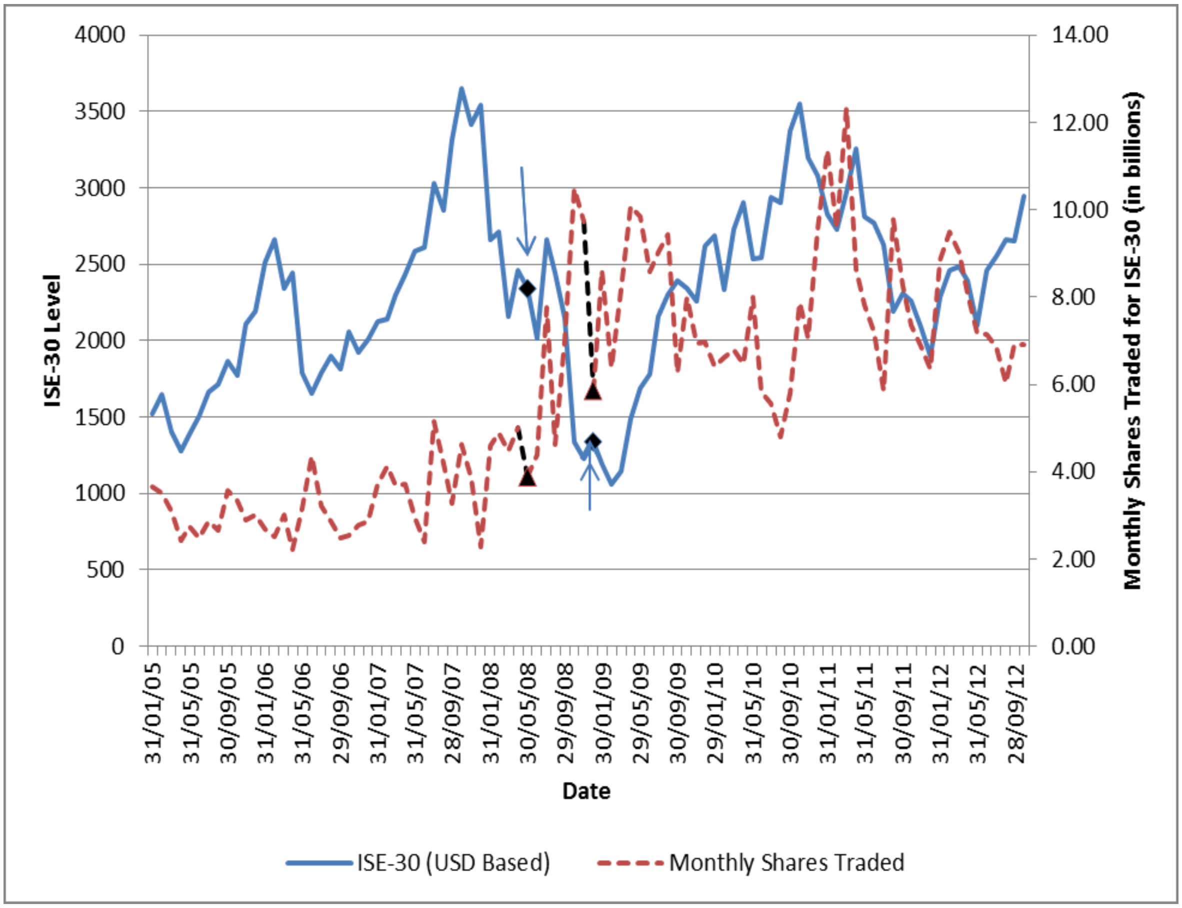

Table 2.1. Trade classification algorithms

This table presents the definitions of the commonly used trade classification algorithms in the microstructure literature. LR refers to the Lee and Ready (1991) algorithm and EMO refers to the Ellis, Michaely and O'Hara (2000) algorithm.

Algorithms	Definition
Tick	Trade is classified as a buy (sell) if the price of the trade to be classified is above (below) the closest different price of a previous trade.
Quote	Classifies a trade as a buy (sell) if the trade price of the trade to be classified is above (below) the mid-point of the bid and ask spread. Trades executed at the mid-spread are not classified.
At-the-quote	Classifies a trade as a buy (sell) if the trade takes place at the ask (bid) quote.
LR	Classifies a trade as a buy (sell) if its price is above (below) the mid-spread (quote algorithm), and uses the tick algorithm if the trade price is at the mid-spread. LR recommend using the mid-spread five-seconds earlier ("5-second" rule) as it reduces trade misclassifications for many of the 150 NYSE firms that they examine.
EMO	Classifies trades at the bid (ask) as sells (buys) and uses the tick algorithm to classify trades within the then prevailing bid-ask spread.

Table 2.2. Summary of the results from studies of trade classification accuracy

This table summarizes the findings of some of the studies that assess the accuracy rates of the trade classification algorithms used for US and International markets. ST refers to short trades & LT to long trades when such a breakdown exists. "SI" refers to seller-initiated trades.

			Trade classification algorithm			
Study	Sample	Time Period	Tick	Quote	LR	EMO
Studies for US Markets						
Asquith, Oman & Safaya (2010)	NASDAQ & NYSE, 100 firms from each	March, June & Dec. 2005			12% - 15% ST as SI no uptick rule & 41% - 44% ST as SI with uptick rule	
Ellis, Michaely & O'Hara or EMO (2000)	NASDAQ, 313 firms	Sept. 1996 - Sept. 1997	76.4%	77.6%	81.1%	81.9%
Chakrabarty *et al.* (2007)	NASDAQ, 750 firms	April-June 2005	75.4%		74.4%	75.8%
Rosenthal(2012)	NASDAQ 1391 firms; NYSE 1420 firms	Dec. 1 & 2, 2004	64.7%		68.4%	65.6%
Lee and Radhakrishna (2000)	TORQ, 144 firms	Nov. 1990 – Jan. 1991			93.0%	
Odders-White (2000)	TORQ, 144 firms	Nov. 1990 - Jan. 1991	75.0%	79.0%	85.0%	
Funicane (2000)	TORQ, 144 firms	Nov. 1990 – Jan. 1991	83.0%		84.0%	
Savickas & Wilson (2003)	CBOE	July 1995 - Dec. 1995	59.0%	83.0%	80.0%	77.0%
Blais & Protter (2011)	S&P, top 50 firms				61.0%	
Chakrabarty, Moulton &Shkilko (2012)	TAQ, 100 firms	June & Dec. 2005			68.2% ST; 69.2% LT	
Studies for International Markets						
Aitken and Frino (1996)	ASX, all firms	June 1992 - June 1994	74.4%			
Theissen (2001)	Frankfurt, 15 firms	25 Sep. – 25 Oct. 1996			72.8%	
Lu & Wei (2009)	Taiwan Stock Exchange, 687 firms	2 Jan. - June 30, 2006	74.0%	92.8%		

Table 2.3. Trade classification accuracy for all trades and during the "first" and last 30 minutes of each daily trading session

First three rows of each panel in this table report average trade classification accuracies (buyer- and seller-initiated trades) in percent for each of five trade classification algorithms using lagged zero, one and five second quotes for all trades (Overall) and for trades in the first 30 (F. 30 m.) minutes and the last 30 minutes (L. 30 m.) of the morning (panel A) and afternoon (panel B) sessions of the trading day for the firms in the BIST-30 Index for the seven months from June 1 to December 31, 2008. The tick algorithm is not based on quotes so its performance is invariant to whether quotes are lagged. Each χ^2 and G-test statistic has been divided by 100 and rounded to the nearest one digit after the decimal point for presentation purposes. The chi-square and G-test statistics (and the associated p-values for both) are for tests of the hypothesis that the frequency of misclassifications is independent of whether the trade occurred in the first or last 30 minutes of each trading session. There are 7,889,985 trades in total, 991,489 and 839,984 trades in the F.30m. for the morning and afternoon sessions, respectively, and 509,089 and 1,294,405 trades in the L.30m. for the morning and afternoon sessions, respectively.

	Trade Classification Algorithm												
	Tick	Quote			At-the-Quote			LR			EMO		
Categories	All	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1 S	5 S
Panel A: Morning trading session													
F. 30 m.	89.05	75.14	95.15	93.07	73.94	93.36	90.60	82.62	96.52	94.08	83.77	90.57	88.71
L. 30 m.	91.23	78.28	94.88	93.93	77.88	94.05	92.53	85.90	96.32	94.94	86.33	91.78	90.86
Overall	90.38	76.32	95.00	93.48	75.22	93.05	90.80	83.87	96.38	94.44	80.88	86.93	85.69
χ^2 (÷ 100)	23.3	18.4	0.6	4.4	28.1	8.4	18.1	27.0	0.6	4.8	132.6	194.4	163.3
G (÷100)	22.8	18.6	0.6	4.4	28.5	8.7	19.1	27.3	0.6	4.9	139.8	210.1	175.9
p-values	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of 'F. 30 m.' versus 'Overall'													
χ^2 (÷ 100)	17.7	6.8	0.4	2.4	7.7	1.3	0.4	10.3	0.6	2.1	48.2	105.5	67.1
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of 'L. 30 m.' versus 'Overall'													
χ^2 (÷ 100)	4.0	10.1	0.1	1.6	18.3	7.5	17.2	14.6	0.0	2.3	93.0	100.7	106.3
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.050	<.001	<.001	<.001	<.001
Panel B: Afternoon trading session													
F. 30 m.	89.37	75.43	94.49	92.22	73.80	91.98	88.55	82.35	95.89	93.17	78.11	84.76	83.10
L. 30 m.	91.92	79.69	95.67	94.53	78.45	93.29	91.35	86.63	96.99	95.41	80.66	85.41	84.50
Overall	90.38	76.32	95.00	93.48	75.22	93.05	90.80	83.87	96.38	94.44	80.88	86.93	85.69
χ^2 (÷ 100)	44.1	78.5	16.7	45.4	77.6	15.3	53.5	84.4	19.5	49.1	37.3	47.6	48.5
G (÷100)	45.2	80.5	17.0	45.2	79.1	14.8	50.8	86.8	19.9	48.7	36.2	46.6	47.2
p-values	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of 'F. 30 m.' versus 'Overall'													
χ^2 (÷ 100)	8.7	3.3	4.1	19.5	8.1	13.2	45.3	12.9	5.1	23.0	37.2	31.2	40.8
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of 'L. 30 m.' versus 'Overall'													
χ^2 (÷ 100)	31.0	70.7	10.9	20.5	63.3	1.0	4.0	63.9	12.2	20.3	0.4	22.5	12.7
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001

Table 2.4. Trade classification accuracy differentiated by their positioning within the BBO

First three rows of this table report average trade classification accuracy in percent for each of the five algorithms based on the positioning of each trade versus the best bid and offer (BBO). The categories are at or outside of the BBO (≥quotes), at the mid-spread, and within the BBO but not at the mid-spread (< quote & ≠ Mid-spread). The number of transactions at 8,106,213 is higher than 7,889,985 because the transactions that take place at the locked quotes appear both in the at the quote trades and in the mid-spread trades. Each χ^2 and G-test statistic has been divided by 100 and rounded to the nearest one digit after the decimal point for presentation purposes. The chi-square and G-test statistics (and the associated p-values for both) are for tests of the hypothesis that the frequency of misclassifications is independent of whether the trade occurred at or outside the quotes, at the mid-spread, and inside the spread but not at the mid-spread. N/A is not applicable. The sample sizes are 7,449,032 for ≥quotes, 639,426 for mid-spread and 17,755 for < quote & ≠ Mid-spread.

	Trade Classification Algorithm												
	Tick	**Quote**			**At-the-Quote**			**LR**			**EMO**		
Category	All	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S
≥quotes	90.17	80.72	94.73	93.19	79.67	92.81	90.53	83.06	96.18	94.19	80.38	86.52	85.26
Mid-spread	88.33	N/A	79.25	84.17	N/A	89.40	90.17	93.19	93.30	92.10	77.12	84.82	85.60
< quote & ≠ Mid-spread	84.46	52.24	95.40	94.63	N/A	45.77	44.11	52.24	95.42	94.70	89.51	91.01	91.06
χ^2 (÷ 100)	28.1	N/A	2327.9	691.4	N/A	653.2	440.2	575.2	126.2	45.9	49.3	17.8	5.3
G (÷ 100)	26.4	N/A	1603.7	551.1	N/A	356.4	239.1	636.2	107.8	42.3	49.6	17.7	5.9
p-values	<.001	N/A	<.001	<.001	N/A	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of '≥quotes' versus 'Mid-spread'													
χ^2 (÷ 100)	22.1	N/A	2325.5	689.8	N/A	99.7	0.9	446.4	126.1	45.8	39.4	14.5	0.5
p-value	<.001	N/A	<.001	<.001	N/A	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of '≥quotes' versus '< quote & ≠ Mid-spread'													
χ^2 (÷ 100)	6.5	92.0	0.2	0.6	N/A	579.5	440.6	119.1	0.3	0.1	9.4	3.1	4.7
p-value	<.001	<.001	<.001	<.001	N/A	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001

Table 2.5. Trade classification accuracy differentiated by the time between trades

First three rows of this table report average trade classification accuracy in percent for each of the five algorithms based on the time between trades. The categories are the 6,012,500 trades with less than or equal to five seconds between trades (<=5 s.), the 1,244,220 trades with more than 5 and less than 30 seconds between trades (>5 & <=30 s.), and the 633,265 trades with more than 30 seconds between trades (>30 s.). The last column reports the total number of transactions in each category. Each χ^2 and G-test statistic has been divided by 100 and rounded to the nearest one digit after the decimal point for presentation purposes. The chi-square and G-test statistics (and the associated p-values for both) are for tests of the hypothesis that the frequency of misclassifications is independent of the time between consecutive trades. There are 7,889,985 trades in total.

	Trade Classification Algorithm												
	Tick	**Quote**			**At-the-Quote**			**LR**			**EMO**		
Category	All	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1 S	5 S
<=5 s.	91.29	71.87	94.75	92.77	71.42	92.72	89.80	81.20	96.29	93.77	80.17	87.47	85.88
>5 & <=30 s.	86.44	89.79	95.26	95.22	87.71	92.87	92.75	91.66	96.19	96.09	81.87	84.24	84.02
>30 s.	89.40	92.11	96.83	96.87	90.86	95.39	95.38	93.88	97.50	97.49	86.21	87.87	87.89
χ^2 (÷ 100)	286.9	2781.3	54.2	231.1	2354.5	62.7	285.0	1344.7	25.5	227.4	144.2	99.8	55.1
G (÷ 100)	266.0	3222.6	60.5	262.0	2674.0	70.1	321.7	1551.2	28.2	260.2	153.6	95.5	55.2
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of '<=5 s' versus '>5 & <=30 s.'													
χ^2 (÷ 100)	281.7	1762.8	5.4	97.5	1429.2	0.3	102.8	799.6	0.3	100.9	19.1	94.6	28.9
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of '<=5 s' versus '>30 s.'													
χ^2 (÷ 100)	25.3	1213.6	51.6	151.2	1105.7	62.7	204.5	635.9	24.4	143.0	134.6	0.8	19.4
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001

Table 2.6. Trade classification accuracy differentiated by trade size

First six rows of this table report average trade classification accuracy (buyer- and seller-initiated trades) in percent for each of the five classification algorithms using lagged zero, one and five second quotes for the 3,280,534 trades with fewer than or equal to 500 shares (<=500 sh.), for the 1,033,029 trades with more than 500 and fewer than or equal to 1000 shares (>500 & <=1000), for the 1,726,491 trades with more than 1000 and fewer than or equal to 5000 shares (>1000 & <=5000), for the 891,260 trades with more than 5000 and fewer than or equal to 15,000 shares (>5000 & <=15000), for the 711,123 trades with more than 15,000 and fewer than or equal to 45,000 shares (>15000 & <=45000) , and for the 247,548 trades with more than 45,000 shares (>45000). The last column reports the total number of trades in each category. The tick algorithm is not based on quotes so its performance is invariant to whether quotes are lagged. Each χ^2 and G-test statistic has been divided by 100 and rounded to the nearest one digit after the decimal point for presentation purposes. The chi-square and G-test statistics (and the associated p-values for both) are for tests of the hypothesis that the frequency of misclassifications is independent of trade size category.

