High-Frequency Trading, Stock Volatility, and Price Discovery

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Abstract

High-frequency trading has become a dominant force in the U.S. capital market, accounting for over 70% of dollar trading volume. This study examines the implication of high-frequency trading for stock price volatility and price discovery. I find that high-frequency trading is positively correlated with stock price volatility after controlling for firm fundamental volatility and other exogenous determinants of volatility. The positive correlation is stronger among the top 3,000 stocks in market capitalization and among stocks with high institutional holdings. The positive correlation is also stronger during periods of high market uncertainty. Furthermore, I find that high-frequency trading is negatively related to the market's ability to incorporate information about firm fundamentals into asset prices. Stock prices tend to overreact to fundamental news when high-frequency trading is at a high volume. Overall, this paper demonstrates that high-frequency trading may potentially have some harmful effects for the U.S. capital market.

Keywords: High-frequency trading, trading volume, volatility, return, price discovery.

JEL: G10, G11, G12, G14, G23, M40, M41

1. Introduction

This paper examines the impact of high-frequency trading (HFT) on the U.S. capital market. HFT refers to fully automated trading strategies with very high trading volume and extremely short holding periods ranging from milliseconds to minutes and possibly hours. Specifically, this study addresses two broad questions: (1) Does HFT decrease or increase stock price volatility? and (2) Does HFT aid or hinder the market's incorporation of news about firm fundamentals into stock prices?

The motivation for this study is twofold. First, HFT has become a dominant driver of trading volume in the U.S. capital market. By most accounts, HFT is responsible for more than half of all equity trades in the United States every day.[1] Given its prominence, the SEC and CFTC have become increasingly concerned about the impact of HFT on capital markets, and are assessing whether changes are needed in the way HFT is regulated. However, little academic research has yet examined the effect of HFT on the U.S. capital market. This paper adds to the accounting/finance literature by documenting a number of consequences associated with HFT.

A second impetus for this study is the fact that HFT strategies are agnostic to a stock's price level and have no intrinsic interest in the fate of companies, leaving little room for a firm's fundamentals (e.g., earnings and cash flows) to play a direct role in its trading strategies. A key objective of the financial reporting system is to provide a firm's fundamental information to the capital markets (e.g., the mission of FASB; Verrecchia 2001). When investors trade stocks on the basis of information about firm fundamentals, in equilibrium stock prices converge to their fundamental values (e.g., Ball and Brown 1968; Kothari 2001; Lee 2001). However, when most trades are based on statistical and often short-lived correlations in stock returns and investors do

[1] The TABB Group, a consulting company in New York City, estimated that, as of 2009, HFT firms account for 73% of all U.S. equity trading volume.
www.tabbgroup.com/PublicationDetail.aspx?PublicationID=505&MenuID=13&ParentMenuID=2&PageID=8..

not hold stocks for the investment purpose (HFT traders typically do not carry any position overnight), the presence of efficient pricing becomes more questionable. Theoretical models (Froot, Scharfstein, and Stein 1992) show that a market with more short-horizon traders performs less efficiently than one with long-term investors, possibly because short-horizon traders may choose to study information unrelated to fundamentals. This paper tests such implications and presents an empirical investigation of the role of HFT in the capital market's incorporation of fundamental information into asset prices.

In this paper, I use a large sample of firms from the CRSP and the Thomson Reuters Institutional Holdings databases during 1985–2009. I find that institutional turnover was remarkably stable (around 20% per quarter) throughout the 1985–2009 sample period, even though institutional holdings steadily increased from 40% in 1985 to over 60% in 2009. From 1985 to 1994, stock turnover was also very stable—around 17% per quarter, a number close to the average institutional turnover over the same time period. However, quarterly stock turnover increased dramatically after 1995, climbing to over 100% by 2009. The drastic divergence between stock turnover and the turnover of institutional holdings coincides with the emergence and rising popularity of HFT. I estimate that high-frequency trading was responsible for about 78% of the dollar trading volume in 2009, up from near zero in 1995. This surge naturally raises concerns regarding the beneficial or harmful effects of HFT for U.S. capital markets.

My investigation reveals that HFT increases stock price volatility. Specifically, stock price volatility is positively correlated with HFT after controlling for the volatility of a firm's fundamentals and other exogenous volatility drivers. This positive correlation is confirmed by using the exogenous shock of NYSE autoquote to HFT. I also consider three institutional features of HFT and examine the cross-sectional and time-series patterns in the volatility–HFT relationship. First, the positive correlation between volatility and HFT is stronger for the top 3,000 stocks in market capitalization—a group whose membership parallels that of the Russell 3000 and is often termed "the investable universe" on Wall Street. Second, the positive correlation is stronger for stocks with high institutional holdings, a result consistent with the view that high-frequency traders often take advantage of large trades by institutional investors. Finally, the positive correlation between HFT and volatility is stronger when market uncertainty is high, a time when markets are especially vulnerable to aggressive HFT strategies and to the withdrawal of HFT market-making activities.

I also find that HFT is negatively associated with the market's ability to incorporate news about a firm's fundamentals into asset prices, a result consistent with the prediction of Froot, Scharfstein, and Stein (1992). Using analyst forecast revisions and earnings surprises as proxies for news about firm fundamentals, this study finds that stock prices react more strongly to news about fundamentals when HFT is at a high volume, However, the incremental price reactions associated with HFT are almost entirely reversed in the subsequent period. Taken together, the evidence suggests that HFT exaggerates otherwise-sound price reaction. The price swings introduced by HFT also represent direct evidence that HFT increases stock price volatility.

This paper contributes to the accounting and finance literature in several important ways. First, this investigation is the first academic study to examine the role of HFT in the capital markets.[2] It provides an empirical method to estimate HFT volume for a large dataset and opens the area for future research. Second, my estimate suggests that HFT accounts for 78% of the total

[2] I noticed recently a contemporaneous study by Brogaard (2010), who studies the intra-day effects of high frequency trading on market quality. My study complements Brogaard (2010) by focusing on the longer-term effects of HFT. The longer-term effects are interesting and informative in many aspects. For example, longer-term stock volatility and price efficiency may be more important from the resource allocation perspective, as they directly affect the efficiency of allocating scarce capital resources to their most productive use, the key objective of the capital market. It is unclear how a price discovery delayed by 50 millisecond or 2 seconds would affect resource allocation efficiency in any meaningful way.

trading volume of 2009, a number very close to the estimate of the TABB Group. From the point of view of market efficiency and social welfare, 78% is clearly excessive if HFT is meant to provide liquidity. If HFT were to provide all of the market's liquidity, the volume of HFT would still be at most 50%, where the 50% threshold is surely overstated since it assumes that all investors trade exclusively with HFT firms, leaving no room for specialists at exchanges or trade among institutional and individual investors. Third, the evidence that HFT hinders the market's incorporation of fundamental news has implications for the financial reporting system and for regulators. This evidence may help regulators determine how to properly regulate HFT to allow capital markets to function more efficiently. Finally, this study shows that stock turnover increased dramatically over the past 15 years owing to the emergence and popularity of HFT. Such intertemporal structural changes in stock trading volume and price dynamics have broad implications for studies that assume volatility, trading volume, or price discovery to be stationary over time (no structural changes are allowed in the classic Fama-MacBeth approach).

The rest of the paper is structured as follows. Section 2 discusses the institutional background of HFT and reviews the prior literature. Section 3 describes the sample data and introduces the empirical approach used to estimate HFT. Section 4 presents the main results, Section 5 conducts robustness checks, and Section 6 concludes.

2. Background, prior literature, and hypotheses

2.1 High-frequency trading

High-frequency trading firms deploy fully automated trading strategies across one or more asset classes which identify and profit from short-term (e.g., intra-day) price regularities. HFT strategies try to earn small amounts of money on each trade—often just a few basis points, and the small profits from individual trades are amplified by high trading volume. High-frequency trading can be roughly classified into two types: market making activities and more aggressive HFT strategies (e.g., statistical arbitrage). HFT is a subset of algorithmic trading, or the use of computer programs for entering trading orders, with the computer algorithm deciding such aspects of the order as the timing, price, and order quantity. However, HFT distinguishes itself from general algorithmic trading in terms of holding periods and trading purposes.

Both traditional institutions and HFT firms widely employ algorithmic trading.[3] However, traditional institutions typically hold a stock for the purpose of long-term investment, whereas HFT firms only hold a stock for a very short period and for the purpose of trading. As shown below, the recent explosion in trading volume in the U.S. stock market is driven not by traditional institutions' algorithmic trading but by a few hundred HFT firms.

During the late 1980s and 1990s, traders abandoned the traditional open-outcry system in favor of electronic trading desks across the world, as deregulation of the financial markets prompted a huge shift to screen-based trading. Since the1990s, increased market liquidity and technological advances have created the ideal conditions for the spread of HFT. The TABB Group estimates that, as of 2009, between 10 and 20 broker–dealer proprietary trading desks and fewer than 20 active large hedge funds employed HFT techniques. The independent proprietary trading firms and hedge funds are believed to number between 100 and 300. The several hundred HFT companies (out of roughly 20,000 firms currently trading in the U.S. markets) are responsible for about 73% of the trading volume in the U.S. stock market.

A debate has emerged in the business media regarding the benefits and detriments of HFT, with tensions developing between hedge funds and traditional institutional investors. Proponents of HFT, who are often hedge fund managers and professionals who provide services

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[3] Pension funds, mutual funds, and other buy-side institutional traders widely use algorithmic trading to divide large orders into small ones to manage market impact and risk.

to high-frequency traders, argue that HFT adds liquidity to the market and reduces transaction costs and spreads for other investors. They also argue that HFT acts as a market maker and aids in price discovery. Opponents of HFT, who are often buy-side institutional investors and professionals who provide services for institutional investors, argue that HFT hurts the ability of traditional institutional investors to execute orders with limited market impact. Opponents argue that in their pursuit of market share in trading volume, exchanges and broker-dealers cater to high-frequency traders at the expense of traditional institutions.

2.2 Prior literature

Several strands of literature touch on related topics, but I am not aware of any academic research directly examining the role of HFT in the capital markets. The absence of any academic research on HFT is surprising given its large share of trading volume in the capital markets.

A related literature examines algorithmic/automated trading. This stream of research generally finds that, as a technology advance over human trading, algorithmic trading is good for the market. For example, algorithmic trading is weakly negatively correlated with volatility in the foreign exchange market (Chaboud et al. 2009). On the Deutsche Boerse, algorithmic trading contributes more than human trading to the discovery of the efficient price (Hendershott and Riordan 2009). Additionally, algorithmic trading increases liquidity (Hendershott et al. 2010). Directly comparing this paper with the literature on algorithmic trading is difficult, because both traditional institutional investors and high-frequency traders widely use algorithmic trading. Algorithmic trading speeds up order execution and thus represents a technological advance over human trading. In contrast, HFT has extremely short holding periods, with the purpose of generating profits. The literature on algorithmic trading examines its benefits and costs relative to human trading in a market microstructure framework, whereas this paper focuses more on the short holding period of HFT and its implications for market efficiency. Of particular interest is the effect of HFT on the market's incorporation of firm fundamental information into stock price. Aggressive HFT strategies are often implemented in dark pools, which have limited data available to the researchers and make market microstructure studies infeasible.

