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Algorithmic Trading and the Market for Liquidity

Terrence Hendershott and Ryan Riordan*

Abstract

We examine the role of algorithmic traders (ATs) in liquidity supply and demand in the 30 Deutscher Aktien Index stocks on the Deutsche Boerse in Jan. 2008. ATs represent 52% of market order volume and 64% of nonmarketable limit order volume. ATs more actively monitor market liquidity than human traders. ATs consume liquidity when it is cheap (i.e., when the bid-ask quotes are narrow) and supply liquidity when it is expensive. When spreads are narrow ATs are less likely to submit new orders, less likely to cancel their orders, and more likely to initiate trades. ATs react more quickly to events and even more so when spreads are wide.

I. Introduction

Frictions related to investors' participation and monitoring of financial markets are important for trading and asset price dynamics (Duffie (2010)). Imperfect monitoring prevents investors from immediately contacting all counterparties. This prolongs search and causes investors to offer greater price concessions to trade quickly, reducing liquidity. Uncertainty in the search process increases liquidity risk. Both the level and uncertainty of liquidity depress prices and lead to misallocations of capital. Technological progress in the form of algorithmic traders (ATs) reduces monitoring frictions, which can improve efficiency in the market for liquidity and facilitate gains from trade.[1]

*Hendershott, hender@haas.berkeley.edu, Haas School of Business, University of California at Berkeley, 545 Student Services Bldg #1900, Berkeley, CA 94720; Riordan, ryan.riordan@uoit.ca, Faculty of Business and Information Technology, University of Ontario Institute of Technology, 2000 Simcoe St N, Oshawa, ONT L1H 7K4, Canada. We thank Hendrik Bessembinder (the editor), Bruno Biais, Doug Foster, Thierry Foucault (the referee), and seminar and conference participants at the University of Texas at Austin, University of Sydney 2010 Annual Microstructure Conference, New York University Courant Institute of Mathematical Sciences 2010 Annual Algorithmic Trading Conference, 2009 Workshop on Information Systems and Economics, 2009 German Finance Association, and Institut D'Economie Industrielle (IDEI)-R Conference on Investment Banking and Financial Markets for helpful comments. Hendershott gratefully acknowledges support from the Net Institute, the Ewing Marion Kauffman Foundation, and the Lester Center for Entrepreneurship and Innovation at the Haas School at University of California at Berkeley. Riordan gratefully acknowledges support from the Stuttgart Exchange. Data were provided by the Deutsche Boerse and by the Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of Reuters.

[1]Technology has revolutionized the financial market structure and trading: Investors use computers to automate their trading processes, and virtually all markets are now electronic limit order books (Jain (2005)). The speed and quality of access to such markets encourages ATs.

We examine the intersection of ATs and investor monitoring for Deutscher Aktien Index (DAX) stocks (the 30 largest market capitalization stocks) traded on the Deutsche Boerse (DB) with data identifying whether or not the order was generated with an algorithm. Directly identifying ATs is not possible in most markets. We study how technology that lowers monitoring costs affects the market for liquidity supply and demand by characterizing the role of investors with lower costs.

Lower monitoring costs for ATs should lead to more frequent activity as ATs can react quickly to liquidity supply and demand dynamics resulting from trading and order submissions. For example, the breaking up of large orders into smaller trades that execute when liquidity is high facilitates the search process without revealing the full trading interest. More generally, the ability to monitor and react to events means that trading can be continuously and dynamically optimized, leading ATs to consume liquidity when it is expensive and supply liquidity when it is cheap. An AT's rapid response to new events should be fastest when liquidity is low.

Algorithms are used to trade in both agency and proprietary contexts (Hasbrouck and Saar (2013)). Institutional investors utilize ATs to trade large quantities gradually over time, thereby minimizing market impact and trading costs. Proprietary algorithms, often used for intermediation, are usually referred to as high-frequency traders (HFTs). HFTs use algorithms to quickly process information contained in order flow to identify when a security's price deviates from the efficient price and trade against the deviations. Studying ATs facilitates our overall understanding of the importance of technological advances in financial markets and how these affect the frictions in participation and monitoring faced by investors and traders.[2]

ATs are identified in our data because of an unusual pricing scheme. Most markets offer volume discounts to attract the most active traders. During our sample period the German competition authority did not allow for generic volume discounts, but rather required that discounts have a cost-sensitive component. The DB successfully asserted that algorithm-generated trading is lower cost and highly sensitive to fee reductions and, therefore, could receive quantity discounts.[3] The fee rebate program also subsidized the investment in costly technology, encouraging more investors to automate and boosting trading volume and liquidity at the DB. The DB provided data on AT orders, generated by members in the fee rebate program, in the DAX stocks for the first 3 weeks of Jan. 2008.

In our sample ATs initiate 52% of trading volume via marketable limit orders. ATs initiate smaller trades, with ATs initiating 68% of volume for trades of fewer than 500 shares and 23% of volume for trades of more than 10,000 shares. ATs cluster their trades together and initiate trade quickly when bid-ask spreads are small. ATs are more sensitive to human trading activity than humans are to AT activity. By splitting large orders into smaller slices, ATs reduce their own market impact but also the volatility of liquidity in general.

[2]Examining HFTs and lower frequency traders separately, which is not possible with our data, can provide insights into an AT's application to particular investment and trading strategies.

[3]In Dec. 2006, the DB introduced its fee rebate program for automated traders. The DB modified the fee rebate program on Nov. 2, 2009, to a volume discount program. This effectively ended the AT-specific fee rebate at the DB.

ATs submit 64% of nonmarketable limit order volume. ATs cancel orders more frequently, leading to ATs supplying liquidity in only 50% of trading volume. When spreads are narrow, ATs are less likely to submit new orders and less likely to cancel their orders. The net effect of their order submissions and cancellations leads ATs to be at the best bid and offer more often than humans, with the difference being more pronounced when spreads are wider. ATs cluster their orders together, and they are more sensitive to human order submission activity than humans are to AT order activity.

These results on trading and order submissions are consistent with ATs closely monitoring market liquidity supply and demand. The dependence of their trades and orders on the size of the spread, in terms of activity and speed, shows that their order placement strategy is not random, but rather part of an efficient demand and supply strategy. Better monitoring allows traders to quickly react to changes in market conditions, leading ATs to supply liquidity more when spreads are wide and to demand liquidity more when spreads are narrow. This reduces uncertainty in liquidity provision, thereby reducing liquidity risk.

To extend our examination of ATs' monitoring, we move beyond the public information contained in the limit order book by studying recent price changes in the futures index market. Futures markets generally lead the underlying stocks, so continuous monitoring of futures price changes is required to prevent limit order from becoming stale. We estimate probit models of algorithmic liquidity-demanding and -supplying trades and order cancellations, controlling for market condition variables that incorporate the state of the limit order book, past volatility, and trading volume. We find evidence that algorithmic liquidity-demanding trades take advantage of stale limit orders, as AT buys are more likely after recent positive index future returns and AT sells are more likely after recent negative index future returns. We find that ATs are more likely to initiate trades when liquidity is high in terms of narrow bid-ask spreads. Algorithmic liquidity-demanding trades are negatively related to volatility and volume in the prior 15 minutes. For liquidity-supplying trades, ATs are more likely to trade when liquidity is low. Algorithmic liquidity-supplying trades are positively related to prior volatility and negatively related to prior volume. An important component in the supply of liquidity is the ability to continuously monitor market conditions and cancel limit orders in the book to avoid being adversely selected. We find that ATs are more likely to cancel orders that are in the opposite direction of recent index future returns, making ATs better able to avoid being adversely selected based on public information.

Section II relates our work to existing literature. Section III describes ATs on the DB. Section IV describes our data. Section V analyzes when and how ATs demand liquidity. Section VI examines order submission strategies. Section VII uses multivariate probit analyses to study when ATs supply and demand liquidity in transactions. Section VIII concludes.

II. Related Literature

Important implications of investors' monitoring/attention and participation decision for the movement of capital and asset prices are extensively reviewed in

Duffie (2010). Electronic limit order markets represent a market for immediacy where limit order submitters offer terms of trade to potential market orders. Limit order submitters must either continuously monitor the market for changing conditions or face being taken advantage of by later arriving traders. Parlour and Seppi (2008) provide a general survey on limit order markets and the importance of the monitoring friction.

