High Price Impact Trades Identification and Its Implication for Volatility and Price Efficiency

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Abstract

We include Limit Order Book (LOB) matchedness as a new trade attribute to identify High Price Impact Trades (HPITs). HPITs are trades associated with large price changes relative to their volume proportion. We show that the inclusion of matchedness provides a finer analysis of the relationship between price contribution and trade categories. We further verify that a stronger presence of HPITs leads to a decline in volatility and improves price efficiency, which suggests a link between HPITs and informed trades.

Keywords: Matched trades, Limit Order Book, Price efficiency, Price discovery

JEL classification: D4 D8 D82 G14

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Abstract

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1 Introduction

Financial markets are characterized by information asymmetry, where certain traders possess superior private information compared to others. Price changes are largely driven by the flow of this information, raising the important question of which categories of trades contribute most to these price movements. Understanding this is crucial, as it sheds light on how informed traders, who possess private information, and uninformed traders, who do not, behave in the market and influence price dynamics. Barclay and Warner (1993) explore empirically informed traders' choice of trade size, and are the first to propose and validate the well-known stealth trading hypothesis that informed traders concentrate their trades on medium sizes to conceal their information. Following this data-driven approach, a large number of studies attempt to identify the trades that contribute most to price discovery from various trade attributes (e.g., roundedness).[1] However, none of them takes into account the information of Limit Order Book (LOB). With the development of the trading system from the quote-driven market to the order-driven market, nowadays, almost all of the world's major exchanges now feature LOB. Therefore, traders are able to use algorithms to continuously observe the dynamics of the open LOB and time their order submissions. Despite the importance of the LOB in price formation, the role of LOB-related trades has been largely ignored in the literature. To fill this gap, our study suggests an important, but hardly explored, dimension: matchedness. A matched buy (sell) trade is a buy-initiated (sell-initiated) trade that matches the exact cumulative quantity standing on the ask (bid) side of the open LOB.[2] Intuitively, matchedness

[1] See, for example, Chakravarty (2001), Alexander and Peterson (2007), Hodrick and Moulton (2005), among others.

[2] Our matched trades are computed in investors' view and are based on the tradable quantity standing in the open LOB. Apart from regular limit order and market orders, the Xetra trading system also allows fully hidden orders and iceberg orders. Fully hidden orders are not observable but tradable. As we observe the state of the LOB before and after the transaction, we can evaluate if a market order hits fully hidden orders or not. Our backtest results show that fewer than 3% of the market orders run into hidden orders, which suggests a very accurant identification of matched trades. As for iceberg order, the hidden part is

measures responsiveness of liquidity demand of traders with respect to liquidity supply available in LOB.

The importance of matched trades is illustrated in Figure 1, showing level-1 and level-2 matched buy market orders of 400 and 700 shares, respectively. Matched trades are a special type of market order that allows traders to profit maximally from the best available prices without waiting. Notably, a market buy order with a volume of less than 400 shares has the same transaction price and price impact as one with 400 shares. Without matching, a trader will face the risk of fluctuations in the best available price in the near future. In a similar way, a market buy order for 700 shares takes advantage of the two best available prices suggested by the sellers. Matched trades are closely linked to high-frequency trading (HFT) algorithms, which continuously monitor the evolution of the limit order book (LOB) and execute trades for the most advantageous quantities. Both informed and uninformed traders have incentives to engage in matched trades. The liquidity concern for informed traders is related to the fact that the market does not provide an infinite quantity for them to exploit arbitrage opportunities. Consequently, informed traders use matched trades when the buy (sell) price is lower (higher) than the target price and the information they hold is short-lived, allowing them to maximize their arbitrage opportunities. On the other hand, uninformed traders, especially when dealing with large volumes, may prefer to execute trades at the best available market price, which can also result in matched trades. Our study seeks to determine which type of traders predominantly drives the occurrence of matched trades. Our empirical results show that matched and unmatched trades do not contribute to the price discovery process in the same way, and not taking matchedness into account may result in misleading conclusions.

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not tradable unless it becomes visible, therefore, it has no impact on our matched trade identification. However, the existence of iceberg orders does hide the actual available liquidity in the market. That being said, the actual LOB is deeper in terms of liquidity when there are iceberg orders.

[Insert Figure 1 here]

Combining matchedness with size and roundedness,[3] we categorize all trades into nine categories by assuming a sequential trade decision making process,[4] as shown in Figure 2. We then identify the price contribution for each trade category and construct our HPIT measure, which, in general, leads to disproportionately large price discovery relative to the proportion of volume.[5] Our first main result is that along with size and roundedness, matchedness is also a convenient criterion to distinguish trades. To the best of our knowledge, this is the first study that uses LOB matchedness of trade to distinguish trades, and also the first study to examine the relation between matched trades and price discovery.

[Insert Figure 2 here]

To further explore the rationality and informativeness of HPITs, we investigate the relationship between HPITs and short-term volatility. The noisy rational expectation models of Hellwig (1980) and Wang (1993) argue that volatility increases with uninformed

[3]The size of a trade falls into categories of small, medium or large when the corresponding trade sizes are smaller than the 30th percentile, between the 30th and 70th percentiles, and larger than the 70th percentile of their own trade size distribution, respectively. A trade is rounded when its size is a multiple of 10, 50, or 100 shares.

[4]The rationale for the sequential trade decision is that when traders trade, they have to first determine the trade size (e.g., small, medium, or large) for each submission if they need to split a large order size into smaller ones. Then, traders should consider if their trades can be made as matched trades or not, which mainly depends on the speed of their trading infrastructure and their order submission strategies. If they are incapable of making matched trades, then they must decide if their trades will be made rounded or not. A series of rounded trades saves submission and execution time but it is also easier to be caught by other sophisticated HFT algorithms. The opposite is true for unrounded trades: it takes a little more time for HFT algorithms or human traders to generate unrounded random trades but such trades are more difficult for other HFT traders to track down. This method of classification results in matched, unmatched-rounded, and unmatched-unrounded categories for each size group.

[5]One may also argue that instead of submitting market orders, informed traders can also submit limit orders and wait for liquidity traders' market orders. In that case, after a buy-initiated (sell-initiated) trade, the midquote might decrease (increase). To address this concern, we compute the daily price contribution of the trades that have the same direction as the resulting midquote change (i.e., buy-initiated (sell-initiated) trades followed by a midquote increase (decrease)) and find that these trades contribute more than 70% of daily price variation. The findings confirm that it is the market orders that drive the daily price dynamics. Our intraday analysis also shows that HPITs have a bigger price impact over time and a much higher hourly contribution to price discovery than non-HPITs.

or liquidity trading. A growing number of empirical studies also attempt to examine the impact of informed trading on volatility (Avramov et al. (2006) and Blasco and Corredor (2017)) and conclude that informed trading is a price-stablizing factor. We show that a stronger presence of HPITs does lead to a decline in volatility. Our results confirm the existence of information content in HPITs and their role as price stabilizers. Further, we investigate the relationship between HPITs and short-term price efficiency. Using the variance ratio (Lo and MacKinlay (1989)) and the absolute value of autocorrelation as efficiency measures, after controlling for various market conditions, we show that the presence of HPITs improves price efficiency.

Our paper contributes to two strands of the literature. First, our study contributes to the literature on stealth trading. Both theoretical and empirical studies (Kyle (1985), Admati and Pfleiderer (1988), Barclay and Warner (1993)) show that informed traders strategically camouflage their trades. With information of LOB, we suggest a novel attribute to distinguish the trades. Our empirical results show that matchedness is an important attribute to evaluate the price discovery. Further, we combine matchedness with size and roundedness to construct the HPITs. The findings provide new evidence of the implication of informed trading in the context of LOB and HFT.

Second, the empirical results also extend the recent literature (Boehmer and Kelley (2009), Chaboud et al. (2014), and Rosch et al. (2016)) regarding the effect of HPITs on short-term price volatility and efficiency. Our results suggest that HPITs lead to a decrease in volatility and increase in efficiency. Further, the magnitude of this decline in volatility varies with information environments.

The rest of the paper is organized as follows. Section 2 presents a literature review. Section 3 describes our dataset and the Xetra trading system. Section 4 highlights the importance of matched trades. Section 5 identifies HPITs and examines their intraday pattern. Section 6 assesses the impact of HPITs on volatility and price efficiency, and

Section 7 concludes the paper.

2 Literature Review

2.1 Stealth Trading and Trade Attributes

In the theoretical models of Kyle (1985) and Admati and Pfleiderer (1988), informed risk-neutral speculators endogenously take their price impact into account and trade strategically by spreading their trades over time and selecting the moments when market liquidity is high. Empirically, Barclay and Warner (1993) explore informed traders' choice of trade size, and are the first to propose and validate the well-known stealth trading hypothesis that informed traders concentrate their trades on medium sizes to conceal their information. They find that the cumulative stock-price change is due to medium-size trades. A generalized version of this hypothesis is that if informed traders are the main cause of convergence of the market price to the expected fundamental value, and if these traders concentrate their trades in certain specific categories to hide their trading intentions, then most of a stock's cumulative price change should fall within these trade categories. Consistent with Barclay and Warner (1993), Chakravarty (2001) evaluates the stealth-trading hypothesis by further categorizing trade sizes by initiator (i.e., retail or institutional investors) and posits that institutions are informed traders. Several studies examine the link between stealth trading and trade clustering.[6]

[6] Ball, Torous, and Tschoegl (1985) and Harris (1991) argue that while a more precise price that is mutually acceptable to both the buyer and the seller can be reached by continuing negotiations, the incremental benefit to each side decreases and the exposure of each side to reporting and price risk increases. As a result, clustering will occur as traders seek to simplify the negotiation process. Another explanation is from a behavioral perspective. Wyckoff (1963) notes that traders think in round numbers and try to trade in round numbers. Niederhoffer and Osborne (1966) argue that the tendency of traders to prefer integers seems to be a fundamental and stable principle of stock market psychology. Ikenberry and Weston (2003) argue that price clustering may be a collective preference by investors to voluntarily trade at particular price levels in order to minimize cognitive processing costs.