A fairly large stream of research examines stock price volatility. These studies often assume that stock price volatility is endogenously determined by the volatility of a stock's underlying fundamental value (Scheinkman and Xiong 2003). This literature also shows that stock price volatility is positively correlated with leverage (Christie 1982), firm age (Pastor and Veronesi 2003), and growth options (Cao et al. 2008). The evidence on institutional holdings is mixed. For example, Potter (1992) finds a positive correlation between stock price volatility and institutional holdings on days surrounding earnings announcements, whereas El-Gazzar (1998) documents a negative correlation using a different sample and a different set of control variables.

2.3 Does HFT reduce stock price volatility?

Stock return volatility is a basic building block for a number of literatures, such as those relating to market efficiency, asset allocation, and risk management. High stock volatility is potentially undesirable for both investors and firms (Bushee and Noe 2000). Risk-averse investors typically require a higher premium to hold high-volatility stocks, and they react slowly to fundamental information about high-volatility stocks (Zhang 2006). From a firm's perspective, high stock price volatility can increase the perceived riskiness of a firm's stock and thus increase a firm's cost of capital (Froot, Perold, and Stein 1992). High stock price volatility can also make stock-based compensation more costly (Baiman and Verrecchia 1995) and increase the likelihood of lawsuits (Francis, Philbrick, and Schipper 1994).

Whether HFT increases or reduces stock price volatility is not obvious. On one hand, HFT, especially its market-making activity, can reduce stock volatility. HFT provides liquidity to the market and enables large block traders to place their trades without significantly affecting stock prices. HFT market-makers do not profit from stock price movement. Rather, they generate revenues from the bid–ask spread as well as incentive rebates provided by electronic communication networks (ECNs), a class of SEC-permitted alternative trading systems.[4]

On the other hand, the interaction between HFT and fundamental investors may increase stock price volatility for at least three reasons. First, as illustrated in the flash crash on May 6th, 2010, high trading volume generated by HFT is not necessarily a reliable indicator of market liquidity, especially in times of significant volatility. The automated execution of large orders by fundamental investors, which typically use trading volume as the proxy for liquidity, could trigger excessive price movement, especially if the automated program does not take prices into account. Second, HFT is often based on short-term statistical correlations among stock returns. A large number of unidirectional trades can create price momentum and attract other momentum traders to the stock, a practice that amplifies price swings and thus increases price volatility. Positive feedback investment strategies may result in excess volatility even in the presence of rational speculators (De Long, Shleifer, Summers, and Waldmann 1990).

Finally, high-frequency traders detect and front-run large orders by institutional investors, a practice that pushes the stock price up (down) if institutional investors have large buy (sell) orders, thereby increasing stock price volatility.[5] One popular, yet controversial, issue related to

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[4] In a credit structure, ECNs make a profit from paying a credit to liquidity providers, such as high-frequency traders, while charging a debit to liquidity removers. Credits range from \$0.002 to \$0.00295 per share for liquidity providers, and debits from \$0.0025 to \$0.003 per share for liquidity removers. The fee can be determined by monthly volume provided and removed or by a fixed structure, depending on the ECN.

[5] For example, suppose an institutional investor wants to buy 10,000 shares of JP Morgan and, without HFT firms, the market supplies 10,000 shares at \$40.15. An HFT firm steps in and buys these 10,000 shares from the market at

front-running is co-locating. HFT firms co-locate their computers physically close to the exchanges' computers to gain millisecond speed advantages, so they can beat slower orders from buy-side institutional investors to the quote.[6] In some cases, HFT firms even co-locate their computers in the same room as an exchange's computers. Another controversial HFT strategy is liquidity detection, which has produced a clash between HFT and traditional investors resembling the drama of cold-war espionage.[7] To avoid revealing large trades to the open market, institutional investors often rely on dark pools of liquidity (e.g., Instinet), which are crossing networks that provide liquidity not displayed on order books. The broker displays only a small part of the order and leaves a large undisplayed quantity below the surface (a so-called iceberg order). High-frequency traders employ pattern-recognition software to detect large institutional orders sitting in dark pools or other liquidity venues. They do so by sending small orders on reconnaissance missions, in which the small orders interact with large orders by being filled very quickly. When these interactions happen repeatedly or when orders are executed in amounts larger than the displayed size, the hidden large order is detected. To counter this HFT effect, institutions use anti-pattern-recognition software to make customer orders harder to see.

2.4 Does HFT improve price discovery?

Although high frequency trading is short-term in nature, a more interesting question is whether HFT has an accumulated longer-term effect (e.g., quarterly) when interacted with fundamental trading. I employ a quarterly window research design for three reasons. First, tick-by-tick research could potentially produce biased results because many HFT strategies, such as

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$40.15 and then sells them to the institutional investor at $40.18. A similar argument applies to a sell order by an institutional investor.

[6] Hyde Park Global Investments, a small trading firm based in Atlanta, Georgia, relocated its computer servers to New York to be close to the exchanges and, as a result, shortened the trade time by 21 milliseconds (Source: the April issue of *Wired* magazine, 2010).

[7] Liquidity detection also applies to orders executed in the open market. Institutional investors often use algorithm trading to break large orders into small pieces, but HFT can use pattern-recognition software to detect such orders.

liquidity detection and other aggressive HFTs, are implemented in dark pools, where transaction data are recorded on the national tape with limited information and with a delay.[8] A tick-by-tick study using open market data is likely to be influenced by HFT's market-making activities, which tend to be more beneficial to the capital market than aggressive HFT strategies. Second, longer-term effects are more interesting and more important from the perspective of market efficiency and resource allocation. Not only is the impact of HFT on price dynamics often incomplete in the short term when interacted with fundamental trading, but the research question becomes less interesting if HFT only delays or accelerates price discovery by milliseconds or seconds without any effect on capital resource allocation. Theoretical models, such as Froot, Scharfstein, and Stein (1992), have specific predictions on the effect of short-term traders on market efficiency. Finally, the HFT measure in this study is estimated quarterly, which restricts my analyses to the quarterly level.

Whether HFT acts to improve price discovery is also not obvious. On one hand, HFT brings liquidity to the market, as evidenced in increasing trading volume and narrower bid–ask spreads. The increased liquidity may allow traditional institutional investors to more easily adjust their portfolios to reflect their fundamentals-based views on company performance. Thus, HFT may improve price discovery by helping to move stock price towards its fundamental value.

On the other hand, HFT is based solely on the statistical properties of short-term stock returns and order imbalance and is agnostic to the price level—high-frequency traders can trade 400 million Citibank shares at a price of $3 or $5. High frequency traders typically hold the position over a very short period of time and have no intrinsic interest in the fate of companies.

[8] Dark pools are recorded to the national consolidated tape, but appear as over-the-counter transactions. Therefore, detailed information about the volumes and types of transactions is often eliminated. Transaction data are typically recorded with a delay. One firm contacted for this study prints dark pool transactions on the tape with a 90-second delay, so the tape does not tell when and where these trades were done.

Given that HFT accounts for the lion's share of trading volume, the interaction between HFT and fundamental trading could plausibly have some accumulated effect on price dynamics over longer term. Froot, Scharfstein, and Stein (1992) show theoretically that short horizon traders may put too much weight on short-term information and not enough on firm fundamentals, a practice making the market less efficient. Vives (1995) suggests that short-horizon traders reduce price informativeness with concentrated arrival of information, which is likely to be the case around earnings news events. A large order by fundamental investor, coupled with illusive market liquidity as proxied by HFT's high trading volume, could also create price momentum or reversal, which could in turn induce other investors, such as momentum traders, to step in. Such successive effects could potentially cause a stock price to deviate from its fundamental value in the longer term. Theoretical models in De Long et al. (1990) and Barberis and Shleifer (2003) suggest that when groups of investors follow simple positive feedback strategies, stock prices are pushed away from their fundamental values. High-frequency traders, whose trading strategies are based on short-term statistical correlations, are classic short-horizon traders and thus are likely to have an impact on market efficiency. This study examines whether HFT as a whole helps or hinders price discovery at the quarterly level.

3. Sample selection and descriptive statistics

3.1 Sample selection

My initial sample contains all stocks covered by the CRSP and Thomson Reuters Institutional Holdings databases between the first quarter of 1985 and the second quarter of 2009. I then delete stocks with a price below $1. As the Thomson Reuters Institutional Holding database contains only data at the quarterly level, the sample is composed of firm-quarter observations. Quarterly stock turnover, which is defined as trading volume divided by outstanding shares, is calculated from CRSP. To account for the double-counting of dealer trades for Nasdaq firms (Gould and Kleidon 1994), Nasdaq trading volume is divided by two. As will be clarified later, I use the 1985–1994 period as the estimation period, and use the 1995–2009 period as the main testing sample, which contains 391,013 firm-quarter observations. The sample size varies in some tests to meet other data requirements, such as non-missing analyst forecast revisions or earnings surprises in the price discovery tests.

I use the Thomson Reuters Institutional Holdings database to calculate institutional holdings and institutional turnover for each stock each quarter. In the U.S., investment companies, which include banks, insurance companies, parent companies of mutual funds, pension funds, university endowments, and numerous other types of professional investment advisors, are required to file the 13f form with the SEC every calendar quarter, which is covered by the Thomson Reuters Institutional Holdings database. However, the Thomson Reuters database does not cover all institutional holdings, since fund managers with less than $100 million assets under their control are not required to file the 13f form, even though they may still choose to do so. Also, fund managers may omit small holdings (fewer than 10,000 shares or $200,000) and confidentiality-related holdings from the 13f. Following the literature (Bushee 1998), I define institutions covered by the 13f as "institutional investors" and calculate institutional holdings for a given company by aggregating stock holdings across all institutional investors and then scaling by the company's outstanding shares. Institutional turnover is defined as the aggregate net change in the holdings of a company's shares across all institutional investors divided by the average of beginning and ending institutional holdings.

In general, institutional holdings and net changes are well specified in the Thomson Reuters database. If a fund manager consistently reports its holdings on each stock, stock holdings from the previous quarter plus net change in the current quarter should be equal to stock holdings at the end of the current quarter. One issue with the data is that net changes are coded incorrectly from the second quarter of 2006 (2006Q2) to the first quarter of 2007 (2007Q1). A manual check of the data revealed that virtually all net changes appear to be coded incorrectly as stock holdings at the end of the previous quarter multiplied by minus one (-1).[9] In light of this data error, I recalculate net changes as the difference in institutional holdings between two adjacent quarters for the period between 2006Q2 and 2007Q1. If every institution reports its holdings each quarter, then the alternative approach to calculate net changes is equivalent to the main approach. To the extent that the institutional investor universe changes from quarter to quarter in the Thomson Reuters database, this alternative methodology for the calculation of net changes is inferior.

Figure 1 plots value-weighted institutional ownership, institutional turnover, and stock turnover from 1985Q1 to 2009Q2. Institutional ownership steadily increases from 40% in 1985 to over 60% in 2009. Institutional turnover is remarkably stable and stays around 20% each quarter throughout the sample period. In contrast, quarterly stock turnover hovers around 17% between 1985 and 1994 and then increases to 115% in 2008, a result in line with the evidence in Chordia et al. (2010). The gradual increase in stock turnover beginning in the mid-1990s coincides with the emergence and rising popularity of HFT. For example, Citadel Investment Group started with bond trades in 1990 and later expanded to the equity side. Now, Citadel accounts for about 8% of daily trading activity on the NYSE and Nasdaq.[10]

3.2 Measuring high-frequency trading

[9] In response to an inquiry about this issue, the Wharton Research Data Service stated that "we provide Thomson data as it is supplied from the vendor, and our policy is to maintain the data integrity so we do not make corrections or any changes to original feed that we receive from the vendor. Unfortunately, Thomson has no plans to fix this problem."

