Trading on Algos*

Johannes A. Skjeltorp†
Norges Bank

Elvira Sojli
Erasmus University Rotterdam

Wing Wah Tham
Erasmus University Rotterdam and Tinbergen Institute

Preliminary Draft
Comments welcome

Abstract

This paper studies the impact of algorithmic trading (AT) on asset prices. We find that the heterogeneity of algorithmic traders across stocks generates predictable patterns in stock returns. A trading strategy that exploits the AT return predictability generates a monthly risk-adjusted performance between 50-130 basis points for the period 1999 to 2012. We find that stocks with lower AT have higher returns, after controlling for standard market-, size-, book-to-market-, momentum, and liquidity risk factors. This effect survives the inclusion of many cross-sectional return predictors and is statistically and economically significant. Return predictability is stronger among stocks with higher impediments to trade and higher predatory/opportunistic algorithmic traders. Our paper is the first to study and establish a strong link between algorithmic trading and asset prices.

Keywords: Asset pricing, Algorithmic trading, Market quality, Liquidity.

JEL Classification: G10; G20; G14.

*The authors thank Schmuel Baruch, Tarun Chordia, Thierry Foucault, Amit Goyal, Terry Hendershott, Albert Menkveld, Ryan Riordan, Norman Schurhoff, Bernt-Arne Ødegaard, and participants at the Northern Finance Association Meeting 2013, ESSFM Gerzensee 2013, and the International Workshop on Market Microstructure and Nonlinear Dynamics for useful comments and suggestions. The views expressed are those of the authors and should not be interpreted as reflecting those of Norges Bank (Central Bank of Norway).

†Corresponding author. Address: Central Bank of Norway, P.O.Box 1179, Sentrum, NO-0107 Oslo, Norway. Email: jsk@nbim.no, Phone: (+47) 22316740. Other authors' email addresses: esojli@rsm.nl (Sojli), tham@ese.eur.nl (Tham).

1 Introduction

Algorithmic trading (AT) has increased enormously in recent years and it is estimated to account for 53% of U.S. daily equity trading volume. The episodes of the Flash crash in 2010 and the runaway trading code of Knight Capital in August 2012, which cost $440 million for its shareholders, highlight the economic importance of understanding the impact of algorithmic trading on asset prices. Despite the growing importance of AT in financial markets, there is no work studying its impact on asset returns. This paper fills the gap by examining the cross-sectional relation between AT and stock returns.

A major challenge in studying the impact of AT on market quality and on asset prices is the availability of long time series of public data. We overcome this issue by constructing an AT measure based on the order-to-trade ratio (OTR) using (publicly available) Trade and Quote (TAQ) data and examine its evolution for the period 1999 to 2012.[1] Using detailed high-frequency trading data (hereafter HFT data) obtained from NASDAQ OMX, we compare our measure with the fraction of trades and quotes by HFT per stock as provided by NASDAQ.[2] This data set is also used by Brogaard, Hendershott, and Riordan (2013) to study the impact of high-frequency trading on price discovery. We find that our measure is highly correlated, with a correlation of 65%-75%, to several measures of AT from the HFT data.

Using a data sample of NYSE, AMEX, and NASDAQ-listed firms from January 1999 to October 2012, we find a raw return differential between the low AT and the high AT portfolio of 9.4% per year. The AT effect is robust to adjustments for risk factors as well as firm characteristics. A portfolio of stocks with low AT outperforms a portfolio of stocks with high AT by 50 to 130 basis points per month after adjusting for the market, size, book-to-market, momentum, and liquidity factors. The negative relation between AT and returns is significant even after controlling for other widely documented return predictors. The return

[1] Hendershott, Jones, and Menkveld (2011) propose the use of message-to-trade ratios as an AT measure for studying the impact of AT on liquidity in NYSE. SEC Chairman Mary Schapiro supports the use of OTR as a measure of AT for policies to curb excessive messaging. The European Parliament's Economic and Monetary Affairs Committee (ECON) suggests to levy a fee for trading members who exceed an OTR of 250:1, see `http://www.thetradenews.com/news/Regions/Europe/MEPs_squeeze_HFT_in_MAD_proposals.aspx`.

[2] Hagströmer and Nordén (2013) show that 98.2% of HFT messages and 96.7% of their trades are generated using algorithms, while only 13.5% of non-HFT messages and 63.6% of messages from hybrid firms are generated by algorithms in the OMXS30 index in 2012.

difference is larger among smaller stocks, more illiquid stocks, and stocks with higher delay in information diffusion. The results are robust to different holding periods and various asset pricing tests.

We propose two potential explanations for the existence of the AT effect. First, the higher returns of stocks with low AT may reflect a delay in information diffusion among these stocks. Biais, Hombert, and Weill (2010) suggest that AT reduces the cognitive inability of human traders to execute their tasks efficiently and quickly. AT can improve the speed of information diffusion through trading algorithms that parse information from news wires and electronic sources almost instantly. More AT represents not only quicker response to news arrivals and the ability to identify short-lived mis-pricings, but also more information coverage and aggregation. Thus, more AT decreases delays in information diffusion and reduces trading frictions, see Chaboud, Chiquoine, Hjalmarsson, and Vega (2009), Hendershott et al. (2011), and Hendershott and Riordan (2012). Using the Hou and Moskowitz (2005) measure of how quickly stock prices respond to information, we find little support for the cognitive inability of human traders hypothesis.

The second explanation is based on the heterogeneity of algorithmic traders across stocks. The diversity of AT strategies implies a considerable heterogeneity in algorithmic trader types. In general, AT strategies are classified as market making and predatory algos, and these different algo types participate in stocks with different characteristics. Hagströmer and Nordén (2013) show that market making algos have higher quote-to-trade ratios and are more prevalent in smaller stocks with wider tick size, since the profit of market making per trade increases with the tick size of a stock. However, predatory algos use their speed advantage over slower traders to respond to news, to anticipate large orders of buy-side institutions, and to exploit cross-market arbitrage activities. Thus, we expect to find more predatory algos in stocks with slower traders and with more buy-side institutions. Given the pick-off risk, slower traders and buy-side institutions will require higher returns.

We test the AT heterogeneity hypothesis using the detailed NASDAQ HFT data with information on liquidity demanders and suppliers as well as trades between faster algorithms and slower human traders. We find that risk adjusted returns are higher in stocks with more active HFT trading against slower passive non-HFT traders and lower for stocks with more market making HFTs. Furthermore, the AT effect is more prevalent in stocks with more institutional investors. These results suggest that the higher risk-adjusted returns in lower AT stocks are associated with higher pick-off risk created by opportunistic algos that prefer to trade with humans and in stocks with more institutional investors.

We also study the role of market frictions/impediments-to-trade on the persistence of the AT effect. A profitable trading opportunity can persist only if there are market frictions that discourage arbitrageurs from exploiting it. We find that the AT effect is stronger among smaller stocks and stocks with higher transaction costs, supporting the impediments-to-trade hypothesis. Overall, these findings suggest that the AT effect arises from the heterogeneity of algorithmic traders across different stocks and impediments-to-trade perpetuate the phenomenon.

This paper is closely related to the literature on liquidity and asymmetric information and asset prices. O'Hara (2003) argues that financial markets can play an important role for asset prices through liquidity and price discovery. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan, Chordia, and Subrahmanyam (1998), Amihud (2002), Chordia, Subrahmanyam, and Anshuman (2002b), Jones (2002), and Brennan, Chordia, Subrahmanyam, and Tong (2012), among many others, provide evidence that liquidity is an important determinant of expected returns. Brennan and Subrahmanyam (1996), Easley, Hvidkjaer, and O'Hara (2002) and Easley and O'Hara (2004), among others, argue that stocks with more information asymmetry should have higher expected returns. We provide support for these two streams of literature by showing how AT affects asset prices via adverse selection and stock liquidity levels.

The paper is also related to the growing literature on understanding the impact of algorithmic and high frequency trading in financial markets. Biais and Woolley (2011) and Jones (2013) provide a survey of the literature on HFT. In theory, algorithmic trading can be beneficial for financial markets as it may mitigate traders cognition limits (Biais et al., 2010), but algorithmic traders can increase predatory behavior and adverse selection (Biais, Foucault, and Moinas, 2011; Foucault, Hombert, and Roşu, 2012) and increase imperfect competition (Biais et al., 2011). The empirical literature addresses the effects of AT on trade execution, liquidity, and market efficiency. Algorithms appear to reduce execution costs and risks (Domowitz and Yegerman, 2005; Engle, Ferstenberg, and Russell, 2012) and improve arbitrageurs' ability to eliminate asset mispricings (Chaboud et al., 2009). Several papers find that AT increases competition among trading venues and liquidity providers, provides liquidity when it is scarce, and improves price efficiency (see Hendershott et al., 2011; Chaboud et al., 2009; Hendershott and Riordan, 2012; Brogaard et al., 2013). However, Kirilenko, Kyle, Samadi, and Tuzun (2012) provide empirical evidence of adverse selection by showing that HFT are able to predict price changes at the expense of slower traders. Chaboud et al. (2009) find more correlated trades among algorithmic traders, which can potentially increase systemic risk in the spirit of Khandan and Lo (2011). Overall, the evidence on whether market quality is higher or lower with AT is mixed. Differently from the existing empirical work in the market microstructure literature, we investigate the impact of AT on financial markets through an asset pricing perspective by studying the relation between AT and asset returns across portfolios with varying algorithmic activity. Our results highlight the importance of accounting for heterogeneity in algos when studying their impact on market quality and asset prices.

This paper is among the first to construct a proxy for AT using publicly available data, which can be used to inform the intense public and academic debate about the impact of AT on market quality. Previous studies have mainly focused on market microstructure issues due to the lack of long time series of publicly available data. So far, measures of AT come from propriety databases and the time series of these measures is short. Chaboud et al. (2009) study the impact of AT on market efficiency in the foreign exchange market using *proprietary* Electronic Broking System (EBS) data from 2003 to 2007. Hendershott et al. (2011) construct measures of AT using electronic message traffic and trades in NYSE's SuperDOT system from the *proprietary* NYSE's System Order Data database from 2001 to 2005. Hasbrouck and Saar (2013) use two months of NASDAQ-ITCH data in 2008 to construct a measure of proprietary algorithms participation in stocks. Hendershott and Riordan (2012) use *proprietary* Deutsche Boerse data which identify whether or not the order was generated with an algorithm for 30 DAX stocks in January 2008. Brogaard et al. (2013) study the role of HFT, a subset of AT, using NASDAQ data that identifies HFT trading activity on a stratified sample of stocks (120 stocks) in 2008 and 2009. Boehmer, Fong, and Wu (2012) construct a proxy for AT in 39 individual exchanges around the world from 2001 and 2009 to study the impact of AT on market quality using the Thomson Reuters Tick History database. Using TAQ data, we construct an AT measure consistent with Hendershott et al. (2011) and Boehmer et al. (2012) for the whole U.S. equity market. We validate the reliability of OTR from TAQ as an appropriate AT measure by comparing it with the shorter but more detailed NASDAQ HFT data. The validation facilitates future research and analysis on the role and impact of AT in broader U.S. based asset pricing and corporate finance studies.