Alexander and Peterson (2007) analyze trade size clustering with data from the NYSE and the NASDAQ, and suggest that rounded medium trade sizes have a greater price impact than do unrounded trades. Hodrick and Moulton (2005) study trade size clustering in a rational expectations framework and argue that when many heterogeneous uninformed investors are present, an asset will be traded at an increasing number of distinct sizes as investors' desire to trade exact quantities increases. Similarly, Moulton (2005) uses the data from foreign exchange markets to test the hypothesis that there is less trade size clustering shortly before the end of calendar quarters because portfolio managers seek to align their portfolios more fully with their given objectives. Moreover, the study provides evidence that the price impact of order flow is greater when customers care more about trading precise quantities. Garvey and Wu (2014) examine quantity choice patterns across trading hours and show that traders submit more non-rounded order sizes and more order sizes overall leading up to a day's market close. Studies that use roundedness to classify trades include those of Cai et al. (2006), Menkhoff and Schmeling (2010) and Ascioglu et al. (2011). The increasing number of distinct trade sizes might be related to another important dimension: matchedness, which measures responsiveness of liquidity demand of high-frequency informed or uninformed traders with respect to liquidity supply.

2.2 Implications of Informed Trades

Friedman (1953) argues that irrational investors destabilize prices by buying when prices are high and selling when prices are low, whereas rational speculators, by trading against irrational investors (e.g., buy when prices are low and sell when high), correct the deviation of prices from fundamentals and stabilize asset prices. Similarly, the noisy rational expectation models of Hellwig (1980) and Wang (1993) argue that volatility increases with uninformed or liquidity trading. Empirically, Avramov et al. (2006) document that the activities of both imitative and nonimitative investors have a significant effect on day-to-day volatility, although in different directions. At the intraday level, Blasco and Corredor (2017) examine the Probability of Informed Trading (PIN) and detect that informed trading is a price-stabilizing factor in heavily traded and highly capitalized stocks. Indirectly, using a monthly firm-level PIN measure and excess return, Lai et al. (2014) find a positive correlation between PIN and volatility in international markets. Recently, Collin-Dufresne and Fos (2016) extended Kyle's (1985) model to a case where noise trading volatility follows a general stochastic process, demonstrating that informed traders choose to trade more aggressively when uninformed trade volume is higher and price impact is lower.

Regarding price efficiency, theoretical models (Diamond (1985), Gao and Liang (2013), Colombo, Femminis, and Pavan (2014), Banerjee et al. (2018), and Dugast and Foucault (2018), among many others), deduce price efficiency as a static precision of the conditional expected price based on fundamental information. Further, a subset of these papers focuses on a "crowding out" effect: greater public disclosure about fundamentals can crowd out private information acquisition, which in turn can reduce price informational efficiency. However, short-term price efficiency is largely ignored. We extend the recent empirical literature (Boehmer and Kelley (2009), Chaboud et al. (2014), and Rosch et al. (2016)) to test the effect of HPITs on short-term price efficiency.

3 Xetra Trading System

The data used in this study are from the Xetra trading system, which is operated by Deutsche Börse at the Frankfurt Stock Exchange (FSE). Xetra trading system imposes a Price-Visibility-Time Priority condition, where the electronic trading system places the incoming order after checking the price and timestamps of all available limit orders in the LOB. Our database includes 20 levels of LOB information, which means that, any registered member can evaluate the liquidity supply dynamics and potential price impact of a market order. A more detailed description of the reconstruction of the LOB is available in the online appendix (Section A1).

Our study focuses on the component stocks in three market indexes, DAX, MDAX, and SDAX, respectively. The DAX consists of the 30 major German companies listed on the Frankfurt Stock Exchange. MDAX includes 50 component stocks and is a stock index for the listed companies that rank below the companies in the DAX index in terms of market capitalization and order book volume (technology companies excluded). Finally, the SDAX is composed of 50 listed stocks that rank directly below the stocks in MDAX. There is a quarterly review to re-rank stocks among these three groups. Using data from the Compustat Global Security Daily files, Table 1 reports the descriptive statistics of daily market variables for DAX, MDAX, and SDAX stocks for six months, from February 1, 2013 to July 31, 2013. A decreasing monotonic trend is observed, from DAX to SDAX stocks, for all variables.

[Insert Table 1 here]

At intraday level, Table 2 presents the descriptive statistics of trades and information environment variables.[7] It follows from Table 2 that DAX stocks, compared with MDAX and SDAX stocks, are traded in a high public disclosure environment with low trading costs and high market transparency.

[7]To measure the information environment, we use the number of monthly news mentions and three analyst measures as the proxies of the information environment. The monthly number of news is the number of times that the company is mentioned in the news and social media registered by RavenPack. The analyst data are extracted from Institutional Brokers' Estimate System (I/B/E/S) for the period of 2011 to 2015. We take the annual earnings per share (EPS) announcement as our target event. Following Barron et al. (1998), we first compute the number of analysts making forecasts about annual EPS up to the firm's actual announcement date. Second, we focus on the earning forecast dispersion, measured by the standard deviation of the forecasted EPS, standardized by the share price at the beginning of the year (Barron and Stuerke (1998) and Johnson (2004)). The third measure is the forecast error, defined as the absolute difference between the mean forecast EPS and actual EPS, standardized by the price at the beginning of the year (Rajan and Servaes (1997) and Gu and Wang (2005)).

[Insert Table 2 here]

4 Prevalence of Matched Trades

We first investigate the existence of LOB-matched trades, and the importance of such trades. A transaction is initiated by either the buy side or sell side. However, the counterparts of transactions are the limit orders standing in the open LOB. With the development of information technology, the speed of submitting an order has become faster than ever before. For instance, Xetra implemented co-location service that allows traders to connect to the central server with much less latency (13 microseconds). Thus, with this speed advantage, traders can match the exact quantities standing in the open LOB when submitting a market or marketable orders. The dimension of matchedness is important because it provides insight into traders' sensibility to price and liquidity. Table 3 shows that percentage of LOB-matched is important, and most matched and unmatched trades take place at the first level of the open LOB. However, for stocks with greater public disclosure, there are more matched trades than unmatched trades (52.84% Vs. 47.16%), and the opposite is true regarding stocks with less public disclosure (42.07% Vs. 57.93%). It should be noted that a medium- or large-sized matched trade can also take place at the first level of the open LOB.

[Insert Table 3 here]

For our LOB-matched-trade identification, one might argue that the marketable orders can also give the illusion of an LOB-matched market order. As we show in Figure 3, a marketable bid (ask) order will both match the exact quantity in the ask (bid) side of the open LOB and increase (decrease) the best bid (ask) price to the price of the matched level. However, a simple buy (sell) market order will only consume the quantity standing in the ask (bid) side without creating a new best bid (ask) price. Therefore, to rule out the marketable orders, we also check the state of the LOB after the transaction to guarantee the accuracy of our matchedness identification.

[Insert Figure 3 here]

5 Price Discovery, Trade Attributes, and HPITs

Now we turn our attention to the HPIT computation. Figure 4 presents the flowchart of HPIT computation. First, we calculate the tick-by-tick price discovery for each trade category. Next, we determine the corresponding proportion of volume for each category. Then, we qualitatively assess the information content by calculating the information ratio, defined as the ratio of cumulative price contribution to the corresponding proportion of volume for each trade category. Following these initial steps, we perform a regression of the weighted price discovery on the proportion of volume to quantitatively identify the trade categories to be included in HPIT. Finally, we aggregate the volume within the selected categories and compute the HPITs.

[Insert Figure 4 here]

5.1 Price Discovery

In order to address the issue of the contribution of different trade categories to the price discovery process, we define the daily price change as the total daily price discovery and take the ratio of the cumulated price change associated with a given category over the full price discovery as the contribution of that trade category. Also, we follow the rationale that if informed trades are the main cause of stock price changes and concentrate their trades in specific trade categories, then most of a stock's price change should take place on these trade categories. In other words, informed trading related trade categories should directly affect stock price, as reported by Collin-Dufresne and Fos (2016). With our comprehensive dataset on the transaction and the open LOB, we can further evaluate how important the size, matchedness, and roundedness of trade are in informed trading identification. Also, we take trade size as our first dimension when distinguishing the trades. Trade-size is expressed in relative terms and defined as small, medium and large. The critical values used to categorize the different groups are the 30th and 70th percentiles of trade sizes.

As in the study by O'Hara et al. (2014), we suppose there are N trades for stock s for day t, and each trade can be categorized into one of J groups. In addition, we define the contribution of a given trade as the log difference between the current trade's price and the price of the previous transaction, i.e., $r_n = logP_n - log(P_{n-1})$. The cumulative price contribution of the trades belonging to category j for stock s on day t is defined as

$$PC_j^{s,t} = \frac{\sum_{n=1}^{N} \delta_{n,j} r_n^{s,t}}{\sum_{n=1}^{N} r_n^{s,t}}, \tag{1}$$

where $\delta_{n,j}$ is an indicator variable that takes the value of one if the n-th trade falls into size category j, and zero otherwise. Following Barclay and Warner (1993), we weigh each stock's price contribution to mitigate the problem of heteroskedasticity, which may be severe for firms with small cumulative changes. Suppose there are N trades for stock s on day t. The weight for stock s on day t is defined as

$$w^{s,t} = \frac{\mid \sum_{n=1}^{N} r_n^{s,t} \mid}{\sum_{s=1}^{S} \mid \sum_{n=1}^{N} r_n^{s,t} \mid}. \tag{2}$$

The weighted price contribution of trades in size category j on day t is defined as

$$WPC_j^t = \sum_{s=1}^{S} w^{s,t} PC_j^{s,t}. \tag{3}$$

Suppose there are T days in total. The weighted price contribution of trades in size category j is defined as

$$WPC_j = \frac{\sum_{t=1}^{T} WPC_j^t}{T}. \tag{4}$$

5.2 Trade Attributes and Price Contribution

Using all transactions from all stocks, we first report the weighted price contribution associated with trade size as in Barclay and Warner (1993). Then we extend our analysis to the weighted price contribution of matchedness and roundedness. Finally, we provide a more detailed analysis by jointly considering trade size, matchedness, and roundedness.