	Trade Classification Algorithm												
	Tick	**Quote**			**At-the-Quote**			**LR**			**EMO**		
Category	All	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1 S	5 S
<=500 sh.	91.86	80.75	95.72	94.93	79.52	93.52	91.81	86.87	96.77	95.69	82.92	87.22	86.45
>500 & <=1000	90.36	75.26	94.74	93.63	73.83	92.37	90.77	83.04	96.08	94.58	80.51	86.69	85.72
>1000 & <=5000	89.24	73.24	94.27	92.78	72.26	92.43	90.39	81.35	96.06	94.02	79.14	86.48	85.24
>5000 & <=15000	88.36	71.49	94.08	91.71	70.78	92.71	89.70	80.20	96.06	92.98	78.27	86.51	84.64
>15000 & <=45000	88.97	73.23	94.57	91.19	72.23	93.04	88.82	82.03	96.01	92.09	79.53	86.98	84.51
>45000	90.00	69.93	96.12	91.51	69.13	95.06	90.11	83.69	96.79	92.13	80.82	88.82	85.64
χ^2 (÷ 100)	166.6	661.7	81.9	251.0	594.8	46.0	90.9	411.6	28.5	239.6	170.4	15.2	34.5
G (÷ 100)	173.5	693.5	85.7	258.8	623.7	49.3	93.3	431.4	29.9	243.0	177.5	16.2	35.8
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of '<=500 sh.' versus '>45000'													
χ^2 (÷ 100)	10.5	168.4	0.9	53.7	148.7	9.0	8.7	20.2	0.0	67.0	7.1	5.4	1.3
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.580	<.001	<.001	<.001	<.001
Paired χ^2 test of '>500 & <=1000' versus '>15000 & <=45000'													
χ^2 (÷ 100)	8.9	9.1	0.2	36.7	5.5	2.7	17.8	3.0	0.0	43.1	2.5	0.3	4.9
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.030	<.001	<.001	<.001	<.001
Paired χ^2 test of '>1000 & <=5000' versus '>5000 & <=15000'													
χ^2 (÷ 100)	4.7	9.1	0.4	9.5	6.3	0.7	3.1	5.0	0.0	10.8	2.7	0.0	4.7
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.850	<.001	<.001	<.001	<.001

Table 2.7. Trade classification accuracy differentiated by long versus short trades

First two rows of this table report average trade classification "accuracy" in percent for each of the five classification algorithms based on long or short trades. The last column reports the total number of trades in each category. The tick algorithm is not based on quotes so its performance is invariant to whether quotes are lagged. Each χ^2 and G-test statistic has been divided by 100 and rounded to the nearest one digit after the decimal point for presentation purposes. The chi-square and G-test statistics (and the associated p-values for both) are for tests of the hypothesis that the frequency of misclassifications is independent of short or long trades. Of the 7,889,985 trades in total, 293,198 and 7,596,787 are short and long, respectively.

	Trade Classification Algorithm												
	Tick	**Quote**			**At-the-Quote**			**LR**			**EMO**		
Category	All	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1 S	5 S
Short trades	92.15	76.06	92.04	90.01	76.10	91.83	89.19	83.82	94.93	91.95	75.19	86.25	83.98
Long trades	90.31	76.33	95.11	93.62	75.18	93.09	90.86	83.88	96.43	94.53	81.10	86.96	85.76
χ^2 (÷ 100)	11.1	0.1	56.1	60.4	1.3	6.9	9.4	0.0	18.2	35.9	63.8	1.3	7.2
G (÷ 100)	11.7	0.1	48.2	52.8	1.3	6.6	9.0	0.0	16.3	31.9	59.8	1.2	7.0
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.410	<.001	<.001	<.001	<.001	<.001

Table 2.8. Trade classification accuracy differentiated by buyer- or seller-initiated trades and by BIST`s trader classifications

First two rows of panel A of this table report average trade classification accuracies in percent for each of the five algorithms based on whether the trade is buyer-or-seller initiated. First three rows of panel B of this table report average trade classification accuracies in percent for each of the five classification algorithms based on the BIST`s trader classifications of institutional and retail clients of the brokerage firms [M(Ins. & Retail)], portfolios of the brokerage firms [P(portfolio)], and the investment funds managed by the brokerage firms [F(fund)]. The last column reports the number of transactions for each category in each panel. In both panels, each χ^2 and G-test statistic has been divided by 100 and rounded to the nearest one digit after the decimal point for presentation purposes. The chi-square and G-test statistics (and the associated p-values for both) are for tests of the hypothesis that the frequency of misclassifications is independent of whether the trade is buyer-or-seller-initiated in panel A and the BIST's trade classifications in panel B. There are 7,889,985 trades in total. There are 4,162,006 and 3,727,979 buyer- and seller-initiated trades in panel A. There are 7,464,484 M(Ins. & Retail) trades, 244,813 P(Portfolio) trades and 180,688 F(Fund) trades in panel B.

	Trade Classification Algorithm												
	Tick	**Quote**			**At-the-Quote**			**LR**			**EMO**		
Category	All	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1-S	5-S	0-S	1 S	5 S
Panel A: Trade classification accuracy differentiated by buyer-or-seller-initiated trades													
Buyer-initiated	89.93	76.35	93.52	91.93	75.08	91.72	89.72	84.06	94.81	92.86	67.59	76.06	74.98
Seller-initiated	90.87	76.29	96.65	95.21	75.37	94.53	92.01	83.66	98.12	96.20	95.72	99.07	97.64
χ^2 (÷ 100)	19.7	0.0	405.4	347.0	0.9	240.6	123.3	2.3	616.7	415.8	10061.7	9166.0	8237.3
G (÷ 100)	19.7	0.0	416.7	353.7	0.9	243.9	124.1	2.3	651.0	426.5	11382.5	11429.2	9641.9
p-value	<.001	<.060	<.001	<.001	<.01	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Panel B : Trade classification accuracy differentiated by BIST`s trader classifications													
M(Ins. & Retail)	90.46	76.44	95.08	93.57	75.26	93.05	90.82	83.95	96.38	94.48	80.99	86.88	85.65
P(Portfolio)	87.31	72.16	92.01	89.89	73.41	92.52	89.26	82.35	95.72	92.46	77.20	86.81	84.93
F(Fund)	91.21	76.96	95.66	94.56	75.98	93.77	92.11	82.82	96.89	95.48	81.33	89.28	88.30
χ^2 (÷ 100)	28.4	24.5	48.6	56.3	4.9	2.5	10.7	6.0	4.3	22.2	22.3	9.0	11.3
G (÷ 100)	26.3	23.7	41.9	49.5	4.9	2.6	10.5	5.9	4.3	20.7	21.4	9.5	11.8
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Paired χ^2 test of 'M(Ins. & Retail)' versus 'P(Portfolio)'													
χ^2 (÷ 100)	26.8	24.1	46.7	52.6	4.4	1.0	6.9	4.5	3.0	18.4	22.1	0.0	1.0
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.280	<.001
Paired χ^2 test of 'M(Ins. & Retail)' versus 'F(Fund)'													
χ^2 (÷ 100)	1.2	0.3	1.3	2.9	0.5	1.5	3.5	1.7	1.3	3.4	0.1	8.9	10.1
p-value	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001

Table 3.1. Proxies used in prior studies for pre- and post-trade prices

This table reports the pre- and post-trade prices used in a selection of prior studies to examine the price impacts of large trades on various markets. ASE is the Australian Stock Exchange. SSM is the Saudi Stock Market. A centisecond and a millisecond is 1/100th and 1/1000th of a second, respectively.[a]indicates that all trades occurring within 5 seconds of each other with the same price are aggregated.

Study	Sample	Data source & time stamp to nearest	Pre-trade	Post-trade
Kraus & Stoll (1972), p. 571	NYSE 402 firm subsample, July 1, 1968 to Sept. 30, 1969	Vickers, not provided	Immediately prior	Day's closing trade
Holthausen, Leftwich & Mayers (1987), p. 243	NYSE firms, 1982	Francis Emory Fitch, Inc., minute	Immediately prior	Day's closing trade
Holthausen, Leftwich & Mayers (1990), pp. 85 & 88	NYSE firms, Dec. 1, 1982 to Jan. 31, 1984	Francis Emory Fitch, Inc., minute	Immediately prior	1st , 3rd & 6th but only report 3rd trade after
Chan & Lakonishok (1993), p. 177	NYSE & AMEX firms, July 1986 to end of 1988	37 large institutional money mgmt. firms trades, no time stamp	Opening price	Day's closing trade
Keim & Madhavan (1996), p. 14	NYSE, AMEX, NASDAQ NMS, 5625 upstairs 1985-1992	Dimensioanl Fund Advisors, not time stamped (in day)	Previous day's close	Day's closing trade
Frino *et al.* (2005), p. 253	All ASE, 1 Jan., 1992 to 31 Dec., 2001	ASE, centisecond	Opening trade	Day's closing trade
Frino *et al.* (2007), p. 98	All ASE, 1 Jan., 1992 to 31 Dec., 2001	ASE, centisecond	5th trade before	5th trade after
Hwang & Qian (2011), p. 17[a]	All NYSE & AMEX, Jan. 1983 to Dec. 2006	ISSM (second)/TAQ (millisecond/second if daily/ monthly TAQ used)	1st to 5th but only report 3rd trade before	1st to 5th but only report 3rd trade after
Frino, Mollica & Romano (2012), p.18	S&P 500 traded on NYSE, 1 Jan. 1997 to quarter 1 of 2001	Thompson Reuters, not provided	Previous day's close, immediately prior	Day's closing trade, & trade price 5 minutes after
Alzahrani, Gregoriou & Hudson (2013), p. 328	All SSM, Jan. 2005 to Oct. 2008	Mubasher, minute	5th trade before (5 trade "minutes")	5th trade after (5 trade "minutes")

Table 3.2. Trade price effects for various trade classifications on the BIST using the first post-trade second price

This table reports the mean price effects in % for various trade classifications for the Borsa Istanbul (BIST) for the 12-month period from April 2008 through March 2009. The temporary, permanent and total effects of a trade on price are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in **first** trade second after the trade of interest. All refers to the total sample of aggregated trade "seconds". Buyer and Seller refer to buyer- and seller-initiated trades, respectively. Shares and value refer to the number and dollar value of shares traded in thousands, respectively. The price effects that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.). P-values for the Kruskal and Wallis (K-W p-val.) test examine if the mean price effects are significantly different from zero when the day's closing price (untabulated), or the first (this table) or the fifth trade second (untabulated) after the trade second being examined is used as the post-trade price.

Sample	Shares	Temp. Effect	K-W p-val.	Perm. Effect	K-W p-val.	Total Effect.	K-W p-val.	Bay. t-val.
All	5824571	0.0002	<.0001	-0.0006[c]	<.0001	-0.0003[a]	0.7255	±3.947
ALL Buy	3245494	0.1678[c,d]	<.0001	0.0163[c,d]	<.0001	0.1841[c,d]	0.0744	±3.872
ALL Sell	2420802	-0.2222[c,d]	<.0001	-0.0235[c,d]	<.0001	-0.2457[c,d]	0.7329	±3.834
Shares>=15	625821	-0.0145[c,d]	<.0001	-0.0021[c,d]	<.0001	-0.0166[c,d]	0.9885	±3.653
Shares<15	5198750	0.0020[c,d]	<.0001	-0.0004[b]	<.0001	0.0016[c,d]	0.6761	±3.932
Shares >=25	408325	-0.0111[c,d]	<.0001	-0.0039[c,d]	<.0001	-0.0150[c,d]	1.0000	±3.594
Shares <25	5416246	0.0011[c,d]	<.0001	-0.0003[a]	<.0001	0.0008[c,d]	0.7134	±3.938
Value>=100	235196	-0.0013[b]	<.0001	-0.0022[c]	<.0001	-0.0035[c,d]	0.9991	±3.517
Value<100	5589375	0.0003	<.0001	-0.0005[c]	<.0001	-0.0002	0.7149	±3.942
Value>=150	125944	0.0001	<.0001	-0.0043[c,d]	<.0001	-0.0042[c,d]	0.9984	±3.427
Value<150	5698627	0.0002	<.0001	-0.0005[c]	<.0001	-0.0002	0.7178	±3.944
Shares>=15&Buyer	297944	0.0418[c,d]	<.0001	0.0808[c,d]	<.0001	0.1225[c,d]	0.4820	±3.550
Shares<15&Buyer	2947550	0.1806[c,d]	<.0001	0.0097[c,d]	<.0001	0.1903[c,d]	0.1266	±3.860
Shares>=25&Buyer	192211	0.0296[c,d]	<.0001	0.0898[c,d]	<.0001	0.1193[c,d]	0.5921	±3.488
Shares<25&Buyer	3053283	0.1765[c,d]	<.0001	0.0116[c,d]	<.0001	0.1882[c,d]	0.1093	±3.864
Value>=100&Buyer	110480	0.0215[c,d]	<.0001	0.0900[c,d]	<.0001	0.1115[c,d]	0.7011	±3.408
Value<100&Buyer	3135014	0.1730[c,d]	<.0001	0.0137[c,d]	<.0001	0.1867[c,d]	0.0939	±3.868
Value>=150&Buyer	58928	0.0152[c,d]	<.0001	0.1014[c,d]	<.0001	0.1166[c,d]	0.8098	±3.314
Value<150&Buyer	3186566	0.1707[c,d]	<.0001	0.0147[c,d]	<.0001	0.1854[c,d]	0.0852	±3.870
Shares>=15&Seller	280481	-0.0742[c,d]	<.0001	-0.0914[c,d]	<.0001	-0.1657[c,d]	0.5259	±3.542
Shares<15&Seller	2140321	-0.2416[c,d]	<.0001	-0.0146[c,d]	<.0001	-0.2562[c,d]	0.8759	±3.818
Shares>=25&Seller	180728	-0.0543[c,d]	<.0001	-0.1052[c,d]	<.0001	-0.1595[c,d]	0.7143	±3.479
Shares<25&Seller	2240074	-0.2358[c,d]	<.0001	-0.0169[c,d]	<.0001	-0.2527[c,d]	0.8300	±3.824
Value>=100&Seller	102267	-0.0248[c,d]	0.7544	-0.1035[c,d]	0.6274	-0.1283[c,d]	0.7219	±3.396
Value<100&Seller	2318535	-0.2309[c,d]	<.0001	-0.0200[c,d]	<.0001	-0.2509[c,d]	0.7953	±3.828
Value>=150&Seller	54665	-0.0152[c,d]	<.0001	-0.1199[c,d]	<.0001	-0.1351[c,d]	0.8183	±3.303
Value<150&Seller	2366137	-0.2270[c,d]	<.0001	-0.0213[c,d]	<.0001	-0.2483[c,d]	0.7688	±3.831
Min		-0.2416		-0.1199		-0.2562		
Max		0.1806		0.1014		0.1903		

Table 3.3. Trade price effects for various trade classifications on the BIST for less frequently traded stocks

This table reports the mean price effects in % for various trade classifications for trades of **less frequently traded** stocks on the Borsa Istanbul (BIST) for the 12-month period from April 2008 through March 2009. The temporary, permanent and total effects of a trade on price are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in the first trade second after the trade of interest. The All sample and single-sorted subsamples are drawn from the complete sample of aggregated trade seconds. Buyer and Seller refer to buyer- and seller-initiated trades, respectively. Shares and value refer to the number and dollar value of shares traded in thousands, respectively. The price effects that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.). P-values for the Mann-Whitney-Wilcoxon (MWW p-val.) test examine if the mean price effects are significantly different from zero between the less frequently traded (this table) and more frequently traded (untabulated) stocks.