2 Data

We employ the trades and quotes reported in TAQ for the period January 1999 to October 2012, to construct a long time series of stock level AT. AT has been taking place since 1999, after the U.S. Securities and Exchange Commission approved the option for electronic systems to register as full-fledged exchanges in 1998.[3] Therefore our sample starts in 1999. We retain stocks listed on the NYSE, AMEX, and NASDAQ for which information is available in TAQ, Center for Research in Security Prices (CRSP), and Compustat. Following the literature, we use only common stocks (Common Stock Indicator Type=0), common shares (Share Code 10 and 11), and stocks not trading on a "when issued" basis. Stocks that change primary exchange, ticker symbol, or CUSIP are removed from the sample (Hasbrouck, 2009; Goyenko, Holden, and Trzcinka, 2009; Chordia, Roll, and Subrahmanyam, 2000). We also remove stocks that have a price lower than \$5 and higher than \$1,000 at the end of a month. To avoid look ahead biases, all filters are applied on a monthly basis and not on the whole sample. There are 5,978 individual stocks in the final sample. Throughout the paper, we use returns of -30% for the delisting month (delisting codes 500 and 520-584), as in Shumway (1997). All returns are calculated using bid-ask midpoint prices, adjusted for splits and cash distributions, to reduce market microstructure noise effects on observed returns (Asparouhova, Bessembinder, and Kalcheva, 2010, 2013). Table A.1 reports the definitions and the construction details for all variables and Table A.2 in the Appendix provides the summary statistics.

[3]Informal talks with HFT trading firms confirm this. Oxford Advisors Ltd launched Oxford High Frequency Trading Equity Fund (OHFT) in January 2001, the Sun Herald discusses benefits and costs of high frequency trading in February 2001. Institutional Investor covers algorithmic trading in January 2002, claiming that it has been around since the late 80's.

2.1 Proxy for algorithmic trading

To investigate the link between AT and asset prices, we need a proxy for stock level AT. Our proxy is the monthly number of quote updates in TAQ relative to the number of trade executions (order-to-trade ratio) across all exchanges. We define a quote update as a change in the best bid or offer price or in the quantity at the best bid/offer price in any exchange. The order-to-trade ratio has recently been applied by several exchanges to reduce the explosion of message traffic resulting from the increase in AT.[4] As many trading algorithms quote and cancel orders very rapidly to detect how the market is moving, to trigger responses by other traders, to identify hidden liquidity, etc., the strategies used by algorithmic traders, and high frequency traders in particular, have contributed to a huge increase in the amount of message traffic relative to trade executions. Thus, the order-to-trade ratio should capture changes in AT both in the cross-section and over time.

We calculate the AT proxy at the monthly frequency for each stock by summing the daily number of quote updates and the number of trades, across all exchanges. AT for stock i in month t is measured by the monthly number of messages across all exchanges divided by the number of trades:

$$AT_{i,t} = \frac{N(quotes)_{i,t}}{N(trades)_{i,t}}, \tag{1}$$

where $N(quotes)_{i,t}$ and $N(trades)_{i,t}$ denote the monthly number of quote updates and trades, respectively, for stock i in month t.[5]

2.2 Consistency of the AT measure

The AT measure proposed is based on the consideration that the more AT there is, the more quote updates there will be. Nonetheless, we need to ensure that the measure we have constructed is reliable and captures AT. We use a set of detailed HFT data obtained

[4] The London Stock Exchange was the first to introduce an "order management surcharge" in 2005 based on the number of trades per orders submitted. They revised this charge in 2010. Euronext, which comprises the Paris, Amsterdam, Brussels, and Lisbon stock exchanges, has operated one since 2007. In 2012 DirectEdge introduced the "Message Efficiency Incentive Program", where the exchange pays full rebates only to traders that have an average monthly message-to-trade ratio less than 100 to 1. In May 2012 the Oslo Stock Exchange introduced an order-to-execute fee, where traders that exceed a ratio of 70 for a month incur a charge of NOK 0.05 (USD 0.0008) per order. Deutsche Börse and Borsa Italiana have announced similar measures in 2012.

[5] Another way to measure algorithmic activity is to construct a ratio of trading volume to quote updates, see Hendershott et al. (2011). Our results remain qualitatively the same when using this measure. The results are available from the authors upon request.

from NASDAQ OMX to compare AT with the fraction of quotes by HFT per stock. The data consists of trade data for a stratified sample of 120 randomly selected stocks listed on NASDAQ and NYSE for 2008 and 2009 and trade and quote data for February 22-26, 2010. Trades identify the liquidity demander and supplier as HFT or non-HFT. Quotes identify the best bid and offer by HFTs or non-HFTs and any updates to the best prices and quantities. More details on this dataset are provided in Brogaard et al. (2013), who use it to study the impact of high-frequency trading on price discovery. To evaluate our AT measure, we use the HFT trade and quote data from February 2010, because it allows us to generate an HFT quote measure that we cannot do with the earlier HFT data from 2008 and 2009.

For each stock and each date, we calculate the number of total quote updates (HFT+non-HFT) in the NASDAQ HFT database $N(quotes)^{NASD}$ and the number of quote updates reported by NASDAQ in TAQ, $N(quotes)^{NASD|TAQ}$. The cross-sectional correlation between these two measures in Table 1 is 94%. We then calculate the daily number of quote updates by HFT, $N(quotes)^{HFT}$, and the daily number of trades by HFT, $N(trades)^{HFT}$. The correlation between $N(quotes)^{HFT}$ and $N(quotes)^{NASD|TAQ}$ is 87%, which means that a large proportion of NASDAQ quote updates reported in TAQ are HFT related. We then calculate $AT^{HFT} = \frac{N(quotes)^{HFT}}{N(trades)^{HFT}}$ which is comparable with our market-wide AT measure based on the TAQ data. The correlation between AT and AT^{HFT} is 57% and highly significant with a t-value of 15.44.

We also compare the AT proxy for the NASDAQ TAQ data, where we only use NASDAQ trades and quotes in TAQ to calculate the AT proxy,

$$AT^{NASD|TAQ} = N(quotes)^{NASD|TAQ}/N(trades)^{NASD|TAQ}$$

with AT^{HFT}. The correlation between $AT^{NASD|TAQ}$ and AT^{HFT} is 75% and highly significant. Overall, the results from comparing the AT measure with actual HFT data show that our AT measure is a valid measure of HFT and AT.

2.3 Algorithmic trading characteristics

Panel A of Figure 1 shows the equally weighted monthly AT over the sample period. AT has increased substantially over time. Panel B shows that the driver behind the increase in AT is the explosion in quote updates relative to executed trades. Panel C shows the time series of AT for market capitalization (MCAP) quintiles constructed at the end of each month. The MCAP1 portfolio includes the smallest stocks and MCAP5 the largest stocks. AT is higher for lower market capitalization stocks, similar to what Hendershott et al. (2011) document using NYSE only data to measure AT.

Table 2 examines the determinants of AT in a regression setting. The dependent variable is the yearly AT measure. We run a two-way fixed effects panel regression with standard errors clustered at the stock level. Table 2 shows that AT is higher in stocks with fewer analyst following and lower institutional ownership, stocks with higher prices and larger spread, and smaller stock with lower trading. To summarize, the descriptive statistics how that there is significant variation in AT across stocks and a dramatic increase in AT over time. Moreover, cross-sectionally, our proxy for AT decreases with market capitalization, consistent with evidence in Hendershott et al. (2011).

3 Algorithmic trading and returns

3.1 Raw returns

We examine the raw return characteristics of AT portfolios across stock characteristics, to analyze the relationship between AT and returns. Table 3 shows the average monthly returns in excess of the risk free rate for portfolios cross-sorted on various characteristics and AT. We use monthly conditional sorts, where first the sample is divided into three portfolios by various firm characteristics, such as size, every month t. We then sort characteristic-based terciles into five AT portfolios. There are approximately 145 stocks in each portfolio each month. We show the equally weighted average excess return of each portfolio and the return difference between the low and high AT portfolios in month $t + 1$. The double-sorts control for firms characteristics one at a time and show the low to high AT portfolio difference is not associated with a particular characteristic, but is pervasive across all cross sorts: Size ($MCAP$), Book-to-Market (BM), relative spread ($SPREAD$), USD trading volume ($USDVOL$), past month return ($R1$), and past 12 month return ($R212$).

3.2 Risk adjusted returns

Next, we test whether the return differential between the low and high AT stocks can be explained by the market, size, value, momentum, and liquidity factors. Each month, all stocks are divided into portfolios based on AT at time *t*. Portfolio returns are the equally weighted average realized returns of the constituent stocks in each portfolio in month *t+1*. We estimate individual portfolio loadings with a 24 months rolling window regression:

$$r_{p,t+1} = \alpha_p + \sum_{j=1}^{J} \beta_{p,j} X_{j,t} + \varepsilon_{p,t+1}, \tag{2}$$

where $r_{p,t+1}$ is the return in excess of the risk free rate for month t+1 of portfolio p constructed at month t AT level, and $X_{j,t}$ is the set of J risk factors: excess market return (r_m), value HML (r_{hml}), size SMB (r_{smb}), Pastor and Stambaugh (2003) liquidity (r_{liq}), and momentum UMD (r_{umd}).[6]

Table 4 reports alphas for 5, 10, 25, and 50 AT portfolios. There are 433, 217, 87, and 43 stocks in each portfolio respectively. The low-AT portfolio (AT1) has a statistically significant monthly alpha (α_1) that ranges between 0.9 and 1.3% across various portfolio splits and asset pricing models. The high-AT portfolio alphas range from -0.2% to 0.3%, but are statistically not different from zero in most specifications and portfolio splits. This suggests that the high AT portfolios are priced well by the factor models. However, the risk-adjusted returns between the low and high AT portfolios are statistically significant and vary between 0.5% to 1.3% per month across different AT portfolios. The profitability of the long-short strategy derives mainly from the long position or the performance of low-AT portfolio (AT1) instead of the short position of AT10, which limits concerns about the impact of short-selling constraints on this strategy.