Panel A of Table 4 summarizes the aggregated results by Size. In line with O'Hara et al. (2014), our dataset shows that small-size trades are associated with disproportionately large price changes relative to their share of the total trading volume. Using a data sample between 1981 and 1984, Barclay and Warner (1993) find that medium-size trades are the trades associated with disproportionately large price changes relative to their proportion of volume. The difference between their findings and ours suggests a migration of informed trades from medium-size to small-size trades. Our explanation is that trading cost decreased over time in financial markets. Informed traders always have to trade off between the gains related to their private information and the costs associated with the trading implementation. In previous quote-driven markets, traders paid, for each transaction, a high order processing cost charged by financial intermediaries. Thus, the practice of cutting large orders into small ones was very costly. However, the transformation from quote-driven to order-driven market and the proliferation of electronic trading reduced dramatically this order processing cost and gave informed traders an incentive to place more small orders. One may argue that the decrease in trading costs also gave incentive to liquidity traders to cut their orders. In fact, as shown by our results, it is the matchedness and roundedness that further distinguish informed traders and liquidity traders for a given size group.

Our main contribution relates to Panel B, which shows the weighted price contributions of trade categories classified by size and matchedness, along with the corresponding information quality. It is important to note that Panel B presents the same findings as Panel A does, but at a distributive level. To see this, consider that the small-size WPC for DAX in Panel A (12.53%) is the sum of the small-matched and small-unmatched WPC for DAX in Panel B ($17.14\% - 4.61\% = 12.53\%$). In this typical example, we already notice that small-matched trades and small-unmatched ones do not have the same contribution to price discovery process. Therefore, considering all small-size trades in the same way without making any further distinction could be misleading. Interestingly, for DAX stocks, small-matched trades are more informative than small-unmatched ones in terms of WPC, while the opposite is true for MDAX and SDAX. Recall that our objective is to identify which type of traders predominantly drives the occurrence of matched trades. The results suggest that informed traders rely more on small-matched trades for DAX, and on small-unmatched trades for MDAX and SDAX. Similarly, the WPC of large-unmatched trades consistently dominates that of large-matched trades, indicating that matchedness can still help differentiate large trades, even when they are primarily used by uninformed traders.

Finally, we analyze WPC with all three dimensions: size, matchedness, and roundedness. Panel C of Table 4 illustrates the WPC of the total of 9 trade categories.

When we compare the ratio of the WPC to its corresponding weight in total trade volumes, for DAX stocks, the most informative trade categories are small-matched, small-unmatched-unrounded, and medium-unmatched-unrounded. Surprisingly, unmatched-rounded trades, regardless of their sizes, contribute negatively to cumulative price changes. The results confirm that the high level of granularity in our trade category analysis is important in informed trading identification. For MDAX stocks, the results are similar, except we now find that unmatched-rounded trades contribute positively to price discovery particularly for small ones. For small trades in SDAX stocks, unmatched-rounded trades contribute more to price discovery than matched and unmatched-unrounded trades. The results imply that for liquid stocks, uninformed traders are likely to place more unmatched trades to meet their given objectives, and informed traders, who are sensitive to both liquidity and price, are likely to submit matched trades when correcting mispricing. However, when there is a liquidity shortage, uninformed traders care more about liquidity and are likely to submit matched trades, and informed traders are likely to submit unmatched trades (e.g., marketable trades).

In summary, we show that size, matchedness, and roundedness are jointly important in trade distinction and informed traders choose different trade categories to reveal their information according to the level of liquidity and information disclosure.

[Insert Table 4 here]

5.3 HPITs with Selected Trade Categories

In previous section, we show that the inclusion of matchedness in HPITs identification is important, and that trade categories of HPITs may also change across different indexes. We now turn to statistically identify HPITs. To do so, we estimate the following regression:

$$PC_j^{s,t} = \sum_{j=1}^{k} \alpha_j \times dummy_j + \beta \times PcntVolume_j^{s,t} + \epsilon_j^{s,t} \quad (5)$$

where $PC_j^{s,t}$ is the price contribution of category j for stock s on day t (defined in equation (1)). $dummy_j$ and $PcntVolume_j^{s,t}$ relate to the dummy variable for category j and the volume percentage of category j for stock s on day t, respectively. If there is no significant contribution of a given trade category to the daily price discovery process, the coefficient of the corresponding dummy variable should not be significantly different from zero.[8]

In Table 5, we present the regression results of the 9 trade categories, classified by trade size, matchedness and roundedness, for the stocks in the three market indexes. A positive and significant coefficient for a dummy variable means that the price change related to such category moves in the same direction as a daily price change, while a negative and significant coefficient implies that the price change related to such category moves against the daily price change. For DAX stocks, we show that the coefficients of five dummy variables are significanlly different from zero at the 1% level: small and medium matched trades, as well as unmatched-unrounded trades, regardless of their sizes. In addition, rounded-unmatched trades, regardless of their sizes, do not have contribution to daily price changes, which confirms what we observed in Table 4. It should be noted that for liquid stocks HPITs' traders also submit large unmatched-unrounded orders. MDAX stocks also have five positive and significant informed trade categories which include small and medium matched trades, small and medium unmatched-unrounded trades, and small unmatched-rounded trades. As for SDAX stocks, there are only four positive and significant informed trade categories: small matched trades, small and medium unmatched-unrounded trades, and small unmatched-rounded trades. For MDAX and SDAX stocks,

[8]Note that our analysis focuses on the cumulative price changes of all trades in an associated trade category. Therefore, an estimated coefficient not significantly different from zero for a given category does not mean that there is no informed trades at all in such trade category. Instead, the associated trade category is dominated by uninformed trades.

large-size trades, regardless of roundedness and matchedness, do not belong to HPITs for any of the three groups.

[Insert Table 5 here]

Note that each HPIT category typically does not exclude uninformed trades: both informed and uninformed trades could be present in any trade category. However, an HPIT category is the group in which the price contribution of informed trades should dominate that of uninformed ones. Also, market capitalisation, liquidity, and informational transparency are the main factors to consider when informed traders choose trade categories (size, matchedness, and roundedness) for their trades.

5.4 Intraday Dynamics of HPITs

We further evaluate their hourly contribution to price discovery during the trading day. We first compute the hourly price contribution by taking the ratios of hourly price change over daily price change, and decompose the resulting hourly price contribution into those associated with HPITs and non-HPITs. For DAX stocks, the contribution to price discovery of HPITs dominates that of non-HPITs during the whole continuous trading session. More specifically, between 9 a.m. and 10 a.m. (during the beginning of a trading session), with similar trading volume, the contribution of HPITs is much higher than that of non-HPITs (30.72% vs. 4.98%). Also, for the time bins after 10 a.m., price dynamics is mainly driven by HPITs and non-HPITs contribute negatively to price discovery. For MDAX, price contribution of HPITs also dominates that of non-HPITs and the trading volumes of non-HPITs are much larger than those of HPITs. More importantly, the hourly volumes of non-HPITs change a lot during the day and exhibit a strong seasonality pattern. That is, the highest trading volumes arrive at the beginning and the end of trading day. However, the hourly trading volumes of HPITs are around 3%

per hour, which is relatively small, and quite stable during the day. The different intraday patterns of trading volumes for HPITs and non-HPITs suggest that non-HPIT traders are more likely to time their trades than are HPIT traders (a more detailed analysis of the MDAX and SDAX stocks can be found in Section A2 of the online appendix).

[Insert Table 6 here]

6 Market Implicaions of HPITs

6.1 Impact of HPITs on Intraday Volatility

Up to now, we show how important HPITs are in daily price contribution and how to identify them. We next turn our attention to their implications for short-term volatilty. The noisy rational expectation model of Hellwig (1980) argues that rational informed investors stabilize prices by taking positions whenever prices deviate from their fundamentals, i.e. take long (short) position when the price is lower (higher) than fundamentals. As the proportion of informed investors increases, their impact on price increases, leading to a decrease in the deviation of price from its fundamental value. Wang (1993) also provides a model of asymmetric information and shows that the conditional volatility of prices increases with uninformed trading. Therefore, if HPITs are associated with informed trading, our results should be in line with these theoretical models.

In order to examine the impact of HPITs on intraday volatility, we analyze the effect of the proportion of HPITs on the 15-min conditional volatility. Given that high-frequency data behaves very differently from low-frequency data, before estimating the model, we first remove seasonality by following a regression approach as did Dufour and Engle (2000). Moreover, the Ljung-Box statistics with 15 lags on the deseasonalized returns and the corresponding volatilities reject independence at all significance levels for most of the stocks in the sample. Thus, taking the model efficiency and parsimony into consideration, we estimate the model with an EGARCH(1,1) for all stocks:

$$Ret_i = \sigma_i \cdot \varepsilon_i \tag{6}$$

$$log(\sigma_i^2) = \omega + \sum_{j=1}^{p} \alpha_j g(Z_{i-j}) + \sum_{j=1}^{q} \beta_j log(\sigma_{i-j}^2) + \gamma HPIT\%_{i-1} \tag{7}$$

with $g(Z_i) = Z_i + \lambda(|Z_i| - E(|Z_i|))$, and where Ret_i is ith 15-min deseasonalized return, $HPIT\%_{i\text{-}1}$ relates to the proportion of HPITs for the period $i-1$, and ε_i is a normally distributed random variable. The parameters β and λ capture the autocorrelation in volatility. γ measures the impact of HPITs on volatility. After estimation, the model is validated again by Ljung-Box statistics (with 15 lags) of the standardized residuals and squared standardized residuals.

Table A.2 in the online appendix shows the estimation results of the proposed model for DAX stocks. The results suggest that 1) there is a high persistence in volatility given that the parameter β has a mean of 0.862. 2) 29 out of 30 DAX stocks have a negative γ, statistically significant at the 1% level. 3) The proposed model effectively captures the dynamics of volatility, which is validated by Ljung-Box statistics. Similar results are obtained for the MDAX and SDAX stocks. For the sake of brevity, we only present a summary of the estimated parameters in Table 7, instead of full estimation results. In sum, HPITs have negative effect on volatility. However, this negative effect varies across different stock indexes. Specifically, this negative effect decreases, in absolute term, from 2.24 for DAX stocks to 1.05 for MDAX stocks, and 0.47 for SDAX stocks.