Sample	Shares	Temp. Effect	MWW p-val.	Perm. Effect	MWW p-val.	Total Effect	MWW p-val.	Bay. t-val.
All	1512431	0.0003	0.7705	-0.0009^{b}	0.1866	-0.0006	0.4530	±3.772
ALL Buy	844520	0.1880^{c,d}	<.0001	0.0282^{c,d}	<.0001	0.2162^{c,d}	<.0001	±3.694
ALL Sell	649080	-0.2423^{c,d}	<.0001	-0.0393^{c,d}	<.0001	-0.2817^{c,d}	<.0001	±3.658
Shares>=15&Buyer	45854	0.0361^{c,d}	<.0001	0.1604^{c,d}	<.0001	0.1965^{c,d}	<.0001	±3.276
Shares<15&Buyer	798666	0.1967^{c,d}	<.0001	0.0206^{c,d}	<.0001	0.2173^{c,d}	<.0001	±3.687
Shares>=25&Buyer	22520	0.0199^{c,d}	<.0001	0.1978^{c,d}	<.0001	0.2177^{c,d}	<.0001	±3.166
Shares<25&Buyer	822000	0.1926^{c,d}	<.0001	0.0236^{c,d}	<.0001	0.2161^{c,d}	<.0001	±3.690
Value>=100&Buyer	10767	0.0118^{c,d}	<.0001	0.1643^{c,d}	<.0001	0.1761^{c,d}	<.0001	±3.048
Value<100&Buyer	833753	0.1902^{c,d}	<.0001	0.0265^{c,d}	<.0001	0.2167^{c,d}	<.0001	±3.692
Value>=150&Buyer	5054	0.0171^{c,d}	0.6398	0.1640^{c,d}	<.0001	0.1811^{c,d}	<.0001	±2.921
Value<150&Buyer	839466	0.1890^{c,d}	<.0001	0.0274^{c,d}	<.0001	0.2164^{c,d}	<.0001	±3.693
Shares>=15&Seller	43072	-0.1160^{c,d}	<.0001	-0.1565^{c,d}	<.0001	-0.2726^{c,d}	<.0001	±3.267
Shares<15&Seller	606008	-0.2513^{c,d}	<.0001	-0.0310^{c,d}	<.0001	-0.2823^{c,d}	0.8225	±3.649
Shares>=25&Seller	21197	-0.1034^{c,d}	<.0001	-0.1992^{c,d}	<.0001	-0.3026^{c,d}	<.0001	±3.156
Shares<25&Seller	627883	-0.2470^{c,d}	<.0001	-0.0340^{c,d}	<.0001	-0.2810^{c,d}	<.0001	±3.654
Value>=100&Seller	9767	-0.0354^{c,d}	0.0003	-0.1488^{c,d}	<.0001	-0.1843^{c,d}	<.0001	±3.032
Value<100&Seller	639313	-0.2455^{c,d}	<.0001	-0.0377^{c,d}	<.0001	-0.2832^{c,d}	<.0001	±3.656
Value>=150&Seller	4572	-0.0380^{c,d}	<.0001	-0.1558^{c,d}	<.0001	-0.1938^{c,d}	<.0001	±2.904
Value<150&Seller	644508	-0.2438^{c,d}	<.0001	-0.0385^{c,d}	<.0001	-0.2823^{c,d}	<.0001	±3.657
Min		-0.2513		-0.1992		-0.3026		
Max		0.1967		0.1978		0.2177		

Table 3.4. Trade price effects for various trade classifications on the BIST for short trades

This table reports the mean price effects in % for various trade classifications for **short** trades on the Borsa Istanbul (BIST) for the 12-month period from April 2008 through March 2009. The temporary, permanent and total effects of a trade on price are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in the first trade second after the trade of interest. The All sample and single-sorted subsamples are drawn from the complete sample of aggregated trade seconds. Buyer and Seller refer to buyer- and seller-initiated trades, respectively. Shares and value refer to the number and dollar value of shares traded in thousands, respectively. The price effects that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.). P-values for the Mann-Whitney-Wilcoxon (MWW p-val.) test examine if the mean price effects are significantly different from zero between the short (this table) and the long (untabulated) trade seconds.

Sample	Shares	Temp. Effect	MWW p-val.	Perm. Effect	MWW p-val.	Total Effect.	MWW p-val.	Bay. t-val.
All	218202	0.1742^{c,d}	<.0001	0.0053^{c,d}	<.0001	0.1795^{c,d}	<.0001	±3.506
ALL Buy	204690	0.1870^{c,d}	<.0001	0.0036^{c,d}	<.0001	0.1906^{c,d}	<.0001	±3.497
ALL Sell	12270	-0.0207^{c,d}	<.0001	0.0300^{c,d}	<.0001	0.0093^{c,d}	<.0001	±3.069
Shares>=15&Buyer	10420	0.0848^{c,d}	<.0001	0.0186^{c,d}	<.0001	0.1033^{c,d}	<.0001	±3.042
Shares<15&Buyer	194270	0.1925^{c,d}	<.0001	0.0028^{c}	<.0001	0.1953^{c,d}	<.0001	±3.490
Shares>=25&Buyer	6134	0.0707^{c,d}	<.0001	0.0191^{c,d}	<.0001	0.0898^{c,d}	<.0001	±2.954
Shares<25&Buyer	198556	0.1906^{c,d}	<.0001	0.0032^{c}	<.0001	0.1937^{c,d}	<.0001	±3.493
Value>=100&Buyer	3142	0.0674^{c,d}	<.0001	0.0224^{c,d}	<.0001	0.0898^{c,d}	<.0001	±2.839
Value<100&Buyer	201548	0.1888^{c,d}	<.0001	0.0034^{c}	<.0001	0.1922^{c,d}	<.0001	±3.495
Value>=150&Buyer	1374	0.0662^{c,d}	<.0001	0.0323^{c,d}	<.0001	0.0986^{c,d}	0.0066	±2.691
Value<150&Buyer	203316	0.1878^{c,d}	<.0001	0.0035^{c,d}	<.0001	0.1912^{c,d}	<.0001	±3.496
Shares>=15&Seller	4299	-0.0251^{c,d}	<.0001	0.0320^{c,d}	<.0001	0.0069^{c,d}	<.0001	±2.893
Shares<15&Seller	7971	-0.0183^{c,d}	<.0001	0.0289^{c,d}	<.0001	0.0106^{c,d}	<.0001	±2.998
Shares>=25&Seller	2962	-0.0296^{c,d}	0.0078	0.0351^{c,d}	<.0001	0.0056^{c,d}	<.0001	±2.829
Shares<25&Seller	9308	-0.0179^{c,d}	<.0001	0.0284^{c,d}	<.0001	0.0105^{c,d}	<.0001	±3.024
Value>=100&Seller	1626	-0.0303^{c,d}	0.5152	0.0365^{c,d}	<.0001	0.0062^{c,d}	<.0001	±2.721
Value<100&Seller	10644	-0.0193^{c,d}	<.0001	0.0290^{c,d}	<.0001	0.0098^{c,d}	<.0001	±3.046
Value>=150&Seller	744	-0.0271^{c,d}	0.1765	0.0293^{c,d}	<.0001	0.0022^{a}	<.0001	±2.575
Value<150&Seller	11526	-0.0203^{c,d}	<.0001	0.0301^{c,d}	<.0001	0.0098^{c,d}	<.0001	±3.059
Min		-0.0303		0.0028		0.0022		
Max		0.1925		0.0365		0.1953		

Table 3.5. Trade price effects for various trade classifications on the BIST for the trader classification M

This table reports the mean price effects in % for various trade classifications for trades of **trader classification M** (institutional and retail clients of the brokerage firms) for the Bolsa Istanbul (BIST) for the 12-month period from April 2008 through March 2009. The temporary, permanent and total effects of a trade on price are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in the first trade second after the trade of interest. The All sample and single-sorted subsamples are drawn from the complete sample of aggregated trade seconds. Buyer and Seller refer to buyer- and seller-initiated trades, respectively. Shares and value refer to the number and dollar value of shares traded in thousands, respectively. The price effects that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.). P-values for the Kruskal and Wallis (KW p-val.) test examine if the mean price effects are significantly different from zero for trader classifications M (this table), P (Table 3.6) and F (Table 3.6).

Sample	Shares	Temp. Effect	KW p-val.	Perm. Effect	KW p-val.	Total Effect	KW p-val.	Bay. t-val.
All	5452075	$0.0056^{c,d}$	<.0001	$0.0009^{c,d}$	<.0001	$0.0065^{c,d}$	<.0001	±3.938
ALL Buy	3150882	$0.1698^{c,d}$	<.0001	$0.0151^{c,d}$	<.0001	$0.1849^{c,d}$	0.0133	±3.868
ALL Sell	2162710	$-0.2308^{c,d}$	<.0001	$-0.0203^{c,d}$	<.0001	$-0.2511^{c,d}$	<.0001	±3.819
Shares>=15&Buyer	265766	$0.0434^{c,d}$	<.0001	$0.0810^{c,d}$	<.0001	$0.1243^{c,d}$	<.0001	±3.534
Shares<15&Buyer	2885116	$0.1815^{c,d}$	<.0001	$0.0090^{c,d}$	<.0001	$0.1905^{c,d}$	<.0001	±3.857
Shares>=25&Buyer	169711	$0.0310^{c,d}$	<.0001	$0.0915^{c,d}$	0.1721	$0.1225^{c,d}$	<.0001	±3.470
Shares<25&Buyer	2981171	$0.1777^{c,d}$	<.0001	$0.0107^{c,d}$	<.0001	$0.1884^{c,d}$	<.0001	±3.861
Value>=100&Buyer	95728	$0.0215^{c,d}$	<.0001	$0.0924^{c,d}$	0.0029	$0.1139^{c,d}$	<.0001	±3.387
Value<100&Buyer	3055154	$0.1745^{c,d}$	<.0001	$0.0127^{c,d}$	<.0001	$0.1871^{c,d}$	<.0001	±3.864
Value>=150&Buyer	51389	$0.0155^{c,d}$	<.0001	$0.1041^{c,d}$	0.0043	$0.1196^{c,d}$	0.0060	±3.294
Value<150&Buyer	3099493	$0.1724^{c,d}$	<.0001	$0.0136^{c,d}$	<.0001	$0.1860^{c,d}$	0.0033	±3.866
Shares>=15&Seller	220281	$-0.0900^{c,d}$	<.0001	$-0.0801^{c,d}$	<.0001	$-0.1701^{c,d}$	<.0001	±3.508
Shares<15&Seller	1942429	$-0.2469^{c,d}$	0.0007	$-0.0135^{c,d}$	<.0001	$-0.2603^{c,d}$	<.0001	±3.805
Shares>=25&Seller	137208	$-0.0708^{c,d}$	<.0001	$-0.0927^{c,d}$	<.0001	$-0.1635^{c,d}$	<.0001	±3.439
Shares<25&Seller	2025502	$-0.2417^{c,d}$	<.0001	$-0.0153^{c,d}$	<.0001	$-0.2571^{c,d}$	<.0001	±3.811
Value>=100&Seller	71766	$-0.0397^{c,d}$	<.0001	$-0.0817^{c,d}$	<.0001	$-0.1214^{c,d}$	0.0090	±3.344
Value<100&Seller	2090944	$-0.2375^{c,d}$	<.0001	$-0.0181^{c,d}$	<.0001	$-0.2556^{c,d}$	<.0001	±3.815
Value>=150&Seller	36627	$-0.0328^{c,d}$	<.0001	$-0.0940^{c,d}$	<.0001	$-0.1268^{c,d}$	0.1288	±3.242
Value<150&Seller	2126083	$-0.2343^{c,d}$	<.0001	$-0.0190^{c,d}$	<.0001	$-0.2533^{c,d}$	<.0001	±3.817
Min		-0.2469		-0.0940		-0.2603		
Max		0.1815		0.1041		0.1905		

Table 3.6. Trade price effects for various trade classifications on the BIST for the trader classifications P and F

This table reports the mean price effects in % for various trade classifications for trades of **trader classification P** (portfolios of the brokerage firms) **and F** (investment funds managed by the brokerage firms) for the Bolsa Istanbul (BIST) for the 12-month period from April 2008 through March 2009. The temporary, permanent and total effects of a trade on price are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in the first trade second after the trade of interest. The All sample and single-sorted subsamples are drawn from the complete sample of aggregated trade seconds. Buyer and Seller refer to buyer- and seller-initiated trades, respectively. Shares and value refer to the number and dollar value of shares traded in thousands, respectively. The price effects that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.).

	Trader Classification P					Trader Classification F				
Sample	Shares	Temp. Effect	Perm. Effect	Total Effect.	Bay. t-val.	Shares	Temp. Effect	Perm. Effect	Total Effect.	Bay. t-val.
All	123274	-0.1021^{c,d}	0.0202^{c,d}	-0.0819^{c,d}	±3.424	103582	-0.1001^{c,d}	0.0188^{c,d}	-0.0812^{c,d}	±3.398
ALL Buy	41293	0.1177^{c,d}	0.0600^{c,d}	0.1777^{c,d}	±3.260	38325	0.1219^{c,d}	0.0528^{c,d}	0.1746^{c,d}	±3.249
ALL Sell	80982	-0.2151^{c,d}	-0.0006	-0.2157^{c,d}	±3.362	64827	-0.2316^{c,d}	-0.0017	-0.2334^{c,d}	±3.329
Shares>=15&Buyer	13277	0.0461^{c,d}	0.0853^{c,d}	0.1315^{c,d}	±3.082	9137	0.0475^{c,d}	0.0908^{c,d}	0.1383^{c,d}	±3.021
Shares<15&Buyer	28016	0.1516^{c,d}	0.0480^{c,d}	0.1996^{c,d}	±3.200	29188	0.1451^{c,d}	0.0409^{c,d}	0.1860^{c,d}	±3.207
Shares>=25&Buyer	8795	0.0312^{c,d}	0.0861^{c,d}	0.1174^{c,d}	±3.014	5580	0.0469^{c,d}	0.0913^{c,d}	0.1381^{c,d}	±2.938
Shares<25&Buyer	32498	0.1411^{c,d}	0.0529^{c,d}	0.1940^{c,d}	±3.223	32745	0.1346^{c,d}	0.0462^{c,d}	0.1809^{c,d}	±3.225
Value>=100&Buyer	6117	0.0360^{c,d}	0.0949^{c,d}	0.1309^{c,d}	±2.954	3172	0.0535^{c,d}	0.0710^{c,d}	0.1246^{c,d}	±2.841
Value<100&Buyer	35176	0.1319^{c,d}	0.0539^{c,d}	0.1858^{c,d}	±3.236	35153	0.1280^{c,d}	0.0511^{c,d}	0.1792^{c,d}	±3.236
Value>=150&Buyer	3088	0.0271^{c,d}	0.1049^{c,d}	0.1321^{c,d}	±2.836	1435	0.0489^{c,d}	0.0755^{c,d}	0.1244^{c,d}	±2.699
Value<150&Buyer	38205	0.1250^{c,d}	0.0564^{c,d}	0.1814^{c,d}	±3.248	36890	0.1247^{c,d}	0.0519^{c,d}	0.1766^{c,d}	±3.243
Shares>=15&Seller	4609	-0.1068^{c,d}	-0.0113^{b}	-0.1181^{c,d}	±2.905	2884	-0.1260^{c,d}	-0.0127	-0.1387^{c,d}	±2.824
Shares<15&Seller	76373	-0.2216^{c,d}	0.0000	-0.2216^{c,d}	±3.353	61943	-0.2366^{c,d}	-0.0012	-0.2378^{c,d}	±3.322
Shares>=25&Seller	2618	-0.0915^{c,d}	-0.0075	-0.0990^{c,d}	±2.807	1337	-0.1133^{c,d}	-0.0167	-0.1300^{c,d}	±2.686
Shares<25&Seller	78364	-0.2192^{c,d}	-0.0004	-0.2196^{c,d}	±3.357	63490	-0.2341^{c,d}	-0.0014	-0.2356^{c,d}	±3.326
Value>=100&Seller	1362	-0.0800^{c,d}	-0.0195^{b}	-0.0995^{c,d}	±2.689	593	-0.0883^{c,d}	-0.0306^{b}	-0.1189^{c,d}	±2.532
Value<100&Seller	79620	-0.2174^{c,d}	-0.0003	-0.2177^{c,d}	±3.359	64234	-0.2330^{c,d}	-0.0015	-0.2344^{c,d}	±3.327
Value>=150&Seller	554	-0.0745^{c,d}	-0.0280^{b}	-0.1025^{c,d}	±2.518	209	-0.0848^{c,d}	-0.0425^{b}	-0.1274^{c,d}	±2.321
Value<150&Seller	80428	-0.2161^{c,d}	-0.0004	-0.2165^{c,d}	±3.361	64618	-0.2321^{c,d}	-0.0016	-0.2337^{c,d}	±3.328
Min		-0.2216	-0.0280	-0.2216			-0.2366	-0.0425	-0.2378	
Max		0.1516	0.1049	0.1996			0.1451	0.0913	0.1860	

Table 3.7. Trade price effects for various trade classifications on the BIST for trade seconds in the last minute of the first and the second sessions

This table reports the mean price effects in % for various trade classifications for trade seconds in the last minute of the first and second sessions in Panels A and B, respectively, for the Borsa Istanbul (BIST) for the 12-month period from April 2008 through March 2009. The temporary, permanent and total effects of a trade on price are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in the first trade second after the trade of interest. The All sample and single-sorted subsamples are drawn from the complete sample of aggregated trade seconds. Buyer and Seller refer to buyer- and seller-initiated trades, respectively. Shares and value refer to the number and dollar value of shares traded in thousands, respectively. The price effects that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.). P-values for the Mann-Whitney-Wilcoxon (MWW p-val.) test examine if the mean price effects are significantly different from zero between the trade seconds in the last minute of the first and last sessions of the trading day (Panels A and B, respectively).