[10] See http://biz.yahoo.com/ic/105/105911.html

High-frequency trading is not directly observable. To empirically estimate the variable *HFT* at the firm level, I classify investors into three categories: institutional investors, individual investors, and high-frequency traders. For the purpose of this paper, I essentially define *HFT* as all short-term trading activities by hedge funds and other institutional traders not captured in the 13f database. Therefore, I can rewrite stock turnover as follows:

$$
\begin{aligned}
TO &= \frac{VOL_{TOTAL}}{SHROUT} \\
&= \frac{VOL_{INST} + VOL_{INDIV} + VOL_{HFT}}{SHROUT} \\
&= \frac{VOL_{INST}}{INSTHLD} * \frac{INSTHLD}{SHROUT} + \frac{VOL_{INDIV}}{INDIVHLD} * \frac{INDIVHLD}{SHROUT} + \frac{VOL_{HFT}}{SHROUT} \\
&= INSTTO * INST + INDIVTO * INDIV + HFT
\end{aligned} \tag{1}
$$

where *TO* is stock turnover; VOL_{TOTAL} is total share volume; VOL_{INST} is share volume traded by institutional investors; VOL_{INDIV} is share volume traded by individual investors; VOL_{HFT} is share volume traded by high-frequency traders; *SHROUT* is shares outstanding; *INSTHLD* is shares held by institutional investors; *INDIVHLD* is shares held by individual investors; *INSTTO* is institutional turnover ($VOL_{INST}/INSTHLD$); *INST* is institutional holdings (*INSTHLD*/*SHROUT*); *INDIVTO* is individual turnover ($VOL_{INDIV}/INDIVHLD$); *INDIV* is individual holdings (*INDIVHLD*/*SHROUT*); and *HFT* is high-frequency trading volume.

The CRSP and Institutional Holding databases allow direct calculation of *TO*, *INSTTO*, and *INST*, but *INDIVTO*, *INDIV*, and *HFT* are not observable. To estimate *HFT*, I make the following three assumptions. Assumption (1): No high-frequency trading existed in the 1985–1994 period. Figure 1 suggests that 1985–1994 reflected a steady state during which both institutional turnover and stock turnover were relatively stable—a fact consistent with the popular press's argument that HFT is a relatively recent phenomenon. Assumption (2): High-frequency traders do not hold any positions at the end of each quarter. Most high-frequency traders have extremely short holding periods, ranging from milliseconds to minutes and possibly hours. Typically, they do not carry any position overnight.[11] Assumption (3): Individual investors' trading behavior relative to the behavior of institutional investors is on average stable over time. This assumption does not require individual investors' trading behavior to be stable. Rather, the assumption states that, if individual investors trade more during some periods, such as the financial crisis, institutional investors should also trade more during the same time periods.

As this paper is the first to estimate HFT from a common database for a large sample of data, these three assumptions are meant to be conservative and as simple as possible. A violation of the first two assumptions is likely to underestimate the magnitude of HFT in the main sample.[12] Regarding the third assumption, the relationship between individual turnover and institutional turnover likely varies with firm characteristics and across industries. A more refined application of assumption (3) is to model individual turnover on firm and industry characteristics. I do not follow this path here to avoid the possibility of data mining. To the extent that a refined model would reduce measurement error in my HFT measure, the results from a refined model are likely to be stronger than those reported in this paper.

Assumption (1) enables calculation of *INDIVTO* and *INDIV* for the 1985–1994 period, given that (1) *INST* + *INDIV* = 1 and (2) *INST***INSTTO* + *INDIV***INDIVTO* = *TO*. Assumption (2) suggests that *INDIV* + *INST* = 1 for the 1995–2009 period. Assumption (3) allows me to quantify individual turnover and estimate it for the 1995–2009 period, which is the main test period for the empirical analyses. The following table summarizes the value-weighted average of key variables for the 1985–1994 time period.

[11] Some HFT strategies, such as statistical arbitrages, carry positions overnight.

[12] A violation of the first assumption would suggest overestimation of individual turnover in both the estimation period and the main sample period. A violation of the second assumption would imply overestimation of individual holdings in the main sample.

	INST	*INSTTO*	*TO*
Calculated from CRSP and Thomson Reuters	44.66%	19.96%	16.85%
	INDIV	*INDIVTO*	*INDIVTO/INSTTO*
Based on the line above and assumptions	54.32%	14.34%	71.81%

The table shows that, on average, individual turnover is about 71.81% of institutional turnover in 1985–1994. Next, using these calculations, for each firm-quarter in the main 1995–2009 sample period, I calculate high-frequency trading as follows:

$$\begin{aligned} HFT &= TO - INSTTO * INST - INDIVTO * INDIV \\ &= TO - INSTTO * INST - (0.7181 * INSTTO) * (1 - INST) \end{aligned} \tag{2}$$

Figure 2 shows the percentage of HFT in total dollar volume (value-weighted *HFT* / *TO*) over time. The percentage increases from zero in early 1995 to around 78% in 2009. In comparison, the TABB Group estimated that, as of 2009, HFT firms account for 73% of all U.S. equity trading volume, a number very close to my estimate. This close comparison makes me feel comfortable about my empirical approach. Once the share of HFT exceeds 50%, in many instances high-frequency traders must be trading with each other, potentially generating a "hot-potato" volume effect as the same positions are rapidly passed back and forth. While high-frequency traders often claim that HFT provides liquidity, it is hard to imagine that high-frequency trading among HFT firms provides any liquidity to the market.

3.3 Descriptive statistics

Table I, Panel A presents summary statistics based on the main testing sample (1995–2009). On average, the firms in the sample have a market value of $300 million and a book-to-market ratio of 0.597. The average firm is 34.1% owned by institutional investors, and has a stock volatility of 3.3%. High-frequency traders, on average, trade 3.1% of outstanding shares each quarter. Panel B of Table I shows the correlation matrix. *HFT* is positively related to stock volatility (*VOLT*), with a Pearson correlation of 0.078 and a Spearman correlation of 0.090, supporting the hypothesis that HFT increases volatility in univariate analysis. *HFT* is highly positively correlated with firm size (*SIZE*), confirming the anecdotal evidence that high-frequency traders focus on large-capitalization stocks. Stock volatility is strongly positively correlated with fundamental volatility (Pearson correlation = 0.412 with *DISP*) and negatively correlated with firm size (Pearson correlation = -0.351).

Panel C of Table I shows the Spearman correlation between contemporaneous stock returns and trading activities. When stock returns are positive, they are positively correlated with trading activities, with correlations of 0.227, 0.221, and 0.053 with *TO*, *INSTTO*, and *HFT*, respectively. When stock returns are negative, they are negatively correlated with trading activities, with correlations of -0.174, -0.158, and -0.077 with *TO*, *INSTTO*, and *HFT*, respectively. These correlations suggest that trading activities are not directional and tend to be more active for both extremely high and extremely low returns.[13]

4. Research design and results

4.1 Research design

Two major issues affect the design of empirical tests. First, as shown in Figure 2, *HFT* is not stationary but increases from near zero in 1995 to about 78% in 2009, suggesting the presence of structural changes in trading behavior between 1995 and 2009. Second, HFT is measured with error, and such measurement error may affect my empirical analyses.

To address these two issues, I use a difference-in-difference-in-difference approach. Specifically, in Sections 4.2 and 4.3, I first employ a fixed-effect model with both firm and time

[13] The prior literature finds that trading volume is positively correlated with past returns (e.g., Lee and Swaminathan 2000) and negatively correlated with future returns (e.g., Datar, Naik, and Radcliffe 1998). One innovation of this paper is to examine the effect of trading activities on stock returns based on the nature of news (positive vs. negative earnings news).

(year-quarter) fixed effects. The model of firm- and time-fixed effects is essentially equivalent to the difference-in-differences approach common in the literature. For example, to examine the impact of HFT on stock volatility in Section 4.2, the fixed-effect model compares changes in stock volatility experienced by high-HFT stocks with changes experienced by low-HFT stocks. The firm fixed effect controls for differences across firms, and the time fixed effect controls for differences over time, forcing the regression to estimate a difference in differences. This fixed-effect approach is widely used to test the impact of structural changes, such as the impact of algorithmic trading on liquidity (Hendershott et al. 2010). To address potential correlation among regression residuals, I allow for residuals to be clustered by firm.

Next, in Section 4.4, I use the difference between the results from the main sample period (1995–2009) and the results from the estimation period (1985–1994) to identify the impact of HFT. By assuming the absence of HFT during 1985–1994, I assume that measurements from the estimation period reflect only systematic measurement error of HFT. As long as systematic measurement error is time-invariant, the difference between the results from the 1985–1994 time period and the results from the 1995–2009 time period should reflect only the incremental effect of HFT on stock volatility and price discovery. I specifically consider the possibility of time-varying measurement error in Section 5.

4.2 Does HFT affect stock volatility?

To examine the effect of HFT on stock volatility, I control for the determinants of stock volatility as suggested in prior literature. Many studies suggest that stock volatility is determined yet not fully explained by a firm's fundamental volatility (Shiller 1981; Scheinkman and Xiong 2003; Paster and Veronesi 2003; Wei and Zhang 2006). Three variables capture fundamental volatility: earnings surprise volatility ($sd\Delta ROE$), sales growth volatility ($sdSGR$), and analyst forecast dispersion (*DISP*). Prior studies show that stock volatility is associated with firm age and institutional holdings (Paster and Veronesi 2003; El-Gazzar 1998), so I include firm age (*AGE*) and institutional holdings (*INST*) as control variables. Prior literature also suggests that leverage and market microstructure affect stock volatility (Christie 1982; Cheung and Ng 1992). Accordingly, I include market leverage (*LEV*) and the inverse of stock price (*1/P*) in the model. Finally, as stock volatility may be related to risk, I include three common return factors (*SIZE*, *BM*, and *RET_12*) as additional controls. In sum, I employ the following regression model:[14]

$$\begin{aligned} VOLT = {} & \beta_0 + \beta_1 HFT + \beta_2 sd\Delta ROE + \beta_3 sdSGR + \beta_4 DISP + \beta_5 LEV \\ & + \beta_6 AGE + \beta_7 INST + \beta_8 (1/P) + \beta_9 SIZE + \beta_{10} BM + \beta_{11} RET\_12 \\ & + FIRM\_fixed\_effects + Time\_fixed\_effects + e_t \end{aligned} \tag{3}$$

where *VOLT* is volatility, *HFT* is high-frequency trading, $sd\Delta ROE$ is earnings surprise volatility, *sdSGR* is sales growth volatility, *DISP* is analyst forecast dispersion, *LEV* is market leverage, *AGE* is firm age, *INST* is institutional holdings, 1/*P* is the inverse of stock price, *SIZE* is firm size, *BM* is the book-to-market ratio, and *RET_12* is the past 12-month stock returns (see the appendix for detailed definitions).

Panel A of Table II presents the results of tests on the relation between HFT and stock price volatility. The dependent variables are stock volatility based on daily returns (*VOLT*) in the first column and stock volatility based on daily highs and lows (*HLVOLT*) in the second column. Both columns reveal that *HFT* exhibits a strong positive correlation with stock price volatility after controlling for other drivers of volatility. For example, the coefficient on *HFT* is 1.084 (t = 59.62) in the first column. Given the mean *VOLT* of 0.033 and the standard deviation of *HFT* of 0.341, a one standard deviation increase in *HFT* increases stock volatility by about 11.2%.

[14] The fixed-effects approach also controls for variations in information flow across firms and across time, which may be correlated with stock volatility (Ross 1989).