Foucault, Roëll, and Sandas (2003) study the equilibrium level of effort that liquidity suppliers should expend in monitoring the market. ATs lower the cost of this kind of monitoring and the adjustment of limit orders in response to market conditions.[4] The monitoring of the state of liquidity in the market and taking it when cheap and making it when expensive are consistent with ATs playing an important role in the make/take liquidity cycle modeled by Foucault, Kadan, and Kandel (2013). If ATs lower the costs of monitoring, then frictions may be reduced and Rosu's (2009) modeling of limit orders as being constantly adjusted is a reasonable simplification for theoretical modeling.

Due to the difficulty in identifying ATs, initial research directly addressing ATs used data from brokers who sell algorithmic products to institutional clients. Engle, Russell, and Ferstenberg (2012) use execution data from Morgan Stanley algorithms to study the trade-offs between algorithm aggressiveness and the mean and dispersion of execution cost. Domowitz and Yegerman (2006) study execution costs of Investment Technology Group buy-side clients, comparing results from different algorithm providers.

Several recent studies use comprehensive data on ATs. Chaboud, Chiquoine, Hjalmarsson, and Vega (2009) study the rise of ATs in the foreign exchange market on the electronic broking system (EBS) in 3 currency pairs: euro-dollar, dollar-yen, and euro-yen. They find little relation between ATs and volatility. Chaboud et al. find that ATs seem to follow correlated strategies, which is consistent with our results on ATs clustering together in time. Hendershott, Jones, and Menkveld (2011) use a proxy for ATs, message traffic, which is the sum of order submissions, order cancellations, and trades. Unfortunately, such a proxy makes it difficult to directly examine when and how ATs behave and their role in liquidity supply and demand. Hendershott et al. use an instrumental variable to show that ATs improve liquidity and make quotes more informative. Our results on AT liquidity supply and demand show the channels by which ATs could lead to more liquid markets.

Algorithms are used by traders who are trying to passively accumulate or liquidate a large position. Bertsimas and Lo (1998) find that the optimal dynamic execution strategies for such traders involve optimally breaking orders into pieces to minimize cost.[5] While such execution strategies predate the widespread

[4]Biais, Hombert, and Weill (2010) theoretically examine the relation between ATs, market monitoring, and liquidity dynamics under limited cognition. See Biais, Foucault, and Moinas (2011) and Pagnotta and Philippon (2011) for models where investors compete on their trading algorithm's speed. Monitoring also has important cross-market competition implications, as in Foucault and Menkveld (2008) and others.

[5]Almgren and Chriss (2000) extend this by considering the risk that arises from breaking up orders and slowly executing them.

appearance of ATs (see also Keim and Madhavan (1995)), brokers now automate the process with algorithmic products.

For each component of the larger transaction, a trader (or algorithm) must choose the type and aggressiveness of the order. Cohen, Maier, Schwartz, and Whitcomb (1981) and Harris (1998) focus on the simplest static choice: market order versus limit order. If a trader chooses a nonmarketable limit order, the aggressiveness of the order is determined by its limit price (Griffiths, Smith, Turnbull, and White (2000), Ranaldo (2004)). Lo, MacKinlay, and Zhang (2002) find that execution times are very sensitive to the choice of limit price. If limit orders do not execute, traders can cancel them and resubmit them with more aggressive prices. A short time between submission and cancellation suggests the presence of ATs. Hasbrouck and Saar (2009) find that a large number of limit orders were canceled within 2 seconds on the INET trading platform (which is now Nasdaq's trading mechanism).

A number of papers analyze the high-frequency trading subset of ATs. Biais and Woolley (2011) provide background and survey research on HFTs and ATs. Brogaard, Hendershott, and Riordan (2013) study the role of overall, aggressive, and passive trading by HFTs in the permanent and transitory parts of price discovery. Kirilenko, Kyle, Samadi, and Tuzun (2011) analyze HFTs in the E-mini S&P 500 futures market during the May 6, 2010, flash crash. Jovanovic and Menkveld (2011) model HFTs as middlemen in limit order markets and study their welfare effects. Menkveld (2013) shows how one HFT firm enabled a new market to gain market share.

III. Deutsche Boerse's Automated Trading Program

DB's order-driven electronic limit order book system is called Xetra (see Hau (2001) for details).[6] Orders are matched using price-time-display priority. Quantities available at the 10 best bid and ask prices and the number of participants at each level are disseminated continuously. See the Appendix for further details on Xetra.

During our sample period, Xetra had a 97% market share of German equities trading. With such a dominant position, the competition authorities (Bundeskartellamt) required approval of all fee changes prior to implementation. The criteria used to evaluate fee changes were: i) All participants are treated equally; ii) changes must have a cost-related justification; and iii) fee changes are transparent and accessible to all participants. Criteria i) and iii) ensure a level playing field for all members and are comparable to regulation in the rest of Europe and North America. The 2nd criterion is the most important for this paper. ATs were viewed as satisfying the cost justification for the change, so the DB could offer lower trading fees for ATs.[7]

[6]Iceberg orders are allowed as on the Paris Bourse (see also Venkataraman (2001)).

[7]The logic was that electronic order generation by algorithms could be less costly for an exchange, making lower fees justifiable. This is debatable. At the end of 2009 the ATP was ended and lower AT fees were replaced by the volume discounts used in most other markets.

In Dec. 2007 the DB introduced its Automated Trading Program (ATP) to increase the volume of automated trading on Xetra. By offering fee rebates, the DB was implicitly subsidizing investment in AT technologies. To qualify for the ATP an electronic system must determine the price, quantity, and submission time for orders. In addition, the DB ATP agreement required that: i) the electronic system must generate buy and sell orders independently using a specific program and data; ii) the generated orders must be channeled directly into the Xetra system; and iii) the exchange fees or the fees charged by the ATP member to its clients must be directly considered by the electronic system when determining the order parameters.

Before being admitted to the ATP, participants were required to submit a high-level overview of the electronic trading strategies they plan to employ. The level of disclosure required was intended to be low enough to not require ATP participants to reveal important details of their trading strategies. Following admission to the ATP, the orders generated by each participant were audited monthly for plausibility. If the order patterns generated did not match those suggested by the participant's submitted strategy plan or were considered likely to have been generated manually, the participant was terminated from the ATP and possibly suspended from trading on Xetra. The ATP agreement and the auditing process ensure that most, if not all, of the orders submitted by an ATP participant are electronically generated and that most, if not all, electronically generated orders are included in our data.[8]

The DB charges fees for executed trades and not for submitted orders. The rebate for ATP participants could be significant and increased with the total trading volume per month. The 1st euro volume rebate level began at 250 million in euro volume and rebated 7.5% of fees. Rebates rose to a maximum of 60% for euro monthly volume above 30 billion. Table 1 provides an overview of the rebate per volume level.

TABLE 1

ATP-Rebate Program

Table 1 presents the fee rebate schedule for ATP participants by volume levels.

Cumulative Monthly ATP-Volume (in mil. euros)	ATP-Rebate (per volume level)
0–250	0.0%
251–500	7.5%
501–1,000	15.0%
1,001–2,000	22.5%
2,001–3,750	30.0%
3,751–7,500	37.5%
7,501–15,000	45.0%
15,001–30,000	52.5%
$\geq$ 30,001	60.0%

[8]Conversations with the DB revealed that a small portion of AT orders may not be included in the data set. The suspicion on the part of the DB is due to the uncommonly high number of orders (message traffic) to executions of certain participants, which is typical of ATs. However, these participants make up less than 1% of trades in total and are, therefore, unlikely to affect our results.

For an ATP participant with 1.9 billion euro volume, the percentage rebate was

$$(1) \quad \frac{250 \times 0\% + 250 \times 7.5\% + 500 \times 15.0\% + 900 \times 22.5\%}{1{,}900} = 15.6\%.$$

In the example above, an ATP participant received a rebate of 15.6% of fees. This translates into roughly 14,000 euros in trading cost savings on 91,200 euros in total fees plus an additional 5,323 euro savings on 61,500 euros in total in clearing and settlement costs. This rebate (14,000 + 5,323) translates into a 0.1-basis-point (bp) saving on the 1.9 billion euros in turnover. For high-frequency trading firms, whose turnover is much higher than the amount of capital invested, these savings are significant.

The fee rebate for ATP participants was the only difference in how orders were treated. AT orders were displayed equivalently in the publicly disseminated Xetra limit order book. The Xetra matching engine did not distinguish between AT and human orders. Therefore, there were no drawbacks for an AT firm to become an ATP participant. Thus, we expect all ATs took advantage of the lower fees by becoming ATP participants. From this point on we equate an ATP participant with an algorithmic trader and use AT for both. We will refer to non-ATP trades and orders as human or human-generated.