Panel A: Last minute of the first session

Sample	Shares	Temp. Effect	MWW p-val.	Perm. Effect	MWW p-val.	Total Effect	MWW p-val.
All	13600	-0.0017	<.0001	0.0060	<.0001	0.0043	0.0029
ALL Buy	8081	0.1750[c,d]	<.0001	0.0077	<.0001	0.1828[c,d]	<.0001
ALL Sell	4890	-0.2889[c,d]	0.0029	0.0024	0.0024	-0.2865[c,d]	<.0001
Shares>=15 Buyer	1198	0.0947[c,d]	<.0001	0.0100	<.0001	0.1047[c,d]	<.0001
Shares<15Buyer	6883	0.1890[c,d]	<.0001	0.0073	<.0001	0.1963[c,d]	<.0001
Shares>=25 Buyer	829	0.0874[c,d]	<.0001	0.0249[a]	0.0104	0.1123[c,d]	<.0001
Shares<25 Buyer	7252	0.1851[c,d]	<.0001	0.0057	<.0001	0.1908[c,d]	<.0001
Value>=100 Buyer	526	0.0895[c,d]	<.0001	0.0074	0.0023	0.0969[c,d]	<.0001
Value<100 Buyer	7555	0.1810[c,d]	<.0001	0.0077	<.0001	0.1887[c,d]	<.0001
Value>=150 Buyer	290	0.0820[c,d]	<.0001	0.0265	0.1363	0.1084[c,d]	<.0001
Value<150 Buyer	7791	0.1785[c,d]	<.0001	0.0070	<.0001	0.1855[c,d]	<.0001
Shares>=15 Seller	819	-0.2114[c,d]	0.1082	-0.0115	0.4901	-0.2229[c,d]	0.5053
Shares<15 Seller	4071	-0.3045[c,d]	0.0001	0.0052	0.0023	-0.2993[c,d]	<.0001
Shares>=25 Seller	554	-0.2085[c,d]	0.3621	-0.0339	0.2397	-0.2424[c,d]	0.4986
Shares<25 Seller	4336	-0.2992[c,d]	0.0003	0.0070	0.0063	-0.2922[c,d]	<.0001
Value>=100 Seller	335	-0.1798[c,d]	0.5582	-0.0206	0.7439	-0.2004[c,d]	0.9154
Value<100 Seller	4555	-0.2969[c,d]	0.0021	0.0041	0.0016	-0.2928[c,d]	<.0001
Value>=150 Seller	175	-0.1667[c,d]	0.6243	-0.0699[b]	0.2980	-0.2366[c,d]	0.4174
Value<150 Seller	4715	-0.2934[c,d]	0.0014	0.0051	0.0043	-0.2884[c,d]	<.0001
Min		-0.3045		-0.0699		-0.2993	
Max		0.1890		0.0265		0.1963	

Table 3.7, Panel B

Panel B: Last minute of the second session				
Sample	Shares	Temp. Effect	Perm. Effect	Total Effect.
All	77235	-0.0214[c,d]	0.0378[c,d]	0.0164[c,d]
ALL Buy	34149	0.2500[c,d]	0.0516[c,d]	0.3016[c,d]
ALL Sell	34607	-0.2819[c,d]	0.0224[c,d]	-0.2595[c,d]
Shares>=15 Buyer	4099	0.1864[c,d]	0.0827[c,d]	0.2692[c,d]
Shares<15Buyer	30050	0.2587[c,d]	0.0473[c,d]	0.3060[c,d]
Shares>=25 Buyer	2563	0.1878[c,d]	0.0845[c,d]	0.2723[c,d]
Shares<25 Buyer	31586	0.2551[c,d]	0.0489[c,d]	0.3039[c,d]
Value>=100 Buyer	1569	0.1594[c,d]	0.0857[c,d]	0.2451[c,d]
Value<100 Buyer	32580	0.2544[c,d]	0.0499[c,d]	0.3043[c,d]
Value>=150 Buyer	810	0.1859[c,d]	0.0849[c,d]	0.2708[c,d]
Value<150 Buyer	33339	0.2516[c,d]	0.0508[c,d]	0.3023[c,d]
Shares>=15 Seller	6263	-0.2571[c,d]	-0.0028	-0.2600[c,d]
Shares<15 Seller	28344	-0.2873[c,d]	0.0279[c,d]	-0.2594[c,d]
Shares>=25 Seller	3660	-0.2510[c,d]	-0.0125	-0.2636[c,d]
Shares<25 Seller	30947	-0.2855[c,d]	0.0265[c,d]	-0.2590[c,d]
Value>=100 Seller	2055	-0.1751[c,d]	-0.034[c,d]	-0.2101[c,d]
Value<100 Seller	32552	-0.2886[c,d]	0.0260[c,d]	-0.2626[c,d]
Value>=150 Seller	1061	-0.1894[c,d]	-0.036[c,d]	-0.2253[c,d]
Value<150 Seller	33546	-0.2848[c,d]	0.0242[c,d]	-0.2606[c,d]
Min		-0.2886	-0.0360	-0.2636
Max		0.2587	0.0857	0.3060

Table 3.8. Summary statistics for the regressors used in the pooled regressions

This table reports summary statistics for the regressors used in the pooled regressions for the trade seconds not differentiated by trade initiator (mixed) and differentiated by buyer- and seller-initiated trades. A clean trade second is one where all the trades in that trade second are exclusively buyer- or seller-initiated (i.e., not mixed as they do not contain both). $ln\left(MktCap_{i-1,j}\right)$ is the natural log of the market cap of firm j for the trade second immediately prior to trade second i for firm j divided by 1,000,000. $RelSpd_{i-1,j}$ is the relative half-spread (i.e., bid-ask spread divided by quote-midpoint) that occurs immediately prior to trade second i for firm j. $ln\left(TradeVal_{i,j}\right)$ is the natural log of the dollar value of shares traded in second i for firm j in TRY (Turkish Lira) divided by 1,000,000. $Mom[-5:-1]_{i,j}$ is the lagged cumulative (compounded) daily return for firm j over the five trading days prior to trade second i for firm j. $SD_{d-1,j}$ is the standard deviation of trade-to-trade prices on the trading day prior to the trading day d of the trade second i for firm j. $Tleft_{i,j,d}$ is the number of hours of trading time (excluding the lunch break) left until the end of trading after trade second i for firm j for that trading day d. $R_{M,d}$ is the market return for the ISE-100 Index (now BIST-100) for day d. $OFI_{i-1,j}$ is the Order Flow Imbalance which is the difference between the volume at the best ask and the volume at best bid for the trade second immediately prior to trade second i for firm j. The OFI values have been divided by 1000 for presentation purposes. D_1 and D_2 are dummy variables that are equal to one if trade second i is in the last minute and the last two through five minutes of the afternoon trading session, respectively, and zero otherwise.

	Mixed full sample (N = 5,793,148)					Clean buyer-initiated sample (N = 3,226,935)					Clean seller-initiated sample (N = 2,408,524)				
Variable	Mean	Median	Std Dev	Min.	Max.	Mean	Median	Std Dev	Min.	Max.	Mean	Median	Std Dev	Min.	Max.
$MktCap$	6084.51	4135.72	5996.67	26.00	31290.00	5910.24	3791.08	5970.90	26.00	31290.00	6224.96	4296.55	6034.19	26.00	31080.00
ln ($MktCap$)	7.9708	8.3274	1.4353	3.2581	10.3511	7.9206	8.2404	1.4489	3.2581	10.3511	8.0116	8.3656	1.4182	3.2581	10.3443
$RelSpd$	0.0118	0.0063	0.0883	0.0015	2.0000	0.0120	0.0064	0.0862	0.0037	2.0000	0.0118	0.0063	0.0929	0.0015	2.0000
$TradeVal$	0.0371	0.0020	0.2105	>0.0000	179.3510	0.0313	0.0013	0.1570	>0.0000	26.7302	0.0394	0.0027	0.2566	>0.0000	179.3510
ln ($TradeVal$)	-6.7039	-6.2146	3.2917	-15.1626	5.1893	-7.0548	-6.6238	3.3116	-15.1248	3.2858	-6.3863	-5.9276	3.2040	-15.1626	5.1893
$Mom[-5:-1]$	-0.0168	-0.0127	0.0889	-0.3602	0.3583	-0.0210	-0.0174	0.0889	-0.3602	0.3583	-0.0109	-0.0066	0.0882	-0.3602	0.3583
SD	0.0041	0.0035	0.0022	0	0.0342	0.0042	0.0035	0.0023	0	0.0342	0.0040	0.0034	0.0021	0	0.0342
$Tleft$	2.7332	2.7031	1.7656	0.0003	5.7489	2.7702	2.7439	1.7484	0.0003	5.7489	2.6795	2.6378	1.7742	0.0003	5.7472
$R_{M,d}$	-0.0006	-0.0004	0.0314	-0.0861	0.1289	-0.0013	-0.0008	0.0315	-0.0861	0.1289	0.0004	0.0002	0.0309	-0.0861	0.1289
OFI	-25.69	-0.12	665.31	-20470.62	6701.23	-120.06	-19.56	677.90	-20470.62	6609.53	99.76	30.05	618.63	-20067.26	6382.53
$D1 \times OFI$	0.0001	0.0000	0.0010	0.0000	0.0164	0.0001	0.0000	0.0009	0.0000	1.0000	0.0001	0.0000	0.0011	0.0000	0.0164
$D2 \times OFI$	0.0013	0.0000	0.0085	0.0000	0.0831	0.0012	0.0000	0.0080	0.0000	1.0000	0.0015	0.0000	0.0090	0.0000	0.0831
$D1$	0.0145	0.0000	0.1195	0.0000	1.0000	0.0115	0.0000	0.1065	0.0000	1.0000	0.0159	0.0000	0.1250	0.0000	1.0000
$D2$	0.0285	0.0000	0.1665	0.0000	1.0000	0.0243	0.0000	0.1541	0.0000	1.0000	0.0332	0.0000	0.1790	0.0000	1.0000

Table 3.9. Summary pooled regression results for the three types of price effects for the clean buyer- and seller-initiated samples

This table reports the summary results from the pooled regressions for the temporary, permanent and total price effects for the clean samples of buyer- and seller-initiated trade seconds. A clean trade second is one where all the trades in that trade second are exclusively buyer- or seller-initiated (i.e., not mixed in that they do not contain both). These price effects are given by $\ln(P_{trade}/P_{post})$, $\ln(P_{post}/P_{prior})$ and $\ln(P_{trade}/P_{prior})$, respectively, where P_{trade} is the price in the trade second whose trade effect is being assessed, P_{prior} is the price in the trade-second before the trade second of interest, and P_{post} is the price in the first trade second after the trade of interest. $ln(MktCap_{i-1,j})$ is the natural log of the market cap of firm j for the trade second immediately prior to trade second i for firm j divided by 1,000,000. $RelSpd_{i-1,j}$ is the relative half-spread (i.e., bid-ask spread divided by quote-midpoint) that occurs immediately prior to trade second i for firm j. $ln(TradeVal_{i,j})$ is the natural log of the dollar value of shares traded in second i for firm j in TRY (Turkish Lira) divided by 1,000,000. $Mom[-5:-1]_{i,j}$ is the lagged cumulative (compounded) daily return for firm j over the five trading days prior to trade second i for firm j. $SD_{d-1,j}$ is the standard deviation of trade-to-trade prices on the trading day prior to the trading day d of the trade second i for firm j. $Tleft_{i,j,d}$ is the number of hours of trading time (excluding the lunch break) left until the end of trading after trade second i for firm j for that trading day d. $R_{M,d}$ is the market return for the ISE-100 Index (now BIST-100) for day d. $OFI_{i-1,j}$ is the Order Flow Imbalance which is the difference between the volume at the best ask and the volume at best bid for the trade second immediately prior to trade second i for firm j. D_1 and D_2 are dummy variables that are equal to one if trade second i is in the last minute and the last two through five minutes of the afternoon trading session, respectively, and zero otherwise. As indicated in the table, a number of coefficients have been multiplied by 1000 or one million for presentation purposes. The coefficient estimates that are significantly different from zero are indicated by superscripts a, b and c for the 10%, 5% and 1% levels, respectively, based on traditional critical t-values and by the superscript d for significance based on the Bayesian adjusted critical t-values (Bay. t-val.).