The coefficients on the control variables are in line with prior literature. First, stock price volatility is positively correlated with proxies for fundamental volatility (earnings surprise volatility, sales growth volatility, and analyst forecast dispersion). Second, stock price volatility is negatively associated with firm age and institutional holdings, consistent with the findings of Paster and Veronesi (2003) and El-Gazzar (1998). Third, stock price volatility exhibits a positive correlation with market leverage, suggesting that stocks with higher leverage tend to be more volatile. Market micro-structure also affects stock volatility, with low-price stocks associated with higher volatility. Lastly, volatility is positively related to firm size and price momentum and negatively related to the book-to-market ratio.

The positive correlation between HFT and volatility is consistent with the view that HFT increases volatility, but it does not establish causality. Next, I consider some exogenous shocks to HFT by exploring the NYSE automated quote dissemination in 2003 (Henderschott et al. 2010). The NYSE started to autoquote the first stock on January 29, 2003 and autoquote the last block of stocks on May 27, 2003. Accordingly, I examine changes in stock volatility and HFT from the last quarter before autoquote (2002Q4) to the first quarter after autoquote (2003Q3). To the extent that autoquote facilitates HFT for NYSE stocks, I expect that increases in HFT are more likely to capture true high-frequency trading for NYSE stocks than for other stocks. Therefore, I expect a positive coefficient on $D*\Delta HFT$ in the following model.

$$\begin{aligned}\Delta VOLT = {} & \beta_0 + \beta_1 D + \beta_2 \Delta HFT + \beta_3 D * \Delta HFT + \beta_4 \Delta sd\Delta ROE + \beta_5 \Delta sdSGR \\ & + \beta_6 \Delta DISP + \beta_7 \Delta LEV + \beta_8 \Delta INST + \beta_9 \Delta(1/P) + \beta_{10} \Delta SIZE + \beta_{11} \Delta BM \\ & + \beta_{12} \Delta RET\_12 + e_t\end{aligned} \tag{4}$$

Where D equals 1 for NYSE stocks and 0 otherwise. All other variables are the change version of the variables in equation (3), where changes are measured from 2002Q4 to 2003Q3. Compared to equation (3), model (4) drops firm age because changes in firm age are constant across firms. In model (4), I essentially use other exchange stocks as the benchmark and test the incremental effect of the NYSE autoquote on HFT and stock volatility. Panel B of Table II shows that the coefficients on $D^*\Delta HFT$ are significantly positive, consistent with my expectation.

To further substantiate the HFT volatility argument, I explore some institutional features of HFT by examining cross-sectional and time-series variations in the relationship between stock price volatility and HFT. First, I consider whether a stock is among the top 3,000 stocks based on the market value of equity at the end of May. The top 3,000 stocks roughly correspond to the Russell 3000 Index, which the capital management industry widely perceives to constitute the investable universe. For a given firm, in a given year the market value of equity in May is assigned to the next 12-month period, because Russell rebalances its index in early June. Theoretically, nothing stops hedge funds from trading small stocks. Nevertheless, every investment firm contacted for this study restricts itself to an "investable universe," which is often limited to the Russell 3000. Therefore, the *HFT* measure should better capture high-frequency trading and thus exhibit a stronger correlation with stock price volatility for the top 3,000 stocks.

Second, I explore the role of time-series variations in HFT. By and large, high-frequency traders fall into two categories: market makers and more aggressive HFT strategies. While more aggressive HFT strategies tend to add to stock price volatility, market-making activities may reduce stock volatility. Unlike specialists at exchanges, who are constrained by regulatory requirements to stay active at all times and provide bids upon request, high-frequency traders are free to engage in or desist from market-making activities as they see fit. High-frequency traders prefer a stable price for their market-making activities, as they do not profit from price movement. They can cease market-making activity if the market conditions are not right for them to make profits—a scenario more likely under conditions of high market uncertainty.[15] On the other hand, big swings in stock prices could create stronger intra-day correlations in stock returns and order imbalance, promoting a larger volume of aggressive HFT. Altogether, HFT should make stocks more volatile when market uncertainty is high (when the *VIX* index is above its historic median).

Third, I examine the role of institutional holdings in HFT. As discussed earlier, practitioners often complain that high-frequency traders take advantage of institutional traders to benefit themselves. One popular approach among high-frequency traders is to front-run large trades by institutional investors, a practice that pushes stock prices too high (low) when institutional investors want to buy (sell). As a result, such HFT behavior naturally increases stock price volatility. Therefore, the positive correlation between HFT and stock price volatility is expected to be greater for stocks with high institutional holdings (*INST* above the median).

Table III reports empirical results on these three empirical predictions. The main variables of interest are the interaction terms between *HFT* and a dummy variable introduced for each empirical test (regression). Consistent with my predictions, I find that the interaction term is positive and significant across all three columns in Table III.

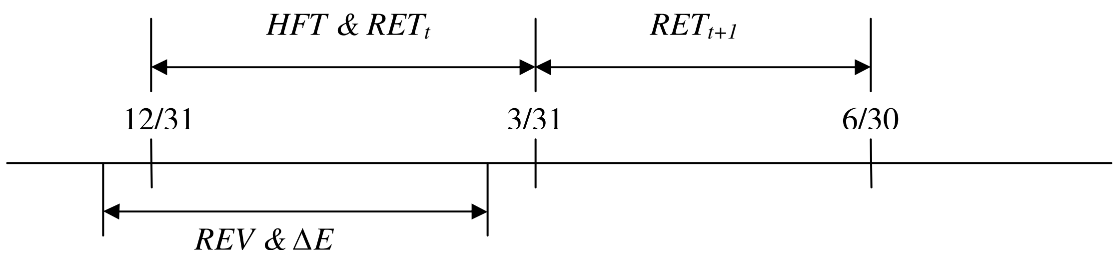
Overall, the evidence strongly supports the idea that HFT increases stock volatility. The positive correlation between HFT and stock price volatility is stronger for stocks in the investable universe, stronger for stocks with high institutional holdings, and stronger during periods of high market uncertainty.

[15] One vivid example of disappearing liquidity is the flash crash on May 6, 2010, when the Dow lost nearly 1,000 points (about 9.2%) in a matter of minutes. During that time, liquidity evaporated from the market, sending shares of some big-name companies (e.g., Accenture) momentarily to a penny when they could not find a bid. To make things worse, the non-transparency that stems from high-frequency trades (which can happen in milliseconds) makes tracking the trades virtually impossible. It took SEC, which has unlimited access to data, more than five months to determine what caused the flash crash.

4.3 Does HFT improve price discovery?

This section addresses the role of HFT in the market's incorporation of news about company fundamentals into stock prices. As discussed earlier, the empirical tests in this investigation are conducted at the quarterly level. Given that the quarterly level is unlikely to be the ideal setting for testing the price discovery hypothesis, the results in this test serve as a lower bound for the possible impact of HFT. If I observe significant results at the quarterly level, it would be relatively safe to conclude that HFT affects price discovery. However, if I do not observe significant results, then HFT may still have an effect.

Specifically, I use analyst earnings revision (*REV*) and earnings surprise (ΔE) to proxy for fundamental news. As the *HFT* measure is quarterly, I construct *REV* and ΔE quarterly to be in line with the *HFT* window. The figure below illustrates how I measure these variables.



REV is the consensus analyst earnings forecast in the last month of each calendar quarter minus the consensus forecast three months prior, scaled by stock price in the last month of the calendar quarter. As I/B/E/S reports its monthly files on the third Thursday of each month, the *REV* window may lead the *HFT* window by 5–10 business days, leaving the market enough time to react to the revision news. ΔE and *HFT* align in such a way that the earnings announcement date falls in the *HFT* window. I require the earnings announcement date to be no more than three months after the fiscal quarter ending date.

For each type of fundamental news, I employ two regression models. Taking *REV* as an example,

$$RET_t = \alpha_0 + (\alpha_1 + \alpha_2 HFT) * REV_t + \alpha_3 HFT_t + \alpha_4 SIZE_{t-1} + \alpha_5 BM_{t-1} + \alpha_6 RET\_12_{t-1} + Firm\_fixed\_effects + Time\_fixed\_effects + e_t \tag{5}$$

$$RET_{t+1} = \beta_0 + (\beta_1 + \beta_2 HFT) * REV_t + \beta_3 HFT_t + \beta_4 SIZE_{t-1} + \beta_5 BM_{t-1} + \beta_6 RET\_12_{t-1} + Firm\_fixed\_effects + Time\_fixed\_effects + e_t \tag{6}$$

In Equation (5) the dependent variable is contemporaneous stock returns, and in Equation (6) the dependent variable is future stock returns. The earnings-return literature suggests that $\alpha_1 + \alpha_2 HFT$ should be positive in Equation (5). A positive coefficient on *REV* ($\beta_1 + \beta_2 HFT$) in Equation (6) indicates a post-news drift, whereas a negative coefficient indicates a reversal. Of interest is the sign of β_2 relative to the signs of α_2 and β_1.

Table IV reports the results of estimations (5) and (6) with respect to analyst forecast revisions. The first three models are based on contemporaneous stock returns. The first column shows that contemporaneous returns and revisions are strongly positively correlated, a result consistent with the general finding in the accounting literature that stock prices react positively to earnings news. The second column shows an $\hat{\alpha}_2$ equal to 0.472 (t = 4.53), suggesting that the market reaction to earnings revisions is stronger for high-*HFT* stocks. Regarding the economic magnitude, one standard deviation increase of HFT strengthens the price reaction by 8.3% (=0.34*0.472/1.925). This basic result is unchanged if the earnings–return relation are allowed to vary with *SIZE*, *BM*, and *RET_12* (as in column (3)). The last three models, columns (4)–(6), are based on future stock returns. Column (4) shows a negative coefficient on *REV*, indicating that stock prices reverse in the subsequent three months. This evidence of price reversal differs from the price drift evidence documented in the prior literature in two respects. First, the price drift is much weaker in more recent years, as compared to the early sample in Stickel (1991). Second, the price drift is stronger for small firms, some of which are excluded from this study's sample owing to missing institutional data. Additionally, the quarterly window used in the paper tends to produce a weaker drift than the monthly window does. When, in Section 5.2, I expand the sample to all firms and to earlier years, I observe a price drift in both the 1977–1984 and 1985–1994 time periods. Column (5) reveals that $\hat{\beta}_2$ is significantly negative ($\hat{\beta}_2$= -0.417, *t*=-3.41), suggesting that stock prices reverse more for high-*HFT* stocks. This result still holds when the earnings–return relation is allowed to vary with *SIZE*, *BM*, and *RET_12* (as in column (6)).

Table V reports the results of estimations (5) and (6) when I use earnings surprises to proxy for fundamental news. The results are qualitatively similar to those reported in Table IV, with positive coefficients on $\Delta E*HFT$ in regressions using contemporaneous returns and negative coefficients on $\Delta E*HFT$ in regressions using future returns. One standard deviation increase of HFT strengthens the price reaction to earnings surprises by 8.4% (=0.34*0.353/1.425).