[Insert Table 7 here]

One plausible explanation for these differences in the impact on volatility is the varying information conditions of DAX, MDAX, and SDAX stocks. Specifically, DAX stocks exhibit higher transparency and lower information asymmetry. As a result, when stock prices deviate from their fundamental value due to buying or selling pressure from uninformed or liquidity traders, informed traders correct the distortion. In contrast, medium- and small-cap stocks are less transparent, with greater information asymmetry and wider bid-ask spreads. Consequently, even though price distortions persist, informed traders may find it difficult to profit due to the high transaction costs (i.e., the large bid-ask spread).

6.2 Impact on Price Efficiency

So far, we have empirically shown that HPITs lead to a decline in intraday volatility by making more contrarian trades, and explained why this decline in volatility is not the same across different groups identified by the difference in their information setting. An extension of our previous results is to investigate the causality links between HPITs and market efficiency using the Generalized Method of Moments (GMM) in a dynamic panel where the number of observations is large and the number of periods is moderately large. Since the seminal work of Arellano and Bond (1991), the GMM procedure has become an important method for estimating parameters with dynamic panel data and individual fixed effects. The GMM method consider the lagged levels of the set of explanatory variables as instruments.

As for market efficiency, theoretical and empirical finance do not always have the same measurements and conclusions, depending on their focus. Specifically, theoretical models emphasize on the static precision of the conditional expected price based on fundamental information (Diamond (1985), Gao and Liang (2013), Colombo et al. (2014), Banerjee et al. (2018), and Dugast and Foucault (2018)), while empirical studies attempt to assess the dynamics aspect of efficiency, that is, statistically, how closely stock prices follow a random walk (Lo and MacKinlay (1988), Boehmer and Kelly (2009), Chaboud et al.

(2014), Conrad et al. (2015), and Rosch et al. (2016)). Given this nuanced divergence in measurement, our study follows the empirical finance literature and uses variance ratio- and autocorrelation-based measurements for price efficiency.

Variance Ratio Evidence

The first measurement we use for price efficiency is derived from the variance ratio proposed by Lo and MacKinlay (1989). For our dataset, we take 30 seconds and 5 minutes as our short and large intervals, respectively. Further, we compute the ratio of variance over 2-hour and 4-hour measurement intervals. To avoid the degeneration of the variance ratio, we require at least 30 non-zero short interval returns in each 2-hour measurement interval. We choose 30 seconds as our short intervals because the interval should be short enough to capture the high-frequency dynamics in price changes and provide sufficient observations to compute the variance. This interval also needs to be long enough to avoid high-frequency noise (more details about variance ratio computation can be found in Section A3 of the online appendix).

To examine the effect of HPITs on price efficiency, we run the following fix-effect dynamic panel regression:

$$\begin{aligned} \mathit{Mrk\_Efficiency}_{i,t} = {} & \delta \times \mathit{Mrk\_Efficiency}_{i,t-1} + \alpha_i + \beta_1 \times \mathit{HPIT}_{i,t-1} \\ & + \beta_2 \times \mathit{log}(\mathit{Price}_{i,t-1}) + \beta_3 \times \mathit{Range}_{i,t-1} + \beta_4 \times \mathit{Spread}_{i,t-1} + \epsilon_{i,t} \,, \end{aligned} \tag{8}$$

where $\mathit{Mrk\_Efficiency}_{i,t}$ is the market efficiency measure for stock i during t-th interval. As mentioned above, we include *Range* to control for volatility and *Spread* for liquidity. If HPITs are informed trades, according to the random walk hypothesis, the future price should be less predictable because more information is incorporated in the price. In other words, the presence of HPITs helps to incorporate information into the price and will make the future prices less predictable or more likely to follow a random walk process. Our dependent variable is the absolute value of $M_r(q) - 1$.[9] Therefore, if our conjecture is correct, we expect a negative effect of HPITs on the dependent variable.

Panel A of Table 8 reports the results of regression (8) based on variance ratio. The results indicate a causal relationship between lagged HPITs and market efficiency. Specifically, for DAX stocks, an increase in HPITs significantly results in price efficiency at the 5% level. This effect decreases and remains significant for MDAX and SDAX stocks at the 1% level. Since the coefficients of the lagged dependent variables are very low in absolute values, these results should not contain any bias effect associated with the method of estimation. Also, it follows that an increase in the spread also makes the future price more efficient for all DAX, MDAX, and SDAX stocks at the 1% level and this effect decreases with liquidity. To understand the relationship between spread and price efficiency, consider that the expected fundamental value of the stock is p_0, which is different from the current midquote price mq_0, and there exists a spread s_0 between the best ask and the best bid price. When s_0 is so large that the expected fundamental price, p_0, falls in the interval $(mq_0 - \frac{s_0}{2}, mq_0 + \frac{s_0}{2})$, this discourages informed trades because the gain from the information cannot cover the transaction cost. As a result, prices remain efficient without trading activity.

[Insert Table 8 here]

Autocorrelation Evidence

The variance ratio measures only one facet of price informational efficiency. More generally, one concern about high-frequency traders is that they cut their large volumes

[9] If prices follow a random walk process, the ratio of scaled large interval return variance over short interval return variance should be equal to one. $abs(M_r(q) - 1) \equiv abs(variance\,ratio - 1)$ with the minimum value of zero corresponding to a pure random walk process

into small ones and span them during a longer horizon, which may cause autocorrelation. We thus access the impact of HPITs on a more general measure of price efficiency: the autocorrelation of high-frequency return. Specifically, we investigate the causal relation between HPITs and the absolute value of the first-order autocorrelation based on five-second returns every two hours. If HPITs are related to informed trades, the returns should be less autocorrelated because more information is incorporated in the price, which suggests a negative effect of HPITs on absolute autocorrelation coefficient. The dynamic panel regression of (8) is estimated by GMM for all DAX, MDAX, and SDAX stocks, with absolute value of the autocorrelation as dependant variables.

Panel B of Table 8 presents the results for autocorrelation-based price efficiency. Similar to the results for the variance ratio, a higher proportion of HPITs causes a decrease in the intraday return autocorrelation for all stocks in our sample. The results on autocorrelation-based efficiency provide more evidence on how HPITs act as a price stabilizer for the DAX, MDAX, and SDAX. Specifically, this effect depends on the characteristics of trading and information environments. For large-cap liquid stocks, price correction informed trades reduce the return autocorrelation, whereas for medium- and small-cap stocks, given that a wide bid-ask spread impedes price correction, the role played by HPITs as price stabilizer is less pronounced.

7 Conclusion

We suggest matchedness as a new trade attribute to classify trades. The matched trades, which represent more than 50% of total trades in our sample, allow traders to profit, to the greatest extent, from the most beneficial price available on the active market. Our empirical results show that trade size, matchedness, and roundedness are jointly important attributes to identify high price impact trades (HPITs) that have disproportionately large cumulative price changes relative to their proportion of volume.

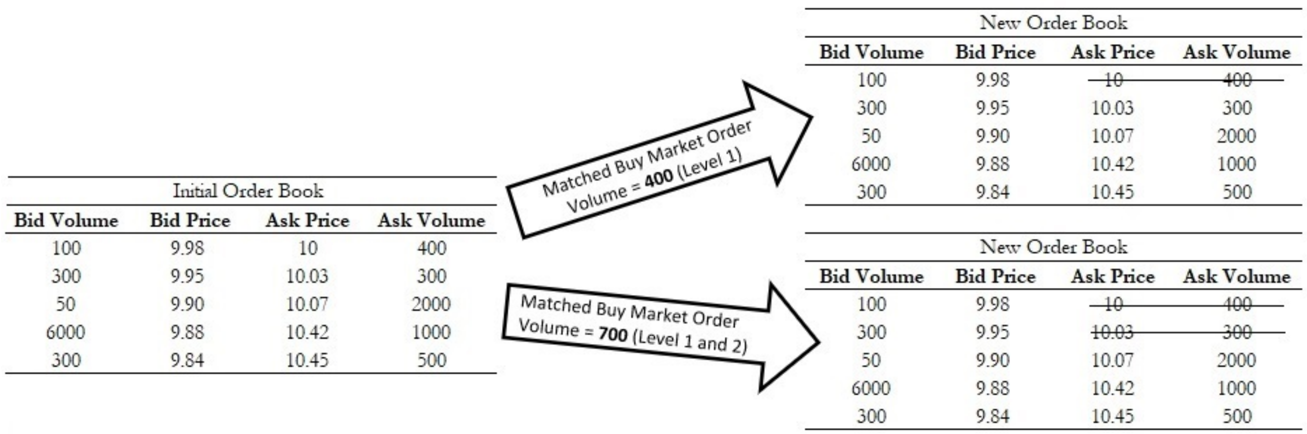
We further test the implications of HPITs for short-term volatility and price efficiency. We show that a stronger presence of HPITs leads to a decline in volatility. However, this negative effect increases in absolute value with the level of stocks' public disclosure. Further, we use variance-ratio and autocorrelation-based price efficiency measures to test whether HPITs cause an increase in price efficiency.

We identify two areas for future research. Our study uses data from a relatively stable period. When applied to different market conditions, such as market turmoil or the presence of circuit breakers, HPIT computation should incorporate additional information related to these specific events. In terms of the type of exchange, our research focuses on exchanges with the LOB (i.e., lit exchanges). In other market settings, such as those with a higher prevalence of hidden orders or dark pools, HPIT computation can be more challenging due to the absence of the LOB. However, given that most price discovery occurs on lit exchanges, the proposed HPIT remains a strong identifier of informed trading.

Our study centers on market orders. Further studies could explore other order types, such as marketable or limit orders. From a practical standpoint, we provide a framework for detecting informed trading that can easily incorporate advanced techniques like machine learning for detecting informed trades. Future research on AI-based trading strategies could also benefit from considering the dimension of matchedness.