	Buyer-initiated						Seller-initiated					
Item	Temp.	V ≥100K	Perm.	V≥100K	Total	V≥100K	Temp.	V≥100K	Perm.	V≥100K	Total	V≥100K
Mean Effect	16.79	2.15	1.62	9.00	18.41	11.15	-22.21	-2.47	-2.34	-10.34	-24.55	-12.81
Intercept	-0.0016^{c,d}	-0.0028^{c,d}	0.0005^{c,d}	0.0045^{c,d}	-0.0011^{c,d}	0.0018^{c,d}	0.0020^{c,d}	0.0020^{c,d}	-0.0008^{c,d}	-0.0042^{c,d}	0.0013^{c,d}	-0.0022^{c,d}
ln $(MktCap)$ x 10^3	0.0673^{c,d}	0.2505^{c,d}	-0.0287^{c,d}	-0.3844^{c,d}	0.0386^{c}	-0.1335^{c,d}	-0.0161	-0.1252^{c,d}	0.0415^{c,d}	0.3335^{c,d}	0.0255	0.2083^{c,d}
$RelSpd$	-0.0013^{c,d}	0.0001	-0.0001^{c,d}	0.0003	-0.0014^{c,d}	0.0004	0.0016^{c,d}	0.0000	0.0002^{c}	0.0005^{c}	0.0018^{c,d}	0.0005^{c,d}
ln $(TradeValue)$ x 10^3	-0.1924^{c,d}	-0.4020^{c,d}	0.0249^{c,d}	0.5774^{c,d}	-0.1671^{c,d}	0.1753^{c,d}	0.2678^{c,d}	0.5217^{c,d}	-0.0446^{c,d}	-0.7005^{c,d}	0.2232^{c,d}	-0.1788^{c,d}
$Mom[-5:-1]$ x 10^3	1.2488^{c,d}	0.6622^{c,d}	0.0782^{c,d}	0.7176^{c,d}	1.3269^{c,d}	1.3798^{c,d}	1.1086^{c,d}	0.6107^{c,d}	0.2292^{c,d}	0.2388	1.3378^{c,d}	0.8495^{c,d}
SD	0.3711^{c,d}	0.0556^{c,d}	0.0115^{c,d}	0.1671^{c,d}	0.3826^{c,d}	0.2227^{c,d}	-0.5965^{c,d}	-0.0982^{c,d}	-0.0137^{c,d}	-0.2169^{c,d}	-0.6102^{c,d}	-0.3152^{c,d}
$Tleft$ x 10^3	-0.0217^{c,d}	-0.0163^{c}	0.0005	0.0018	-0.0211^{c}	-0.0018^{b}	-0.0232^{c,d}	-0.0009	-0.0169^{c,d}	-0.0291^{c,d}	-0.0400^{c,d}	-0.0301^{c,d}
$R_{M,d}$ x 10^3	0.4406	2.8195^{c,d}	0.1767^{b}	-0.4394	0.6174	2.3801^{c,d}	1.3386^{c}	-0.6602^{a}	2.0963^{c,d}	3.4013^{c,d}	3.4349^{c,d}	2.7411^{c,d}
OFI x 10^6	0.0004^{c,d}	-0.0002^{c,d}	0.0001^{c,d}	0.0004^{c,d}	0.0005^{c,d}	0.0002^{c,d}	0.0005^{c,d}	-0.0004^{c,d}	0.0002^{c,d}	0.0005^{c,d}	0.0007^{c,d}	0.0002^{c,d}
$Tleft \times D1$	0.1036^{c,d}	0.1048^{c,d}	0.0101^{c,d}	0.0075	0.1138^{c,d}	0.1123^{c,d}	-0.0486^{c,d}	-0.1176^{c,d}	0.030^{c,d}	0.0526^{c,d}	-0.0186^{c,d}	-0.0650^{c,d}
$Tleft \times D2$	0.0134^{c,d}	0.0137^{c,d}	-0.0011^{c,d}	0.0011	0.0123^{c,d}	0.0125^{c,d}	-0.0040^{c,d}	-0.0087^{c,d}	0.0018^{c,d}	0.0037^{c}	-0.0022^{c,d}	-0.0050^{c,d}
N	3226935	110242	3226935	110242	3226935	110242	2408524	102115	2408524	102115	2408524	102115
Adj. R^2	0.0832	0.0325	0.0006	0.0389	0.0866	0.0228	0.1503	0.0386	0.0019	0.0490	0.1583	0.0223
Bay. t-val.	±3,871		±3,871		±3,871	±3,407	±3,833		±3,833		±3,833	±3,396

Table 4.1. Summary statistics for the price-limit hits on the BIST

This table reports the number of price-limit hits triggered at the upper and lower price limits in total and for various categories for the stocks in the BIST-50 during the thirteen months from March 2008 to March 2009, inclusive. The categories are price-limit hits triggered during the first and last 30 minutes of each session, and price-limit hits that remained in effect at the close of trading for the session during which they were triggered.

Price-limit at:	Total	First Session: First 30 minutes	First Session: Last 30 minutes	Second Session: First 30 minutes	Second Session: Last 30 minutes	Still in place at close
Lower	328	133	29	16	30	79
Upper	267	77	30	9	39	127

Table 4.2. Number of trade seconds for the sample of price-limit hits on the BIST

This table reports the distribution of the number of trade seconds in the 30-minute periods before and after the sample of price-limit hits at the upper and lower price limits on the BIST. The left or right bracket (parenthesis) indicates that its adjacent value is included (not included). To illustrate, [5, 12) indicates that the number of trade seconds begins with 5 but does not include 12.

Number of trade seconds	Lower Price-limit Hits: Pre-hit	Lower Price-limit Hits: Post-hit	Upper Price-limit Hits: Pre-hit	Upper Price-limit Hits: Post-hit
[7, 12)	3	1	1	0
[12, 30)	26	25	14	7
[30, 60)	70	45	40	32
[60, 120)	93	90	70	63
[120, 240)	87	100	83	70
[240,480]	39	55	49	76
(480, ∞]	10	12	10	19
Total	328	328	267	267

Table 4.3. Volatility changes around limit hits that are triggered by the down limit

This table reports various summary statistics for estimates for five volatility measures in the pre- and post-thirty minute windows centered on limit hits triggered by hitting a down limit. The volatility values and tests thereof reported in the third column for each volatility measure are based on the paired difference in the post- minus pre-windows for each limit hit. Panels A, B, C and D present the results for the full sample, the hits in the first 30 minutes of the first session, the hits in the last 30 minutes of the first and second sessions, and the locks that are still in place at the end of a session's trading. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	Vol_{1ij}			Vol_{2ij}			Vol_{3ij}			Vol_{4ij}			Vol_{5ij}		
	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.
Panel A: All price-limit hits triggered by hitting the lower price limit (N = 328)															
Mean	1.2189	1.0333	-0.1855	0.9391	0.8180	-0.1211	3.6568	3.1001	-0.5567	0.0842	0.0590	-0.0251	4.9711	4.1887	-0.7824
Median	0.9277	0.8389	-0.0240	0.7707	0.6751	-0.0400	2.7831	2.5167	-0.0730	0.0314	0.0264	-0.0010	3.9000	3.5719	0.0001
Std. Dev.	0.8666	0.6656	0.9202	0.6252	0.5313	0.6770	2.5999	1.9969	2.7607	0.1216	0.0993	0.1116	3.5223	2.6337	4.1306
Min	0.0000	0.0000	-4.0643	0.0000	0.0000	-2.5890	0.0000	0.0000	-12.1930	0.0000	0.0000	-0.6544	0.4750	0.4106	-14.7630
Max	4.3052	5.0717	2.3239	3.3907	4.2864	1.6132	12.9150	15.2150	6.9719	0.7001	0.7196	0.3541	15.9060	22.8630	12.4060
Skewness	1.21	1.91	-0.98	1.11	2.09	-0.52	1.21	1.91	-0.98	2.50	3.99	-1.78	0.74	1.99	-0.25
Kurtosis	0.88	5.95	2.03	1.05	7.59	1.13	0.88	5.95	2.03	6.91	18.95	7.96	-0.53	8.26	0.41
t-test	25.47	28.12	-3.65	27.20	27.88	-3.24	25.47	28.12	-3.65	12.54	10.76	-4.08	25.56	28.80	-3.43
p-value	<.0001	<.0001	0.0003	<.0001	<.0001	0.0013	<.0001	<.0001	0.0003	<.0001	<.0001	<.0001	<.0001	<.0001	0.0007
Wilcoxon	26814	26163	-3750	26814	26163	-4415	26814	26163	-3749	25680	26163	-4147	26978	26978	-4447
p-value	<.0001	<.0001	0.0289	<.0001	<.0001	0.0100	<.0001	<.0001	0.0289	<.0001	<.0001	0.0156	<.0001	<.0001	0.0068
Panel B: Price-limit hits triggered by hitting the lower price limit during the first 30 minutes of the first session (N = 133)															
Mean	1.5319	0.9881	-0.5438	1.1362	0.7876	-0.3486	4.5959	2.9644	-1.6315	0.1152	0.0480	-0.0671	6.2897	4.1687	-2.1209
Median	1.2872	0.8149	-0.1600	1.1029	0.6435	-0.1860	3.8615	2.4447	-0.4790	0.0574	0.0239	-0.0160	5.9423	3.6534	-1.5380
Std. Dev.	1.0068	0.5544	1.1113	0.6948	0.4399	0.7842	3.0206	1.6633	3.3340	0.1330	0.0731	0.1381	4.1189	2.6615	4.6758
Min	0.0000	0.0000	-4.0643	0.0000	0.0000	-2.5890	0.0000	0.0000	-12.1930	0.0000	0.0000	-0.6544	0.4751	0.4106	-14.7630
Max	4.3052	3.1013	1.5936	3.1234	2.3555	1.4337	12.9150	9.3040	4.7809	0.6580	0.5846	0.3541	15.9060	22.8630	12.4060
Skewness	0.53	1.20	-0.71	0.41	1.17	-0.43	0.53	1.20	-0.71	1.74	4.28	-1.53	0.17	2.91	-0.06
Kurtosis	-0.66	1.43	0.31	-0.63	1.46	0.18	-0.66	1.43	0.31	3.38	24.39	4.59	-1.39	17.36	-0.13
t-test	17.55	20.55	-5.64	18.86	20.65	-5.13	17.55	20.55	-5.64	9.99	7.58	-5.60	17.61	18.06	-5.23
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Wilcoxon	4389	4389	-1975	4389	4389	-1913	4389	4389	-1975	4323	4389	-2103	4456	4456	-1952
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 4.3. Cont'd

	Vol_{1ij}			Vol_{2ij}			Vol_{3ij}			Vol_{4ij}			Vol_{5ij}		
	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.
Panel C: Price-limit hits triggered by hitting the lower price limit during the last 30 minutes of the first and second session (N =59)															
Mean	0.8745	1.1086	0.2340	0.7008	0.8533	0.1525	3.3258	0.7022	3.3258	0.0462	0.0630	0.0168	3.3901	4.4684	1.0782
Median	0.7037	0.9650	0.2821	0.5971	0.7788	0.1675	2.8951	0.8462	2.8951	0.0210	0.0321	0.0085	2.7588	4.2111	1.0363
Std. Dev.	0.5304	0.6550	0.6598	0.4084	0.4834	0.5161	1.9650	1.9794	1.9650	0.0813	0.0929	0.0947	2.5077	2.2351	3.0782
Min	0.2736	0.0000	-2.2153	0.2261	0.0000	-1.8054	0.0000	-6.6460	0.0000	0.0000	0.0000	-0.4108	0.5089	1.3245	-10.6130
Max	2.7214	3.3096	2.3239	1.8237	2.5760	1.6132	9.9288	6.9719	9.9288	0.4548	0.5049	0.3184	13.5540	10.9190	7.2831
Skewness	1.72	1.21	-0.44	1.49	1.35	-0.78	1.21	-0.44	1.21	3.63	3.06	-0.96	2.17	0.86	-0.86
Kurtosis	2.92	1.97	3.96	1.80	2.93	3.44	1.97	3.96	1.97	14.24	10.39	9.59	6.28	0.50	2.93
t-test	12.66	13.00	2.72	13.18	13.56	2.27	13.00	2.72	13.00	4.36	5.22	1.37	10.38	15.36	2.69
p-value	<.0001	<.0001	0.0085	<.0001	<.0001	0.0269	<.0001	0.0085	<.0001	<.0001	<.0001	0.1762	<.0001	<.0001	0.0093
Wilcoxon	885	827	434	885	827	384	827	434	827	827	827	406	885	885	415
p-value	<.0001	<.0001	0.0007	<.0001	<.0001	0.0030	<.0001	0.0007	<.0001	<.0001	<.0001	0.0016	<.0001	<.0001	0.0009
Panel D: Price-limit hits triggered by hitting the lower price limit during the trading day that were in place at market close (N = 79)															
Mean	0.9923	0.9931	0.0007	0.8012	0.7837	-0.0175	2.9771	2.9794	0.0023	0.0573	0.0462	-0.0110	4.2072	4.2810	0.0738
Median	0.8166	0.8558	0.0412	0.6857	0.6699	-0.0110	2.4497	2.5673	0.1236	0.0264	0.0295	0.0020	3.4786	3.8319	0.1896
Std. Dev.	0.6519	0.4945	0.6794	0.5159	0.3970	0.5593	1.9559	1.4837	2.0384	0.0793	0.0508	0.0689	3.1609	2.1062	3.2457
Min	0.0000	0.0000	-2.2153	0.0000	0.0000	-1.8054	0.0000	0.0000	-6.6460	0.0000	0.0000	-0.2545	0.5509	0.8439	-8.5282
Max	3.0249	2.4245	1.6548	2.4484	2.0679	1.3113	9.0749	7.2735	4.9645	0.4565	0.3094	0.1437	13.6570	11.0000	7.8400
Skewness	1.36	0.89	-0.58	1.26	0.89	-0.47	1.36	0.89	-0.58	2.74	2.59	-1.58	0.97	0.81	-0.11
Kurtosis	1.49	0.34	1.49	1.54	0.51	1.35	1.49	0.34	1.49	8.92	9.00	3.70	0.12	0.79	0.07
t-test	13.53	17.85	0.01	13.80	17.55	-0.28	13.53	17.85	0.01	6.42	8.09	-1.43	11.83	18.07	0.20
p-value	<.0001	<.0001	0.9919	<.0001	<.0001	0.7817	<.0001	<.0001	0.9919	<.0001	<.0001	0.1579	<.0001	<.0001	0.8403
Wilcoxon	1541	1541	100	1541	1541	-19	1541	1541	100	1463	1541	-25	1580	1580	107
p-value	<.0001	<.0001	0.6281	<.0001	<.0001	0.9267	<.0001	<.0001	0.6281	<.0001	<.0001	0.9037	<.0001	<.0001	0.6042

Table 4.4. Volatility changes around limit hits that are triggered at an upper limit

This table reports various summary statistics for estimates for five volatility measures in the pre- and post-thirty minute windows centered on limit limits triggered by hitting an upper limit. Each volatility value is based on ten 3-minute returns. The volatility values and tests thereof reported in the third column for each volatility measure are based on the paired difference in the post- minus pre-windows for each limit hit. Panels A, B, C and D present the results for the full sample, the hits in the first 30 minutes of the first session, the hits in the last 30 minutes of the first and second sessions, and the locks that are still in place at the end of the session's trading. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	Vol_{1ij}			Vol_{2ij}			Vol_{3ij}			Vol_{4ij}			Vol_{5ij}		
	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.
Panel A: All price-limit hits triggered by hitting the upper price limit (N = 267)															
Mean	1.1232	0.9166	-0.2065	0.8700	0.7360	-0.1340	3.3696	2.7500	-0.6196	0.0762	0.0450	-0.0311	5.0221	3.7484	-1.2737
Median	0.8837	0.7542	-0.0880	0.7167	0.6212	-0.0710	2.6512	2.2627	-0.2640	0.0279	0.0192	-0.0040	4.0822	3.3006	-0.4320
Std. Dev.	0.8032	0.5745	0.8375	0.5561	0.4653	0.6041	2.4097	1.7237	2.5127	0.1193	0.0838	0.1232	3.5815	2.4821	4.2918
Min	0.0000	0.0000	-3.5436	0.0000	0.0000	-2.1666	0.0000	0.0000	-10.6310	0.0000	0.0000	-0.6130	0.0000	0.0000	-13.5540
Max	4.1825	4.8243	3.0833	2.9430	4.1378	3.0217	12.5470	14.4730	9.2499	0.6775	0.8783	0.8086	16.9680	28.5380	24.5210
Skewness	1.59	2.52	-1.22	1.20	2.75	-0.22	1.59	2.52	-1.22	2.93	5.82	-0.81	1.00	4.59	0.11
Kurtosis	2.63	10.44	4.03	1.31	12.88	3.59	2.63	10.44	4.03	9.44	46.06	14.40	0.48	38.68	4.86
t-test	22.85	26.07	-4.03	25.56	25.84	-3.62	22.85	26.07	-4.03	10.44	8.78	-4.13	22.91	24.68	-4.85
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0003	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Wilcoxon	17490	17490	-3929	17490	17490	-4052	17490	17490	-3928	17227	17227	-5750	17490	17756	-5149
p-value	<.0001	<.0001	0.0017	<.0001	<.0001	0.0012	<.0001	<.0001	0.0017	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel B: Price-limit hits triggered by hitting the upper price limit during the first 30 minutes of the first session (N = 77)															
Mean	1.6734	1.1015	-0.5718	1.2451	0.8870	-0.3580	5.0202	3.3046	-1.7155	0.1530	0.0698	-0.0831	7.5360	4.2237	-3.3123
Median	1.4036	0.8875	-0.3730	1.1710	0.6478	-0.3320	4.2109	2.6626	-1.1180	0.0918	0.0240	-0.0400	7.1263	3.3738	-2.6390
Std. Dev.	1.0291	0.8008	1.2429	0.6502	0.6575	0.8415	3.0875	2.4025	3.7287	0.1699	0.1322	0.2010	4.1699	3.7964	5.9409
Min	0.2955	0.2929	-3.5436	0.1393	0.2382	-2.1666	0.8866	0.8787	-10.6310	0.0043	0.0000	-0.6130	0.9852	0.9302	-13.5540
Max	4.1825	4.8243	3.0833	2.9430	4.1378	3.0217	12.5470	14.4730	9.2499	0.6698	0.8783	0.8086	16.9680	28.5380	24.5210
Skewness	0.81	2.29	-0.50	0.51	2.45	0.43	0.81	2.29	-0.50	1.52	4.34	0.20	0.38	4.07	1.06
Kurtosis	-0.27	6.47	0.68	-0.46	7.78	2.50	-0.27	6.47	0.68	1.46	21.96	5.38	-0.79	22.40	4.99
t-test	14.27	12.07	-4.04	16.80	11.84	-3.73	14.27	12.07	-4.04	7.90	4.64	-3.63	15.86	9.76	-4.89
p-value	<.0001	<.0001	0.0001	<.0001	<.0001	0.0004	<.0001	<.0001	0.0001	<.0001	<.0001	0.0005	<.0001	<.0001	<.0001
Wilcoxon	1502	1502	-707	1502	1502	-742	1502	1502	-707	1502	1463	-866	1502	1502	-947
p-value	<.0001	<.0001	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 4.4. Cont'd