IV. Data and Descriptive Statistics

The DB provided data contain all AT orders submitted in DAX stocks, the leading German stock market index composed of the 30 largest and most liquid stocks, between Jan. 1 and Jan. 18, 2008, a total of 13 trading days. This is combined with Reuters DataScope Tick History data provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). The SIRCA data contain 2 separate data sets: one for transactions and another for order book updates.

We generate a data set similar to Biais, Hillion, and Spatt (1995). Using the order book snapshots, we recreate the order causing the observed book changes. To identify trades, which, when observing order book updates, are similar to cancels at the best, we match these orders with the public transaction data set. We match the generated events (insert, cancel, trade) with the DB-provided AT order data set. As in Biais et al. (1995), we truncate the order book at the first 5 levels to focus on orders closest to the best bid and ask. The resulting data contain all orders submitted by ATs and humans at the first 5 levels on the bid and ask sides of the book.

Table 2 describes the 30 stocks in the DAX index. Market capitalization is as of Dec. 31, 2007, in billions of euros.[9] The smallest firm (TUI AG) is large at 4.81 billion euros but is more than 20 times smaller than the largest stock in the sample, Siemens AG. The standard deviation of daily returns is calculated for each stock during the sample period. All other variables are calculated daily during the sample period for each stock (30 stocks for 13 trading days for a total

[9]Firms' market capitalization is gathered from the DB Web site (http://deutsche-boerse.com) and cross-checked against data posted directly on each company's Web site.

TABLE 2

Summary Statistics

Table 2 presents descriptive statistics for the 30 constituents of the DAX index between Jan. 1, 2008, and Jan. 18, 2008. The data set combines Deutsche Boerse (DB) Automated Trading Program system order data and SIRCA trade, quote, and order data. Market capitalization data are gathered from the DB Web site (http://deutsche-boerse.com) and cross-checked against data posted directly on the company's Web site and are the closing market capitalizations on Dec. 31, 2007. Other variables are averaged per stock and day (390 observations), and the mean, standard deviation, maximum, and minimum of these stock-day averages are reported.

Variable	Mean	Std. Dev.	Min.	Max.
Mkt. Cap. (euro billion)	32.85	26.03	4.81	99.45
Price (euros)	67.85	42.28	6.45	155.15
Std. Dev. of Daily Return (%)	3.12	1.40	1.47	9.29
Daily Trading Volume (euro million)	250	217	23	1,509
Daily Number of Trades per Day	5,344	3,003	1,292	19,252
Trade Size (euro)	40,893	15,808	14,944	121,710
Quoted Spread (bp)	2.98	3.01	1.24	9.86
Effective Spread (bp)	3.49	3.05	1.33	10.05
Depth (euro 10 million)	0.0177	0.0207	0.0044	0.1522
Depth3 (euro 10 million)	0.1012	0.1545	0.0198	1.0689

of 390 observations). Means and standard deviations, along with the minimum and maximum values, are reported across the 390 stock-day observations.

DAX stocks are quite liquid. The average trading volume is 250 million euros per day, with 5,344 trades per day on average. This implies that our data set contains roughly 2 million transactions (5,344 $\times$ 390). Quoted half-spreads are calculated when trades occur. The average quoted half-spread of 2.98 bp is comparable to large and liquid stocks in other markets. The effective spread is the absolute value of the difference between the transaction price and the mid-quote price (the average of the bid and ask quotes). Average effective spreads are only slightly larger than quoted spreads, evidence that market participants seldom submit marketable orders for depth at greater than the best bid or ask.

We measure depth in two ways. The first is the standard measure of the depth at the inside quotes: the average depth in euros at the best bid price and the best ask price. As with spreads, depth is measured at the time of transactions. More depth allows traders to execute larger trades without impacting the price, corresponding to higher liquidity. However, if the width of the spread varies over time, then comparisons of depth at the inside do not clearly correspond to levels of liquidity; for example, 50,000 euros at an inside spread of 10 bp need not represent more liquidity than 5,000 euros at an inside spread of 5 bp if in the latter case there is sufficient additional depth between 5 and 10 bp. To account for time variation in the spread, we calculate a 2nd depth measure using the limit order book. For each stock, we aggregate the depth at bid and ask prices that have a distance of less than 3 times that stock's average quoted half-spread from the quote midpoint at the time of transaction. We refer to this measure of depth that does not depend on the spread at the time of the transaction as depth3. A similar measure is used in Foucault and Menkveld (2008) to capture depth away from the best prices.

V. Trading

Trades represent liquidity demand and are arguably the most important events in limit order markets. Trades allow investors to manage risk and adjust their portfolio throughout the trading day, and they are not subject to later cancellation as with nonmarketable limit orders. Large liquidity-demanding orders placed during periods of low liquidity can have substantial price impact and disrupt market liquidity and stability for long periods of time. Breaking the same order up into smaller pieces and submitting these conditional on market conditions can reduce the negative impact of the overall order. Therefore, better monitoring by ATs should lead their trades to be more sensitive to market conditions than human trades.

To measure AT liquidity demand, we create marketable order (trade) and limit order variables for ATs and humans, labeled AT and HUM, respectively. The AT variable takes the value 1 when a trade or order is from an AT, and 0 otherwise. The HUM variable takes the value 1 when a trade or order is from a human and 0 otherwise. Panel A of Table 3 reports the fraction of euro trading volume for algorithmic-initiated trades by trade size and overall. For simplicity and comparability, we use the U.S. Securities and Exchange Commission (SEC) Rule 605 trade-size categories based on the number of shares traded. Panel B of Table 3 reports the fraction of trades initiated by ATs by trade size and overall. Overall, ATs initiate 52% of euro volume and more than 60% of all trades. AT initiation declines as trade size increases. The proportion of ATs exceeds 68% and 57% in the 2 smallest trade-size categories (0–499 shares and 500–999 shares) and decreases to 23% in the largest trade-size category (10,000 + shares). ATs' decline with trade size is consistent with several possibilities: ATs are breaking up large orders into smaller trades as suggested by Bertsimas and Lo (1998) and HFTs using tight risk-management strategies as in Menkveld (2013). ATs' use of smaller liquidity-demanding trades may help to reduce the volatility of liquidity.

TABLE 3

Trade Participation by Size Category

Table 3 reports participation by ATs and humans in 5 size categories. Panel A reports volume-weighted trade participation. Panel B reports transaction-weighted trade participation.

	Trades		
Size Categories	AT	HUM	All
Panel A. Volume-Weighted			
0–499	68%	32%	21%
500–999	57%	43%	21%
1,000–4,999	42%	58%	43%
5,000–9,999	30%	70%	7%
10,000+	23%	77%	8%
All	52%	48%	100%
Panel B. Transaction-Weighted			
0–499	61%	39%	62%
500–999	62%	38%	18%
1,000–4,999	53%	47%	18%
5,000–9,999	39%	61%	1%
10,000+	31%	69%	1%
All	59%	41%	100%

Panels A and B of Table 4 provide the same statistics as Table 3 for nonmarketable limit order submissions. The AT share of limit orders is substantially higher than its share of trades, 64% versus 52%. This difference declines in trade size. For nonmarketable limited orders that eventually execute, ATs represent only

TABLE 4
Order Participation by Size Category

Table 4 reports participation by ATs and humans in 5 size categories. Panel A reports order size-weighted participation for nonmarketable limit orders. Panel B reports order-weighted participation for nonmarketable limit orders.

	Nonmarketable Limit Orders		
Size Categories	AT	HUM	All
Panel A. Size-Weighted			
0–499	78%	22%	32%
500–999	74%	26%	24%
1,000–4,999	55%	45%	35%
5,000–9,999	30%	70%	5%
10,000+	20%	80%	4%
All	64%	36%	100%
Panel B. Order-Weighted			
0–499	77%	23%	62%
500–999	74%	26%	20%
1,000–4,999	60%	40%	16%
5,000–9,999	31%	69%	1%
10,000+	24%	76%	1%
All	73%	27%	100%

50% of volume. Therefore, ATs submit more orders than they execute either by submitting uncompetitive orders away from best prices or by canceling and replacing orders close to the best prices.

Because nonmarketable limit order submissions are reversible and because limit orders vary by the aggressiveness of their prices, we first focus on transactions before turning to order submission strategies more generally. To better understand how monitoring affects liquidity demand conditional on past trading, we perform a series of analyses similar to those found in Biais et al. (1995) for algorithmic and human trades. Examining algorithmic and human trades separately doubles the number of variables, requiring some adaptations. First, we report the results of 2 separate and related analyses in Table 5. The 1st column of Table 5, labeled unconditional, provides the fraction of trade sequences (i.e., AT followed by AT, AT followed by human, etc.) we expect if algorithmic and human trades are randomly ordered. The other columns in Panel A are essentially a contingency table documenting the probability of observing a trade of a specific type after observing a previous trade of a given type. Rows sum up to 100% and can be interpreted as probability vectors.