So far we have only considered one month holding (portfolio re-balancing) periods, but

[6]Since we are using portfolios conditional on AT, we only have portfolio returns from February 1999. We use a 24 month estimation window to increase the sample period. For the individual stock regressions, we use a 48 month rolling window to estimate factor loadings.

the AT effect we document might be a transient phenomenon caused by short-term reversals and continuations. If the AT effect is temporary, then we expect stocks to switch across AT portfolios very frequently and the alphas of the AT long-short strategy to vanish over longer holding periods. To investigate the reversal hypothesis, we examine the persistence of the AT characteristic in two ways: (1) calculate the average portfolio rank and (2) examine the average AT in each portfolio. We assign stocks into portfolios based on AT levels at t and examine the average AT level for these portfolios in month $t+k$ keeping the portfolio constituents fixed for k months, where k is 1, 3, 6, 12, and 24 months.

Panel A of Table 5 shows the average portfolio rankings, and Panel B shows the average AT level of the portfolios for different horizons. Both panels suggest that the AT characteristic of the underlying portfolio stocks is very persistent. While there is some convergence in ranking and average AT, when increasing the holding horizon, there is still a large and significant difference in AT ranking and level among the portfolios even at the 24 month horizon. Panel B shows an increase in the average AT level across portfolios as the horizon increases. This might be associated with the market-wide increase in the AT activity over the sample period.

We study the average monthly risk adjusted returns (alphas) of the AT long-short strategies for different holding and formation periods, as an alternative exercise, to examine if the AT effect is transient. Table 6 shows the alphas for strategies that long the low AT portfolio and short the high AT portfolio for different holding horizons and formation periods. The holding horizons reflect the number of months for which the portfolio constituents are kept fixed after the formation point, i.e. portfolios are re-balanced every k months. We construct the long-short strategies for different numbers of portfolios (5, 10, 25, and 50) and examine 4 different formation periods, i.e. conditioning on different sets of information about AT. Panel A conditions on AT information from time t, Panels B, C, and D condition on the 3, 6, and 12-month moving average AT level respectively. We only show alphas from a five factor model.[7] Table 6 shows that the long-short alpha persist for holding horizons up to one year and is very stable across different portfolios. The AT effect is stronger for 3-12 month holding periods when conditioning on longer AT information in Panels B to D.

[7]The results are robust to other factor model specifications and to the creation of more portfolios. These results are available upon request.

Figure 2 shows the risk adjusted returns for the high and low AT portfolios for different holding horizons and formation periods for 5 AT portfolios. Stocks are assigned into portfolios based on their average AT level over the past 1, 3, 6, and 12 months (formation period) and the risk adjusted portfolio returns are for holding periods of 1 to 12 months. The figure shows that the AT effect is very persistent. For the low AT portfolio there is a slightly decreasing trend as the holding period increases, while the alphas for the high AT portfolios are very stable across horizons.

The overall conclusion from the above analysis is that AT is a strong predictor of future *abnormal* returns (where expected returns are measured by loadings to the three-, four-, and five-factor models) and this effect is not transient. This finding is consistent with papers showing that market microstructure and trading activities can be important for understanding asset returns (Amihud and Mendelson, 1986; Amihud, 2002; Brennan and Subrahmanyam, 1996; Chordia, Roll, and Subrahmanyam, 2002a; Chordia et al., 2000, 2002b; Easley et al., 2002; Duarte and Young, 2009, among many others).

4 Explaining the algorithmic trading effect

In this section, we investigate and discuss two possible causes for the existence of the AT effect: the diversity of algorithmic traders and the cognitive inability of human traders. In addition, we study the role of impediments to trade in explaining the persistence of the AT effect.

4.1 Diversity of algorithmic traders

There is diversity and heterogeneity in the strategies implemented by algorithmic and high frequency traders. On one hand, HFTs and algorithmic traders can be liquidity providers or new market makers as documented in Hendershott et al. (2011), Jovanovic and Menkveld (2010), and Menkveld (2013). Thus, stocks with higher market-making AT should have better liquidity and lower excess returns. On the other hand, Hagströmer and Nordén (2013) document that there are some HFTs/ATs that follow "opportunitistic" strategies such as arbitrage, order anticipation, and momentum ignition trading strategies. Such predatory

HFTs/ATs can impose a new form of adverse selection costs associated with the speed superiority of HFT over other market participants consistent with Biasis, Foucault, and Moinas (2013), Foucault et al. (2012) and Foucault, Kozhan, and Tham (2014). As a result, stocks with more opportunistic HFTs should have higher excess returns. If the AT effect is related to the type of algorithmic traders in different portfolios, then the AT variable should be positively correlated to market making algos and negatively correlated with opportunistic/predatory algos.

Given that predatory algos exploit their speed advantage over other slower traders, we proxy for predatory algos using the trades initiated (liquidity demanding) by HFT and liquidity supplied by non-HFT (slower traders) in the NASDAQ HFT data.

We first examine the relation between market making and predatory algos with the AT variable. Panel A of Table 7 shows the Fama and MacBeth (1973) coefficients from the monthly contemporaneous regression of AT on HFT type: opportunistic alogs, *HFT TAKE*, and market making algos, *HFT MAKE*. *HFT TAKE* is the total number of trades (in millions) for stock i in month t, where an HFT takes liquidity and a non-HFT is a passive party in the trade. *HFT MAKE* is the total number of trades, where an HFT provides liquidity (being the passive party in the trade) and the non-HFT take liquidity. We use the NASDAQ HFT data for 120 stocks for the period 2008 to 2009. Column (1) of Panel A shows that *HFT TAKE* is negatively related to AT, while *HFT MAKE* is positively related to AT. This result is consistent with Hagströmer and Nordén (2013)'s observation that market making HFTs have higher order-to-trade ratios. The correlation between AT and *HFT MAKE* and *TAKE* suggests that high AT portfolios contain stocks with more market making algos while low AT portfolios contain stocks with more predatory algos, consistent with the algo heterogeneity hypothesis. Column (2) excludes *HFT MAKE* and *HFT TAKE* and the R^2 drops significantly, which suggest that HFT explains a significant amount of the cross-sectional variation in AT.

Following the above observation, we investigate if stocks with more market making HFT have lower risk-adjusted returns compared to stocks with more predatory HFT. Panel B of Table 7 shows the Fama-Macbeth regression of the risk adjusted returns from estimating Equation 8 on *HFT MAKE* and *HFT TAKE*. Column (1) shows the result for the full cross section of stocks (i.e. not limited to the 120 HFT sample stocks) for the period 2008-9. AT is negative and highly significant in this period. Column (2) replaces the AT variable with *HFT TAKE* and *HFT MAKE*. *HFT MAKE* has a negative coefficient, similar to AT, while *HFT TAKE* is positive and significant. Overall these results support the algo heterogeneity hypothesis, where stocks with higher risk-adjusted returns are associated with higher amount of predatory algos and lower amount of market making algos.

Given that order anticipation strategies employed by predatory algos target institutional investors such as pension and mutual funds, the AT effect should be stronger in stocks with higher institutional ownership if AT is related to algo heterogeneity. To investigate this, we examine the abnormal returns of the AT long-short strategy across portfolio with different percentage of institutional ownership. Stocks are divided into terciles based on the level of institutional ownership in the previous year. Stocks within each institutional ownership tercile are divided in 10 AT portfolios, and we compute the alpha of the long-short strategy based on AT portfolios. Results from Table 8 provide support for the algo heterogeneity hypothesis. The AT effect is strongest among stocks with the highest institutional ownership. The monthly abnormal returns for portfolios with the highest institutional ownership is 1.7% and 0.65% for the portfolios with the lowest institutional ownership. The difference in the abnormal returns across different institutional ownership groups is statistically and economically significant. It appears that predatory algos are more prevalent in stocks with more institutional investors and returns are higher in these stocks because of pick-off risk.

In summary, the results above suggest that the AT effect is more likely to be driven by the algo heterogeneity hypothesis and less likely to be explained by the cognitive inability of human traders hypothesis.

4.2 Cognitive inability hypothesis

Biais et al. (2010) suggest that AT reduces the cognitive inability of human traders to execute their tasks efficiently and quickly. For example, trading algorithms parse information from newswires and electronic sources and use it as trading signals and price adjustments. Thus, AT can potentially reduce delays in information diffusion. If AT improves information diffusion, then its effect should only be present among stocks with slower speed in incorporating information.

We employ three measures of how a firm's stock price responds to information proposed by Hou and Moskowitz (2005). The market return is used as the relevant news to which stocks respond. Differently from Hou and Moskowitz (2005), we use daily returns instead of weekly returns, because with recent technological advancements we expect a stock to respond to changes in market return in days rather than weeks. We run a regression of each stock's daily return on contemporaneous and 5 days of lagged returns of the CRSP value-weighted market portfolio over a year at the end of December:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{5} \delta_i^{(n)} R_{m,t-n} + \epsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the return on stock i and $R_{m,t}$ is the return of CRSP value-weighted portfolio on day t. β_i will be significantly different from zero and all $\delta_i^{(n)}$ will be statistically insignificant from zero if the speed of response to market news is immediate. $\delta_i^{(n)}$ will be significantly different from zero if the speed of information diffusion is slow.

We use the results of the estimation of Equation 3 to compute three measures. The first measure is based on an F-test of the joint significance of the lagged variables scaled by the amount of total variation explained only by $R_{m,t}$. This measure is one minus the ratio of the R_i^2 of the estimation of Equation 3 for each stock with the restriction $\delta_i^{(n)} = 0$ and the R_i^2 of the estimation without restrictions:

$$D1_i = 1 - \frac{R^2_{\delta_i^{(n)}=0, \forall n \in [1,5]}}{R^2}. \tag{4}$$

Larger D1 reflects a higher delay in response to new information as more return variation is captured by the lagged terms. We also use two alternative measures to account for the precision of the estimates and the lagged specification of the model:

$$D2_i = \frac{\sum_{n=1}^{5} n\delta_i^{(n)}}{\beta_i + \sum_{n=1}^{5} \delta_i^{(n)}} \tag{5}$$

$$D3_i = \frac{\sum_{n=1}^{5} n\delta_i^{(n)}/s.e.(\delta_i^{(n)})}{\beta_i/s.e.(\beta_i) + \sum_{n=1}^{5} \delta_i^{(n)}/s.e.(\delta_i^{(n)})}, \tag{6}$$

where $s.e.$ is the standard error of the coefficient estimates.