	Vol_{1ij}			Vol_{2ij}			Vol_{3ij}			Vol_{4ij}			Vol_{5ij}		
	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.
Panel C: Price-limit hits triggered by hitting the upper price limit during the last 30 minutes of the first and second session (N =69)															
Mean	0.8333	0.8120	-0.0213	0.6686	0.6536	-0.0149	2.5001	2.4362	-0.0639	2.5001	2.4362	-0.0639	3.8745	3.5197	-0.3547
Median	0.7210	0.7539	0.0570	0.6075	0.6176	0.0190	2.1630	2.2617	0.1720	2.1630	2.2617	0.1720	3.3152	2.9853	-0.1240
Std. Dev.	0.4812	0.3753	0.4274	0.3687	0.2873	0.3640	1.4437	1.1259	1.2824	1.4437	1.1259	1.2824	2.6014	1.5372	2.4438
Min	0.2108	0.0000	-1.1448	0.1266	0.0000	1.3285	0.6324	0.0000	-3.4345	0.6324	0.0000	-3.4345	0.3944	1.1173	-8.8292
Max	2.2271	2.1165	1.1339	1.7439	1.4110	0.7918	6.6815	6.3497	3.4017	6.6815	6.3497	3.4017	12.9670	7.3025	5.4884
Skewness	1.00	0.91	-0.27	0.89	0.58	-0.76	1.00	0.91	-0.27	1.00	0.91	-0.27	0.93	0.67	-0.67
Kurtosis	0.39	1.39	0.39	0.52	0.10	1.89	0.39	1.39	0.39	0.39	1.39	0.39	0.84	-0.28	1.50
t-test	14.38	17.97	-0.41	15.06	18.90	-0.34	14.38	17.97	-0.41	14.38	17.97	-0.41	12.37	19.02	-1.21
p-value	<.0001	<.0001	0.6803	<.0001	<.0001	0.7338	<.0001	<.0001	0.6803	<.0001	<.0001	0.6803	<.0001	<.0001	0.2321
Wilcoxon	1208	1173	-15	1208	1173	17	1208	1208	-15	1208	1208	-15	1208	1208	-152
p-value	<.0001	<.0001	0.9317	<.0001	<.0001	0.9223	<.0001	<.0001	0.9317	<.0001	<.0001	0.9317	<.0001	<.0001	0.3568
Panel D: Price-limit hits triggered by hitting the upper price limit during the trading session that were in place at the session's close (N = 127)															
Mean	0.9878	0.9412	-0.0465	0.7784	0.7690	-0.0093	2.9635	2.8238	-0.1397	0.0594	0.0405	-0.0189	4.0992	4.3811	0.2818
Median	0.7779	0.8715	0.0890	0.6349	0.6871	0.0650	2.3337	2.6146	0.2680	0.0226	0.0230	0.0010	2.9342	3.8915	0.8883
Std. Dev.	0.7463	0.4775	0.7562	0.5395	0.3904	0.5237	2.2390	1.4327	2.2686	0.1086	0.0486	0.1009	3.2295	2.8673	4.1303
Min	0.0000	0.0000	-3.2644	0.0000	0.0000	-1.8696	0.0000	0.0000	-9.7933	0.0000	0.0000	-0.6130	0.0000	0.0000	-12.9330
Max	4.1825	2.8184	1.3678	2.9430	2.5124	0.9639	12.5470	8.4553	4.1036	0.6698	0.3003	0.1393	16.9680	28.5380	24.5210
Skewness	1.96	1.34	-1.67	1.61	1.51	-1.15	1.96	1.34	-1.67	4.03	2.70	-3.95	1.55	5.07	0.82
Kurtosis	4.89	2.86	4.83	3.16	3.73	2.11	4.89	2.86	4.83	18.44	8.77	19.72	2.59	39.81	9.82
t-test	14.92	22.21	-0.69	16.26	22.20	-0.20	14.92	22.21	-0.69	6.17	9.39	-2.11	14.30	17.22	0.77
p-value	<.0001	<.0001	0.4890	<.0001	<.0001	0.8402	<.0001	<.0001	0.4890	<.0001	<.0001	0.0365	<.0001	<.0001	0.4433
Wilcoxon	3875	3938	296	3875	3938	387	3875	3938	296	3813	3938	-185	4001	4001	730
p-value	<.0001	<.0001	0.4785	<.0001	<.0001	0.3538	<.0001	<.0001	0.4785	<.0001	<.0001	0.6580	<.0001	<.0001	0.0789

Table 4.5. Changes in mean returns around price-limit hits that are triggered by hitting lower and upper price limits

This table reports various summary statistics for estimates of the mean returns in the pre- and post-30 minute windows centered on price-limit hits for four samples (full sample, hits in first 30 minutes of first session, hits in last 30 minutes of first and second sessions, and locks that are still in place at the end of a trading session). The values and tests thereof reported in the third column for each sample are based on the paired difference in the post- minus pre-window mean returns for each price-limit hit. Panels A and B present summary results for the price-limit hits triggered by hitting lower and upper price limits, respectively. N is the sample size. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	All			During first 30 min. of first session			During last 30 min. of first & second session			During the trading session and still in place at session's close		
	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.
Panel A: Price-limit hits triggered by hitting an lower price limit												
Mean	-0.3843	0.0769	0.4612	-0.4804	0.0791	0.5595	-0.2375	0.0086	0.2461	-0.3237	-0.0384	0.2852
Median	-0.2740	0.0873	0.3872	-0.4450	0.0985	0.5504	-0.2080	0.0000	0.3052	-0.2350	-0.0560	0.2817
Std. Dev.	0.3633	0.2560	0.4624	0.4650	0.2347	0.5394	0.1806	0.2815	0.3015	0.3371	0.2502	0.4467
Min	-1.5906	-0.7410	-1.3003	-1.5906	-0.7410	-1.3003	-0.8388	-0.6959	-0.4533	-1.2588	-0.7410	-1.3003
Max	0.6632	1.3883	1.8050	0.6632	0.6394	1.7049	0.0000	0.7410	1.0086	0.6632	0.5043	1.3916
Skewness	-0.58	0.17	0.19	-0.08	-0.81	-0.23	-0.99	-0.02	-0.17	-0.53	-0.11	-0.18
Kurtosis	-0.35	3.18	0.02	-1.18	1.49	-0.25	1.16	0.29	0.00	0.50	0.56	1.34
t-test	-19.16	5.44	18.06	-11.91	3.89	11.96	-10.10	0.24	6.27	-8.53	-1.37	5.68
p-value	<.0001	<.0001	<.0001	<.0001	0.0002	<.0001	<.0001	0.8143	<.0001	<.0001	0.1758	<.0001
Wilcoxon	-24131	9152	23216	-3825	1651	3830	-827	24	650	-1407	-266	1049
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.8538	<.0001	<.0001	0.1448	<.0001
N			328			133			59			79
Panel B: Price-limit hits triggered by hitting an upper price limit												
Mean	0.4082	-0.0998	-0.5080	0.6019	-0.1318	-0.7338	0.3307	-0.0629	-0.3937	0.3160	-0.0714	-0.3874
Median	0.2985	-0.1200	-0.4070	0.5884	-0.1310	-0.8000	0.2817	-0.0820	-0.3180	0.2208	-0.0840	-0.3050
Std. Dev.	0.3625	0.2259	0.4406	0.4635	0.2703	0.5151	0.2687	0.2257	0.3526	0.3256	0.2561	0.4114
Min	-0.1612	-0.7796	-1.9151	-0.1612	-0.7796	-1.9151	-0.0579	-0.4467	-1.6404	-0.1593	-0.7796	-1.9151
Max	1.6285	1.1523	0.6116	1.6285	1.1523	0.6116	1.2967	0.7061	0.3946	1.6285	0.7145	0.3946
Skewness	0.94	0.91	-0.51	0.25	1.37	0.14	0.93	0.81	-0.96	1.53	0.23	-1.05
Kurtosis	0.51	4.27	-0.19	-0.69	7.05	-0.51	1.06	1.44	1.78	2.96	0.89	1.36
t-test	18.40	-7.22	-18.84	11.40	-4.28	-12.50	10.23	-2.32	-9.27	10.94	-3.14	-10.61
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0236	<.0001	<.0001	0.0021	<.0001
Wilcoxon	16565	-9189	-16706	1433	-991	-1447	1157	-419	-1123	3498	-1306	-3558
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0065	<.0001	<.0001	0.0009	<.0001
N			267			77			69			127

Table 4.6. Buyer-initiated trading activity around price-limit hits triggered by down price limits

This table reports various summary statistics for estimates for three trading activity measures for buyer-initiated trades in the pre- and post-thirty minute windows centered on limit hits triggered by hitting a down price limit. The trading activity values and tests thereof reported in the third column for each measure are based on the paired difference in the post- minus pre-windows for each price limit hit. Panels A, B, C and D present the results for the full sample, the hits in the first 30 minutes of the first session, the hits in the last 30 minutes of the first and second sessions, and the hits that are still in place at the end of a session's trading. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	TotalBuyerTransactions			TotalBuyerSharesTraded (000)			TotalBuyerDollarVolume (000 TYL)		
	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.
Panel A: All price-limit hits triggered by hitting lower price limit (N = 328)									
Mean	137.5	214.2	76.7	543.3	1031.9	488.6	1251.9	2030.7	778.8
Median	84.5	124.0	34.0	139.4	246.6	54.1	225.3	485.1	120.0
Std. Dev.	198.3	281.6	180.7	1605.2	2928.6	1821.8	3854.4	6449.7	4038.2
Min	1.0	4.0	-373.0	0.0	0.7	-1834.0	0.1	4.2	-11533.8
Max	2276.0	2282.0	1461.0	20648.9	31941.2	24843.0	37899.4	76736.2	57935.3
Skewness	6.10	4.12	3.42	8.47	7.08	8.89	6.70	7.57	9.82
Kurtosis	54.45	22.59	19.83	88.93	60.32	103.93	50.62	69.57	129.59
t-test	12.56	13.77	7.68	6.13	6.38	4.86	5.88	5.70	3.49
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0005
Wilcoxon	26978	26978	16214.5	26978	26978	16522	26978	26978	15764
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel B: Price-limit hits triggered by hitting lower price limit during first 30 minutes of first session (N = 133)									
Mean	156.4	244.3	88.0	548.4	1264.8	716.4	1447.7	2659.6	1211.9
Median	116.0	149.0	32.0	177.4	249.7	40.4	380.3	515.1	60.5
Std. Dev.	149.5	318.7	240.1	956.4	3380.0	2615.0	3544.1	7974.5	5907.1
Min	1.0	6.0	-373.0	0.0	0.7	-401.8	0.1	4.2	-10966.3
Max	821.0	2282.0	1461.0	7098.2	31941.2	24843.0	31917.2	76736.2	57935.3
Skewness	1.97	3.49	3.28	3.84	6.64	6.96	6.13	7.08	7.53
Kurtosis	4.67	15.75	14.28	19.52	54.02	57.80	45.66	59.56	67.85
t-test	12.06	8.84	4.22	6.61	4.32	3.16	4.71	3.85	2.37
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0020	<.0001	0.0002	0.0194
Wilcoxon	4455.5	4455.5	2246.5	4455.5	4455.5	2116.5	4455.5	4455.5	1840.5
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel C: Price-limit hits triggered by hitting lower price limit during last 30 minutes of first and second session (N =59)									
Mean	169.3	263.0	93.7	888.0	1418.7	530.6	1905.9	2958.8	1052.9
Median	70.0	152.0	53.0	148.1	318.6	126.6	202.9	635.2	258.5
Std. Dev.	365.7	380.0	136.5	3053.5	4210.2	1438.8	6087.0	8208.3	2599.5
Min	7.0	12.0	-213.0	0.8	2.8	-952.0	1.2	5.0	-1216.5
Max	2276.0	2124.0	511.0	20648.9	26565.5	7411.1	37899.4	46006.5	14993.7
Skewness	4.8	4.0	1.0	5.6	4.9	3.8	5.1	4.7	3.9
Kurtosis	24.6	17.4	2.0	33.4	25.7	14.5	26.7	22.2	16.7
t-test	3.6	5.3	5.3	2.2	2.6	2.8	2.4	2.8	3.1
p-value	0.0008	<.0001	<.0001	0.0294	0.0122	0.0063	0.0194	0.0075	0.0029
Wilcoxon	885	885	885	885	885	727	885	885	724
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel D: Price-limit hits triggered by hitting lower price limit that were in place at session's close (N = 79)									
Mean	110.7	219.1	108.4	275.1	533.0	257.8	527.1	1215.0	688.0
Median	67.0	144.0	47.0	92.3	178.3	50.8	198.3	321.8	119.0
Std. Dev.	122.4	274.0	227.2	443.1	929.3	738.2	965.7	2608.1	2058.6
Min	1.0	9.0	-373.0	0.0	0.7	-396.3	0.1	4.2	-579.7
Max	670.0	1627.0	1324.0	2572.0	5477.9	4750.8	6088.9	15164.7	12966.4
Skewness	2.56	3.19	2.92	2.75	3.49	4.77	3.72	3.91	4.71
Kurtosis	7.86	11.80	12.10	9.56	14.43	25.52	16.48	16.39	24.17
t-test	8.03	7.11	4.24	5.52	5.10	3.10	4.85	4.14	2.97
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0027	<.0001	<.0001	0.0040
Wilcoxon	1580	1580	1111	1580	1580	954	1580	1580	968
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 4.7. Buyer-initiated trading activity around price-limit hits triggered by up price limits