TABLE 5
Trade Frequency Conditional on Previous Trade

Table 5 reports the conditional frequency of observing algorithmic and human trades after observing trades of other participants. In column and row headings, t indexes trades. AT represents algorithmic trades and HUM represents human trades.

Ordering	Unconditional	Frequency	$\text{BUY}_{t-1}\text{BUY}_t$	$\text{SELL}_{t-1}\text{SELL}_t$	$\text{BUY}_{t-1}\text{SELL}_t$	$\text{BUY}_{t-1}\text{BUY}_t$
$\text{AT}_{t-1}\text{AT}_t$	37.0	40.7	13.7	10.9	7.8	8.2
$\text{AT}_{t-1}\text{HUM}_t$	23.8	20.1	5.5	5.0	5.4	4.1
$\text{HUM}_{t-1}\text{AT}_t$	23.8	20.1	6.4	5.6	3.8	4.1
$\text{HUM}_{t-1}\text{HUM}_t$	15.3	19.0	5.4	5.3	3.7	4.4
Total		100.0	31.1	27.0	20.9	20.9

The 1st row in Table 5 shows that if algorithmic and human trades were randomly ordered, 37% of the transactions would be AT followed by AT, while in the data this occurs 40.7% of the time. This shows that algorithmic trades are more likely to follow algorithmic trades than we would expect unconditionally. In addition, algorithmic trades are more likely to be repeated on the same side of the market. The same is true for human trades. This suggests that human and algorithmic liquidity-demanding trading strategies execute at different times while having related characteristics. Table 5 also shows ATs to be relatively more sensitive to human order flow than humans are to an algorithmic order flow. The conditional probability of an algorithmic following a human trade is 51.4% as compared to 66.9% following an algorithmic trade. Human trades follow algorithmic trades with a conditional probability of 33.1% as compared to 48.6% following a human trade.

Table 6 extends the analysis of algorithmic and human trade sequences to include trade-size categories. As in Biais et al. (1995), we highlight in bold the 3 largest values in a column to illustrate the interdependence of trade sequences. The results are similar to the diagonal results reported in Biais et al. (1995) and predicted theoretically in Parlour (1998). The diagonal finding implies that trades of the same type (algorithmic or human trades in the same trade-size category) follow other similar trades. This leads to a diagonal effect, where the highest probabilities lie on the diagonal. The largest probability by far is for small algorithmic trades: The $AT^1_{t-1}AT^1_t$ probability of 48.7% is much higher than the unconditional probability of 31.6%. This suggests that: i) ATs repeatedly use small trades to hide their information; ii) ATs limit their transitory price impact; or iii) different ATs are following related strategies. All of these strategies are consistent with ATs closely monitoring market conditions.

TABLE 6

Trade Frequency Conditional on Previous Trade

Table 6 reports conditional frequencies based on the previous trade's size and participant. The 3 highest values per column are highlighted in bold. In column and row headings, t indexes trades. AT represents algorithmic trades and HUM represents human trades. Superscripts represent trade sizes with lower numbers corresponding to smaller trade sizes. Each row adds to 100.

$t-1$	AT^5_t	AT^4_t	AT^3_t	AT^2_t	AT^1_t	HUM^5_t	HUM^4_t	HUM^3_t	HUM^2_t	HUM^1_t
AT^5_{t-1}	**8.3**	**9.4**	**18.1**	16.7	7.8	**8.1**	**6.0**	6.7	7.9	10.5
AT^4_{t-1}	**3.8**	**7.8**	**15.9**	23.3	11.7	**4.5**	4.6	7.3	9.9	10.9
AT^3_{t-1}	1.3	2.7	12.0	**28.9**	20.6	2.2	2.7	6.2	11.1	12.0
AT^2_{t-1}	0.2	0.7	4.6	**27.1**	**33.8**	0.6	1.1	4.0	11.8	15.7
AT^1_{t-1}	0.0	0.1	1.7	16.6	**48.7**	0.2	0.5	2.2	9.9	19.9
HUM^5_{t-1}	**5.4**	**6.5**	**13.7**	17.5	8.3	**10.3**	**7.2**	**8.7**	10.3	12.1
HUM^4_{t-1}	1.8	3.4	10.4	22.5	14.4	4.2	**6.4**	**9.8**	13.5	13.6
HUM^3_{t-1}	0.5	1.4	6.7	**23.5**	21.2	1.7	2.8	**10.2**	**16.4**	**15.6**
HUM^2_{t-1}	0.2	0.5	3.4	19.2	28.4	0.7	1.3	4.9	**19.8**	**21.5**
HUM^1_{t-1}	0.1	0.3	2.2	14.9	**33.1**	0.6	0.9	3.4	**13.9**	**30.5**
Uncond.	0.4	0.7	3.4	17.1	31.6	1.0	1.0	3.9	15.1	26.2

VI. Order Submissions

ATs' greater sensitivity to past trading activity is consistent with better monitoring and lower frictions in the trading process. AT monitoring should enable their trading and entire submission strategy, including liquidity provision, to incorporate the most current information on other traders' orders in the limit order book. This should lead their trades, order submissions, and order cancellations to be more sensitive to past orders and the current state of the limit order book (e.g., the bid-ask spread) than human submission strategies.

Table IV in Biais et al. (1995) examines orders and trades conditional on the prior order or trade. Tables 5 and 6 study this using our data for algorithmic and human trades. Table 7 incorporates order submissions. To make the table size manageable, we narrow the scope of trade sizes and orders relative to Biais et al. (1995) by using one trade size and not including limit order submissions away from the best prices.

Table 7 reports that the diagonal effect for trades also holds for orders, as actions of similar type are more likely to be repeated. As in Tables 5 and 6, ATs react more to human orders than humans respond to algorithmic orders. This can be seen visually in the pattern of bold numbers, which are more prevalent in the lower left quadrant than the upper right quadrant. The conditional probabilities can also be calculated across various human orders and algorithmic orders. Similar to the calculations above for Table 5, using all order types, the relative difference in conditional probabilities for ATs following algorithmic versus human trades is smaller than the difference in conditional probabilities for humans following human versus algorithmic trades.

Tables 5–7 provide evidence on the clustering and interdependence of algorithmic and human trades and orders. To study how the monitoring of market conditions captured in the limit order book affect algorithmic and human order submissions, Table 8 examines order frequencies conditional on the bid-ask spread. As in Biais et al. (1995), spread-size categories are calculated for each stock separately. Large spreads occur when spreads are in their widest quartile for that stock, whereas small spreads are the lowest quartile.

Panel A of Table 8 provides the order frequencies for ATs and humans for each spread category. Within each spread category, the order frequencies across ATs and humans sum to 100. Panel B calculates the order frequency differences between small spreads and large spreads. We calculate the order frequencies for each stock each day. Statistical inference is conducted across the 390 stock-day observations, controlling for contemporaneous cross-sectional correlation and within-stock correlation by double clustering standard errors on stock and day as suggested by Petersen (2009) and Thompson (2011).

Overall algorithmic order activity is greater in all spread categories, and the AT-human difference increases in the spread, with algorithmic orders representing 66.4% of orders when spreads are small and 75.3% when spreads are large. Algorithmic orders worse than the best bid and ask prices are not sensitive to the spread, whereas algorithmic limit orders at or within the best prices become more frequent as spreads increase: AT orders at or inside the best prices make up 16.3% of orders when spreads are small and 22.7% of orders when spreads are wide.[10] Algorithmic trade initiations decline as spreads widen, falling from 10.3% of

[10]It is interesting to note that ATs are less likely to cancel orders at the best price when spreads are narrow. This could represent the value of time priority when spreads are lower.

TABLE 7

Order Conditional on Past Order

Table 7 reports the conditional frequencies of 8 order types, based on the previous order type and participant. The 3 highest values per column are highlighted in bold. AT represents algorithmic orders and HUM represents human orders. Each row adds to 100.