I also explore the exogenous shock of the NYSE autoquote in the price discovery test. Specifically, I use the last quarter before autoquote (2002Q4) and the first quarter after autoquote (2003Q3) as my sample and run the following regressions.

$$\begin{aligned} RET_t = {} & \alpha_0 + \alpha_1 * REV_t + \alpha_2 HFT_t + \alpha_3 HFT * REV_t + \alpha_4 D_{after} * HFT * REV_t \\ & + \alpha_5 D_{after} * D_{NYSE} * HFT * REV_t + \alpha_6 * D_{after} + \alpha_7 * D_{NYSE} \\ & + \alpha_8 SIZE_{t-1} + \alpha_9 BM_{t-1} + \alpha_{10} RET\_12_{t-1} + e_t \end{aligned} \tag{7}$$

$$\begin{aligned} RET_{t+1} = {} & \beta_0 + \beta_1 * REV_t + \beta_2 HFT_t + \beta_3 HFT * REV_t + \beta_4 D_{after} * HFT * REV_t \\ & + \beta_5 D_{after} * D_{NYSE} * HFT * REV_t + \beta_6 * D_{after} + \beta_7 * D_{NYSE} \\ & + \beta_8 SIZE_{t-1} + \beta_9 BM_{t-1} + \beta_{10} RET\_12_{t-1} + e_t \end{aligned} \tag{8}$$

Where D_{after} equals 1 for 2003Q3 and 0 otherwise, D_{NYSE} equals 1 for NYSE stocks and 0 otherwise.

The main variable of interest is $D_{after} * D_{NYSE} * HFT * REV$. To the extent that autoquote facilitates HFT for NYSE stocks, I expect HFT to have a stronger effect for NYSE stocks than for other-exchange stocks in 2003Q3 relative to 2002Q4. In untabulated analysis, I find that $D_{after} * D_{NYSE} * HFT * REV$ has a positive coefficient (α_5=3.16, t=2.18) in model (7) and a negative coefficient (β_5=-3.78, t=-2.92) in model (8), suggesting that NYSE autoquote is related to a stronger contemporaneous price reaction and a stronger subsequent reversal for NYSE stocks in the post-autoquote period.

Taken together, these results suggest that HFT hinders price discovery. HFT pushes stock prices too far in the direction of earnings news and, as a result, stock prices reverse in the subsequent months after the initial reaction. In fact, $\hat{\alpha}_2$ and $\hat{\beta}_2$ are very similar in magnitude but have opposite signs, suggesting that the incremental HFT-related market reaction to earnings news is almost fully reversed in the subsequent months. HFT-related price reaction and subsequent reversal are at least consistent with two possible mechanisms. First, HFT and traditional investors' trading are independent. HFT first reacts to earnings news and moves the stock price. Traditional investors trade stocks subsequently and further move the price, without adjusting for the initial price reaction introduced by HFT. Second, HFT interacts with traditional investors. It is possible that HFT front-runs large orders of institutional investors, who tend to trade in the direction of earnings news, a practice driving up (down) the price following good (bad) news. It is also possible that HFT induces more momentum traders to trade in the direction of earnings news and thus may create a short-term overreaction.[16] Data limitations preclude me from identifying the exact underlying mechanism, which I leave for future research.

[16] Another possibility is that HFT identifies mispricing opportunities and trade more as an arbitrageur when traditional investors overreact more to earnings news. I view this mechanism to be less likely for two reasons. First,

4.4 Quantifying the effect of measurement error on the variable *HFT*

As HFT is not directly observable, some simplifying assumptions apply to empirically estimating *HFT*. Consequently, *HFT* is estimated with error. This section presents an attempt to gauge the effect of measurement error on the key findings.

As shown in Section 3.2, the *INDIVTO/INSTTO* ratio estimated in the 1985–1994 period is used to calculate *HFT* for each firm-quarter in the 1995–2009 period. Similarly, I can calculate *HFT* for each firm-quarter in the 1985–1994 period using Equation (2). Under the assumption that no HFT exists in the 1985–1994 period, this *HFT* estimate captures measurement error introduced in the estimation process.[17] By construction, the value-weighted average of *HFT* across all firm-quarters should be zero for 1985–1994.[18] I redo the main tests presented in Tables 2, 4, and 5 using the 1985–1994 sample. If measurement error has no impact on my results, the coefficients on key variables of interest should be close to zero.

In the volatility test (column (1) in Panel A of Table II), I find the coefficient on *HFT* to be positive ($\hat{\beta}_1$ = 0.538) and highly significant (t = 27.94), suggesting that measurement error does affect stock volatility. As *HFT* is measured relative to the value-weighted *INDIVTO/INSTTO* ratio, a positive coefficient on *HFT* means higher than average stock turnover is positively related to stock volatility. In essence, measurement error in the *HFT* variable

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HFT typically does not trade on fundamental earnings news and is less likely than traditional investors to identify mispricing opportunities. Second, my results show that stock price reverses in subsequent quarters whereas HFT has extremely short holding periods. So HFT cannot profit from price reversal if they do not hold their positions long enough. Another possible mechanism is dealers' inventory risk controls. Dealers may act in order to control their inventories. They increase (decrease) stock prices when they want to increase (decrease) their inventory following good (bad) news, which may explain the stronger correlation between earnings news and contemporaneous stock returns for high-HFT stocks. But it is unclear how the inventory risk story applies to HFT, which typically does not carry any position over night, and why we observe a subsequent reversal in the following months.

[17] Note that this study conservatively assumes no HFT in the 1985–1994 period. To the extent that HFT existed in 1985–1994, the effect of measurement error is likely to be overstated because so-called measurement error actually captures HFT.

[18] In a regression framework as used in the paper, the mean value of HFT is irrelevant because it is captured by the intercept (firm and time dummies).

captures the positive correlation between trading volume and volatility that is not due to HFT (e.g., Lee et al. 1994). More importantly, the coefficient estimate of 0.538 is much smaller than the estimate of 1.084 reported in Table II. By conservatively assuming that *HFT* only captures measurement error in the 1985–1994 period, I view that the difference between these two coefficient estimates (1.084 – 0.538 = 0.546) represents the incremental effect of HFT on stock volatility. This incremental coefficient (0.546) is still highly significant (t = 28.21).

Table VI reports the results of the price discovery test. Panel A is based on analyst forecast revisions and Panel B is based on earnings surprises. In both panels, the coefficients on fundamental news are highly positive in column (1), confirming the earnings–return relationship for the 1985–1994 period. More importantly, the coefficients on *HFT*REV* and $HFT*\Delta E$ are insignificantly different from zero across all models, suggesting that the market's incorporation of fundamental news is uncorrelated with measurement error.

Overall, I conclude that measurement error in HFT accounts for about 50% of the volatility results but does not affect the price discovery results. Measurement error has a smaller impact on the price discovery test possibly because of its better research design of using the interaction terms.

5. Robustness checks

5.1 Is HFT measurement error time-varying?

The approach described in Section 4.4 is effective as long as HFT measurement error is time-invariant. However, for at least three reasons measurement error could change over time. First, individual investors have become more active over time in stock trading owing to technological advances such as the availability of online trading. As a result, overall stock turnover has increased over time and the *HFT* measure captures this increase in individual trading behavior.[19] Second, over time traditional institutional investors have engaged in more intra-quarter trades (the purchase and subsequent sale of a stock in a single calendar quarter). Yet these trades are not captured by the measure of institutional turnover as institutions only file 13f forms quarterly. Finally, in recent years institutions have tended to use more principal bids. When using a principal bid, an institution turns over its trading list to a large broker, such as Goldman Sachs, in lieu of trading the list by itself. Most principal bids are submitted before the market opens at 9:30am. The broker then nets out buys and sells from different client institutions and trades the net balance in dark pools or in the open market.

The first possible source of time-variant measurement error—more activity from individual investors—is my main concern and is empirically examined in this section. The second possible source—more intra-quarter trading—is of less importance because traditional institutions have a fixed annual turnover budget and typically cannot buy and sell stocks in the same quarter.[20] The typical institution's budget allows for approximately 130–150% turnover per year and does not change much over time. In fact, institutions often have to explain intra-quarter trades to their clients because these trades are perceived as abnormal when compared to the typical stock holding period of 9–12 months. The last possible source—more principal bids—is not a matter of much concern because institutional turnover includes all principal trades.

To test for the presence of the first source of time-variant measurement error, the following model explores cross-sectional and time-series variations in *HFT*:

$$\begin{aligned} HFT = {} & \beta_0 + \beta_1 INDIV + \beta_2 SIZE + \beta_3 BM + \beta_4 RET\_12 + \beta_5 sd\Delta ROE \\ & + \beta_6 sdSGR + \beta_7 DISP + \beta_8 LEV + \beta_9 (1/P) + e_t \end{aligned} \tag{9}$$

[19] Note that this alternative explanation is inconsistent with anecdotal evidence of the rising popularity and dominance of HFT in the U.S. capital market (as discussed earlier).

[20] Short-term trading strategies by an increasing number of hedge funds are, by definition, captured by my HFT measure.

The main variable of interest here is *INDIV*. If individual investors have traded more frequently in recent years and *HFT* captures such individual trading behavior, then *HFT* should be higher for stocks with higher individual holdings, resulting in a positive coefficient on *INDIV*.

Table VII reports the results of three incrementally richer specifications of Equation (7). Model (1) is a univariate regression of *HFT* on *INDIV*. The coefficient on *INST* is highly negative. This finding is not consistent with an increase in individual investors' trading behavior relative to that of institutional investors over time. In Model (2), I add three common return factors. I control for firm size, because size often proxies for liquidity. Model (2) shows that *HFT* is positively correlated with firm size, the book-to-market ratio, and price momentum. More importantly, the coefficient on *INDIV* remains highly negative. In Model (3), I add additional proxies for fundamental volatility (*sd*Δ*ROE*, *sdSGR*, and *DISP*), market leverage, and the reciprocal of the stock price. Market leverage and stock price also capture liquidity in the absence of HFT.[21] The coefficient on *INDIV* remains highly significant, with *t*-statistics over 20.

Overall, the results are inconsistent with the view that *HFT* captures increased individual trading behavior over time. As institutional holdings and individual holdings sum to one, the negative correlation between *HFT* and individual holdings implies a positive correlation between *HFT* and institutional holdings—a result consistent with the theory that high-frequency traders target traditional institutional investors. This evidence is also in line with anecdotal observations that some HFT strategies, such as liquidity detection, are deliberately implemented to front-run trades by institutional investors.

5.2 Does HFT simply reflect the trading volume effect?

[21] Traditional liquidity measures, such as trading volume and bid-ask spread, are not included in the model as these measures are affected by HFT.

As institutional holdings and institutional turnover are relatively stable over time, *HFT* and stock turnover (*TO*) are highly correlated in the 1995–2009 sample period, with a Spearman correlation coefficient of 0.60. Given such a high degree of correlation, one might wonder whether the HFT measure simply reflects a universal trading volume effect (Lee and Swaminathan 2000). As the analysis in Section 4.4 shows, *HFT* does not play any significant role in price discovery in the base estimation period (1985–1994), a result inconsistent with the universal trading volume effect. However, the insignificant results in the 1985–1994 sub-period may be sample-specific. In this section, I expand my sample to include all stocks with non-missing values of *TO* and extend the sample period back to 1977 when analyst forecast data are first available in I/B/E/S. Then, I partition the sample period into three sub-periods: 1977–1984, 1985–1994, and 1995–2009. If trading volume has a consistent effect on price discovery, I expect high-*TO* stocks to overreact to fundamental news and to subsequently exhibit a reversal in all three sub-periods, paralleling the HFT results documented in Tables 4 and 5.