The findings of our study have important policy implications. Our proposed algorithm can assist regulators in enhancing surveillance systems to detect signs of illegal insider information leaks. By identifying high price impact trades based on the attributes suggested in our paper, regulators can link these trades to suspicious abnormal trading patterns or price movements, particularly during periods of M&As or earnings reports. By further investigating traders' access to information, regulators can better determine whether the traders are engaging in illegal insider activity.

Figure 1: Matched Market Orders



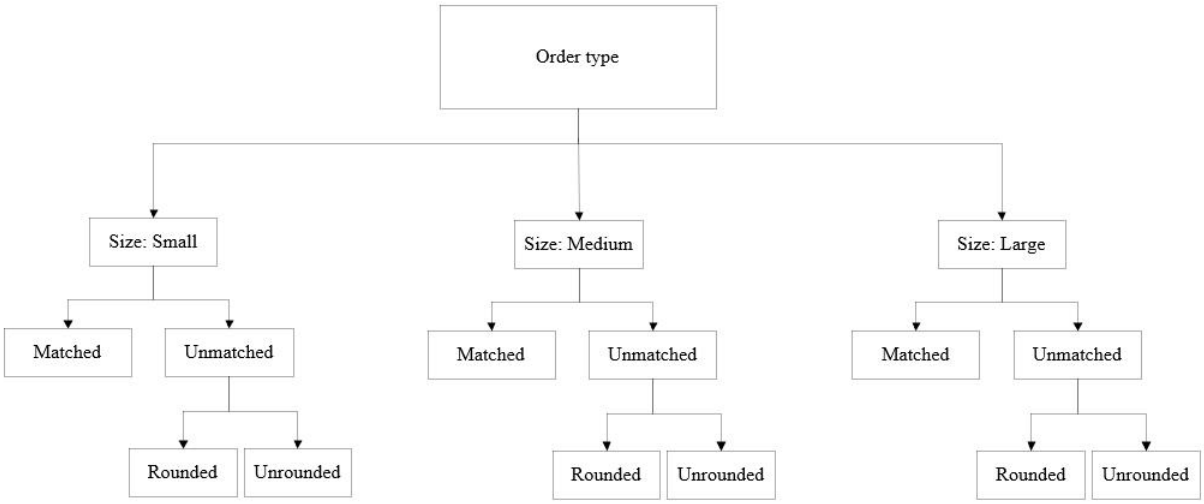
Initial Order Book			
Bid Volume	**Bid Price**	**Ask Price**	**Ask Volume**
100	9.98	10	400
300	9.95	10.03	300
50	9.90	10.07	2000
6000	9.88	10.42	1000
300	9.84	10.45	500

New Order Book			
Bid Volume	**Bid Price**	**Ask Price**	**Ask Volume**
100	9.98	~~10~~	~~400~~
300	9.95	10.03	300
50	9.90	10.07	2000
6000	9.88	10.42	1000
300	9.84	10.45	500

New Order Book			
Bid Volume	**Bid Price**	**Ask Price**	**Ask Volume**
100	9.98	~~10~~	~~400~~
300	9.95	~~10.03~~	~~300~~
50	9.90	10.07	2000
6000	9.88	10.42	1000
300	9.84	10.45	500

The figure presents the outcomes of two matched orders. One is the level-1 matched buy market order and the other levels 1 and 2. Note that a market buy order less than 400, which is identified as unmatched trade, has the same transaction price and price impact as a market buy order of 400, which is identified as matched trade.

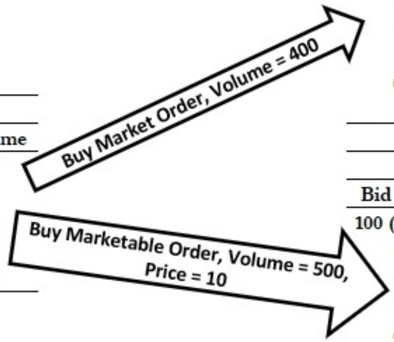
Figure 2: Decision Tree for Order Category



The figure presents how order category is decided by traders. Specifically, traders first consider the dimension of size. Then, they verify if they are capable of making matched trades. If not, they consider submitting rounded or unrounded trades.

Figure 3: Marketable Orders Vs. Market Orders

Initial Order Book			
Bid Volume	**Bid Price**	**Ask Price**	**Ask Volume**
100	9.98	10	400
300	9.95	10.03	300
50	9.90	10.07	2000
6000	9.88	10.42	1000
300	9.84	10.45	500

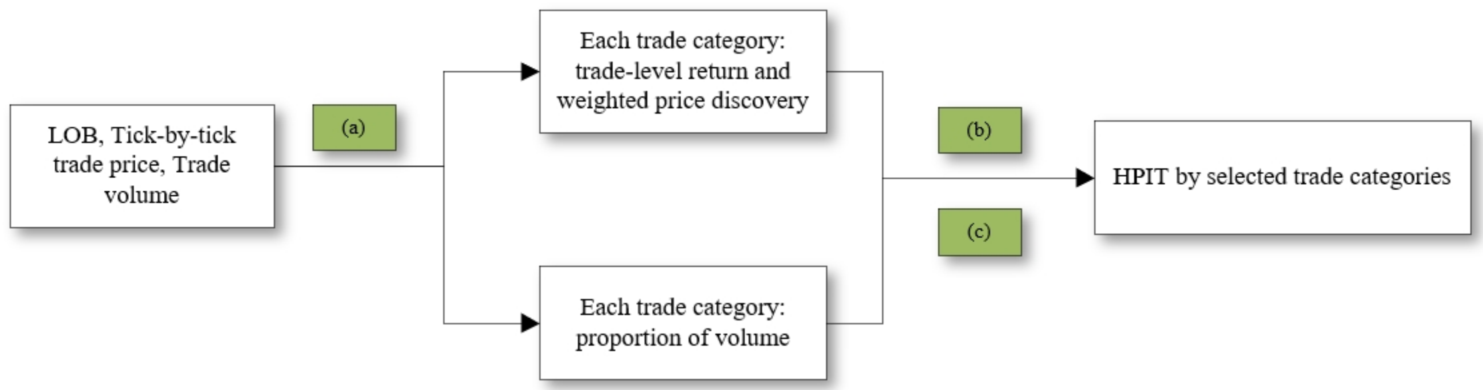


New Order Book			
Bid Volume	**Bid Price**	**Ask Price**	**Ask Volume**
100	9.98	~~10~~	~~400~~
300	9.95	10.03	300
50	9.90	10.07	2000
6000	9.88	10.42	1000
300	9.84	10.45	500

New Order Book			
Bid Volume	**Bid Price**	**Ask Price**	**Ask Volume**
100 (unfilled)	10	~~10~~	~~400~~
100	9.98	10.03	300
300	9.95	10.07	2000
50	9.90	10.42	1000
6000	9.88	10.45	500

The figure presents and compares the different outcomes of market and marketable orders. The market order is submitted with volume of 700 shares. The marketable order is submitted with volume of 500 shares and price of 10.00 Euros.

Figure 4: Computation of HPITs



The figure presents the procedure we follow to compute the HPITs. (a): classify trades into different categories based on size, matchedness, and roundedness, (b): assess the information content by calculating the information ratio, defined as the ratio of cumulative price contribution to the corresponding proportion of volume for each trade category. (c): perform a regression of the weighted price discovery on the proportion of volume.

Table 1: Summary Statistics for DAX, MDAX, and SDAX Stocks

	DAX	MDAX	SDAX
A. Sample			
Number of days	125	125	125
Number of stocks	30	50	50
B. Daily market			
Avg. Market Capitalization (in billion Euros)			
Mean	26.69	3.68	0.50
Median	18.40	2.21	0.36
Standard deviation	21.01	4.80	0.40
Avg.Daily Price (in Euros)			
Mean	62.81	48.22	27.60
Median	57.48	34.09	16.44
Standard deviation	43.07	45.54	41.74
Avg.Daily Trading Volume (in million shares)			
Mean	4.08	0.35	0.21
Median	2.09	0.19	0.03
Standard deviation	6.71	0.52	0.58
Avg. Daily Turnover (in percentage)			
Mean	0.50%	0.31%	0.25%
Median	0.41%	0.26%	0.16%
Standard deviation	0.29%	0.17%	0.38%
Avg. Daily Return (in percentage)			
Mean	0.04%	0.03%	-0.07%
Median	0.03%	0.02%	-0.03%
Standard deviation	0.24%	0.13%	0.48%

This table reports the statistics for the average market capitalization (in billion Euros), the average daily price (in Euros), the average daily trading volume (in million shares), the average daily turnover (in percentage) defined as the trading volume over the outstanding shares and the average daily (log) return for the stocks in DAX, MDAX and SDAX indexes, from February 1, 2013 to July 31, 2013. All data are from the Compustat Global Security Daily files and based on the primary issues.

Table 2: Trade and Information Environment Statistics for DAX, MDAX, and SDAX Stocks

	DAX	MDAX	SDAX
A. Sample			
Number of days	125	125	125
Number of stocks	30	50	50
B. Trade environment			
Relative bid-ask spread			
Mean	5.45E-04	1.57E-03	5.20E-03
Median	6.02E-04	1.43E-03	4.68E-03
Standard deviation	1.49E-04	6.11E-04	2.45E-03
LOB depth ask (cum.5-level)			
Mean	11508	1388	2667
Median	3405	925	1544
Standard deviation	27368	1204	4770
LOB depth bid (cum.5-level)			
Mean	11873	1338	2854
Median	3390	913	1207
Standard deviation	29515	1107	5818
Shares/trade			
Mean	668	209	481
Median	259	144	251
Standard deviation	1138	182	744
Volumes (ï¿œ)/trade			
Mean	17283.21	5982.99	4074.04
Median	15142.64	5467.92	3972.78
Standard deviation	6219.74	2054.80	1042.54
Duration (second)/per trade			
Mean	9.40	46.37	268.03
Median	8.87	35.49	294.24
Standard deviation	4.57	28.88	108.74
Daily number of trades			
Mean	4527	1025	185
Median	3954	1012	125
Standard deviation	2149	479	143
C. Information environment			
Monthly Number of news per stock in average			
Mean	606	104	21
Median	236	41	16
Standard deviation	752	288	14
Number of analysts			
Mean	29.77	2.88	2.02
Median	30	3	2
Standard deviation	4.55	0.45	0.51
Forecast dispersion			
Mean	0.008	0.009	0.032
Median	0.005	0.005	0.006
Standard deviation	0.015	0.014	0.146
Forecast error			
Mean	0.007	0.013	0.055
Median	0.002	0.004	0.005
Standard deviation	0.015	0.023	0.226

This table reports the statistics for trading and information environment variables. The best bid-ask spread is the relative bid-ask spread defined as log(best ask) - log(best bid). LOB depth ask (bid) is the cumulative quantity available for the first three levels at the ask (bid) side of the LOB. Duration/trade is the time between two consecutive trades. The monthly number of news is the number of times that the company is mentioned in the mass media and the news data are from the RavenPack dataset. Finally, trades hit by hidden orders is the proportion of market orders that are matched with iceberg or hidden orders embedded in the open LOB.