	Panel A. AT								*Panel B. Human Trading*							
t − 1	Buy	Order At Ask	Cancel At Ask	Order New Bid	Sell	Order At Bid	Cancel At Bid	Order New Ask	Buy	Order At Ask	Cancel At Ask	Order New Bid	Sell	Order At Bid	Cancel At Bid	Order New Ask
AT Buy	**24.9**	7.5	3.9	6.2	5.5	8.5	6.7	5.9	5.6	3.9	3.3	2.7	3.0	2.8	5.0	**4.5**
AT Order At Ask	5.8	9.1	**6.1**	**9.6**	4.4	**20.1**	16.5	4.8	2.8	3.2	2.0	2.6	2.9	4.2	4.1	1.7
AT Cancel At Ask	4.3	**18.3**	**15.1**	5.7	4.2	10.6	11.8	**8.6**	2.7	3.1	2.1	1.6	2.3	2.8	4.8	2.2
AT Order New Bid	5.0	8.5	8.4	5.3	4.2	**26.9**	17.4	7.1	2.1	2.1	1.5	1.4	2.4	3.1	2.5	2.2
AT Sell	**11.0**	7.6	3.4	5.0	**24.5**	6.5	6.4	6.4	3.1	2.8	1.7	**4.2**	**5.5**	3.1	5.8	2.9
AT Order At Bid	4.7	10.7	5.8	**11.2**	3.7	**17.3**	**17.8**	**8.5**	2.3	2.8	1.6	2.5	2.6	3.1	3.6	1.9
AT Cancel At Bid	3.6	**12.2**	5.5	**12.7**	3.1	14.7	**19.1**	**12.0**	1.8	2.4	1.2	2.3	2.2	2.1	3.2	2.0
AT Order New Ask	5.0	**23.7**	1.4	6.6	4.2	8.5	**24.7**	5.8	2.1	3.3	0.3	2.0	2.1	2.0	6.6	1.6
HUM Buy	**8.2**	5.5	2.8	3.8	3.6	5.8	4.6	4.0	**28.5**	3.1	**8.8**	1.9	3.2	2.5	8.6	**5.2**
HUM Order At Ask	6.5	11.9	5.7	3.1	4.2	7.7	8.0	6.7	3.6	**12.4**	**9.5**	1.8	3.4	4.9	6.8	4.0
HUM Cancel At Ask	6.6	5.8	4.2	3.7	3.0	7.0	4.8	2.5	**14.0**	**10.0**	**12.6**	2.4	3.0	5.2	**12.7**	2.5
HUM Order New Bid	5.5	7.1	**12.4**	3.5	**8.4**	13.8	6.8	4.8	2.7	2.9	3.5	2.2	5.5	**6.4**	10.7	3.9
HUM Sell	4.5	5.2	2.0	2.9	**7.1**	4.9	5.1	3.6	**11.1**	2.6	2.1	2.5	**26.6**	2.6	**15.3**	2.1
HUM Order At Bid	5.3	8.0	5.5	6.4	5.5	11.8	8.0	3.5	3.3	**5.6**	4.7	**3.7**	3.9	**10.5**	**12.0**	2.2
HUM Cancel At Bid	3.8	6.7	2.9	7.7	4.3	6.3	7.9	5.5	4.7	4.6	2.8	**12.5**	**9.8**	**5.5**	10.6	**4.2**
HUM New Bid	6.9	9.3	0.6	3.5	3.5	5.6	16.1	3.1	2.9	5.1	1.1	2.3	2.0	2.1	33.9	2.0
Unconditional	6.8	12.1	5.8	6.5	5.7	11.8	12.2	6.9	4.4	4.6	2.8	2.8	4.3	4.0	6.5	2.9

TABLE 8

Order Frequency Conditional on Spread

Table 8 reports the frequency of 6 order types conditional on contemporaneous spread broken down by AT and human participants. Panel A reports order frequencies conditional on spread size (small, small medium, medium, and large). We calculate conditional spread sizes by taking time-series quartiles for each stock and comparing these to the contemporaneous spread. If the spread is lower than or equal to the 25th percentile, we classify it as small. If the spread is greater than or equal to the 75th percentile, we classify it as large. Rows report frequencies of orders. The AT-Human column reports the difference between AT and human frequencies in that row. The *t*-Stat column reports the *t*-statistics for the AT-Human column accounting for both within stock time-series and contemporaneous cross-sectional correlation. In Panel B we report the difference between small and large spread order frequencies for ATs and humans. * and ** indicate significance at the 5% and 1% levels, respectively.

	AT	Human	AT-Human	*t*-Stat.
Panel A. Spread Categories				
Small Spreads				
New Bid-Ask inside	6.6	5.2	1.3	4.42**
New Bid-Ask at	9.7	4.8	4.9	11.17**
New Bid-Ask outside	16.9	6.2	10.7	12.55**
Cancel At	5.6	5.2	0.4	1.39
Cancel Away	17.3	6.2	11.1	13.39**
Trade Initiation	10.3	6.0	4.3	10.79**
Small-Medium Spreads				
New Bid-Ask inside	6.4	3.2	3.2	9.42**
New Bid-Ask at	11.7	4.9	6.8	11.76**
New Bid-Ask outside	17.6	6.8	10.8	12.08**
Cancel At	7.9	5.0	2.9	6.11**
Cancel Away	18.3	6.6	11.7	13.62**
Trade Initiation	6.9	4.7	2.2	12.42**
Medium Spreads				
New Bid-Ask inside	7.0	2.1	4.9	12.06**
New Bid-Ask at	13.6	4.5	9.2	15.72**
New Bid-Ask outside	17.6	6.4	11.2	14.32**
Cancel At	10.4	4.6	5.8	11.14**
Cancel Away	18.8	6.1	12.7	15.23**
Trade Initiation	5.1	4.0	1.1	7.14**
Large Spreads				
New Bid-Ask inside	7.8	1.4	6.4	11.15**
New Bid-Ask at	14.8	3.7	11.1	11.54**
New Bid-Ask outside	16.7	5.9	10.9	9.79**
Cancel At	13.6	4.7	8.9	8.44**
Cancel Away	18.7	5.5	13.2	10.47**
Trade Initiation	3.6	3.4	0.2	1.64
Panel B. Differences: Small-Large Spreads				
New Bid-Ask inside	−1.3	3.8	−5.0	−12.19**
New Bid-Ask at	−5.1	1.1	−6.2	−9.43**
New Bid-Ask outside	0.1	0.3	−0.2	−0.47
Cancel At	−8.0	0.4	−8.5	−10.21**
Cancel Away	−1.3	0.7	−2.1	−1.97
Trade Initiation	6.7	2.6	4.1	11.42**

orders when spreads are narrow to 3.6% of orders when spreads are large. Because order frequencies sum to 100, the human frequencies generally decline as spreads widen.

These results are consistent with ATs monitoring market conditions to optimize their liquidity supply and demand activities. There are several possible underlying strategies that would account for the increase in new algorithmic liquidity supply and the decline in algorithmic liquidity demand as spreads widen. The same algorithm could switch from supply to demand as spreads narrow. Alternatively, liquidity supply and liquidity demand algorithms could be entirely separate,[11] but both types of algorithms are sensitive to market conditions related

[11] See Menkveld (2013) for an example of a high-frequency algorithm that almost exclusively supplies liquidity.

to the competition for liquidity supply and demand. For example, a liquidity-demanding algorithm could increase its trade initiations when spreads are tighter, and a liquidity-supplying algorithm could increase its limit order submissions when spreads widen. Without data identifying specific algorithms, we cannot establish which of these strategies drives the results, but we expect it is likely that all are present. These represent healthy competitive responses to market conditions and likely lead to less volatility in liquidity supply and demand.

The order frequencies in Table 8 demonstrate the sensitivity of algorithmic orders to market conditions. However, calculating frequencies does not capture how the rate at which events occur depends on market conditions. To better understand the impact of monitoring on time in order submission dynamics, we continue to follow Biais et al. (1995) in Table 9 to report the average time between orders conditional on the same spread categories as in Table 8. For brevity we do not report details for each spread-size category, but report the overall time between events and the small-large spread differences. The small-spread times between events are equal to the average times plus ½ of the small-large differences.

TABLE 9

Time Interval Between Events and At Best Bid-Ask

Table 9 reports the time in seconds between events in Panel A and how long ATs or humans spend at the best bid-ask. Panel A reports the time in seconds between events. The columns report time between events for ATs, humans, and ATs-humans and *t*-statistics. The rows report average time between events and the difference for small-large spread times. Small spreads are defined as spreads that are equal to or below the 25th percentile, and large are defined as spreads that are greater than the 75th percentile. Percentiles are calculated as the time-series mean for each stock. Panel B reports the number of seconds ATs are at the best bid and ask quotes minus the number of seconds human traders are at the best quotes. The remainder of the time, both ATs and humans are at the best quotes. Small/Small-Medium (Small) spreads are spreads that are below the time-series mean. Medium/Large (Large) spreads are above their time-series mean. The *t*-statistics account for both within stock time-series and contemporaneous cross-sectional correlation. * and ** indicate significance at the 5% and 1% levels, respectively.