Table VIII reports the empirical results from the analysis on trading volume, where I use analyst forecast revisions and earnings surprises to proxy for fundamental news in panel A and B, respectively. The main variables of interest are *REV*TO* and $\Delta E{*}TO$. In Panel A, the first block shows regressions of contemporaneous stock returns. Returns are positively correlated with analyst revisions, and the positive correlation is stronger for high-*TO* stocks in all three sub-periods. The second block of Panel A shows regressions of future stock returns. In Models 1 and 3 the coefficients on *REV* are significantly positive, suggesting a price drift after analyst revisions in the 1977–1984 and 1985–1994 sub-periods. Model 5 reports a negative coefficient on *REV*, indicating a price reversal in the 1995–2009 sub-period. More importantly, the coefficient on *REV*TO* is significantly negative only in Model 6, suggesting a stronger price reversal for high-*TO* stocks in the 1995–2009 sub-period that echoes the HFT results in Table IV. The insignificant coefficients on *REV*TO* in the 1977–1984 and the 1985–1994 sub-periods suggest that *HFT* does not capture a universal trading volume effect.

The results from the earnings surprises regressions in Panel B are largely similar. The market shows a stronger response to earnings surprises for high-*TO* stocks. In all three sub-periods, stock prices drift in the direction of earnings news after the initial market reaction. In the 1977–1984 and 1985–1994 sub-periods, trading volume does not have a significant impact on post-surprise drift, and in the 1995–2009 sub-period trading volume tends to attenuate the drift.

Taken together, the above results reveal that the impact of trading volume on price discovery is not universal throughout the whole sample period (1977–2009). The results offer no evidence of price reversals and the associated effect on trading volume in the 1977–1984 and the 1985–1994 sub-periods. The results on trading volume in the 1995–2009 sub-period are more similar to the HFT results documented in Tables 4 and 5. Overall, the evidence is more consistent with the HFT effect than with the trading-volume effect.

5.3 Different windows to determine the *INDIVTO/INSTTO* ratio

The main analysis uses the 1985–1994 time period to determine the ratio of institutional turnover to individual turnover. The choice of 1985–1994 is arbitrary, although Figure 1 suggests that during this period both stock turnover and institutional turnover were in a steady state. In a robustness check, I use the 1985–1989 time period as the baseline for key calculations (see section 3.2), and the tenor of the original findings remains unchanged. For example, the coefficient on *HFT* becomes 1.051 (t = 62.19) in column (1) of Panel A, Table II. The coefficients on *REV*HFT* come to equal 0.466 (t = 4.71) and -0.453 (t = -3.79) in columns (2) and (5) of Table IV, respectively. I also rerun my analysis using 1988–1989 as the baseline time period, which excludes the crash of 1987. Again, the results are qualitatively similar to the original findings.

5.4 The double-count issue for Nasdaq firms

To account for market-maker activity in calculating Nasdaq trading volume, I divide Nasdaq firms' trading volume by two in the main analysis. As a robustness check, I treat trading volume as it is and redo the analysis. This alternative specification does not significantly alter the original findings. For example, the coefficient on *HFT* is newly estimated to equal 0.901 (t = 64.43) in column (1) of Panel A, Table II. The coefficients on *REV*HFT* come to equal 0.641 (t = 8.64) and -0.283 (t = -3.27) in columns (2) and (5) of Table IV, respectively. Since market-maker activity varies across Nasdaq firms and over time, a uniform cutoff may still introduce measurement error into the trading volume measure. As an alternative approach, I exclude Nasdaq firms from the sample and find the tenor of the paper unchanged.[22] For example, the coefficient on *HFT* is re-estimated to equal 0.809 (t = 39.14) in column (1) of Panel A, Table II. The coefficients on *REV*HFT* come to equal 0.324 (t = 2.55) and -0.493 (t = -3.33) in columns (2) and (5) of Table IV, respectively.

6. Conclusions and discussion

In this paper, I empirically estimate the volume of HFT in the U.S. capital market and examine the effect of HFT on stock price volatility and price discovery. Analysis shows that, in terms of trading volume, HFT has become the dominant force in the equity market, accounting for about 78% of total dollar trading volume in the first two quarters of 2009 (the most recent data available). From the liquidity perspective, 78% is clearly excessive. If HFT provides all

[22] Conceptually, it is suboptimal to exclude Nasdaq firms from the sample. Nasdaq was at the forefront of electronic trading. Most high-frequency traders started their HFT strategies from Nasdaq.

liquidity needed in the market, the maximum percentage is 50%, where the maximum is surely overstated as it assumes everybody trades with HFT firms. HFT has brought total share turnover to over 100% per quarter in recent years. In contrast, quarterly institutional turnover has been remarkably stable over time, averaging about 20% over the past 25 years.

More importantly, this study shows that HFT is positively correlated with stock price volatility after controlling for the volatility of a stock's fundamentals and other volatility drivers. This positive correlation is especially strong for the top 3,000 stocks in market capitalization, stronger for stocks with high institutional holdings, and stronger during periods of high market uncertainty. Taken together, the results are consistent with the view that HFT increases volatility. This study also offers evidence that HFT hinders price discovery. The market apparently overreacts to a firm's fundamental news (proxied by analyst forecast revision and earnings surprises) when HFT is at a high volume. The incremental price changes associated with HFT are almost entirely reversed in the subsequent periods. In terms of the economic magnitude, one standard deviation increase of HFT on average increases stock volatility by 5.6% (=11.2%*50%) and increases price reaction to earnings news by 8% after taking measurement error into account.

This analysis warrants several caveats. First, as HFT is not directly observable, estimating the volume of HFT requires some simplifying assumptions. While I conduct a number of analyses to assess the effects of measurement errors on my results and am confident that the results are not driven by measurement errors in estimated HFT, my results must be interpreted with that caveat in mind. Second, HFT is measured at the quarterly level owing to data limitations. The quarterly research design has some important advantages: it gives a good overall picture of HFT's share of total U.S. trading volume, and it describes the prolonged effect HFT has on price dynamics and on market efficiency. However, the quarterly research design has some limitations. Data permitting, it would be interesting to use intra- or inter-day data to study the impact of HFT, especially on the underlying mechanism of the price discovery results. The last caveat is the issue of endogeneity in the volatility test. This paper argues that HFT increases volatility. However, the possibility of reverse causality could be used as a counter-argument since volatile stocks and volatile markets could attract high-frequency traders. I use the exogenous shock of NYSE autoquote and variations in the HFT-volatility relation to partially address this issue. In addition, the finding that HFT causes stock prices to over-react to news about fundamentals, and that this over-reaction is subsequently corrected, represents direct evidence supporting the hypothesis that HFT creates volatility.

Given that HFT constitutes the lion's share of trading volume in today's capital markets, the paucity of academic research on HFT is surprising. While this study sheds light on the role of HFT in the capital market, it raises more questions than answers. For example, what is the underlying mechanism of HFT in price discovery? Does HFT reduce volatility in certain scenarios, such as during periods of very low uncertainty? Do HFT's market-making activities and more aggressive strategies have different implications for market efficiency? Do high-frequency traders withdraw liquidity when uncertainty is extremely high, as evidenced in the flash crash on May 6, 2010? What is the overall benefit of HFT, relative to its costs to the market? Would a small tax on financial transactions, such as a 0.1% tax on the value of traded stock, make HFT more beneficial for the market?[23] I leave these questions for future research.

[23] From a policy perspective, reining in the scope of HFT would be fairly easy if HFT were found to be harmful to the capital market. A small tax on financial transactions would dramatically reduce the volume of high-frequency trading. For example, one top hedge fund contacted for this study claims to use a strategy that makes five basis points per trade with an average transaction cost of three basis points. A tax of 0.05% would undermine this particular hedge fund's high-frequency trades.

References

Baiman, S. and R. Verrecchia. 1995. Earnings and price-based compensation contracts in the presence of discretionary trading and incomplete contracting. *Journal of Accounting and Economics* 20, 93-121.

Ball, R. and P. Brown. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6, 159-178.

Barberis, N. and A. Shleifer. 2003. Style investing. Journal of Financial Economics 68, 161-199.

Brogaard, J. 2010. High frequency trading and its impact on market quality, Northwestern University working paper.

Bushee, B. 1998. The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review* 73, 19-45.

Bushee, B. and C. Noe. 2000. Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of Accounting Research* 38, 171-202.

Cao, C., T. Simin, and J. Zhao. 2008. Can growth options explain the trend in idiosyncratic risk? *Review of Financial Studies* 21, 2599-2633.

Chaboud, A., B. Chiquoine, E. Hjalmarsson, and C. Vega. 2009. Rise of the machines: algorithmic trading in the foreign exchange market. Federal Reserve Board, working paper.

Cheung Y. and L. Ng. 1992. Stock price dynamics and firm size: An empirical investigation. The Journal of Finance 47 (5), 1985-1997.

Christie A. 1982. The stochastic behavior of common stock variances: value, leverage and interest rate effects. *Journal of Financial Economics* 10, 407-432.

Chordia, T., R. Roll, and A. Subrahmanyam. 2010. Recent trends in trading activity. Emory University and UCLA working paper.

Datar, V., N. Naik, and R. Radclifffe. 1998. Liquidity and asset returns: An alternative test. *Journal of Financial Markets* 1, 203-220.

De Long, B.J., A. Shleifer, L. Summers, and R. Waldmann. 1990. Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance* 45, 379-396.

El-Gazzar, S. 1998. Predisclosure information and institutional ownership: A cross-sectional examination of market revaluations during earnings announcement periods. *The Accounting Review* 73, 119-130.

Francis, J., D. Philbrick, and K. Schipper. 1994. Shareholder litigation and corporate disclosures.

Journal of Accounting Research 32, 137-164.

Froot, K, A. Perold, and J. Stein. 1992. Shareholder trading practices and corporate investment horizons. *Journal of Applied Corporate Finance*, 42-58.

Froot, K, D. Scharfstein, and J. Stein. 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. *Journal of Finance* 47, 1461-1484.

Gould, J. and A. Kleidon. 1994. Market maker activity on Nasdaq: Implications for trading volume. *Stanford Journal of Law, Business, and Finance* 1, 1-17.

Hendershott, T., C. Jones, and A. Menkveld. 2010. Does algorithmic trading improve liquidity? *Journal of Finance*, forthcoming.

Hendershott, T. and R. Riordan. 2009. Algorithmic trading and information. UC Berkeley, working paper.

Kothari, S.P., 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31, 105-231.

Lee, C. 2001. Market efficiency and accounting research. *Journal of Accounting and Economics* 31, 233-253.

Lee, C., M. Ready, and P. Seguin. 1994. Volume, volatility, and NYSE trading halts. *Journal of Finance* 49, 183-214.

Lee, C. and B. Swaminathan. 2000. Price momentum and trading volume. *Journal of Finance*, 2017-2069.

Pastor, L. and P. Veronesi. 2003. Stock valuation and learning about profitability. *Journal of Finance* 58, 1749–1789.

Potter, G. 1992. Accounting earnings announcements, institutional investor concentration, and common stock returns. *Journal of Accounting Research* 30, 146-155.

Ross, S. 1989. Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *The Journal of Finance* 25, 1-17.

Scheinkman, J. and W. Xiong. 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111, 1183-1219.

Shiller, R. 1981. Do stock prices move too much to be justified by subsequent changes in dividend? *American Economic Review* 71, 421-436.

Stickel, S. 1991. Common stock returns surrounding earnings forecast revisions: More puzzling evidence. The Accounting Review 66, 402-416.

Verrecchia, R. 2001. Essays on disclosure. *Journal of Accounting and Economics* 32, 97-180.

Vives, X. 1995. Short-term investment and the informational efficiency of the market. *Review of Financial Studies* 8, 125-160.

Wei, S. and C. Zhang. 2006. Why did individual stocks become more volatile? *The Journal of Business* 79 (1).