Table 9 reports monthly alphas of a long-short strategy that longs low AT stocks and short high AT stocks within each level of the delay measure from different factor models. First the sample is divided into three portfolios by delay measure each month, and then we construct ten AT portfolios within each tercile. Finally, we long the low AT portfolio and short the high AT portfolio. For D1, there are abnormal returns in all delay groups, and the highest returns occur in the high information delay category. Abnormal returns are significant across all delay groups for D2 and D3. The results suggest that information delay plays some role in explaining the existence of the AT effect.

As an alternative analysis to investigate the impact of information diffusion on the abnormal returns, we estimate Fama and MacBeth (1973) cross-sectional regressions of monthly individual stock risk adjusted returns on different firm characteristics including the AT variable. We use individual stocks as test assets to avoid the possibility that tests may be sensitive to the portfolio grouping procedure. First we estimate monthly rolling regressions to obtain individual stocks' risk adjusted returns using a 48 month estimation window. We use a similar procedure as in Brennan et al. (1998) and Chordia, Subrahmanyam, and Tong (2011), to first obtain risk adjusted returns $er_{i,t}$:

$$er_{i,t} = r_{i,t} - \sum_{j=1}^{J} \beta_{i,j,t-1} F_{j,t}, \tag{7}$$

where $r_{i,t}$ is a stock's monthly return in excess of the risk free rate, $\beta_{i,j,t-1}$ are the factor loadings estimated for each stock by a rolling time series regression up to $t-1$, and $F_{j,t}$ are the realized value of the risk factors at t: the market, SMB, HML, liquidity, and momentum. Then we regress the risk adjusted returns from equation 7 on lagged stock characteristics:

$$er_{i,t} = c_{0,t} + \sum_{m=1}^{M} c_{m,t} Z_{m,i,t-k} + e_{i,t}, \tag{8}$$

where $Z_{m,i,t-k}$ is the characteristic m for security i at time $t-k$, and M is the total number of characteristics. We use $k = 1$ months for all characteristics.[8] The procedure ensures unbiased estimates of the coefficients, $c_{m,t}$, without the need to form portfolios, because errors in the estimation of the factor loadings are included in the dependent variable. The t-statistics are obtained using the Fama-Macbeth standard errors with Newey-West correction with 12 lags.

Table 10 reports the Fama and MacBeth (1973) coefficients for different regressions. Column (1) includes only the AT and delay variables. AT is negative and highly significant and only D1 is significantly positive at the 10% level. The addition of liquidity variables in column (2) makes D1 insignificant. AT remains negative and highly significant when we include all control variables in column (3). These results show little support that the AT effect is related to the delay in information diffusion and the potential explanation of cognitive inability hypothesis as discussed in Biais et al. (2010).

4.3 Impediments to trade effects

Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), and Hasbrouck (2009) show that liquidity level plays an important role for the required returns of stocks. Given algorithms' role in liquidity provision in today's financial markets (Menkveld, 2013), the relation between AT and returns might be due to algorithmic activities proxying for liquidity levels. Furthermore, the persistence of the AT effect might be caused by impediments to trade or transaction cost. To determine the role of liquidity and impediments to trade, we first sort stocks into terciles based on liquidity proxies (ILR, relative spread, and dollar trading volume), and then create ten AT portfolios within each liquidity tercile. We examine the alphas from a strategy that long the low AT stocks and short the high AT stocks within each liquidity tercile. If illiquidity level explains AT, abnormal profits should concentrate in the most illiquid group and the size of the risk adjusted returns should be of the same magnitude as the cost of transacting in U.S. equity market. Also abnormal returns for the most illiquid group should not be statistically different from zero.

Results in Table 11 provide some support for the illiquidity hypothesis. The strongest AT effect occurs among the most illiquid stocks across all illiquidity proxies. For the five factor model, the abnormal return for the most illiquid group is about 180 basis points and

[8] Panel A of Table A.4 in the Appendix shows the estimation results where $k = 2$, except for $R1$ and $R212$.

70 basis point for the most liquid group across all three illiquidity proxies. The difference in abnormal returns across these illiquidity groups implies a difference in average transaction costs (impediment to trade), of 110 basis points between the illiquid and liquid group of stocks. Most importantly the abnormal returns for the most illiquid group are statistically and economically different from zero.

Table 12 reports the Fama and MacBeth (1973) coefficients for cross-sectional regressions of individual stock risk adjusted returns on illiquidity variables as in Section 4.1. AT has a highly significant and negative coefficient, i.e. stocks with higher AT activity have lower next month risk adjusted returns. We are also interested in the coefficients of the liquidity proxies. Column (1) includes only $SPREAD$ and AT, column (2) includes only AT and ILR, and column (3) includes both liquidity proxies. $SPREAD$ and ILR are positive and significant, and AT remains negative and significant. When including other stock characteristics as control variables AT continues to be highly significant, while the liquidity variables remain insignificant.

5 Conclusion

We examine the relation between algorithmic trading and stock returns. We find a significant risk adjusted return difference between stocks with low and high AT. A trading strategy that attempts to exploit the AT return predictability generates an annualized risk-adjusted performance between 7-12% for the period 1999 to 2012. Return predictability is stronger among stocks with higher impediments to trade and higher information diffusion delay. The risk adjusted return difference is not only statistically significant but also economically large.

We show that the AT effect is robust to different specifications of asset pricing tests and well-known return anomalies, and it is not driven by short-term return reversals and continuations. The AT effect can be explained by the heterogeneity among algorithmic traders and impediments to trade. Our work contributes to the debate on the role of algorithmic trading in today's financial market. It supports the microstructure literature that argues that AT is in general beneficial for financial markets but only in stocks with higher market making algorithms. In stocks with more predatory algorithms, we observe higher returns because of pick-off risk.

Table 1
AT proxy comparison

The table shows the correlation between different measures of HFT activity based on NASDAQ HFT data and proxies for AT (AT) calculated using the TAQ data. $NASD$ indicates data from the NASDAQ HFT data, HFT indicates data for HFTs only from the NASDAQ HFT data, and $NASD|TAQ$ indicates data from TAQ reported by NASDAQ only. AT is the market-wide proxy for algorithmic trading in Equation 1 using TAQ data, $AT^{HFT} = N(quotes)^{HFT}/N(trades)^{HFT}$. $AT^{NASD|TAQ} = N(quotes)^{NASD|TAQ}/N(trades)^{NASD|TAQ}$. The sample is 120 stocks for the period 22-26 February 2010. t-statistics are presented in square brackets.

	$N(quotes)^{NASD}$	$N(quotes)^{HFT}$	$AT^{NASD\|TAQ}$	AT^{HFT}
$N(quotes)^{NASD\|TAQ}$	0.94	0.87		
	[59.65]	[37.39]		
AT			0.65	0.57
			[18.04]	[15.44]
$AT^{NASD\|TAQ}$				0.75
				[25.08]

Table 2
Determinants of algorithmic trading

The table shows the two-way fixed effects panel regression on the determinants of AT. The dependent variable is the average AT across the year. *Analyst Following* is the log of one plus the number of analysts following the firm as of the previous year end. *Analyst Dispersion* is the natural log of one plus the dispersion of analyst forecasts divided as of the previous year end. *Institutional Ownership* is the holdings of institutions at the end of the year constructed from 13F files as of the previous year end. BM is the book to market as of the previous year end. r_i are last month returns. *MCAP* (log market capitalization), the log of price (*PRC*), trading volume in shares (*VOLUME*), the Amihud illiquidity ratio (*ILR*), and relative spread (*SPREAD*) are contemporaneous. Standard errors are clustered at the stock level.

	Coefficient	t-stat	p-value
Analyst Following	-2.12	-2.10	0.04
Analyst Dispersion	0.00	0.00	1.00
Institutional Ownership	-18.91	-6.30	0.00
BM	-0.24	-0.23	0.82
r_i	-34.76	-4.99	0.00
MCAP	-17.70	-8.21	0.00
PRC	23.15	7.61	0.00
VOLUME	-0.07	-4.93	0.00
ILR	-202.86	-3.28	0.00
SPREAD	-156.01	-1.25	0.21
Adj.R^2	0.21		

Table 3
Algorithmic trading and stock returns: Uni-variate comparisons

The table shows the average monthly returns for stocks cross-sorted by AT and different characteristics. Each month t we divide the sample in terciles based on end of month characteristic (size, book-to-market, relative spread, trading volume in USD, past month returns, and past 12 month return). Within each characteristic we sort stocks into five AT portfolios, where the AT1 portfolio contains stocks with the lowest AT and AT5 stocks with the highest AT. We then compute the equal-weighted average return over for month $t+1$ for the five AT portfolios within each characteristic and the return difference between the low and high AT portfolios. All returns are calculated using bid-ask midpoint prices (adjusted for splits and cash distributions) and corrected for delisting bias, -30% return for stocks with delisting codes 500 and 520-584. *t-stat* shows the t-statistic for the difference in returns test for AT1-AT5.

	Average monthly (%) returns (er_{t+1})						
	AT (t)						
	AT1	AT2	AT3	AT4	AT5	AT1-AT5	t-stat
	Panel A: by MCAP						
Low MCAP	2.48	2.04	1.63	1.22	1.00	1.48	5.77
Med MCAP	1.47	1.07	0.64	0.90	0.67	0.81	1.68
High MCAP	0.56	0.47	0.60	0.59	0.55	0.00	0.01
	Panel B: by BM						
Low BM	1.05	0.90	0.71	0.63	0.60	0.45	0.96
Med BM	1.54	1.18	0.78	0.81	0.64	0.90	2.66
High BM	1.85	1.63	1.27	1.37	0.89	0.96	3.64
	Panel C: by SPREAD						
Low SPREAD	0.79	0.79	0.79	0.66	0.44	0.35	0.76
Med SPREAD	1.66	1.35	0.72	0.70	0.69	0.97	2.53
High SPREAD	2.30	1.79	1.21	1.14	0.74	1.55	5.74
	Panel D: by USDVOL						
Low USDVOL	2.22	1.71	1.31	1.07	0.73	1.49	7.22
Med USDVOL	2.07	1.32	0.82	0.95	0.74	1.33	3.15
High USDVOL	0.68	0.66	0.59	0.59	0.48	0.20	0.37
	Panel E: by R1						
Low R1	1.37	1.24	0.89	0.89	0.75	0.62	1.46
Med R1	1.50	1.12	0.93	0.96	0.61	0.89	3.18
High R1	1.49	1.16	0.98	0.87	1.06	0.43	1.16
	Panel F: by R212						
Low R212	1.57	1.39	0.97	0.98	0.72	0.85	2.36
Med R212	1.24	0.99	0.82	0.82	0.75	0.49	2.05
High R212	1.37	1.33	1.14	0.93	1.11	0.27	0.60

Table 4
Risk adjusted returns for algorithmic trading portfolios

The table shows the percentage risk adjusted returns (α) for different AT portfolios. The monthly returns of the AT portfolios are risk adjusted using the market model (Market), Fama and French (1992) model (FF), a model that adds the Pastor and Stambaugh (2003) traded illiquidity factor (4 factor), and a five factor model that adds a momentum factor (5-factor). We show the alpha for the lowest and highest AT portfolios and the alpha for the difference in returns between the low and high portfolios. In Panel A, stocks are assigned to five portfolios based on their AT level in month t. Then returns are calculated for each portfolio for month $t+1$. Panels B to E show stocks assigned to 10, 25, and 50 portfolios. ***, **, and * indicate rejection of the null hypothesis that the risk adjusted portfolio returns are significantly different from zero at the 1%, 5%, and 10% level, respectively.