Table 3: Matched and Unmatched Trades

			BID					ASK				
	Level of open LOB		>3	3	2	1	0	1	2	3	>3	Total
DAX	Nb.Trade	Matched	0.001%	0.001%	0.009%	26.450%	N/A	26.369%	0.009%	0.001%	0.001%	52.84%
		Non_Matched	0.142%	0.393%	1.839%	20.951%	0.151%	21.372%	1.810%	0.379%	0.130%	47.16%
	Volume	Matched	0.010%	0.003%	0.018%	25.757%	N/A	25.629%	0.019%	0.003%	0.011%	51.45%
		Non_Matched	1.062%	1.551%	3.791%	17.988%	0.099%	17.934%	3.786%	1.516%	0.995%	48.55%
MDAX	Nb.Trade	Matched	0.003%	0.002%	0.012%	25.927%	N/A	25.817%	0.013%	0.003%	0.004%	51.78%
		Non_Matched	0.305%	0.458%	2.049%	21.177%	0.151%	21.409%	2.021%	0.438%	0.281%	48.22%
	Volume	Matched	0.024%	0.007%	0.024%	25.337%	N/A	25.607%	0.026%	0.010%	0.036%	51.07%
		Non_Matched	2.492%	1.367%	3.299%	17.386%	0.115%	17.678%	3.315%	1.396%	2.547%	48.93%
SDAX	Nb.Trade	Matched	0.015%	0.008%	0.051%	21.290%	N/A	20.637%	0.028%	0.011%	0.026%	42.07%
		Non_Matched	0.879%	1.056%	4.135%	22.830%	0.151%	23.896%	3.789%	0.857%	0.712%	57.93%
	Volume	Matched	0.076%	0.032%	0.073%	19.884%	N/A	19.433%	0.063%	0.035%	0.091%	41.69%
		Non_Matched	8.420%	2.951%	6.588%	16.200%	0.079%	17.122%	6.093%	2.421%	6.145%	58.31%

This table reports the distribution of matched and non-matched trades and their corresponding volume proportions at different levels of the open LOB for DAX, MDAX, and SDAX stocks. For non-matched trades, the level is the highest level that is partially depleted. For instance, for DAX stocks, 1.839% of trades involve sell-initiated trades that consume the total liquidity at the best bid and part of the liquidity at the second bid. Trade at level zero relates to a transaction inside the best bid and ask. There are two possible scenarios: 1) a market buy (sell) order trades against a hidden sell (buy) limit order with a price lower (higher) than the best ask (bid), and 2) both buy and sell orders arrive at the market simultaneously and are matched automatically.

Table 4: Price Contribution, Roundedness And Matchedness of Trade Sizes

		WPC			Volume			WPC/Volume		
Panel A: Size										
DAX	Small	12.53%			5.41%			2.316		
	Medium	45.60%			26.05%			1.751		
	Large	41.87%			68.54%			0.611		
MDAX	Small	35.12%			5.63%			6.235		
	Medium	39.71%			27.55%			1.441		
	Large	25.17%			66.82%			0.377		
SDAX	Small	20.80%			5.24%			3.967		
	Medium	35.33%			26.23%			1.347		
	Large	43.88%			68.52%			0.640		
Panel B: Size × Matchedness										
		Matched	Unmatched		Matched	Unmatched		Matched	Unmatched	
DAX	Small	17.14%	-4.61%		2.68%	2.73%		6.394	-1.687	
	Medium	26.35%	19.25%		15.23%	10.82%		1.730	1.780	
	Large	17.57%	24.29%		34.45%	34.09%		0.510	0.713	
MDAX	Small	14.99%	20.14%		2.81%	2.82%		5.335	7.131	
	Medium	15.03%	24.68%		14.77%	12.78%		1.017	1.932	
	Large	4.59%	20.58%		34.64%	32.17%		0.132	0.640	
SDAX	Small	6.12%	14.67%		2.28%	2.97%		2.691	4.945	
	Medium	5.81%	29.52%		11.63%	14.60%		0.499	2.022	
	Large	16.67%	27.21%		28.10%	40.43%		0.593	0.673	
Panel C: Size × Matchedness × Roundedness										
		Matched	Unmatched		Matched	Unmatched		Matched	Unmatched	
			Rounded	Unrounded		Rounded	Unrounded		Rounded	Unrounded
DAX	Small	17.14%	-17.22%	12.61%	2.68%	1.03%	1.70%	6.394	-16.777	7.405
	Medium	26.35%	-8.47%	27.72%	15.23%	4.19%	6.63%	1.730	-2.021	4.184
	Large	17.57%	-3.68%	27.97%	34.45%	11.72%	22.37%	0.510	-0.314	1.250
MDAX	Small	14.99%	4.12%	16.02%	2.81%	0.80%	2.03%	5.335	5.173	7.900
	Medium	15.03%	4.17%	20.51%	14.77%	4.40%	8.38%	1.017	0.949	2.448
	Large	4.59%	5.08%	15.50%	34.64%	12.11%	20.06%	0.132	0.419	0.773
SDAX	Small	6.12%	5.11%	9.56%	2.28%	0.96%	2.01%	2.691	5.330	4.762
	Medium	5.81%	8.65%	20.87%	11.63%	5.79%	8.81%	0.499	1.493	2.370
	Large	16.67%	13.75%	13.46%	28.10%	19.07%	21.36%	0.593	0.721	0.630

This table reports the weighted price contribution for each order category classified by size, roundedness, and matchedness. WPC is the weighted price contribution. Volume relates to the percentage of trades (volume) in each size type. Panel A, B, and C reports the results for Size, Size × Matchedness, and Size × Matchedness × Roundedness.

Table 5: Price Discovery of Different categories of Trades

			DAX	MDAX	SDAX
Matched		Small	0.006***	0.003***	0.001**
		Medium	0.010**	0.001***	-0.002*
		Large	0.009	-0.004***	-0.005**
Unmatched	Unrouned	Small	0.004***	0.003***	0.003***
		Medium	0.010***	0.003***	0.004***
		Large	0.012**	0.001	-0.004*
	Rounded	Small	-0.006***	0.001***	0.001**
		Medium	-0.002**	0.000	0.001
		Large	-0.000	-0.001**	-0.003***
Volume			-0.010	0.013***	0.039***
Adjusted R^2			0.009	0.006	0.004
Num_Obs			33678	56142	31455

This table reports the results of weighted least square regressions of WPC on the percentage of the volume and dummies based on matchedness, roundedness, and size, $PC_j^{s,t} = \sum_{j=1}^{k} \alpha_j \times dummy_j + \beta \times PcntVolume_j^{s,t} + \epsilon_j^{s,t}$, for DAX, MDAX, and SDAX stocks. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at 1%, 5%, and 10%, respectively. Num_Obs is the number of observations in the regression. From the sample, we exclude the days that have the same open and close prices.

Table 6: Intraday Price Discovery and Volume Proportion of HPITs and non-HPITs for DAX, MDAX and SDAX Stocks

Index	Total Sample				DAX				MDAX				SDAX			
	Price discovery (%)		Volume proportion (%)		Price discovery (%)		Volume proportion (%)		Price discovery (%)		Volume proportion (%)		Price discovery (%)		Volume proportion (%)	
Trading hour	HPITs	No.HPITs	HPITs	No.HPITs	HPITs	No.HPITs	HPITs	No.HPITs	HPITs	No.HPITs	HPITs	No.HPITs	HPITs	No.HPITs	HPITs	No.HPITs
9h-10h	20.14%	12.06%	4.35%	9.66%	30.72%	4.98%	7.94%	7.78%	20.16%	13.03%	3.44%	9.42%	9.54%	18.17%	1.68%	11.79%
10h-11h	8.56%	2.89%	3.54%	8.10%	10.82%	-1.68%	5.96%	6.27%	9.85%	2.94%	3.16%	7.86%	5.00%	7.40%	1.49%	10.18%
11h-12h	9.17%	2.32%	3.28%	7.47%	12.99%	-1.42%	5.33%	5.60%	8.72%	2.56%	3.05%	7.46%	5.80%	5.82%	1.46%	9.34%
12h-13h	5.83%	1.90%	2.65%	6.04%	8.45%	-0.96%	4.11%	4.36%	5.78%	1.50%	2.61%	6.07%	3.26%	5.16%	1.24%	7.69%
13h-14h	4.70%	1.19%	2.36%	5.32%	7.23%	-1.84%	3.67%	3.88%	4.22%	1.71%	2.33%	5.77%	2.64%	3.71%	1.08%	6.30%
14h-15h	6.09%	1.16%	2.90%	6.64%	8.89%	-1.63%	4.51%	4.67%	5.70%	1.36%	2.79%	6.59%	3.69%	3.74%	1.39%	8.66%
15h-16h	8.24%	1.55%	3.66%	8.43%	13.80%	-2.90%	5.77%	6.25%	7.41%	2.24%	3.50%	8.55%	3.51%	5.32%	1.71%	10.51%
16h-17h	7.88%	1.56%	4.54%	10.50%	13.64%	-3.81%	6.86%	7.59%	6.41%	2.65%	4.57%	11.30%	3.61%	5.85%	2.17%	12.61%
17h-17h30	4.08%	0.67%	3.21%	7.36%	5.25%	-2.53%	4.47%	4.99%	2.38%	1.38%	3.32%	8.20%	4.62%	3.15%	1.84%	8.88%
Total	74.70%	25.30%	30.48%	69.52%	111.79%	-11.79%	48.62%	51.38%	70.63%	29.37%	28.78%	71.22%	41.66%	58.34%	14.05%	85.95%

This table reports intraday price discovery and volume proportion of HPITs and non-HPITs for total, DAX, MDAX and SDAX stocks. HPITs are high price impact trades and non-HPITs are the other trades. Price discovery is the associated price change expressed as a percentage of daily price change, and volume proportion is the associated volume expressed as a percentage of daily trade volumes.