Zhang, X. F. 2006. Information uncertainty and stock returns. *Journal of Finance* 61, 105-137.

Appendix: Variable Definitions

INST	Institutional holdings, defined as the average of beginning and ending shares held by institutional investors divided by the average of beginning and ending outstanding shares in each calendar quarter. Both shares held by institutional investors and outstanding shares are from the Thomson Reuters Institutional Holdings database (tfn.s34).
INSTTO	Institutional turnover, defined as |CHANGE| divided by the average of beginning and ending shares held by institutional investors, where |CHANGE| is total shares traded by all institutional investors measured as the sum of the absolute value of CHANGE across all institutional investors in tfn.s34. Beginning shares equal ending shares minus net change from tfn.s34, except for the 2006Q2–2007Q1 sub-period when net changes are coded incorrectly in tfn.s34 (see Section 3 for more details). Beginning shares are derived from ending shares in the prior quarter and, together with ending shares, are used to calculate net changes for the 2006Q2–2007Q1 sub-period.
TO	Total share turnover, defined as trading volume divided by the average of beginning and ending outstanding shares in each calendar quarter. Trading volume is divided by two for Nasdaq firms in the main analysis to account for the double-count issue.
HFT	High-frequency trading volume, defined as TO – INST*INSTTO – (1– INST)*INSTTO* MULTIPLE, where MULTIPLE is the value-weighted average ratio of individual holding turnover to institutional holding turnover in the 1985–1994 period. This study assumes no high-frequency trading in the 1985–1994 period and estimate HFT for the 1995–2009 period.
VOLT	Stock volatility, defined as the standard deviation of daily stock returns in each calendar quarter.
HLVOLT	High-low stock volatility, defined as the standard deviation of daily log(ASKHI/BIDLO) in each calendar quarter, where ASKHI and BIDLO are ask high and bid low, respectively.
ΔE	Earnings surprises, defined as earnings per share (IBQ/(CSHOQ*AJEXQ)) in quarter q minus earnings per share in quarter q-4, deflated by stock price (PRCCQ/AJEXQ) in quarter q. All items are from Compustat quarterly.
SIZE	Firm size, defined as the logarithm of the market value of equity (CSHOQ*PRCCQ) at the beginning of quarter q. All items are from Compustat quarterly.
BM	Book-to-market ratio, defined as the ratio of the book value of equity (CEQQ) to its market value (CSHOQ*PRCCQ) at the beginning of quarter q. All items are from Compustat quarterly.
RET_12	Past 12-month stock returns starting from 15 months prior to quarter-end to 4 months prior to quarter-end. I allow a one-month lag relative to the starting date of quarterly VOLT and HFT measures.
ERET_12	Past 12-month stock returns with respect to earnings surprises, defined as accumulated 12-month stock returns starting from 12 months prior to a firm's fiscal quarter-end to 1 month prior to fiscal quarter-end.
$sd\Delta ROE$	Earnings surprise volatility, measured as the standard deviation of earnings changes relative to four quarter ago scaled by average book value of equity over the past 12 quarters.
sdSGR	Sales growth volatility, measured as the standard deviation of sales growth relative to four quarters prior ($(Sales_q - Sales_{q-4})/Sales_{q-4}$) over the past 12 quarters.
DISP	Analyst forecast dispersion, measured as the standard deviation of analysts' one-quarter-ahead earnings forecasts scaled by stock price. Quarterly DISP is calculated as the average of analyst forecast dispersion across three months.
LEV	Market leverage, defined as the sum of short-term and long-term debt (DLTTQ+DLCQ) scaled by the market value of equity. All items are from Compustat quarterly.
P	Stock price from CRSP monthly file, unadjusted for stock splits and stock dividends.

Figure 1 The time-series pattern of institutional ownership, institutional turnover, and stock turnover

This figure plots the time-series pattern of quarterly institutional ownership, institutional turnover, and stock turnover from the first quarter of 1985 to the second quarter of 2009. Institutional ownership is the percentage of stock shares owned by institutions as defined in the Thomson Reuters Institutional Holdings database. Institutional turnover is the turnover of institutional holdings, defined as the number of shares traded by all institutions each quarter divided by the average of beginning and ending institutional holdings. Stock turnover is total trading volume each quarter divided by outstanding shares. The sample includes all firms covered by CRSP and Thomson Reuters Institutional Holdings databases with stock prices no less than $1. All three series are value-weighted averages across all firms in the sample.

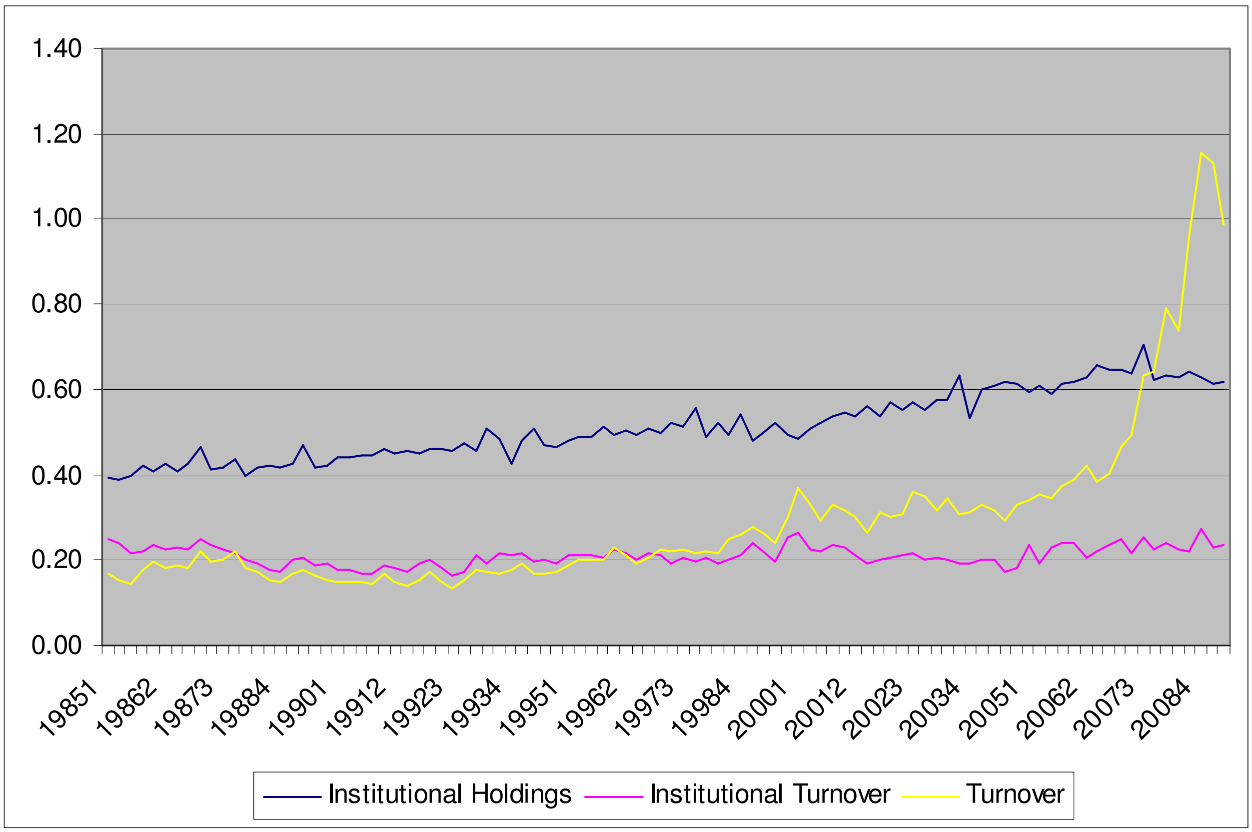

Figure 2 The percentage of high-frequency trading in total dollar trade volume

This figure plots the estimated volume of high-frequency trading as a percentage of total dollar trading volume from the first quarter of 1995 to the second quarter of 2009. Trading volume by high frequency traders is calculated by subtracting trading volume by institutional and individual investors from total trading volume. Please see Section 3.2 for more details on the calculation process. The sample includes all firms covered by CRSP and Thomson Reuters Institutional Holdings databases with stock prices of at least $1.

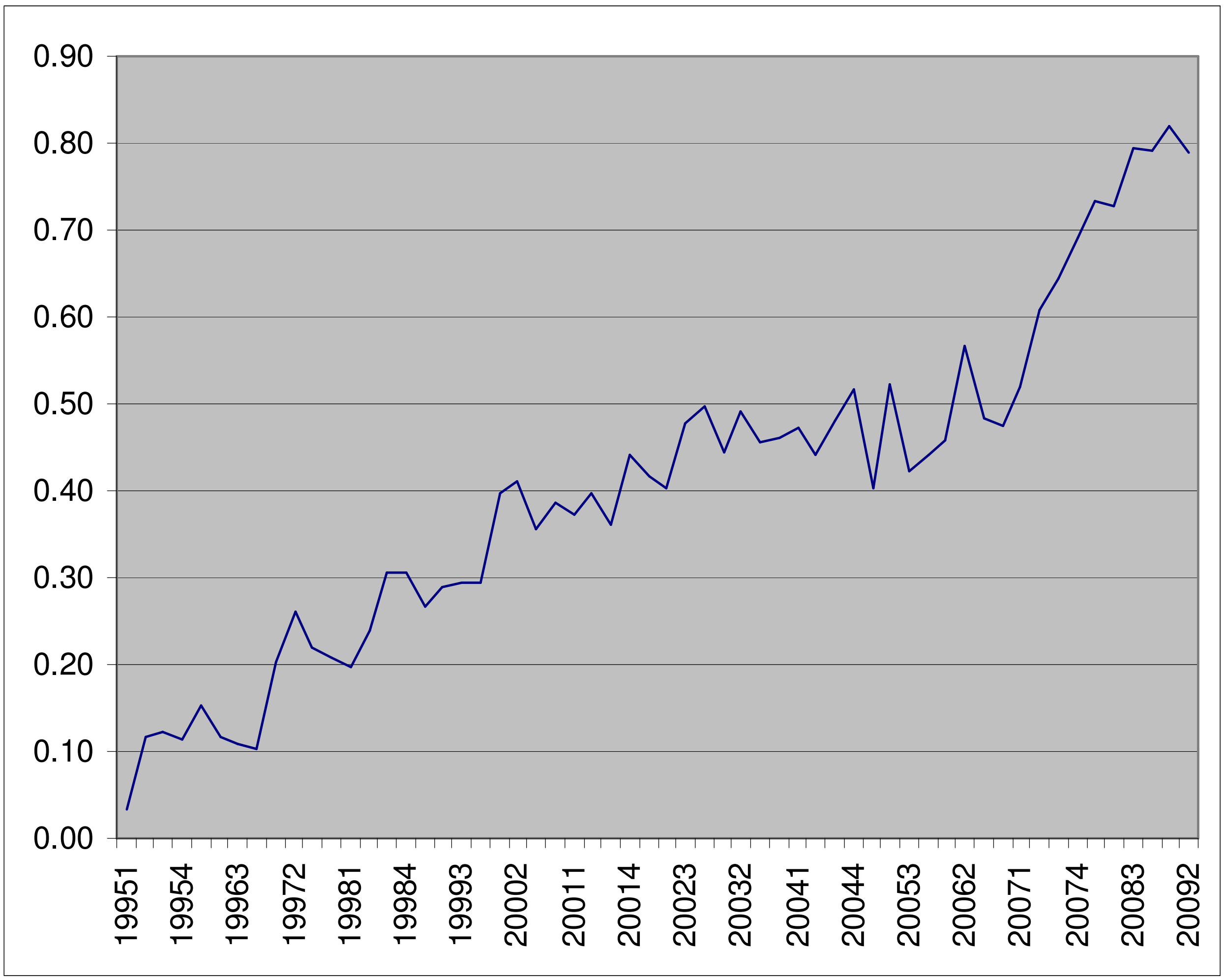

Table I Descriptive statistics

Panel A presents descriptive statistics for variables used in the paper and Panel B provides Pearson and Spearman correlations among key variables. *INST* is institutional holdings. *INSTTO* is institutional turnover. *HFT* is high-frequency trading volume. *VOLT* is stock volatility. *HLVOLT* is high–low stock volatility. ΔE is earnings surprises. *SIZE* is firm size. *BM* is the book to market ratio. *RET_12* is the past 12-month stock returns. $sd\Delta ROE$ is earnings surprise volatility. *sdSGR* is sales growth volatility. *DISP* is analyst forecast dispersion. *LEV* is market leverage. P is stock price. *TO* is stock turnover. Please see the appendix for detailed variable definitions. The sample consists of 391,013 firm-quarter observations between 1995Q1 and 2009Q2 with non-missing values of *HFT* and *VOLT*. All variables are winsorized at 1% and 99%.