	Risk adjusted (%) returns (α)			
	Market	FF	4-factor	5-factor
		Panel A: 5 AT portfolios		
α_1	1.20***	0.89***	0.88***	0.93***
α_5	0.65***	0.31**	0.27**	0.28**
α(AT1-AT5)	0.55*	0.58***	0.61***	0.65***
		Panel B: 10 AT portfolios		
α_1	1.20***	0.92***	0.95***	1.02***
α_{10}	0.58***	0.24	0.21	0.23
α(AT1-AT10)	0.62*	0.68***	0.73***	0.78***
		Panel C: 25 AT portfolios		
α_1	1.21***	1.01***	1.08***	1.16***
α_{25}	0.32	-0.01	-0.06	-0.03
α(AT1-AT25)	0.88**	1.03***	1.14**	1.19***
		Panel D: 50 AT portfolios		
α_1	1.05***	0.98***	1.08***	1.17***
α_{50}	0.10	-0.25	-0.30*	-0.27
α(AT1-AT50)	0.95**	1.23***	1.38***	1.44***

Table 5
Persistence of algorithmic trading characteristic

The table shows the variation of the AT characteristic for different portfolio re-balancing horizons. Panel A shows the average ranking and Panel B shows the average AT level for portfolios constructed at time t and holding periods $t+k$. We hold the portfolios fixed for k=1, 3, 6, 12, and 24 months and calculate the average AT ranking and AT level of the portfolios at time $t+k$. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Average portfolio rank at increasing horizons

	Average AT portfolio rank (t+k)				
Portfolio	t+1	t+3	t+6	t+12	t+24
AT1	1.37	1.55	1.69	1.86	2.07
AT2	2.11	2.16	2.23	2.29	2.43
AT3	2.86	2.81	2.78	2.77	2.84
AT4	3.89	3.82	3.75	3.67	3.50
AT5	4.77	4.67	4.59	4.48	4.21
AT5-AT1	3.40***	3.12***	2.90***	2.61***	2.14***

Panel B: Average AT level at increasing horizons

	Average AT portfolio level (t+k)				
Portfolio	t+1	t+3	t+6	t+12	t+24
AT1	10.05	11.88	13.72	16.56	24.38
AT2	13.68	15.03	16.88	19.22	25.82
AT3	18.41	19.98	22.06	24.43	32.43
AT4	31.20	34.86	37.80	41.47	48.44
AT5	145.54	140.88	138.44	139.46	133.36
AT5-AT1	135.50***	129.00***	124.72***	122.90***	108.97***

Table 6
Different formation and holding periods

The table reports the monthly alphas for the long-short portfolio that longs low AT stocks and shorts high AT stocks. The columns show the alphas for different numbers of portfolios, i.e. α(AT1-AT5) is the alpha from a long-short strategy for stocks assigned to 5 AT portfolios, α(AT1-AT50) is the alpha from a long-short strategy for stocks assigned to 50 AT portfolios. Panels A to D show the returns conditioning on different levels of AT. results for different formation periods. Panel A conditions on AT at time t, Panel B conditions the 3-month moving average AT level, and Panels C and D condition on the 6 and 12-month moving average AT level, respectively. All alphas are obtained by risk adjusting the long-short portfolio returns using a five factor model. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

Holding horizon	α(AT1-AT5)	α(AT1-AT10)	α(AT1-AT25)	α(AT1-AT50)
		Panel A: Formation Period = 1 month		
1	0.65***	0.78***	1.19***	1.44***
2	0.64***	0.73***	0.98***	1.00***
3	0.54***	0.68***	0.97***	1.04***
6	0.47**	0.57**	0.83***	0.90***
9	0.37*	0.41*	0.61**	0.55
12	0.32*	0.38*	0.52**	0.59*
		Panel B Formation Period = 3 months		
1	0.61***	0.78***	1.15***	1.20***
2	0.61***	0.76***	1.01***	0.98***
3	0.58***	0.70***	0.93***	1.10***
6	0.47**	0.68***	0.85***	1.22***
9	0.42**	0.48**	0.61**	0.93**
12	0.38*	0.44**	0.38	0.60
		Panel C Formation Period = 6 months		
1	0.59***	0.79***	1.25***	1.30***
2	0.55***	0.78***	1.02***	1.09***
3	0.51**	0.70***	0.93***	1.09***
6	0.45**	0.67***	0.78***	1.02***
9	0.46**	0.60***	0.69**	0.90**
12	0.36*	0.46**	0.47*	0.50
		Panel D Formation Period = 12 months		
1	0.59***	0.80***	1.15***	1.16***
2	0.58***	0.69***	0.94***	0.99***
3	0.54***	0.67***	0.98***	0.98***
6	0.50**	0.55**	0.82***	0.97***
9	0.48**	0.64***	0.72***	0.75**
12	0.37*	0.48**	0.58**	0.87**

Table 7
Algorithmic trading and HFT heterogeneity

The table shows the relation between AT and HFT heterogeneity. Panel A reports the Fama and MacBeth (1973) coefficients from the contemporaneous regression of AT on HFT type. *HFT TAKE* is the number of trades where a HFT is the aggressor and *HFT MAKE* is the total number of trades where an HFT provides liquidity (is the passive part of the trades) and a non-HFT takes liquidity. Sample is 120 stocks in the NASDAQ HFT data and the period is 2008 and 2009. Panel B reports the Fama and MacBeth (1973) coefficients from the regression of next period risk adjusted individual stock returns on AT, HFT TAKE, HFT MAKE. Column (1) use the full cross section of stocks for the 2008-2009 period, while column (2) only uses only the 120 stocks included in the NASDAQ HFT sample. Standard errors are corrected by using the Newey-West method with 12 lags, and ***, **, * indicate a significant coefficient at the 1%, 5% and 10% level, respectively.

Panel A: Explaining AT with HFT trading data (120 stocks)

	(1)	(2)
Const.	0.590	0.305
$HFT\ TAKE_{i,t}$	-1.984***	
$HFT\ MAKE_{i,t}$	1.688***	
$MCAP_{i,t}$	-0.017*	0.005
$BM_{i,t}$	0.044*	0.046*
$SPREAD_{i,t}$	2.490***	2.626***
$ILR_{i,t}$	0.002	0.001
$R1_{i,t}$	0.055	0.019
$R212_{i,t}$	0.072	0.062
$PRC_{i,t}$	0.345***	0.283***
$USDvol_{i,t-1}$	-0.058***	-0.058***
$IDIOVOL_{i,t}$	-3.644***	-4.913***
R^2	75.4 %	72.6 %
Time series (months)	23	23

Panel B: Explaining risk adjusted returns with HFT heterogeneity

	(1)	(2)
Const.	0.081**	0.175**
$AT_{i,t-1}$	-0.394***	
$MCAP_{i,t-1}$	-0.333	-1.406**
$BM_{i,t-1}$	-0.263	-0.060
$SPREAD_{i,t-1}$	-0.361	2.273
$ILR_{i,t-1}$	-0.112*	-0.392
$R1_{i,t-1}$	-14.428***	-11.159***
$R212_{i,t-1}$	-3.205**	-3.374***
$PRC_{i,t-1}$	-0.359***	-0.152
$USDvol_{i,t-1}$	-0.002	0.476
$IDIOVOL_{i,t-1}$	2.416	-3.755
$HFT\ TAKE_{i,t-1}$		0.222***
$HFT\ MAKE_{i,t-1}$		-0.067
R^2	6.5 %	21.4 %
Time series (months)	23	22

Table 8
Institutional ownership and algorithmic trading

The table reports monthly alphas of a long-short strategy that longs low AT stocks and shorts high AT stocks (within each level of the institutional ownership measure) from different factor models. Institutional ownership (*Inst. Ownership*) is constructed from 13F filings. We first divide stocks into three groups based on the level of institutional ownership as of previous year end. Then, within each institutional ownership group, we construct ten portfolios based on the level of AT, and short the high AT portfolio and long the low AT portfolio. All portfolio returns are equally weighted. The monthly returns from these ex-ante strategies are then risk adjusted using a market model (Market), Fama and French (1992) model (FF), a model that adds the Pastor and Stambaugh (2003) illiquidity factor (4 factor), and a five factor model that adds the momentum factor (5-factor). T-values are presented in parenthesis. Standard errors are corrected by using the Newey-West method with 12 lags, and ***, **, * indicate a significant coefficient at the 1%, 5% and 10% level, respectively.

	Market	FF	4-factor	5-factor
low Inst. Ownership	0.59	0.58*	0.62**	0.65**
	(1.54)	(1.97)	(2.05)	(2.18)
med Inst. Ownership	0.55	0.74**	0.89***	0.96***
	(1.29)	(2.38)	(2.84)	(3.26)
high Inst. Ownership	1.32***	1.42***	1.60***	1.71***
	(2.87)	(3.86)	(4.36)	(5.13)

Table 9
Price efficiency and AT activity

The table reports monthly alphas from different factor models of a long-short strategy that longs low AT stocks and shorts high AT stocks (within each level of the delay measure). The delay measures (D1, D2 and D3) are estimated up to the previous month on daily data with a one year estimation window. We first divide all stocks (at t) into three groups based on the level of delay. Then, within each delay group, we construct ten portfolios based on the level of AT, and short the high AT portfolio and long the low AT portfolio. All portfolio returns are equally weighted. The monthly returns from these ex-ante strategies are then risk adjusted using a market model (Market), Fama and French (1992) model (FF), a model that adds the Pastor and Stambaugh (2003) traded illiquidity factor (4 factor), and a five factor model that adds a momentum factor (5-factor). T-values are presented in parenthesis, and significance at the 10%, 5% and 1% level is indicated by *, **, respectively. The three panels report the results from the long-short AT strategies within low, medium, and high levels of delay in information dissemination.