This table reports various summary statistics for estimates for three trading activity measures for buyer-initiated trades in the pre- and post-thirty minute windows centered on limit hits triggered by hitting a upper price limit. The trading activity values and tests thereof reported in the third column for each measure are based on the paired difference in the post- minus pre-windows for each price-limit hit. Panels A, B, C and D present the results for the full sample, the hits in the first 30 minutes of the first session, the hits in the last 30 minutes of the first and second sessions, and the hits that are still in place at the end of a session's trading. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	TotalBuyerTransactions			TotalBuyerSharesTraded (000)			TotalBuyerDollarVolume (000 TYL)		
	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.	Pre-Hit	Post-Hit	Paired Dif.
Panel A: All price-limit hits triggered by hitting upper price limit (N = 267)									
Mean	326.8	265.0	-61.8	1865.4	1482.5	-382.9	3939.0	3313.5	-625.5
Median	229.0	160.0	-60.0	697.6	356.1	-150.2	1594.1	902.3	-294.2
Std. Dev.	318.4	318.2	227.3	3705.4	4147.1	2134.5	9421.4	10825.4	4863.0
Min	10.0	7.0	-642.0	4.2	0.1	-9619.7	10.5	0.4	-28879.3
Max	2269.0	2172.0	1248.0	33994.2	42422.9	15841.1	108784.6	113325.6	42039.2
Skewness	2.68	3.22	1.32	5.29	6.82	2.26	7.65	8.36	2.53
Kurtosis	10.67	13.89	7.78	37.19	55.51	20.96	72.84	77.71	33.83
t-test	16.77	13.61	-4.44	8.23	5.84	-2.93	6.83	5.00	-2.10
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0037	<.0001	<.0001	0.0365
Wilcoxon	17889	17889	17889	17889	17889	-9326	17889	17889	-8041
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel B: Price-limit hits triggered by hitting upper price limit during first 30 minutes of first session (N = 77)									
Mean	404.1	359.4	-44.7	2612.6	2477.1	-135.5	5675.2	5531.9	-143.3
Median	308.0	184.0	-70.0	1087.7	608.8	-91.9	1375.2	1105.3	-96.2
Std. Dev.	401.8	454.0	315.9	4761.9	5471.2	3028.5	14082.8	15286.9	7537.3
Min	10.0	11.0	-622.0	7.3	0.1	-7740.2	10.5	0.4	-28879.3
Max	2196.0	2172.0	1248.0	33994.2	33966.2	15841.1	108784.6	113325.6	42039.2
Skewness	2.12	2.22	1.98	4.49	4.20	2.76	5.70	5.64	1.42
Kurtosis	5.72	5.09	5.93	25.52	20.02	12.71	38.82	35.79	15.70
t-test	8.83	6.95	-1.24	4.81	3.97	-0.39	3.54	3.18	-0.17
p-value	<.0001	<.0001	0.2182	<.0001	0.0002	0.6958	0.0007	0.0022	0.8679
Wilcoxon	1502	1502	-615	1502	1502	-561	1502	1502	-355
p-value	<.0001	<.0001	0.0014	<.0001	<.0001	0.0038	<.0001	<.0001	0.0716
Panel C: Price-limit hits triggered by hitting upper price limit during last 30 minutes of first and second session (N =69)									
Mean	294.6	255.9	-38.7	1179.5	873.7	-305.7	3150.1	2304.0	-846.2
Median	245.0	195.0	-51.0	539.8	333.5	-150.2	1714.4	1034.1	-418.3
Std. Dev.	212.5	200.4	144.1	1808.8	1767.2	763.8	3615.8	3415.7	2203.7
Min	20.0	16.0	-429.0	14.8	3.3	-3761.8	27.3	18.0	-9931.4
Max	1014.0	1047.0	277.0	11231.8	12970.2	1738.3	17506.6	20892.2	4152.9
Skewness	1.27	1.26	-0.38	3.52	5.15	-2.05	2.14	3.28	-1.37
Kurtosis	1.55	2.25	0.74	15.22	32.73	8.76	4.98	13.67	4.29
t-test	11.52	10.61	-2.23	5.42	4.11	-3.32	7.24	5.60	-3.19
p-value	<.0001	<.0001	0.0291	<.0001	<.0001	0.0014	<.0001	<.0001	0.0022
Wilcoxon	1208	1208	-353	1208	1208	-706	1208	1208	-603
p-value	<.0001	<.0001	0.0338	<.0001	<.0001	<.0001	<.0001	<.0001	0.0002
Panel D: Price-limit hits triggered by hitting upper price limit that were in place at session's close (N = 127)									
Mean	346.6	338.7	-7.9	2078.5	1857.5	-221.0	4449.9	4261.7	-188.2
Median	240.0	245.0	-14.0	809.7	533.3	-112.5	1971.8	1472.5	-247.6
Std. Dev.	338.6	344.8	245.5	3951.7	4324.6	2349.5	10833.5	12045.3	5356.1
Min	20.0	16.0	-622.0	4.2	3.3	-7973.2	62.4	18.0	-22593.0
Max	2196.0	2172.0	1248.0	33994.2	33966.2	15841.1	108784.6	113325.6	42039.2
Skewness	2.54	2.93	1.47	5.05	5.44	3.00	7.64	7.20	3.62
Kurtosis	8.76	11.21	7.13	34.75	34.58	21.95	69.90	59.01	33.29
t-test	11.54	11.07	-0.36	5.93	4.84	-1.06	4.63	3.99	-0.40
p-value	<.0001	<.0001	0.7176	<.0001	<.0001	0.2911	<.0001	0.0001	0.6928
Wilcoxon	4064	4064	-458.5	4064	4064	-1627	4064	4064	-1289
p-value	<.0001	<.0001	0.2716	<.0001	<.0001	<.0001	<.0001	<.0001	0.0017

Table 4.8. Measures of market quality before and after lower price-limit hits

This table reports various summary statistics for estimates for five market quality measures in the pre- and post-thirty minute windows centered on price-limit hits triggered by hitting a lower price limit. The market quality values and tests thereof that are reported in the third column for each measure are based on the paired difference in the post- minus pre-windows for each price-limit hit. Panels A, B, C and D present the results for the full sample, the hits in the first 30 minutes of the first session, the hits in the last 30 minutes of the first and second sessions, and the hits that are still in place at the end of a session's trading. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	Prop. quoted spread (%)			Prop. effective spread (%)			Share Depth (000)			Dollar Depth (000 TRY)			Composite Liquidity (x10,000)		
	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.
Panel A: All price-limit hits triggered by hitting lower price limit (N = 328)															
Mean	1.2482	2.3277	1.0795	3.9890	5.6251	1.6350	232.1	185.4	-46.8	367.2	279.6	-87.6	0.0144	0.0130	-0.0013
Median	0.8639	0.9120	0.0419	3.2260	3.8763	0.6160	55.7	40.7	-5.0	111.2	79.4	-18.8	0.0013	0.0022	0.0004
t-test	21.859	3.5212	1.6332	30.118	8.4050	2.4356	8.9037	9.4019	-3.4530	6.2223	5.6928	-2.7028	2.6784	5.4415	-0.2290
p-value	<.0001	<.0001	0.1034	<.0001	<.0001	0.0154	<.0001	<.0001	0.0006	<.0001	<.0001	0.0072	0.0078	<.0001	0.8193
Wilcoxon	26978	26978	10651	26978	26978	8045	26978	26978	-11132	26978	26978	-13115	26978	26978	9611
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel B: Price-limit hits triggered by hitting lower price limit during first 30 minutes of first session (N = 133)															
Mean	1.2216	3.3888	2.1673	4.1206	6.1474	2.0267	208.8	173.3	-35.4	383.8	309.0	-74.8	0.0250	0.0138	-0.0113
Median	0.9060	0.8438	0.0568	3.2302	3.4629	0.3539	63.4	42.0	-6.8	130.9	91.1	-26.0	0.0013	0.0020	0.0001
t-test	15.819	2.1211	1.3562	19.353	3.8314	1.2586	6.1834	6.1744	-1.7635	4.6936	4.2690	-1.7997	2.0036	3.5961	-0.8592
p-value	<.0001	0.0358	0.1773	<.0001	0.0002	0.2104	<.0001	<.0001	0.0801	<.0001	<.0001	0.0742	0.0472	0.0005	0.3918
Wilcoxon	4456	4456	639	4456	4456	-29	4456	4456	-1860	4456	4456	-2268	4456	4456	418
p-value	<.0001	<.0001	0.1523	<.0001	<.0001	0.9493	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.3504
Panel C: Price-limit hits triggered by hitting lower price limit during last 30 minutes of first and second session (N =59)															
Mean	1.2302	1.4892	0.2589	3.4066	5.5972	2.1905	299.4	163.9	-135.5	601.0	272.7	-328.3	0.0120	0.0114	-0.0006
Median	0.8262	0.9356	0.0725	2.5003	5.1454	2.1873	65.6	39.4	-15.4	128.3	77.6	-45.9	0.0010	0.0034	0.0016
t-test	7.5908	10.571	2.0583	10.757	19.263	7.3797	3.9928	4.4889	-2.9989	2.6865	3.0410	-2.4140	1.2858	4.8409	-0.0615
p-value	<.0001	<.0001	0.0441	<.0001	<.0001	<.0001	0.0002	<.0001	0.0040	0.0094	0.0035	0.0190	0.2036	<.0001	0.9511
Wilcoxon	885	885	638	885	885	733	885	885	-774	885	885	-826	885	885	749
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel D: Price-limit hits triggered by hitting lower price limit that were in place at session's close (N = 79)															
Mean	1.2558	4.9624	3.7065	3.7072	8.9910	5.2838	140.8	87.9	-52.9	294.3	150.9	-143.5	0.0054	0.0135	0.0081
Median	0.8654	0.9055	0.0747	2.8964	4.7556	1.9079	38.6	14.8	-6.7	82.1	38.8	-26.2	0.0023	0.0054	0.0025
t-test	10.114	1.8508	1.3811	14.306	3.3706	1.9844	4.2844	4.1768	-3.2183	2.1005	2.5294	-1.7188	4.4242	5.3255	3.0927
p-value	<.0001	0.0680	0.1712	<.0001	0.0012	0.0507	<.0001	<.0001	0.0019	0.0389	0.0134	0.0896	<.0001	<.0001	0.0028
Wilcoxon	1580	1580	412	1580	1580	1009	1580	1580	-1109	1580	1580	-1143	1580	1580	911
p-value	<.0001	<.0001	0.0433	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 4.9. Measures of market quality before and after upper price-limit hits

This table reports various summary statistics for estimates for five market quality measures in the pre- and post-thirty minute windows centered on price-limit hits triggered by hitting a upper price limit. The market quality values and tests thereof that are reported in the third column for each measure are based on the paired difference in the post- minus pre-windows for each price-limit hit. Panels A, B, C and D present the results for the full sample, the hits in the first 30 minutes of the first session, the hits in the last 30 minutes of the first and second sessions, and the hits that are still in place at the end of a session's trading. T- and Wilcoxon tests of the means and medians, respectively, and their associated p-values are presented in the table.

	Prop. quoted spread			Prop. effective spread			Share Depth			Dollar Depth			Composite Liquidity		
	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.	Pre-	Post-	Dif.
Panel A: All price-limit hits triggered by hitting upper price limit (N = 267)															
Mean	1.08464	1.0561	-0.0284	3.2752	4.3703	1.095	295.2	266.1	-29.1	397.0	334.9	-62.1	0.0032	0.0098	0.0066
Median	0.7087	0.7504	-0.0100	2.7040	3.8955	1.0321	71.3	49.3	-6.3	178.2	128.2	-16.5	0.0006	0.0009	0.0001
t-test	12.417	22.533	-0.3799	24.707	33.884	8.1933	7.9968	7.1706	-1.5680	7.4968	8.3227	-2.2567	4.0821	2.5323	1.7292
p-value	<.0001	<.0001	0.7043	<.0001	<.0001	<.0001	<.0001	<.0001	0.1181	<.0001	<.0001	0.0248	<.0001	0.0119	0.0849
Wilcoxon	17889	17889	-3425.5	17889	17889	10499	17889	17889	-6219	17889	17889	-5410	17889	17889	7261
p-value	<.0001	<.0001	0.0062	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel B: Price-limit hits triggered by hitting upper price limit during first 30 minutes of first session (N = 77)															
Mean	1.5061	1.2223	-0.2837	4.2702	3.9788	-0.2910	374.7	435.4	60.8	501.9	555.0	53.1	0.0081	0.0163	0.0082
Median	0.9347	0.8220	-0.0710	3.4590	3.3880	-0.0640	100.1	99.3	5.6	172.4	180.7	18.1	0.0009	0.0008	-0.0001
t-test	5.5368	11.386	-1.1125	12.579	16.035	-1.0364	5.1383	4.6874	1.1846	3.1823	4.6541	0.6775	3.0736	1.4248	0.7276
p-value	<.0001	<.0001	0.2694	<.0001	<.0001	0.3033	<.0001	<.0001	0.2398	0.0021	<.0001	0.5001	0.0029	0.1583	0.4691
Wilcoxon	1502	1502	-890	1501.5	1501.5	-128.5	1502	1502	226	1502	1502	493	1502	1502	-517
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.5177	<.0001	<.0001	0.2548	<.0001	<.0001	0.0114	<.0001	<.0001	0.0079
Panel C: Price-limit hits triggered by hitting upper price limit during last 30 minutes of first and second session (N =69)															
Mean	0.6636	0.8567	0.1930	2.4264	4.6914	2.2650	121.2	71.2	-50.0	316.8	192.8	-124.0	0.0010	0.0136	0.0126
Median	0.6368	0.7411	0.0114	2.2648	4.4800	2.2130	55.5	26.8	-14.6	193.1	100.6	-65.1	0.0003	0.0015	0.0007
t-test	21.536	18.647	4.9714	20.445	24.236	10.463	5.7564	5.5321	-3.9347	6.4182	5.7408	-3.8857	5.27444	1.7491	1.6223
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0002	<.0001	<.0001	0.0002	<.0001	0.0848	0.1094
Wilcoxon	1207.5	1207.5	632.5	1207.5	1207.5	1131.5	1207.5	1207.5	-919.5	1207.5	1207.5	-917.5	1207.5	1207.5	1077.5
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
Panel D: Price-limit hits triggered by hitting upper price limit that were in place at session's close (N = 127)															
Mean	1.1388	1.0594	-0.0794	3.0289	4.8720	1.8430	334.4	241.2	-93.1	504.9	365.6	-139.3	0.0024	0.0025	0.0001
Median	0.7229	0.8083	-0.0070	2.3887	4.4329	1.9365	99.1	55.7	-26.1	204.7	124.3	-51.7	0.0004	0.0011	0.0004
t-test	6.7823	17.321	-0.5175	14.747	29.106	9.798	5.8291	5.4683	-4.0802	4.9881	5.1422	-2.6952	2.1991	7.0148	0.1198
p-value	<.0001	<.0001	0.6057	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0080	0.0297	<.0001	0.9048
Wilcoxon	4064	4064	-151	4064	4064	3591	4064	4064	-2646	4064	4064	-2386	4064	4064	2961
p-value	<.0001	<.0001	0.7179	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 4.10. Volatility and mean return changes around lower price-limit hits using trade-by-trade returns

This table reports mean and median estimates for the means and variances in the pre- and post-windows centered on lower limit hits using trade-by-trade returns. The means and medians are obtained from an ARIMA(1,0,0) or AR(1) model given by $r_{it} = \alpha_i + \rho_i r_{it-1} + \varepsilon_{it}$ and an ARIMA(0,0,1) or MA(1) model given by $r_{it} = \mu_i + \epsilon_{it} + \theta_i \epsilon_{it-1}$ where $\rho_i$is the correlation between successive return observations in the AR(1) model, and ε_{it} and ϵ_{it} are assumed to be IID normal. The mean return is given by $\alpha_i/(1-\rho_i)$ for the AR(1) model and as μ_i for the MA(1) model. The adjusted variance is computed as $\sigma_i^2(\varepsilon_{it})/(1-\rho_1^2)$ for the AR(1) model and as $\sigma_i^2(\epsilon_{it})(1+\theta_1^2)$ for the MA(1) model. The ρ_i statistics are reported in panels A1, B1, C1 and D1, and the θ_i statistics are reported in panels A2, B2, C2 and D2. First-order $\rho_i$for the MA(1) are given by $\theta_1/(1+\theta_1^2)$ but are not reported in this table. α_i, σ, Adj. σ and Mean are in %.