	AT	Human	AT-Human Diff.	*t*-Stat.
Panel A. Time Between				
Trades	6.78	9.27	−2.48	−18.97**
Small-Large Spreads	−4.36	−2.34	−2.02	−23.42**
t-statistics	−38.73**	−15.53**		
Spread Narrowing and Trade	4.33	4.63	−0.30	−1.24
Small-Large Spreads	5.52	1.35	4.17	11.23**
t-statistics	14.23**	2.06*		
Spread Widening and Narrowing Order	3.22	4.11	−0.89	−2.38*
Small-Large Spreads	3.36	5.36	−2.00	−6.84**
t-statistics	9.87**	11.21**		
Panel B. Time At				
Best Bid-Ask	4,482	1,118	3,360	7.00**
Small-Large Spreads	−2,149	−704	−1,445	−7.21**
t-statistics	−12.22**	−2.01*		

Panel A of Table 9 gives results for the times between 2 trades, between the spread narrowing and a trade, and between the spread widening and an order narrowing the spread. On average 6.78 seconds pass between when a trade occurs and the next algorithmic trade. Human trades are less frequent, and consequently there is an average of 9.27 seconds from the time of a trade until a human trade. Both ATs and humans trade more quickly when spreads are narrower. The human time decreases by 2.34 seconds from large to small spreads versus a decline of 4.36 seconds for ATs. The difference-in-difference of 2.02 seconds between algorithmic large spread minus algorithmic small spread and human large spread minus human small spread is statistically significant and economically large. Panel A of Table 9 also shows that ATs trade more quickly than humans following the spread narrowing. These results are consistent with the frequency results in Table 8, suggesting that ATs more actively monitor market conditions when demanding liquidity.

The make/take liquidity cycle examined in Foucault et al. (2013) alternates between two phases. First, an order from a liquidity supplier narrows the spread by offering a better price. Second, a liquidity demander monitors the market and reacts to the narrow spread by initiating a trade. The trade causes the spread to widen and the cycle repeats. The above discussion of the time from a narrowing order to a trade is consistent with ATs having lower monitoring costs in the 2nd phase of the Foucault et al. (2013) cycle. To examine the initial phase of the make/take cycle, where a liquidity supplier monitors the market for a wide quote and offers a better price, Panel A of Table 9 also provides the time between the spread widening due to a trade or cancellation and an order narrowing the spread. ATs react faster to a widening spread, with the difference increasing in the width of the spread. This is consistent with ATs attempting to capture the liquidity supply profits in the Foucault et al. (2013) make/take liquidity cycle.

Monitoring the limit order book and the resulting liquidity cycles are manifestations of search frictions for investors seeking gains from trade. Lower monitoring costs implicitly lowers search costs. Lower search costs typically result in greater competition among traders due to lower bargaining frictions. In limit order books, these frictions are a form of market power and are a component of the bid-ask spread. Therefore, lower monitoring by ATs can lead to better liquidity, as found by Hendershott et al. (2011). However, the benefits of ATs are not necessarily equally distributed between ATs and humans.

Table 8 documents algorithmic and human activity conditional on spreads. We see that ATs are more likely to submit a new bid-ask at the inside or better overall and when spreads are wide. Because ATs are also more likely to cancel their orders, Table 8 is not fully informative about the overall impact of algorithmic activity (inserts and cancels) on the best quotes over the entire trading day. In Panel B of Table 9 we report the number of seconds ATs and humans spend alone at the best bid-ask across the trading day. Panel B of Table 9 shows that ATs are on average at the inside for almost 1 hour more per day than humans. The small-large spread difference examines whether or not ATs are more likely to be present at the inside when spreads are wide or narrow. As before, we identify times when spreads are wider and narrower for each stock. We then calculate the amount of time ATs and humans are on the inside during the large- and small-spread times. Table 9 shows that ATs are on the inside more often during both large- and small-spread periods, but the AT-human difference is significantly higher during the large-spread periods. This shows that ATs are more likely to offer to supply liquidity when it is expensive.

For ATs to be on the inside more often yet only provide liquidity for 50% of volume, AT orders must be smaller or times when humans are alone at the inside are more likely to have transactions. One natural explanation for trades occurring more often when humans are alone at the inside quote is that the human quote is stale and is picked off. Our next analysis of liquidity supply and demand moves beyond the unconditional and single-dimension conditioning thus far and attempts to examine potentially stale limit orders.

VII. Multivariate Liquidity Supply and Demand Analysis

Up to this point we have studied how the increased ability of ATs to monitor the limit order book impacts liquidity demand and supply dynamics. To broaden our examination of ATs' differential reaction to public information, we move beyond the limit order book itself by studying recent price changes in the futures index market. To attempt to measure public information about when unexecuted limit orders may be stale, we use the fact that index futures price changes typically lead price changes in the underlying stocks (e.g., Kawaller, Koch, and Koch (1987)). We measure returns on DAX futures in the 30 seconds prior to each trade.[12] A sell limit order could be thought of as stale if the previous DAX return is positive, as the systematic component of the stock price will have increased since limit order placement. If the limit order executes before incorporating changes in the index value, it could be stale.

If futures prices lead the underlying, then sell limit orders after positive futures returns and buy limit orders after negative futures returns are more likely to be stale. To capture these, we interact lagged 30-second futures returns with a BUYSELL indicator variable set to +1 if the trade is buyer initiated and -1 if the trade is seller initiated. To limit the number of estimates while providing information on the potential staleness of the DAX returns, we also decompose the 30-second return into the return over the prior second, 2–10 seconds earlier, and 11–30 seconds earlier. The lagged futures returns are calculated as $\text{RTN}_{t-x,t-X} = \ln(\text{MIDPOINT}_{t-x}/\text{MIDPOINT}_{t-X})$, where $x = 0, 2$, and 11, and $X = 1, 10$, and 30. We interact positive and negative futures returns separately with trade direction as follows: $\text{RTN}^{+}_{t-1,t-30} \times \text{BUYSELL}$ and $\text{RTN}^{-}_{t-1,t-30} \times \text{BUYSELL}$.

Because these reflect marketwide factors that may be correlated with the state of the limit order book in each stock, we also account for contemporaneous and lagged liquidity measures and market conditions. Following Barclay, Hendershott, and McCormick (2003), we use the liquidity variables summarized in Table 2 along with past return volatility and trading volume. Lagged volatility is the absolute value of the stock return over the 15 minutes prior to the transaction. Lagged volume is the euro trading volume in the 15 minutes prior to the transaction.

Table 10 gives the univariate correlations between dummy variables for algorithmic-initiated trades, AT_{INIT}; trades where an AT's nonmarketable limit order executes, AT_{PASS}; algorithmic order cancellations, $\text{AT}_{\text{CANCEL}}$; the futures

[12] To analyze the lead-lag relationship, we calculate the cross autocorrelation of the front month DAX future and DAX index prints at 5-second frequencies. For the future, we take the prevailing midpoint on Eurex, and for the index, DB uses the last transaction price for each index constituent. The cross autocorrelations of the lagged future (in 5-second intervals) and the contemporaneous index are 0.21, 0.08, 0.04, 0.02, 0.02, and 0.01, all of which are significant at the 1% level. The cross autocorrelations of the lagged index (in 5-second intervals) and the contemporaneous future are 0.06, 0.03, 0.01, 0.01, 0.00, and 0.00; the first 4 lags are significant at the 1% level.

TABLE 10

Correlation of Order Flow and Liquidity Measures

Table 10 reports the correlation of AT_{INIT} and AT_{PASS} trading and AT_{CANCEL} orders with liquidity variables and DAX future returns. AT_{INIT} takes the value of 1 if the trade is initiated by an AT. AT_{PASS} takes the value of 1 if an AT supplies at least 1 share of a trade. AT_{CANCEL} takes the value of 1 if an AT cancels an order at the best and takes the value of 0 if a human cancels an order at the best. $RTN^{\pm}_{t-1,t-30} \times BS$ is the return on the DAX future between $t-1$ and $t-30$ seconds $\times$ a buy/sell indicator for positive and negative DAX returns, respectively. Depth is the depth at best. Depth3 is the depth at 3 times the average quoted at the bid and ask side. Depth and Depth3 are reported in 10 million euros. Lagged volatility is the absolute value of the stock return in the 15 minutes prior to the trade. Lagged volume is the sum of the volume in the 15 minutes prior to the trade.