	Market	FF	4-factor	5-factor
		Panel A: Diffusion 1 (D1)		
low D1	0.22	0.58	0.77**	0.88***
	(0.42)	(1.54)	(2.05)	(2.63)
med D1	0.77**	0.78**	0.82**	0.87***
	(2.11)	(2.43)	(2.49)	(2.71)
high D1	1.51***	1.39***	1.34***	1.31***
	(4.06)	(4.38)	(4.14)	(4.07)
		Panel B:Diffusion 2 (D2)		
low D2	0.53	0.67**	0.71**	0.74***
	(1.54)	(2.51)	(2.60)	(2.75)
med D2	0.72	0.94**	1.02***	1.13***
	(1.47)	(2.56)	(2.72)	(3.39)
high D2	1.10***	0.99***	1.05***	1.04***
	(2.93)	(3.29)	(3.42)	(3.38)
		Panel C: Diffusion 3 (D3)		
low D3	0.54	0.68**	0.71**	0.74***
	(1.56)	(2.52)	(2.58)	(2.73)
med D3	0.66	0.87**	0.93**	1.05***
	(1.35)	(2.36)	(2.49)	(3.14)
high D3	1.12***	1.01***	1.08***	1.07***
	(2.98)	(3.35)	(3.52)	(3.48)

Table 10
Risk adjusted returns and price efficiency

The table shows the average coefficients from the Fama and MacBeth (1973) cross-sectional regressions in equation 8. The dependent variable is monthly individual stock risk adjusted returns from equation 7. The independent variables are: AT, delay measures $D1$, $D2$ and $D3$, relative bid/ask spread ($RSPR$), Amihud illiquidity ratio (ILR), log market value of equity ($MCAP$), log book to market ratio (BM) calculated as the log of the book value of equity divided by the market value of equity measured for the previous fiscal year, previous month return ($R1$), and the cumulative return from month $t-2$ to $t-12$ ($R212$), idiosyncratic volatility ($IDIOVOL$) measured as the standard deviation of the residuals from a Fama and French (1992) three factor model regressed on daily raw returns within each month as in Ang, Hodrick, Xing, and Zhang (2009), log USD volume ($USDVOL$), and log price PRC. All coefficients are multiplied by 100. Standard errors are corrected by using the Newey-West method with 12 lags, and ***, **, * indicate a significant coefficient at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)
Const.	0.010***	0.018***	0.049***
$AT_{i,t-1}$	-0.329***	-0.442***	-0.167**
$D1_{i,t-1}$	0.610	0.252	0.502
$D2_{i,t-1}$	-0.178**	-0.182**	-0.279*
$D3_{i,t-1}$	0.180**	0.183**	0.279*
$SPREAD_{i,t-1}$		0.103	0.008
$ILR_{i,t-1}$		0.067	-0.016
$MCAP_{i,t-1}$			-0.277**
$BM_{i,t-1}$			-0.100
$R1_{i,t-1}$			-6.092***
$R212_{i,t-1}$			-0.528
$IDIOVOL_{i,t-1}$			-5.718
$USDVOL_{i,t-1}$			0.175
$PRC_{i,t-1}$			-0.487***
R^2	0.01	0.01	0.05
Time series (months)	164	164	164

Table 11
Illiquidity and algorithmic trading

The table shows monthly alphas of a long-short strategy that longs low algorithmic trading stocks and shorts high algorithmic activity stocks (within three levels of liquidity) at the end of month t from various factor models. We first assign all stocks to three portfolios based on their liquidity levels. Then, we construct ten portfolios based on the level of AT within each liquidity portfolio, and long the low AT portfolio and short the high AT portfolio. All portfolio returns are equally weighted. The monthly portfolio returns are risk adjusted using the market model (Market), Fama and French (1992) model (FF), a model that adds the Pastor and Stambaugh (2003) illiquidity factor (4 factor), and a five factor model that adds the momentum factor (5-factor). t-values are reported in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Panels A to C report the results from the long-short AT strategies within groups of stocks with low, medium and high Amihud (2002) illiquidity (*ILR*), relative bid/ask spread *SPREAD*, and USD trading volume (*USDVOL*), respectively.

	Market	FF	4-factor	5-factor
		Panel A: ILR		
low ILR	-0.06	0.10	0.29	0.42
	(-0.12)	(0.28)	(0.83)	(1.39)
med ILR	1.11**	1.05***	1.08***	1.17***
	(2.50)	(3.18)	(3.20)	(3.74)
high ILR	1.70***	1.72***	1.69***	1.67***
	(6.09)	(6.84)	(6.61)	(6.54)
		Panel B: SPREAD		
low SPREAD	0.16	0.38	0.55	0.67**
	(0.33)	(1.06)	(1.56)	(2.15)
med SPREAD	1.07***	0.86***	0.96***	1.01***
	(2.68)	(2.64)	(2.93)	(3.14)
high SPREAD	1.84***	1.76***	1.72***	1.73***
	(6.27)	(6.33)	(6.08)	(6.12)
		Panel C: USDVOL		
low USDVOL	1.79***	1.84***	1.80***	1.79***
	(7.30)	(7.62)	(7.35)	(7.28)
med USDVOL	1.59***	1.44***	1.51***	1.60***
	(3.82)	(4.32)	(4.47)	(5.14)
high USDVOL	0.28	0.38	0.64*	0.78**
	(0.51)	(0.97)	(1.67)	(2.41)

Table 12
Risk adjusted returns, algorithmic trading, and liquidity

The table reports the Fama and MacBeth (1973) coefficients from a regression of risk adjusted returns for single stocks, as in equation 7. The firm characteristics are measured in month $t-1$. The variables included are: relative bid/ask spread ($SPREAD$), Amihud illiquidity ratio (ILR), log market value of equity ($MCAP$), log book to market ratio (BM) calculated as the log of the book value of equity divided by the market value of equity measured for the previous fiscal year, previous month return ($R1$), and the cumulative return from month $t-2$ to $t-12$ ($R212$), idiosyncratic volatility ($IDIOVOL$) measured as the standard deviation of the residuals from a Fama and French (1992) three factor model regressed on daily raw returns within each month as in Ang et al. (2009), log USD volume ($USDVOL$), and log price PRC. All coefficients are multiplied by 100. The standard errors are corrected by using the Newey-West method with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Const.	0.008***	0.020***	0.017***	0.047***	0.046***
$AT_{i,t-1}$	-0.294***	-0.355***	-0.395***	-0.122*	-0.161***
$SPREAD_{i,t-1}$	0.279***		0.172*		0.093
$ILR_{i,t-1}$		0.096***	0.070*		-0.009
$MCAP_{i,t-1}$				-0.218**	-0.215**
$BM_{i,t-1}$				-0.047	-0.049
$R1_{i,t-1}$				-5.756***	-5.594***
$R212_{i,t-1}$				-0.488	-0.495
$IDIOVOL_{i,t-1}$				-5.234*	-7.470**
$USDVOL_{i,t-1}$				0.138	0.132
$PRC_{i,t-1}$				-0.561***	-0.517***
R^2	0.01	0.01	0.01	0.04	0.04
Time series (months)	164	164	164	164	164

Figure 1
Development in algorithmic trading

Figures show the time series of the algorithmic trading proxy $AT_{i,t} = \frac{N(quotes)_{i,t}}{N(trades)_{i,t}}$. Panel A shows the monthly time series of the cross-sectional mean, median, 25th, and 75th percentile of the AT variable. Panel B shows the monthly average number of quote updates and number of trades. Panel C shows the AT proxy for five market capitalization (MCAP) groups, where MCAP1 contains the smallest stocks and MCAP5 contains the largest stocks.