	Pre-limit hit					Post-limit hit					Paired Difference				
Statistic	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ
Panel A1: All lower price-limit hits, ARIMA(1,0,0), N=321															
mean	-0.0552	0.0059	-0.34	-0.0433	0.0073	0.0114	0.0051	-0.37	0.0091	0.0063	0.0666	-0.0008	-0.03	0.0525	-0.0010
median	-0.0360	0.0021	-0.39	-0.0260	0.0026	0.0077	0.0019	-0.40	0.0054	0.0023	0.0445	-0.0001	-0.02	0.0322	-0.0000
t-test	-13.24	10.53	-30.80	-13.08	9.59	4.14	8.65	-39.27	4.03	8.80	12.58	-1.87	-1.74	12.20	-1.62
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0624	0.08	<.0001	0.1069
Wilcoxon	-21898	25841	-24295	-21870	25841	8755	25841	-24925	8661	25841	21421	-3624	-3547	21212	-3864
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0292	0.03	<.0001	0.0200
Panel A2: All lower price-limit hits, ARIMA(0,0,1), N=319															
mean		0.0055	0.49	-0.0419	0.0074		0.0046	0.51	0.0093	0.0065		-0.0009	0.02	0.0511	-0.0009
median		0.0019	0.55	-0.0260	0.0026		0.0017	0.54	0.0057	0.0023		-0.0001	0.00	0.0294	-0.0001
t-test		10.75	28.91	-12.98	9.89		9.41	37.12	4.08	8.48		-2.50	1.08	12.22	-1.46
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		0.0131	0.28	<.0001	0.1461
Wilcoxon		25520	24757	-22718	25520		25520	25273	8889	25520		-3787	1586	20837	-3659
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		0.0214	0.34	<.0001	0.0262
Panel B1: Lower price-limit hits during first 30 minutes of first session, ARIMA(1,0,0), N=130															
mean	-0.0625	0.0073	-0.30	-0.0521	0.0083	0.0128	0.0041	-0.37	0.0107	0.0049	0.0753	-0.0032	-0.07	0.0628	-0.0034
median	-0.0390	0.0032	-0.32	-0.0310	0.0037	0.0081	0.0019	-0.41	0.0061	0.0024	0.0504	-0.0010	-0.09	0.0380	-0.0010
t-test	-8.01	7.79	-17.19	-8.23	7.42	2.59	5.66	-24.75	2.52	6.11	7.74	-4.82	-3.03	7.74	-4.63
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0106	<.0001	<.0001	0.013	<.0001	<.0001	<.0001	0.02	<.0001	<.0001
Wilcoxon	-3418	4258	-4000	-3437	4258	1668	4258	-4051	1677	4258	3442	-1968	-1407	3455	-1964
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.01	<.0001	0.0001
Panel B2: Lower price-limit hits during first 30 minutes of first session, ARIMA(0,0,1), N=130															
mean		0.0068	0.44	-0.0496	0.0086		0.0037	0.52	0.0107	0.0049		-0.0031	0.08	0.0603	-0.0037
median		0.0030	0.47	-0.0270	0.0037		0.0017	0.55	0.0059	0.0024		-0.0010	0.06	0.0366	-0.0010
t-test		7.79	15.72	-8.22	7.29		5.53	24.00	2.52	6.07		-5.01	2.40	7.72	-4.46
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.0129	<.0001		<.0001	0.02	<.0001	<.0001
Wilcoxon		4258	4090	-3572	4258		4258	4190	1807	4258		-2028	1065	3437	-1945
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		<.0001	0.01	<.0001	0.0001

Table 4.10. Cont'd.

Statistic	Pre-limit hit					Post-limit hit					Paired Difference				
	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ
Panel C1: Lower price-limit hits during last 30 minutes of both sessions, ARIMA(1,0,0), N=58															
mean	-0.0451	0.0037	-0.42	-0.0338	0.0052	-0.0025	0.0051	-0.36	-0.0016	0.0063	0.0427	0.0014	0.05	0.0322	0.0011
median	-0.0340	0.0015	-0.47	-0.0230	0.0020	-0.0030	0.0019	-0.38	-0.0020	0.0022	0.0311	0.0002	0.04	0.0218	0.0002
t-test	-6.17	4.61	-16.03	-5.50	4.55	-0.45	4.77	-17.59	-0.38	4.67	4.66	2.27	1.63	4.10	1.45
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.6543	<.0001	<.0001	0.7045	<.0001	<.0001	0.0267	0.11	<.0001	0.1517
Wilcoxon	-765	856	-765	-765	856	-84	856	-851	-96	856	599	260	254	565	213
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.5119	<.0001	<.0001	0.4529	<.0001	<.0001	0.0435	0.05	<.0001	0.1003
Panel C2: Lower price-limit hits during last 30 minutes of both sessions, ARIMA(0,0,1), N=58															
mean		0.0033	0.57	-0.0330	0.0049		0.0046	0.50	-0.0024	0.0066		0.0013	-0.07	0.0306	0.0018
median		0.0013	0.64	-0.0210	0.0019		0.0019	0.51	-0.0030	0.0022		0.0002	-0.15	0.0185	0.0002
t-test		4.63	13.96	-5.44	4.56		4.90	16.07	-0.55	4.36		2.41	-1.36	3.96	2.05
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.5832	<.0001		0.0193	0.18	0.0002	0.0454
Wilcoxon		856	799	-842	856		856	851	-134	856		308	-297	560	219
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.3054	<.0001		0.0159	0.02	<.0001	0.0909
Panel D1: Lower price-limit hits that remained in place at session close, ARIMA(1,0,0), N=79															
mean	-0.0553	0.0037	-0.36	-0.0443	0.0045	-0.0067	0.0036	-0.38	-0.0058	0.0044	0.0486	-0.0001	-0.02	0.0385	-0.0001
median	-0.0470	0.0016	-0.39	-0.0360	0.0021	-0.0050	0.0018	-0.38	-0.0030	0.0025	0.0377	0.0001	0.00	0.0294	0.0000
t-test	-8.43	5.46	-15.63	-7.54	5.26	-1.71	7.79	-21.75	-1.82	7.49	6.01	-0.14	-0.64	5.52	-0.20
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0921	<.0001	<.0001	0.072	<.0001	<.0001	0.8921	0.52	<.0001	0.8437
Wilcoxon	-1406	1580	-1499	-1407	1580	-418	1580	-1573	-434	1580	1200	209	-92	1164	152
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0403	<.0001	<.0001	0.033	<.0001	<.0001	0.3101	0.66	<.0001	0.4611
Panel D2: Lower price-limit hits that remained in place at session close, ARIMA(0,0,1), N=77															
mean		0.0034	0.51	-0.0436	0.0047		0.0033	0.50	-0.0056	0.0045		-0.0001	-0.01	0.0380	-0.0002
median		0.0014	0.60	-0.0300	0.0021		0.0018	0.51	-0.0050	0.0024		0.0001	0.00	0.0245	0.0001
t-test		5.35	13.36	-7.20	5.39		7.93	19.39	-1.70	7.38		-0.19	-0.22	5.18	-0.30
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.0923	<.0001		0.8482	0.82	<.0001	0.7673
Wilcoxon		1502	1405	-1412	1502		1502	1497	-427	1502		165	-78	1040	105
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.0294	<.0001		0.4071	0.70	<.0001	0.5990

Table 4.11. Volatility and mean return changes around upper price-limit hits using trade-by-trade returns

This table reports mean and median estimates for the means and variances in the pre- and post-windows centered on upper limit hits using trade-by-trade returns. The means and medians are obtained from an ARIMA(1,0,0) or AR(1) model given by $r_{it} = \alpha_i + \rho_i r_{it-1} + \varepsilon_{it}$ and an ARIMA(0,0,1) or MA(1) model given by $r_{it} = \mu_i + \epsilon_{it} + \theta_i \epsilon_{it-1}$ where $\rho_i$is the correlation between successive return observations in the AR(1) model, and ε_{it} and ϵ_{it} are assumed to be IID normal. The mean return is given by $\alpha_i/(1-\rho_i)$ for the AR(1) model and as μ_i for the MA(1) model. The adjusted variance is computed as $\sigma_i^2(\varepsilon_{it})/(1-\rho_1^2)$ for the AR(1) model and as $\sigma_i^2(\epsilon_{it})(1+\theta_1^2)$ for the MA(1) model. The ρ_i statistics are reported in panels A1, B1, C1 and D1, and the θ_i statistics are reported in panels A2, B2, C2 and D2. First-order $\rho_i$for the MA(1) are given by $\theta_1/(1+\theta_1^2)$ but are not reported in this table. α_i, σ, Adj. σ and Mean are in %.

	Pre-limit hit					Post-limit hit					Paired Difference				
Statistic	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ
Panel A1: All upper price-limit hits, ARIMA(1,0,0), N=265															
mean	0.0504	0.0047	-0.39	0.0385	0.0060	-0.0145	0.0036	-0.41	-0.0106	0.0048	-0.0649	-0.0011	-0.02	-0.0491	-0.0012
median	0.0321	0.0014	-0.41	0.0230	0.0016	-0.0090	0.0013	-0.43	-0.0060	0.0016	-0.0400	-0.0000	-0.02	-0.0270	-0.0000
t-test	11.67	8.29	-41.67	11.13	8.37	-7.73	8.89	-51.75	-6.59	8.07	-12.75	-2.53	-1.77	-12.07	-2.19
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.012	0.08	<.0001	0.0292
Wilcoxon	15963	17623	-17468	16104	17623	-10242	17623	-17347	-10050	17623	-16878	-3272	-2220	-17008	-2760
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0086	0.07	<.0001	0.0269
Panel A2: All upper price-limit hits, ARIMA(0,0,1), N=265															
mean		0.0043	0.53	0.0370	0.0059		0.0030	0.58	-0.0107	0.0047		-0.0012	0.05	-0.0477	-0.0012
median		0.0013	0.55	0.0221	0.0016		0.0012	0.59	-0.0060	0.0016		-0.0000	0.05	-0.0270	-0.0000
t-test		8.20	38.18	11.16	8.40		9.61	44.39	-6.58	8.50		-2.89	3.20	-12.33	-2.31
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		0.0042	0.00	<.0001	0.0219
Wilcoxon		17623	17601	16394	17623		17623	17608	-10800	17623		-3832	4119	-17171	-2357
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		0.002	0.00	<.0001	0.059
Panel B1: Upper price-limit hits during first 30 minutes of first session, ARIMA(1,0,0), N=76															
mean	0.0699	0.0090	-0.35	0.0564	0.0107	-0.0177	0.0046	-0.42	-0.0133	0.0061	-0.0875	-0.0044	-0.07	-0.0697	-0.0046
median	0.0395	0.0033	-0.38	0.0304	0.0040	-0.0110	0.0016	-0.44	-0.0080	0.0020	-0.0540	-0.0010	-0.09	-0.0410	-0.0010
t-test	6.03	5.62	-17.53	5.88	5.75	-4.87	5.17	-27.87	-4.54	4.95	-7.18	-3.30	-3.41	-6.77	-3.24
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0015	0.00	<.0001	0.0018
Wilcoxon	1328	1463	-1453	1339	1463	-1113	1463	-1462	-1119	1463	-1450	-957	-624	-1451	-844
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.00	<.0001	<.0001
Panel B2: Upper price-limit hits during first 30 minutes of first session, ARIMA(0,0,1), N= 76															
mean		0.0083	0.47	0.0548	0.0106		0.0038	0.63	-0.0129	0.0061		-0.0045	0.16	-0.0677	-0.0045
median		0.0032	0.50	0.0291	0.0039		0.0015	0.65	-0.0080	0.0020		-0.0010	0.12	-0.0400	-0.0010
t-test		5.52	15.71	5.66	5.79		5.47	26.28	-4.45	5.07		-3.46	5.15	-6.59	-3.18
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		0.0009	<.0001	<.0001	0.0021
Wilcoxon		1463	1452	1287	1463		1463	1462	-1204	1463		-1044	879	-14470	-838
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001

Table 4.11. Cont'd.

Statistic	Pre-limit hit					Post-limit hit					Paired Difference				
	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ	α_i	σ	ρ or θ	Mean	Adj. σ
Panel C1: Upper price-limit hits during last 30 minutes of both sessions, ARIMA(1,0,0), N=69															
mean	0.0390	0.0021	-0.38	0.0003	0.0027	-0.0096	0.0019	-0.41	-0.0001	0.0023	-0.0486	-0.0002	-0.03	-0.0004	-0.0005
median	0.0296	0.0011	-0.39	0.0002	0.0014	-0.0040	0.0011	-0.44	-0.0000	0.0013	-0.0300	-0.0000	-0.04	-0.0002	0.0000
t-test	8.13	3.73	-24.58	8.1653	3.35	-2.34	4.87	-28.60	-2.0280	5.40	-6.71	-0.79	-1.49	-5.8931	-1.02
p-value	<.0001	0.0004	<.0001	<.0001	0.0013	0.0224	<.0001	<.0001	0.0465	<.0001	<.0001	0.4348	0.14	<.0001	0.3123
Wilcoxon	1160	1208	-1208	1160	1208	-416	1208	-1204	-395	1208	-1091	11	-298	-1091	67
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0083	<.0001	<.0001	0.0125	<.0001	<.0001	0.9505	0.07	<.0001	0.694
Panel C2: Upper price-limit hits during last 30 minutes of both sessions, ARIMA(0,0,1), N=69															
mean		0.0018	0.52	0.0277	0.0026		0.0017	0.55	-0.0079	0.0023		-0.0001	0.03	-0.0357	-0.0004
median		0.0010	0.53	0.0207	0.0013		0.0010	0.57	-0.0030	0.0013		0.0000	0.05	-0.0220	0.0000
t-test		4.25	25.25	8.09	3.47		4.83	24.23	-1.94	5.00		-0.50	1.22	-6.17	-1.03
p-value		<.0001	<.0001	<.0001	0.0009		<.0001	<.0001	0.0566	<.0001		0.616	0.23	<.0001	0.3044
Wilcoxon		1208	1208	1192	1208		1208	1205	-396	1208		4	308	-1126	15
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.0169	<.0001		0.9835	0.07	<.0001	0.9317
Panel D1: Upper price-limit hits that remained in place at session close, ARIMA(1,0,0), N=126															
mean	0.0362	0.0030	-0.41	0.0260	0.0039	-0.0075	0.0032	-0.44	-0.0053	0.0041	-0.0437	0.0001	-0.02	-0.0313	0.0002
median	0.0249	0.0012	-0.44	0.0177	0.0015	-0.0060	0.0014	-0.45	-0.0040	0.0017	-0.0290	0.0001	-0.02	-0.0210	0.0002
t-test	8.09	6.21	-32.55	8.04	6.23	-3.17	6.51	-49.11	-3.06	6.34	-9.10	0.58	-1.60	-8.90	0.92
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0019	<.0001	<.0001	0.0027	<.0001	<.0001	0.5609	0.11	<.0001	0.3584
Wilcoxon	3619	4001	-4001	3613	4001	-1522	4001	-4001	-1490	4001	-3732	568	-601	-3737	795
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	0.0001	<.0001	<.0001	0.0002	<.0001	<.0001	0.168	0.14	<.0001	0.0527
Panel D2: Upper price-limit hits that remained in place at session close, ARIMA(0,0,1), N=126															
mean		0.0027	0.56	0.0258	0.0038		0.0028	0.60	-0.0057	0.0041		0.0001	0.03	-0.0314	0.0002
median		0.0012	0.57	0.0168	0.0016		0.0013	0.61	-0.0050	0.0017		0.0001	0.04	-0.0210	0.0002
t-test		6.46	29.96	7.68	6.29		6.87	40.18	-3.30	6.43		0.42	1.71	-8.78	0.95
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.0013	<.0001		0.6752	0.09	<.0001	0.3464
Wilcoxon		4001	4001	3671	4001		4001	4001	-1616	4001		536	659	-3737	776
p-value		<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001		0.1934	0.11	<.0001	0.0587

Figure 4. 1. Cumulative mean returns for the price-limit hits

This figure plots the cumulative cross-sectional mean returns for four samples of price-limit hits differentiated by whether they are triggered by hitting the lower or upper price limits. The cross-sectional mean returns are cumulated over the ten 3-minute intervals before and after the limit hits.