	AT_{INIT}	AT_{PASS}	AT_{CANCEL}	Spread	$RTN^{+}_{t-1,t-30} \times BS$	$RTN^{-}_{t-1,t-30} \times BS$	Size	Depth	Depth3	Lagged Volatility	Lagged Volume
AT_{INIT}	1.00										
AT_{PASS}	−0.02	1.00									
AT_{CANCEL}	—	—	1.00								
Quoted Spread	−0.08	0.10	0.03	1.00							
$RTN^{+}_{t-1,t-30} \times BS$	0.02	0.00	0.01	0.01	1.00						
$RTN^{-}_{t-1,t-30} \times BS$	−0.01	0.00	−0.01	−0.02	0.12	1.00					
Size	−0.09	0.00	−0.13	0.16	0.01	−0.01	1.00				
Depth	−0.05	−0.08	−0.10	−0.01	0.00	0.00	0.22	1.00			
Depth3	−0.05	−0.04	−0.10	−0.01	−0.01	0.01	0.26	0.63	1.00		
Lagged Volatility	0.01	0.01	−0.06	−0.05	0.02	0.04	0.01	0.01	0.04	1.00	
Lagged Volume	−0.05	−0.04	−0.01	−0.12	0.04	−0.05	0.04	0.14	0.14	−0.17	1.00

return variables; and the market condition variables. Consistent with Tables 3 and 4, larger trades are less likely to be initiated by ATs. AT_{PASS} is positively correlated with trade size. This reflects the fact that AT_{PASS} captures trades that are entirely supplied by ATs and trades that are supplied by both ATs and humans because they are large. Consistent with Tables 8 and 9, narrower spreads are positively correlated with algorithmic-initiated trades and negatively correlated with passive algorithmic trades and AT cancellations.

Table 11 reports coefficients estimates from probit regressions for algorithmic-initiated trades, passive trades, and AT cancellations along with their corresponding linear probability slopes and *p*-values. To control for stock effects and time-of-day effects, we include, but do not report, firm dummy variables (30) and time-of-day dummy variables (17, one for each ½-hour period). The only significant time-of-day effects are that algorithmic trading becomes less likely at the end of the trading day, primarily in the last ½ hour of continuous trading.

The probit results show that AT_{INIT} is more likely when spreads are narrow and when trading volume over the prior 15 minutes is low. As in Table 3, larger trades are less likely to be initiated by ATs. Volatility over the prior 15 minutes is negatively related to AT_{INIT}. Depth at the inside (depth) and depth measured independently of the inside spread (depth3) are negatively related to AT_{INIT}. The negative relations between AT initiation and spreads and between AT initiation and lagged volatility provide no evidence to support a hypothesis that ATs exacerbate volatility.

The probit results show that AT_{PASS} is more likely when spreads are wide. Volatility over the prior 15 minutes is somewhat positively related to AT_{PASS}. Depth at the inside (depth) and depth measured independently of the inside spread

TABLE 11

AT Probit Regression

In the first 2 columns the dependent variable (AT_{INIT}) is equal to 1 if the trade is initiated by an AT, and 0 otherwise. In the 3rd and 4th columns the dependent variable (AT_{PASS}) is equal to 1 if at least 1 share in the trade is supplied by an AT, and 0 otherwise. In the last 2 columns the dependent variable (AT_{CANCEL}) takes the value of 1 if an AT cancels an order at the best and takes the value of 0 if a human cancels an order at the best. Size is the euro volume of a trade divided by 100,000. Depth is the depth at the best bid and ask. Depth3 is the depth at 3 times the average quoted spread on the bid and ask side. Depth and Depth3 are reported in 10 million euros. $RTN^{\pm}_{t,t-x} \times$ BUYSELL is the return on the DAX future for t and $t-x$ seconds $\times$ a buy/sell indicator variable for positive and negative DAX returns, respectively. Lagged volatility is the absolute value of the stock return in the 15 minutes prior to the trade. Lagged volume is the sum of the volume in the 15 minutes prior to the trade. Firm fixed effects and time-of-day dummy variables for each ½ hour of the trading day are not reported. The *p*-values are calculated using standard errors that account for both time-series and cross-sectional correlation. * and ** indicate significance at the 5% and 1% levels, respectively.

	AT_{INIT}		AT_{PASS}		AT_{CANCEL}	
Variable	Model A	Model A1	Model B	Model B1	Model C	Model C1
AT_{PASS}	−0.02	−0.02	—	—	—	—
Probability Slope	−0.02	−0.02	—	—	—	—
p-value	(0.00**)	(0.00**)	—	—	—	—
Quoted Spread	−0.016	−0.016	0.035	0.035	0.04	0.04
Probability Slope	−0.01	−0.01	0.01	0.01	0.01	0.01
p-value	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)
Size	−0.11	−0.12	0.02	0.00	−0.57	−0.57
Probability Slope	−0.09	−0.09	0.02	0.01	−0.21	−0.21
p-value	(0.15)	(0.05*)	(0.00**)	(0.00**)	(0.00**)	(0.00**)
Depth	−0.10	—	−0.73	—	−1.91	—
Probability Slope	−0.06	—	−0.28	—	−0.80	—
p-value	(0.00**)	—	(0.00**)	—	(0.00**)	—
Depth3	—	0.01	—	−0.02	—	−0.58
Probability Slope	—	−0.01	—	0.00	—	−0.26
p-value	—	(0.00**)	—	(0.00**)	—	(0.00**)
$RTN^{+}_{t,t-1} \times$ BUYSELL	20.70	20.75	17.96	17.94	25.02	24.98
Probability Slope	8.56	8.58	7.00	6.98	9.49	9.48
p-value	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)
$RTN^{+}_{t-2,t-10} \times$ BUYSELL	34.33	34.21	2.81	1.58	42.55	42.18
Probability Slope	14.40	14.22	0.84	0.35	15.86	15.71
p-value	(0.00**)	(0.00**)	(0.51)	(0.55)	(0.00**)	(0.00**)
$RTN^{+}_{t-11,t-30} \times$ BUYSELL	50.50	50.45	3.80	2.84	49.72	49.52
Probability Slope	20.06	19.95	1.38	1.01	18.36	18.28
p-value	(0.00**)	(0.00**)	(0.55)	(0.66)	(0.00**)	(0.00**)
$RTN^{-}_{t,t-1} \times$ BUYSELL	−21.18	−21.21	−13.52	−13.35	−29.19	−29.11
Probability Slope	−8.79	−8.80	−5.22	−5.14	−11.02	−11.00
p-value	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)
$RTN^{-}_{t-2,t-10} \times$ BUYSELL	−38.71	−38.77	−7.09	−6.43	−68.52	−67.92
Probability Slope	−15.87	−15.77	−2.59	−2.33	−25.55	−25.31
p-value	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)
$RTN^{-}_{t-11,t-30} \times$ BUYSELL	−39.69	−39.63	−5.55	−4.60	−58.12	−57.70
Probability Slope	−16.11	−15.97	−2.02	−1.65	−21.59	−21.41
p-value	(0.00**)	(0.00**)	(0.47)	(0.54)	(0.00**)	(0.00**)
Lagged Volatility	−0.01	−0.01	0.02	0.02	−0.01	−0.01
Probability Slope	−0.01	−0.01	0.01	0.01	−0.01	−0.01
p-value	(0.03*)	(0.05)	(0.01*)	(0.01*)	(0.00**)	(0.00**)
Lagged Volume	−0.08	−0.09	−0.37	−0.41	−0.05	−0.05
Probability Slope	−0.11	−0.11	−0.12	−0.14	−0.02	−0.02
p-value	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)	(0.00**)
No. of obs.	2,084,347	2,084,347	2,084,347	2,084,347	3,208,761	3,208,761

(depth3) are negatively related to AT_{PASS}. The positive relation between AT liquidity supply and spreads and lagged volatility, and the negative relation to depth, could lead to AT liquidity supply reducing volatility and smoothing liquidity. AT_{PASS} having a negative coefficient in the AT_{INIT} regression shows that ATs are less likely to supply liquidity when they are demanding liquidity even after controlling for market conditions.

The coefficients on lagged futures return variables are consistent with AT_{INIT} picking off stale human limit orders. Following past positive futures returns, AT_{INIT} buy markets orders are more likely. Conversely, when past futures returns are negative, AT_{INIT} sell orders are more likely. If futures prices lead the underlying stock prices, then the trades initiated by ATs impose adverse selection costs on the nonmarketable limit orders they execute against. AT_{PASS} has some relation to the lagged futures return variables, suggesting that AT nonmarketable limit orders may also be adversely selected.