Table 7: Summary of the Effect of HPITs on 15-min Conditional Volatility for DAX , MDAX and SDAX Stocks

	DAX			MDAX			SDAX		
Param	Average	Std	Nb_Sig/30	Average	Std	Nb_Sig/50	Average	Std	Nb_Sig/49
ω	-1.67	1.02	30	-1.73	0.85	50	-2.02	1.63	46
α	-0.01	0.03	20	-0.01	0.03	37	-0.02	0.06	39
θ	0.23	0.10	30	0.28	0.08	50	0.25	0.11	49
β	0.86	0.08	30	0.85	0.07	50	0.81	0.17	49
γ	-2.24	1.20	29	-1.05	0.45	50	-0.47	0.50	45
Q(15)_raw	17.84	5.99		29.73	13.89		35.95	23.69	
Q2(15)_raw	15.45	19.89		12.29	7.18		11.84	9.74	
Q(15)_res	27.54	19.21		39.68	19.01		54.88	46.40	
Q2(15)_res	170.45	221.21		252.82	197.20		153.84	279.90	

The table compares the estimated results of the EGARCH model, $log(\sigma_i^2) = \omega + \sum_{j=1}^{p} \alpha_j g(Z_{i-j}) + \sum_{j=1}^{q} \beta_j log(\sigma_{i-j}^2) + \gamma HPIT_{i-1}\%$, for DAX, MDX and SDAX stocks. Q(15) and Q(15)_raw relate to Ljung-Box statistics on 15 lagged standardized residuals derived from the model and raw deseasonalized returns. Q(15)_res (Q(15)_raw) and Q2(15)_res (Q2(15)_raw) are Ljung-Box statistics on 15 lagged standardized residuals (raw deseasonalized returns) and squared standardized residuals (raw deseasonalized returns) derived from the model. The 5% critical value is 24.99. Nb_Sig is the number of stocks with significant parameters. ** indicates that the *t*-statistics of the differences of the parameters between the actual group and the other two groups are significant at the 5% level. For SDAX stocks, we excluded one stock that had fewer than 50 observations.

Table 8: The Effect of HPITs on Market Efficiency

	Panel A: Variance Ratio-based Measure			Panel B: Autocorrelation-based Measure		
	DAX	MDAX	SDAX	DAX	MDAX	SDAX
$Mrk\_Efficiency_{t-1}$	0.123	0.048*	0.065**	0.026	0.055	0.001
	(1.068)	(1.671)	(2.148)	(0.557)	(1.252)	(0.003)
$HPIT_{t-1}$	-0.086**	-0.044***	-0.068***	-0.036***	-0.007**	-0.019***
	(-1.993)	(-3.843)	(-7.185)	(-5.369)	(-2.466)	(-2.982)
$Price_{t-1}$	-1.110	0.024	0.004	0.055	-0.002	-0.003
	(-0.343)	(0.358)	(0.499)	(1.199)	(-0.103)	(-0.954)
$Range_{t-1}$	0.014**	-0.004**	0.006***	0.007***	-0.002**	0.002***
	(2.136)	(-1.970)	(6.799)	(3.732)	(-2.375)	(4.903)
$Spread_{t-1}$	-0.023***	-0.004***	-0.001***	-0.005***	-0.001***	-0.0005***
	(-4.616)	(-12.417)	(-8.039)	(-5.296)	(-10.533)	(-5.833)
$Constant$	4.559	0.271	0.316***	-0.099	0.112*	0.120***
	(0.370)	(1.113)	(13.967)	(-0.562)	(1.831)	(11.564)
Pvalue_AB Test Lag 1	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Pvalue_AB Test Lag 2	0.543	0.458	0.176	0.357	0.502	0.176
Observations	14,938	24,902	13,931	14,938	24,902	13,931
No.tickers	30	50	49	30	50	49

The table presents the fix-effect dynamic panel regression results, using GMM as estimation method, on price efficiency for DAX, MDAX, and SDAX stocks with 4h measurement interval. Panel A reports the results on variance-ratio based price efficiency measure. Panel B presents the results on autocorrelation based price efficiency measure. $HPIT_{i,t-1}$ is the the proportion of HPITs for stock i during the period $i-1$, $Range_{i,t-1}$ relates to the range between maximum and minimum price, and $Spread_{i,t-1}$ and $Price_{i,t-1}$ are the average spread and price. Results remain qualitatively similar for 2h measurement interval. No.tickers is the number of tickers used in estimation. For SDAX stocks, we excluded the ticker HBH3 (HORNBACH HOLD.VZO O.N) that had only 15 trades on daily average. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5%, and 10% levels, respectively.

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Online Appendix for

"High Price Impact Trades Identification and Its Implication for Volatility and Price Efficiency"

Abstract

This appendix contains 3 sections. Section A1 provides further details on the reconstruction of the LOB. Section A2 shows intraday dynamics of HPITs, and Section A3 demonstrates variance ratio computation.

A1. Reconstruction of the LOB

The reconstruction of the LOB is predominantly based on two main types of data streams: delta and snapshot. Delta tracks all the possible updates in the LOB such as entry, revision, cancellation, and expiration, whereas snapshot gives an overview of the state of the LOB and is sent after a constant time interval for a given stock. Xetra original data with delta and snapshot messages are first processed using the XetraParser algorithm, developed by Bilodeau (2013). XetraParser reconstructs the real-time order book sequence including all the information for both auctions and continuous trading by implementing the Xetra trading protocol and Enhanced Broadcast. Then the raw LOB information is put in order and in a readable format for each update time. Useful and accurate information about the state of the LOB and the precise timestamp of order modifications and transactions during continuous trading are also retrieved. There is no information on the identities of market participants.

A2. Intraday Dynamics of HPITs

As Table 6 illustrates, a similar trend is found for MDAX stocks, but the dominance of HPITs over non-HPITs is less pronounced than that of DAX stocks. Surprisingly, for SDAX stocks, even though the information quality of HPITs is always higher than that of non-HPITs ($\frac{41.66}{14.05}$ vs. $\frac{58.34}{85.95}$), the daily price contribution of HPITs is less than that of non-HPITs (41.66% vs. 58.34%). One possible explanation is that HPITs are impeded by a high trading cost, a serious obstacle faced by intraday traders. Generally, the net profit of intraday informed trades is the difference between the gains derived from their information and the trading costs related to the order execution. In a market with a lower trading cost, informed traders can get rewarded easily and have more incentive to trade against uninformed traders. In contrast, in a less liquid market that features a higher trading cost, informed traders have less incentive to trade against uninformed ones.

To qualitatively investigate the relationship between trading cost and the contribution of HPITs across different markets, we present, in Figure A.1, the intraday evolution of average relative bid-ask spread, which is defined as the ratio of bid-ask spread to midquote price. Two interesting insights arise from this figure. First, on average, the best bid-ask spread of SDAX stocks is much larger than those of DAX and MDAX stocks. More precisely, the spread of SDAX stocks is almost six times and three times as large as that of DAX and MDAX stocks, respectively. This means that informed traders in SDAX stocks have to bear an extremely high cost before getting rewarded. Second, the average spreads for stocks in different indexes decrease during the trading day, with an exception in the middle of the trading session. These findings seem to confirm that: 1) most of the information is diffused at the beginning of the trading session; and 2) at the opening, the market exhibits a higher degree of information asymmetry, and liquidity providers face a high risk of adverse selection. To protect themselves, liquidity providers increase the bid-ask spread.

[Insert Figure A.1 here]

A3. Variance Ratio

According to the notation of Lo and MacKinlay (1989), x_t represents a log price process,[1] and there are n non-overlapping long-horizon intervals in the measurement interval and q non-overlapping short-horizon intervals in each long-horizon interval. Moreover, each interval is equally spaced so that there exist $T = nq$ returns in the measurement interval. In such a setting, the estimate of the mean drift in prices is equal to:

$$\hat{\mu} = \frac{1}{nq} \sum_{k=1}^{nq} (x_k - x_{k-1}) = \frac{1}{nq}(x_{nq} - x_0), \tag{A.1}$$

[1]We use midquote price instead of trade price to avoid the negative autocorrelation caused by the bid-ask bounce.

and the estimates of the variance are as follow

$$\overline{\sigma}_a^2(q) = \frac{1}{nq-1} \sum_{k=1}^{nq} (x_k - x_{k-1} - \hat{\mu})^2, \tag{A.2}$$