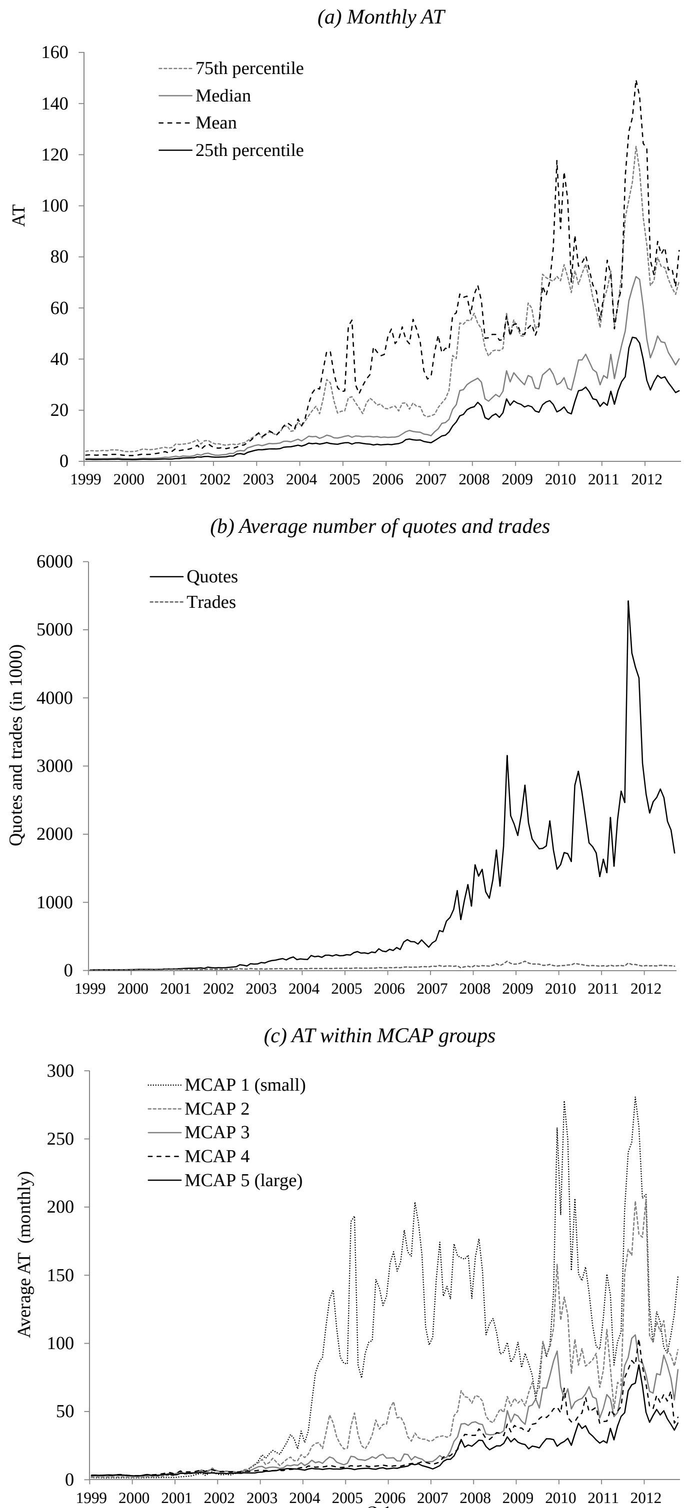
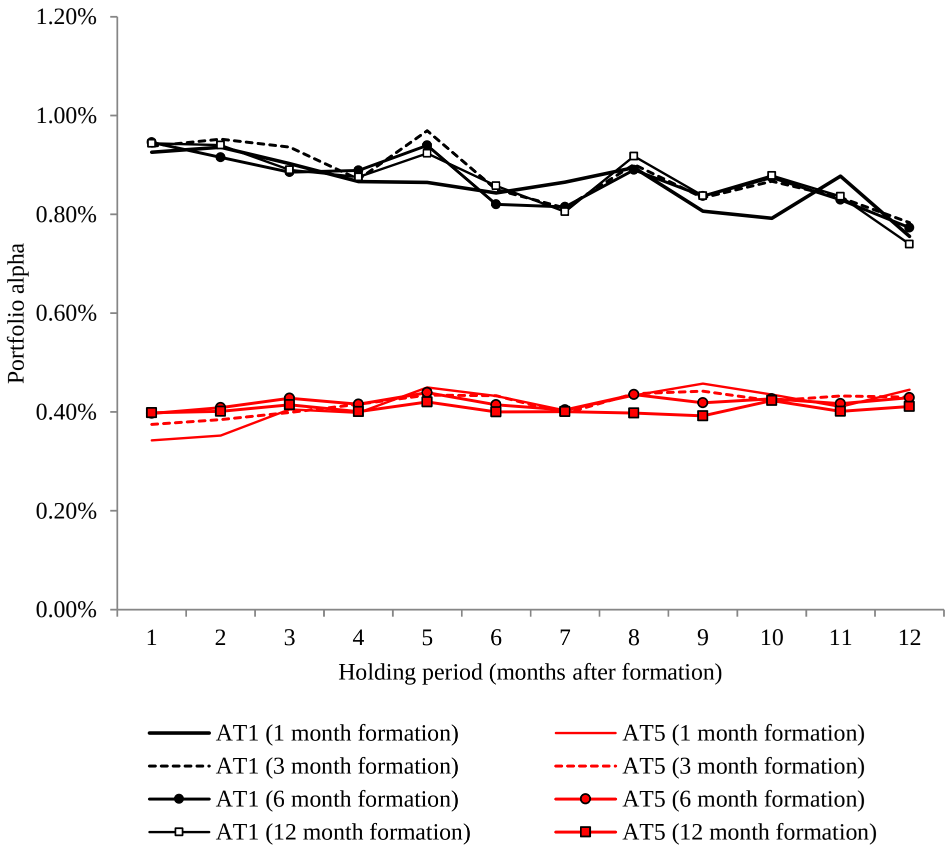


Figure 2
Portfolio alphas for different holding horizons and formation periods

The figure shows the risk adjusted returns for low-AT (AT1) and high-AT (AT5) portfolios for 5 AT portfolios across different holding and formation periods. The alphas are estimated using a five factor model with the market factor, Fama and French (1992) factors, the Pastor and Stambaugh (2003) liquidity factor, and a momentum factor (UMD). Stocks are assigned into portfolios based on their AT level over the past 1, 3, 6, and 12 months (formation period) and holding horizons range from 1 to 12 months.



Appendix

Table A.1
Variable description

$N(quotes)_{i,t}$	Total number of quote updates in stock i over period t. (Source: TAQ)
$N(trades)_{i,t}$	Total number of trade executions in stock i over period t. (Source: TAQ)
$AT_{i,t} = \frac{N(quotes)_{i,t}}{N(trades)_{i,t}}$	Proxy for algorithmic trading activity for stock i over period t. (Source: TAQ)
$N(quotes)_{i,t}^{HFT}$	Total number of quote updates by 120 HFT firms in stock i over period t on NASDAQ. (Source: NASDAQ OMX)
$N(trades)_{i,t}^{HFT}$	Total number of trades by 120 HFT firms in stock i over period t on NASDAQ. (Source: NASDAQ OMX)
$AT_{i,t}^{HFT} = \frac{N(quotes)_{i,t}^{HFT}}{N(trades)_{i,t}^{HFT}}$	Measure of algorithmic trading activity for stock i over period t. (Source: NASDAQ OMX)
$R_{f,t}$	Risk free rate, one month Treasury bill rate. (Source: WRDS/Kenneth French Webpage)
$R_{m,t}$	Value weighted return on the market portfolio (Source: WRDS/Kenneth French Webpage)
$R_{i,t}$, $R_{p,t}$	return on stock i or portfolio p (Source: WRDS/CRSP)
$r_{m,t} = R_{m,t} - R_{f,t}$	Excess return on the market. (Source: WRDS/Kenneth French Webpage)
$r_{i,t} = R_{i,t} - R_{f,t}$	Excess return on stock i. (Source: WRDS/TAQ)
$r_{p,t} = R_{p,t} - R_{f,t}$	Excess return on portfolio p. (Source: WRDS/TAQ)
$er_{i,t}$	Risk adjusted return on stock (or portfolio) i. (Source: WRDS/TAQ)
$r_{hml,t}$	Value factor constructed by Kenneth French. (Source: WRDS/Kenneth French Webpage)
$r_{smb,t}$	Size factor constructed by Kenneth French. (Source: WRDS/Kenneth French Webpage)
$r_{umd,t}$	Momentum factor (up-minus-down) constructed by Kenneth French. (Source: WRDS/Kenneth French Webpage)
$r_{liq,t}$	Liquidity factor constructed by Pastor and Stambaugh (2003). (Source: WRDS)
$QSPREAD_{i,t}$	Quoted spread. Difference between best ask quote and best bid quote (measured in USD). (Source: TAQ)
$SPREAD_{i,t}$	Relative spread. The quoted spread divided by the bid ask midpoint price (measured in %). (Source: TAQ)
$PRC_{i,t}$	Price in USD (Source: WRDS/TAQ)
$USDVOL_{i,t}$	Trading volume in USD (measured in mill. USD) (Source: WRDS/TAQ)
$VOLUME_{i,t}$	Share volume (measured in mill.) (Source: WRDS/TAQ)
$ILR_{i,t}$	Amihud (2002) illiquidity ratio for stock i over period t calculated as $ILR_{i,t} = [\sum(USDvol_{i,t})/\lvert r_{i,t}\rvert] \cdot 10^6$ (Source: WRDS/TAQ)
$VOLA_{i,t}$	Return volatility for stock i calculated as absolute return over period t. (Source: WRDS/TAQ)
$IDIOVOL_{i,t}$	Idiosyncratic volatility for stock i measured as the standard deviation of the residual from a three-factor Fama/French model on daily data as in Ang et al. (2009). (Source: WRDS/TAQ)
$MCAP_{i,t}$	Market Capitalization of a stock, calculated as the number of outstanding shares multiplied by price. (measured in mill. USD)
$BM_{i,t}$	Book-to-Market value for stock i calculated as the log of the book value of equity divided by the market value of equity measured for the previous fiscal year.
Analyst following	Log of one plus the number of analysts following the firm. (Source: IBES)
Analyst dispersion	Log of one plus the dispersion of analyst forecasts divided by the price at year end. (Source: IBES)
Institutional ownership	Holdings of institutions at the end of the year constructed from 13F files. (Source: WRDS)

Table A.2
Sample stock descriptives

The table presents the monthly time-series averages of the cross-sectional 25th percetiles, means, medians, 75th percentiles, and standard deviations of the variables for the sample stocks. The sample period is January 1999 through October 2012, and only NYSE/AMEX and NASDAQ listed stocks are included in the sample. Stocks with a price less than USD 5, above USD 1000, or with less than 100 trades in month t-1 are removed. Stocks that change listings exchange, CUSIP or ticker symbol are removed.

	p25	Mean	Median	p75	Std.dev
Number of sample stocks (whole sample=6278)	2000	2273	2319	2480	304
MCAP (in mill. USD)	133	3393	418	1491	16493
PRC (Price in USD)	12	26	20	33	29
USDVOL (in mill. USD)	6	552	44	253	2845
VOLUME (in 1000 shares)	428	15943	2407	9711	65861
N(quotes) (in 1000)	28	1548	220	1038	4722
N(trades) (in 1000)	3	85	17	64	259
AT (proxy for algorithmic trading)	4.76	43.37	11.27	32.51	157.74
RSPREAD (%)	0.17	1.42	0.67	1.92	2.03
SPREAD	0.03	0.25	0.13	0.35	0.50
ILR (%)	0.020	2.785	1.518	0.931	54.572
VOLA	0.005	0.023	0.012	0.025	0.043
BM (log)	0.29	0.64	0.50	0.80	0.67
r_m (value weighted excess market return)	-0.022	0.006	0.015	0.036	0.046
r_i (indiv. stock midpoint excess returns, delist adj.)	-0.056	0.011	0.005	0.070	0.138
r_{smb} (SMB factor return)	-0.021	0.002	-0.002	0.023	0.038
r_{hml} (HML factor return)	-0.015	0.003	0.002	0.019	0.035
r_{umd} (UMD factor return)	-0.011	0.006	0.008	0.031	0.054
r_{liq} (Pastor/Stambaugh liquidity factor return)	-0.015	0.007	0.004	0.029	0.040
Institutional Ownership	0.433	0.628	0.667	0.834	0.267
R1 (lagged 1 month return in month t-1)	-0.054	0.016	0.006	0.073	0.150
R212 (cumulative returns month t-12 through t-2)	-0.090	0.168	0.121	0.358	0.479