In the AT_{CANCEL} regressions, the coefficients on lagged positive and negative DAX futures confirm the conjecture that ATs are able to cancel limit orders quickly before they become stale. ATs being able to cancel orders before they become stale may also allow ATs to offer tighter spreads throughout the trading day by reducing their adverse selection costs. ATs are also more likely to cancel their orders when spreads are wide and less likely to cancel when depth at the inside and depth independent of the inside spread are high. Volatility and volume over the prior 15 minutes are negatively related to AT_{CANCEL}.

Consistent with prior univariate results, the probit results suggest that ATs help smooth out liquidity over time and are consistent with ATs having lower monitoring costs in the liquidity make/take cycle proposed by Foucault et al. (2013). There is some evidence of aggressive ATs adversely selecting stale limit orders. However, we cannot determine whether or not the introduction of ATs increased this adverse selection or if ATs execute spot/future arbitrage that was previously executed manually. This latter possibility is quite plausible, as spot/future arbitrage is one of the easiest strategies to automate.

VIII. Conclusion

We study algorithmic traders' (ATs') use of technology that reduces their monitoring frictions and their role in liquidity supply and demand dynamics. We find that ATs consume liquidity when it is cheap and provide liquidity when it is expensive, likely reducing the volatility of liquidity. ATs closely monitor the market and respond more quickly to changes in market conditions. The results are consistent with technology facilitating ATs to more closely resemble the Friedman (1953) stabilizing speculator in terms of market liquidity. Further examinations of particular types of algorithmic (e.g., high-frequency) trading should provide insight into the potentially differing impact that types of AT strategies may have.

Our results have important implications for academics, regulators, and market operators. Theoretical models of limit order books should allow for a significant fraction of traders who closely monitor the market. These traders would constantly reprice their orders and prevent spreads from widening beyond a certain point; both of these features can help simplify theoretical models as they reduce the dimensionality of the state space (see also Goettler, Parlour, and Rajan (2009)). Given the slow progress in the modeling of theoretical limit order markets, this may have significant value.

Monitoring costs and limited attention are frictions limiting trade. In models without information asymmetry, better market monitoring increases trading and investors' gains from trade (see, e.g., Foucault et al. (2013), Biais et al. (2010)). Our results support the intuitive notion that ATs reduce trading frictions and the use of the reduced form assumption that ATs increase the probability of finding a counterparty (as in Biais et al. (2011)).

While lower monitoring costs for investors can be beneficial for important aspects of liquidity supply and demand, heterogeneous monitoring costs could also impose information asymmetry on slower traders. Slower traders face adverse selection if faster traders have an information advantage due to access to better and more current information about market conditions. Our results on net buying and selling of AT-initiated trades being correlated with the direction of past index futures returns is consistent with this. If ATs increase the scope of adverse selection sufficiently, liquidity and welfare could decline. While there is little empirical evidence supporting such a negative impact of technology in the trading process, it is an important avenue for future research, particularly if the adverse selection costs fall disproportionally on certain types of investors.

The increase in ATs has important implications for both regulators and designers of trading platforms. For example, the U.S. Securities and Exchange Commission's Regulation National Market System (NMS) (SEC (2005)) tries to promote competition among liquidity suppliers.[13] ATs lowering the monitoring costs for liquidity suppliers must also ensure vigorous competition among them. Trading venues should compete for ATs by lowering development and implementation costs by facilitating the production of useful information and metrics for ATs. Markets allowing ATs to co-locate their servers in the markets' data center should attempt to place all market participants on an equal footing. Finally, markets and brokers can offer additional order types with features designed to lower investors' monitoring costs (e.g., pegged orders). Incorporating AT features into the market mechanism itself can lessen infrastructure costs for investors and mitigate arms races in technology investment.

Appendix. Xetra and AT Matching Details

A. Xetra

The Xetra trading system is the electronic trading system operated by the DB and handles more than 97% of German equities trading by euro volume in DAX stocks (2007 Deutsche Boerse Factbook). The DB is a publicly traded company that also operates the Eurex derivatives trading platform and the Clearstream European clearing and settlement system. DB admits participants that want to trade on Xetra based on regulations set and monitored by German and European financial regulators. After being admitted, participants can only connect electronically to Xetra; floor trading is operated separately, with no interaction between the 2 trading segments.

Xetra is implemented as an electronic limit order book with trading split into phases as follows:

[13]ATs lowering monitoring costs should also improve linkages and integration among markets, potentially reducing concerns about liquidity fragmenting across many trading platforms. The DB's dominant market share during our sample period precludes us from studying this.

- opening call auction with a random ending that opens trading at 9:00,
- a continuous trading period,
- a 2-minute intraday call auction at 1:00 with a random ending,
- a 2nd continuous trading period,
- a closing call auction beginning at 5:30 with a random ending after 5:35.

We focus our analysis on trade occurring during the 2 continuous trading periods. Liquidity in DAX stocks is provided by public limit orders displayed in the order book of each stock. Orders execute automatically when an incoming market or marketable limit order crosses with an outstanding nonmarketable limit order. Order execution preference is determined using price-time-display priorities. Three types of orders are permitted: limit, market, and iceberg orders. Iceberg orders are orders that display only a portion of the total size of an order. Iceberg orders sacrifice time priority on the nondisplayed portion. Pretrade transparency includes the 10 best bid and ask prices and quantities but not the identity of the submitting participant (as on the Paris Bourse (Venkataraman (2001)). Trade price and size are disseminated immediately to all participants. The tick size for most stocks is 1 euro cent, with the exception of 2 stocks that trade in 1/10ths of a cent.[14]

B. Matching

To create the final data set of trades and orders, we use 3 separate data sources: AT order data from DB, public order book data from SIRCA, and public transactions data from SIRCA. Because SIRCA time stamps reflect routing delays between DB and Thompson-Reuters, the SIRCA data sets are subject to time lags relative to the AT system order. The time stamp or SIRCA order book data is lagged by up to 250 milliseconds (ms). The SIRCA transactions data set is lagged by up to 500 ms. The matching process for orders and trades is described in more detail below.

1. Order Matching

We generate orders from successive order book updates similar to Biais et al. (1995). We match AT orders with the SIRCA public order book-generated orders for the 5 best levels (bid and ask). To match the AT order data to the public data, we use the following criteria:

- Symbol
- Price
- Size
- Side (bid or ask)
- Order type (insert or delete)
- Time stamp (microsecond)

Adjustments are made for a lag between the AT and SIRCA order book data sets. The publicly available data are time-stamped to the microsecond but, due to transmission and additional system processing, they lag the system order data. We allow for a time window of up to 250 ms in the public data when looking for a match of the remaining criteria. The 250-ms-maximum lag was determined by manual inspection of a large number of AT orders and SIRCA order books. We match the AT order with the next public order that matches the above criteria. If we do not find a match, we delete the AT record. Approximately 5% of AT orders cannot be matched in the public data, many of these because they are outside the 5 best bid and ask prices in the SIRCA order book.

[14]Both Deutsche Telekom AG and Infineon AG have trade prices below 15 euros. Stocks with prices lower than 15 euros have a tick size of 1/10th of a cent.

2. Trade Matching

For trades we match 2 separate types of data, the DB-supplied AT order data and the public transactions record. Algorithmic trades are matched with trades in the SIRCA public data record. To match algorithmic trades to the SIRCA data, we use the following criteria:

- Symbol
- Price
- Size
- Trade direction
- Time stamp (microsecond)

We identify the trade direction in the SIRCA public data using the Lee and Ready (1991) trade direction algorithm with the Bessembinder (2003) modifications to determine the trade direction in the public data. Liquidity-demanding (AT_{INIT}) trades match trade size and price in the public data. AT liquidity-supplying trades (AT_{PASS}) may be smaller than the total trade size, as the marketable order may execute against multiple limit orders. We identify AT_{PASS} using the same criteria as for AT_{INIT} and modify the size criteria to be less than or equal to the size reported in the public data.

Adjustments are made for a lag in the time stamp between the AT and SIRCA transaction data sets. As with orders, the publicly available trade data are time-stamped to the microsecond but, due to transmission and additional system processing, they lag the system order data. We allow for a time window of 500 ms in the public transactions data when looking for a match on the remaining criteria. If we do not find a match, we delete the algorithmic trade. Roughly 97% of all algorithmic trades are matched in the public data.

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