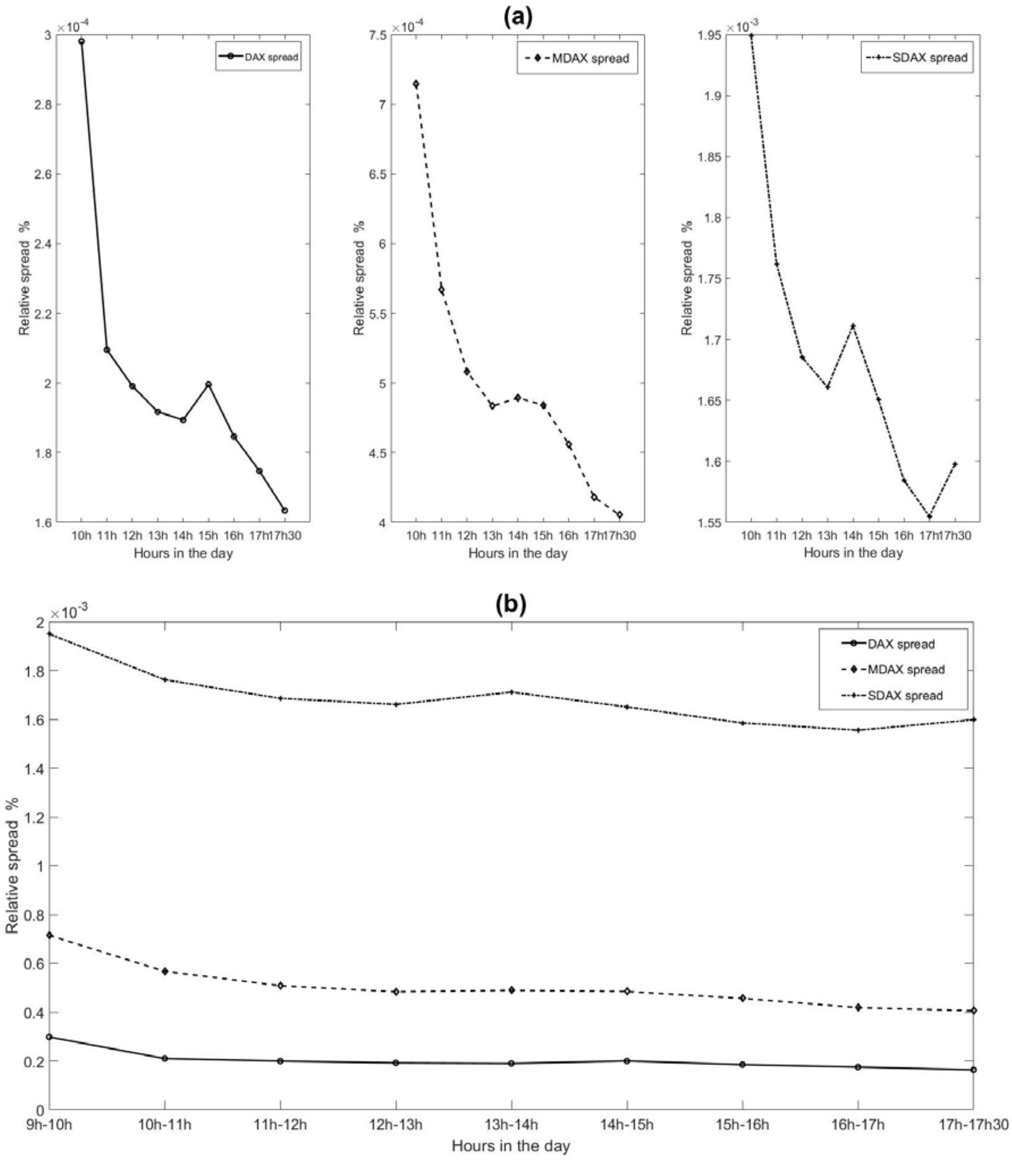
$$\overline{\sigma}_c^2(q) = \frac{1}{m} \sum_{k=q}^{nq} (x_k - x_{k-q} - q\hat{\mu})^2, \tag{A.3}$$

where $m = q(nq - q + 1) \times (1 - \frac{q}{nq})$, and $\overline{\sigma}_a^2$ and $\overline{\sigma}_c^2(q)$ are short and large interval return variances, respectively.

If prices follow a random walk process, the variances should be linear in the measurement interval. This implies that the ratio of scaled large interval return variance over short interval return variance, $\overline{\sigma}_c^2(q)/\overline{\sigma}_a^2$, should be equal to one. Specifically, the test based on the random walk hypothesis is

$$M_r(q) - 1 \equiv \frac{\overline{\sigma}_c^2(q)}{\overline{\sigma}_a^2} - 1 = 0. \tag{A.4}$$

Figure A.1: Average Intraday Dynamics of Spread



Panel (a) illustrates separately the intraday evolution of average relative bid-ask spread for DAX (solid lines), MDAX (dashed lines), and SDAX (dotted lines) stocks. Panel (b) compares the intraday evolution of average relative bid-ask spread for DAX (solid lines), MDAX (dashed lines), and SDAX (dotted lines) stocks. The sample period covers 6 months from February 1, 2013 to July 31, 2013. Relative bid-ask spread is defined as the ratio of bid-ask spread to midquote price.

Table A.1: Detailed Trade category Distributions

Param	Matched Volume (%)	UM-RD Volume (%)	UM-UR Volume (%)
ADS	57.58	29.19	13.23
ALV	44.49	31.97	23.54
BAS	51.60	29.34	19.06
BAYN	55.86	29.75	14.38
BEI	58.87	28.42	12.71
BMW	54.76	29.86	15.38
CBK	42.34	32.51	25.15
CON	54.66	31.52	13.82
DAI	52.63	29.97	17.40
DB1	53.80	30.43	15.77
DBK	52.01	29.36	18.63
DPW	49.06	31.48	19.45
DTE	50.27	33.03	16.71
EOAN	46.65	31.30	22.04
FME	56.47	29.33	14.20
FRE	58.97	27.62	13.41
HEI	54.08	30.45	15.47
HEN3	59.01	27.75	13.24
IFX	52.25	32.31	15.44
LHA	49.34	33.01	17.65
LIN	52.26	31.14	16.60
LXS	53.72	31.59	14.69
MRK	54.25	31.32	14.44
MUV2	50.30	31.09	18.61
RWE	52.48	30.94	16.58
SAP	52.85	30.03	17.12
SDF	49.70	32.16	18.13
SIE	52.85	29.20	17.95
TKA	50.64	31.89	17.46
VOW3	46.54	33.19	20.27
Mean	52.34	30.71	16.95
Min	42.34	27.62	12.71
Max	59.01	33.19	25.15

This table presents DAX stocks' trade volume distribution among different trade categories: matched trades, unmatched-rounded trades, and unmatched-unrounded trades. UM, UR, and RD stand for unmatched, unrounded and rounded trades.

Table A.2: The Effect of HPITs of DAX Stocks on 15-min Conditional Volatility

Param	ω	a	ϑ	β	γ	Q(15)	Q2(15)
ADS	-1.913***	-0.003	0.259***	0.844***	-2.038***	19.437	4.736
ALV	-2.002***	-0.045***	0.226***	0.836***	-1.304***	18.437	11.759
BAS	-1.900***	-0.025***	0.168***	0.845***	-2.703***	29.021	12.665
BAYN	-2.356***	-0.017**	0.216***	0.807***	-1.753***	17.841	5.99
BEI	-4.302***	0.018**	0.360***	0.657***	-0.616***	7.74	5.314
BMW	-0.113***	-0.011***	0.051***	0.990***	-3.372***	11.222	17.983
CBK	-0.696***	-0.041***	0.204***	0.935***	-4.686***	14.641	71.819
CON	-2.370***	-0.003	0.291***	0.800***	-1.856***	18.392	11.536
DAI	-2.081***	-0.011	0.255***	0.824***	-2.936***	12.624	6.698
DB1	-0.999***	0.083***	0.246***	0.915***	-3.134***	16.612	2.19
DBK	-1.197***	-0.034***	0.167***	0.896***	-4.077***	14.323	14.066
DPW	-1.998***	-0.013*	0.314***	0.840***	-0.674***	14.102	9.605
DTE	-0.907***	0.025***	0.181***	0.927***	-3.290***	17.744	8.499
EOAN	-0.862***	-0.006	0.201***	0.928***	-2.202***	24.647	9.591
FME	-1.231***	0.007	0.277***	0.900***	-1.026***	27.202	30.148
FRE	-1.896***	-0.011*	0.249***	0.847***	0.042	21.283	2.736
HEI	-1.995***	0.004	0.262***	0.831***	-1.139***	23.82	3.953
HEN3	-2.813***	0.025**	0.220***	0.773***	-0.526***	17.332	6.467
IFX	-1.241***	-0.016**	0.262***	0.894***	-2.893***	12.089	13.434
LHA	-2.668***	-0.009	0.378***	0.772***	-1.817***	12.108	7.082
LIN	-2.146***	-0.053***	0.167***	0.831***	-1.201***	28.365	12.719
LXS	-2.338***	-0.023***	0.313***	0.800***	-3.273***	21.534	8.092
MRK	-2.213***	0.005	0.253***	0.821***	-1.225***	10.916	5.292
MUV2	-1.404***	-0.014*	0.237***	0.886***	-1.587***	15.929	11.834
RWE	-0.101***	0	0.080***	0.991***	-3.750***	16.025	21.425
SAP	-0.052***	-0.015***	0.039***	0.996***	-2.682***	14.974	44.754
SDF	-0.154***	-0.033***	0.129***	0.986***	-3.136***	14.905	89.477
SIE	-0.282***	-0.039***	0.099***	0.977***	-4.240***	32.804	5.469
TKA	-3.460***	0.030***	0.459***	0.697***	-1.886***	17.009	4.041
VOW3	-2.295***	-0.117***	0.413***	0.805***	-2.265***	12.062	4.271
Mean	-1.666	-0.011	0.233	0.862	-2.241	17.838	15.455
Min	-4.302	-0.117	0.039	0.657	-4.686	7.740	2.190
Max	-0.052	0.083	0.459	0.996	0.042	32.804	89.477

This table reports the estimated results of the EGARCH model, $log(\sigma_i^2) = \omega + \sum_{j=1}^{p} \alpha_j g(Z_{i-j}) + \sum_{j=1}^{q} \beta_j log(\sigma_{i-j}^2) + \gamma HPIT_{\text{i-1}}\%$, for 15-min deseasonalized returns for DAX stocks. The results remain qualitatively similar for the 30-min interval. Q(15) and Q2(15) relate to Ljung-Box statistics on 15 lagged standardized residuals and squared standardized residuals derived from the model. The 5% critical value is 24.99. ***, ** and * denote either coefficient estimates that are significantly different from zero or test statistics that are significant at the 1%, 5%, and 10%, respectively.