Table A.3
FMB regressions for separate listings exchanges

The table reports the Fama and MacBeth (1973) coefficients from a regression of risk adjusted returns for single stocks listed on different exchanges. The firm characteristics are measured in month $t-1$. The variables included are: relative bid/ask spread ($SPREAD$), Amihud illiquidity ratio (ILR), log market value of equity ($MCAP$), log book to market ratio (BM) calculated as the log of the book value of equity divided by the market value of equity measured for the previous fiscal year, previous month return ($R1$), and the cumulative return from month $t-2$ to $t-12$ ($R212$), idiosyncratic volatility ($IDIOVOL$) measured as the standard deviation of the residuals from a Fama and French (1992) three factor model regressed on daily raw returns within each month as in Ang et al. (2009), log USD volume ($USDVOL$), and log price PRC. All coefficients are multiplied by 100. The standard errors are corrected by using the Newey-West method with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	NYSE/AMEX	NASDAQ
Const.	0.046***	0.065***
$AT_{i,t-1}$	-0.136**	-0.463***
$SPREAD_{i,t-1}$	0.032	0.096
$ILR_{i,t-1}$	-0.063	0.046
$MCAP_{i,t-1}$	-0.231**	-0.400***
$BM_{i,t-1}$	0.017	-0.049
$R1_{i,t-1}$	-5.087***	-6.356***
$R212_{i,t-1}$	-0.577	-0.689**
$IDIOVOL_{i,t-1}$	-8.311*	-1.040
$USDVOL_{i,t-1}$	0.035	0.179
R^2	0.05	0.04
Time series (months)	164	164

Table A.4
FMB regressions using t-2 information

The table reports the Fama and MacBeth (1973) coefficients from a regression of risk adjusted returns for single stocks listed on different exchanges. The firm characteristics are measured in month $t-2$, except $R1$ and $R212$. The variables included are: relative bid/ask spread ($SPREAD$), Amihud illiquidity ratio (ILR), log market value of equity ($MCAP$), log book to market ratio (BM) calculated as the log of the book value of equity divided by the market value of equity measured for the previous fiscal year, previous month return ($R1$), and the cumulative return from month $t-2$ to $t-12$ ($R212$), idiosyncratic volatility ($IDIOVOL$) measured as the standard deviation of the residuals from a Fama and French (1992) three factor model regressed on daily raw returns within each month as in Ang et al. (2009), and log USD volume ($USDVOL$). All coefficients are multiplied by 100. The standard errors are corrected by using the Newey-West method with 12 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Panel A presents the results for information delay and Panel B presents the results on liquidity.

Panel A: Risk adjusted returns and price efficiency using t-2 information

	(1)	(2)	(3)
Const.	0.009***	0.017***	0.046***
$AT_{i,t-2}$	-0.295***	-0.438***	-0.244***
$D1_{i,t-2}$	0.809*	0.189	0.327
$D2_{i,t-2}$	-0.249	-0.238	-0.184
$D3_{i,t-2}$	0.257	0.245	0.189
$SPREAD_{i,t-2}$		0.233**	0.065
$ILR_{i,t-2}$		0.063	-0.036
$MCAP_{i,t-2}$			-0.148
$BM_{i,t-2}$			-0.075
$R1_{i,t-2}$			-6.616***
$R212_{i,t-2}$			-0.458
$IDIOVOL_{i,t-2}$			3.621
$USDVOL_{i,t-2}$			0.029
$PRC_{i,t-2}$			-0.413***
R^2	0.01	0.01	0.05
Time series (months)	163	163	163

Panel B: Risk adjusted returns and liquidity using t-2 information

	(1)	(2)	(3)	(4)	(5)
Const.	0.008***	0.020***	0.015***	0.044***	0.043***
$AT_{i,t-2}$	-0.273***	-0.306***	-0.361***	-0.198**	-0.232***
$SPREAD_{i,t-2}$	0.401***		0.285**		0.134
$ILR_{i,t-2}$		0.107***	0.062		-0.026
$MCAP_{i,t-2}$				-0.070	-0.085
$BM_{i,t-2}$				-0.049	-0.052
$R1_{i,t-2}$				-6.180***	-6.177***
$R212_{i,t-2}$				-0.477	-0.439
$IDIOVOL_{i,t-2}$				-3.425	-4.967
$USDVOL_{i,t-2}$				-0.007	-0.006
$PRC_{i,t-2}$				-0.519***	-0.481***
R^2	0.01	0.01	0.01	0.04	0.04
Time series (months)	163	163	163	163	163

References

Amihud, Y. (2002). "Illiquidity and stock returns: Cross-section and time-series effects." *Journal of Financial Markets*, 5, 31 – 56.

Amihud, Y. and H. Mendelson (1986). "Asset pricing and the bid-ask spread." *Journal of Financial Economics*, 17, 223–249.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009). "High idiosyncratic volatility and low returns: International and further U.S. evidence." *Journal of Financial Economics*, 91, 1–23.

Asparouhova, E., H. Bessembinder, and I. Kalcheva (2010). "Liquidity biases in asset pricing tests." *Journal of Financial Economics*, 96, 215–237.

Asparouhova, E., H. Bessembinder, and I. Kalcheva (2013). "Noisy prices and inference regarding returns." *Journal of Finance*, 68.

Biais, B., T. Foucault, and S. Moinas (2011). "Equilibrium algorithmic trading." Working paper, IDEI Toulouse School of Economics.

Biais, B., J. Hombert, and P.-O. Weill (2010). "Trading and liquidity with limited cognition." Working Paper 16628, NBER.

Biais, B. and P. Woolley (2011). "High frequency trading." Working paper, IDEI Toulouse School of Economics.

Biasis, B., T. Foucault, and S. Moinas (2013). "Equilibrium fast trading." Working paper, HEC Paris.

Boehmer, E., K. Y. L. Fong, and J. J. Wu (2012). "International evidence on algorithmic trading." Working papers series, EDHEC Business School.

Brennan, M. and A. Subrahmanyam (1996). "Market microstructure and asset pricing: On the compensation for illiquidity in stock returns." *Journal of Financial Economics*, 41, 441–464.

Brennan, M. J., T. Chordia, and A. Subrahmanyam (1998). "Alternative factor specifications, security characteristics and the cross-section of expected stock returns." *Journal of Financial Economics*, 49, 345–373.

Brennan, M. J., T. Chordia, A. Subrahmanyam, and Q. Tong (2012). "Sell-order liquidity and the cross-section of expected stock returns." *Journal of Financial Economics*, 105, 523 – 541.

Brogaard, J., T. Hendershott, and R. Riordan (2013). "High frequency trading and price discovery." *Review of Financial Studies*, forthcoming.

Chaboud, A., B. Chiquoine, E. Hjalmarsson, and C. Vega (2009). "Rise of the machines: Algorithmic trading in the foreign exchange market." Working paper, FRB International Finance.

Chordia, T., R. Roll, and A. Subrahmanyam (2000). "Commonality in liquidity." *Journal of Financial Economics*, 56, 3 – 28.

Chordia, T., R. Roll, and A. Subrahmanyam (2002a). "Order imbalance, liquidity, and market returns." *Journal of Financial Economics*, 65, 111–130.

Chordia, T., A. Subrahmanyam, and V. Anshuman (2002b). "Trading activity and expected stock returns." *Journal of Financial Economics*, 59, 3–32.

Chordia, T., A. Subrahmanyam, and Q. Tong (2011). "Trends in the cross-section of expected stock returns." Working paper.

Domowitz, I. and H. Yegerman (2005). "The cost of algorithmic trading: A first look at comparative performance." In B. R. Bruce (Ed.), "Algorithmic Trading: Precision, Control, Execution," Institutional Investor.

Duarte, J. and L. Young (2009). "Why is PIN priced?" *Journal of Financial Economics*, 91, 119–138.

Easley, D., S. Hvidkjaer, and M. O'Hara (2002). "Is information risk a determinant of asset returns?" *Journal of Finance*, 57, 2185–2221.

Easley, D. and M. O'Hara (2004). "Information and the cost of capital." *Journal of Finance*, 59, 1553–1583.

Engle, R., R. Ferstenberg, and J. Russell (2012). "Measuring and modeling execution cost and risk." *Journal of Portfolio Management*, 38, 14–28.

Fama, E. and J. MacBeth (1973). "Risk, return, and equilibrium: Empirical tests." *Journal of Political Economy*, 81, 607–636.

Fama, E. F. and K. R. French (1992). "The cross-section of expected stock returns." *Journal of Finance*, 47, 427–465.

Foucault, T., J. Hombert, and I. Roşu (2012). "News trading and speed." Working paper, HEC Paris.

Foucault, T., R. Kozhan, and W. W. Tham (2014). "Toxic arbitrage." Working paper, HEC Paris.

Goyenko, R. Y., C. W. Holden, and C. A. Trzcinka (2009). "Do liquidity measures measure liquidity?" *Journal of Financial Economics*, 92, 153 – 181.

Hagströmer, B. and L. Nordén (2013). "The diversity of high-frequency traders." *Journal of Financial Markets*, forthcoming.

Hasbrouck, J. (2009). "Trading costs and returns for U.S. equities: Estimating effective costs from daily data." *Journal of Finance*, 64, 1445–1477.

Hasbrouck, J. and G. Saar (2013). "Low-latency trading." *Journal of Financial Markets*, 16, 645–678.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). "Does algorithmic trading improve liquidity." *Journal of Finance*, 66, 1–33.

Hendershott, T. and R. Riordan (2012). "Algorithmic trading and information." *Journal of Financial and Quantitative Analysis*.

Hou, K. and T. Moskowitz (2005). "Market frictions, price delay and the cross-section of expected returns." *Review of Financial Studies*, 18, 981–1020.

Jones, C. (2002). "A century of stock market liquidity and trading costs." Working paper, Columbia Business School.

Jones, C. M. (2013). "What do we know about high-frequency trading?" Working paper, Columbia Business School.

Jovanovic, B. and A. Menkveld (2010). "Middlemen in limit-order markets." Working paper, New York University.

Khandan, A. E. and A. Lo (2011). "What happened to the quants in august 2007? Evidence from factors and transactions data." *Journal of Financial Markets*, 14, 1–46.

Kirilenko, A., A. Kyle, M. Samadi, and T. Tuzun (2012). "The flash crash: The impact of high frequency trading on an electronic market." Working paper, University of Maryland.

Menkveld, A. (2013). "High-frequency trading and the new market makers." *Journal of Financial Markets*, forthcoming.

O'Hara, M. (2003). "Liquidity and price discovery." *Journal of Finance*, 58, 1335–1354.

Pastor, L. and R. F. Stambaugh (2003). "Liquidity risk and expected stock returns." *Journal of Political Economy*, 111, 642–685.

Shumway, T. (1997). "The delisting bias in CRSP data." *Journal of Finance*, 52, 327–340.