Panel A: Descriptive statistics

	N	Mean	SD	Min	Q1	Median	Q3	Max
INST	391013	0.341	0.284	0.000	0.081	0.276	0.570	1.000
INSTTO	391013	0.303	0.325	0.000	0.116	0.214	0.362	2.000
HFT	391013	0.031	0.341	-1.186	-0.072	0.004	0.102	1.610
VOLT	391013	0.033	0.023	0.005	0.017	0.027	0.043	0.118
HLVOLT	391013	0.027	0.022	0.004	0.012	0.021	0.036	0.117
ΔE	301467	-0.003	0.073	-0.416	-0.007	0.001	0.007	0.321
SIZE	309355	5.704	1.938	1.940	4.270	5.538	6.954	10.888
BM	308199	0.597	0.481	-0.260	0.280	0.498	0.778	2.692
RET_12	386170	0.130	0.583	-0.810	-0.195	0.052	0.310	2.951
$sd\Delta ROE$	260537	0.096	0.208	0.002	0.014	0.032	0.082	1.543
sdSGR	285734	0.588	1.740	0.026	0.099	0.194	0.391	14.498
DISP	189880	0.003	0.006	0.000	0.000	0.001	0.003	0.041
LEV	314318	0.669	1.294	0.000	0.017	0.210	0.713	8.541
P	391013	31.59	947.89	1.00	6.94	14.42	26.50	141600

Panel B: Correlation matrix (Pearson coefficients are above the diagonal and Spearman correlations are below)

	HFT	*VOLT*	*DISP*	*LEV*	*SIZE*	*BM*	*RET_12*	ΔE
HFT	1	0.078	0.084	0.011	0.316	-0.084	0.051	-0.035
VOLT	0.090	1	0.412	0.055	-0.351	0.059	-0.095	-0.095
DISP	0.035	0.299	1	0.313	-0.233	0.255	-0.260	-0.247
LEV	-0.028	-0.186	0.191	1	-0.087	0.319	-0.151	-0.118
SIZE	0.331	-0.383	-0.283	0.005	1	-0.347	0.095	0.001
BM	-0.124	-0.073	0.281	0.358	-0.333	1	-0.255	-0.124
RET_12	0.017	-0.243	-0.372	-0.107	0.169	-0.250	1	0.122
ΔE	-0.010	-0.057	-0.156	-0.047	-0.004	-0.083	0.225	1

Panel C: Spearman correlation between trading activity and returns

		TO	INSTTO	HFT
When $RET_t > 0$	RET_t	0.227	0.221	0.053
When $RET_t < 0$	RET_t	-0.174	-0.158	-0.077

Table II Regressions of stock volatility on HFT

In panel A, the dependent variable is stock volatility (*VOLT* or *HLVOLT*) in percentage points. *VOLT* is stock volatility. *HLVOLT* is high–low stock volatility. *HFT* is high-frequency trading volume. *sdΔROE* is earnings surprise volatility. *sdSGR* is sales growth volatility. *DISP* is analyst forecast dispersion. *AGE* is firm age defined as the number of years since the firm was first covered by CRSP. *INST* is institutional holdings. *LEV* is market leverage. 1/*P* is the inverse of stock price. *SIZE* is firm size. *BM* is the book-to-market ratio. *RET_12* is the past 12-month stock returns. Please see the appendix for detailed variable definitions. The sample consists of 391,013 firm-quarter observations between 1995Q1 and 2009Q2 with non-missing values of *HFT* and *VOLT*. For other variables, I set the missing values to their means in the regressions. All variables are winsorized at 1% and 99%. The regressions are pooled regressions with firm- and year-quarter fixed effects. Standard errors are clustered at the firm level. Panel B reports regressions of changes in stock volatility from the last quarter before NYSE automated quote dissemination (2002Q4) to the first quarter after (2003Q3). D is a dummy variable with the value of 1 for NYSE stocks and 0 otherwise. Changes of each variable are measured from 2002Q4 to 2003Q3. The sample includes 2,423 NYSE stocks and 3,125 non-NYSE stocks.

Panel A: Overall regressions

	Dep. Var. = *VOLT*	Dep. Var. = *HLVOLT*
	(1)	(2)
HFT	1.084 (59.62)	0.678 (43.03)
sdROE	0.279 (7.36)	0.214 (5.85)
sdSGR	0.035 (7.43)	0.025 (5.80)
DISP	45.13 (32.87)	37.16 (27.33)
AGE	-0.021 (-11.28)	-0.005 (-2.77)
INST	-0.937 (-26.25)	-0.848 (-25.94)
LEV	0.256 (29.85)	0.219 (26.17)
1/P	3.616 (60.37)	3.831 (62.14)
SIZE	0.175 (15.69)	-0.015 (-1.48)
BM	0.008 (0.43)	-0.002 (-0.14)
RET_12	0.072 (10.20)	0.058 (8.88)
Firm and time fixed effects	YES	YES
R^2	0.405	0.361

Panel B: NYSE automated quote dissemination

	Dep. Var. = Δ*VOLT*	Dep. Var. = Δ*HLVOLT*
	(1)	(2)
D	-0.185 (-3.84)	-0.012 (-0.30)
ΔHFT	1.389 (8.11)	0.635 (4.62)
ΔHFT*D	0.637 (2.47)	0.884 (4.26)
Δ*sdROE*	0.030 (0.13)	0.337 (1.84)
Δ*sdSGR*	-0.026 (-0.66)	0.009 (0.29)
Δ*DISP*	49.70 (7.48)	58.28 (10.93)
Δ*INST*	-1.078 (-5.00)	-0.808 (-4.67)
Δ*LEV*	0.186 (4.42)	0.098 (2.90)
Δ*1/P*	3.884 (11.36)	2.870 (10.46)
Δ*SIZE*	1.137 (14.49)	0.753 (11.95)
Δ*BM*	0.365 (4.41)	0.181 (2.72)
Δ*RET_12*	-0.100 (-1.77)	-0.008 (-0.18)
R^2	0.308	0.285

Table III Variations in the relation between stock volatility and HFT

The dependent variable is stock volatility (*VOLT*) in percentage. *HFT* is high-frequency trading volume. In model (1), *D* is a dummy variable with the value of 1 if the stock is in top 3,000 in terms of May market value of equity and 0 otherwise. The May market value of equity is assigned to the next 12 months for each stock. In model (2), *D* is a dummy variable with the value of 1 if the VIX index is above the median and 0 otherwise. In model (3), *D* is a dummy variable with the value of 1 if institutional holding is above the median and 0 otherwise. *sdΔROE* is earnings surprise volatility. *sdSGR* is sales growth volatility. *DISP* is analyst forecast dispersion. *AGE* is firm age defined as the number of years since the firm was first covered by CRSP. *INST* is institutional holdings. *LEV* is market leverage. 1/*P* is the inverse of stock price. *SIZE* is firm size. *BM* is the book-to-market ratio. *RET_12* is the past 12-month stock returns. Please see the appendix for detailed variable definitions. The sample consists of 391,013 firm-quarter observations between 1995Q1 and 2009Q2 with non-missing value of *HFT* and *VOLT*. For other variables, I set the missing values to their means in the regressions. All variables are winsorized at 1% and 99%. The regressions are pooled regressions with firm- and year-quarter fixed effects. Standard errors are clustered at the firm level.

	D=1 for top 3,000 stocks	D=1 if VIX is above the median	D=1 if institutional holdings are above the median
	(1)	(2)	(3)
HFT	0.897 (41.99)	0.946 (42.08)	0.759 (37.70)
D	0.034 (8.71)		0.013 (3.52)
*HFT*D*	0.507 (15.97)	0.224 (8.30)	1.015 (31.13)
sdROE	0.273 (7.23)	0.276 (7.32)	0.264 (7.05)
sdSGR	0.035 (7.32)	0.036 (7.45)	0.034 (7.14)
DISP	44.44 (32.60)	44.96 (32.92)	42.72 (31.42)
AGE	-0.023 (-11.97)	-0.021 (-11.35)	-0.024 (-13.05)
INST	-0.968 (-27.04)	-0.934 (-26.17)	-1.013 (-28.32)
LEV	0.254 (29.56)	0.255 (29.84)	0.248 (28.99)
1/P	3.610 (60.47)	3.620 (60.46)	3.596 (60.48)
Log(MV)	0.160 (14.49)	0.175 (15.67)	0.147 (13.26)
BM	0.005 (0.27)	0.008 (0.42)	0.001 (0.03)
RET_12	0.071 (10.02)	0.072 (10.32)	0.067 (9.54)
Firm and time fixed effects	YES	YES	YES
R^2	0.406	0.405	0.411

Table IV Regressions of stock returns on analyst forecast revision and HFT

The dependent variable is either contemporaneous stock returns (RET_t) or future stock returns (RET_{t+1}). *HFT* is high-frequency trading volume. *REV* is analyst forecast revision. *SIZE* is firm size. *BM* is the book to market ratio. *RET_12* is the past 12-month stock returns. Please see the appendix for detailed variable definitions. The sample consists of 217,516 firm-quarter observations between 1995Q1 and 2009Q2 with non-missing value of *HFT* and *REV*. For other variables, I set the missing values to their means in the regressions. All variables are winsorized at 1% and 99%, except for RET_t and RET_{t+1}. The regressions are pooled regressions with firm- and year-quarter fixed effects. Standard errors are clustered at the firm level.

	Dep. Var. = RET_t			Dep. Var. = RET_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
REV	1.949 (70.45)	1.925 (69.26)	2.016 (67.36)	-0.239 (-6.33)	-0.220 (-5.72)	-0.164 (-4.39)
HFT		0.027 (4.33)	0.026 (4.28)		-0.027 (-6.44)	-0.028 (-6.61)
*REV*HFT*		0.472 (4.53)	0.549 (4.99)		-0.417 (-3.41)	-0.286 (-2.26)
*REV*SIZE*			-0.086 (-1.79)			-0.264 (-3.60)
*REV*BM*			-0.163 (-2.25)			-0.045 (-0.47)
*REV*RET_12*			0.251 (5.49)			0.338 (5.40)
SIZE	-0.089 (-51.15)	-0.091 (-47.51)	-0.091 (-47.41)	-0.085 (-48.20)	-0.083 (-45.63)	-0.083 (-45.86)
BM	0.016 (4.08)	0.015 (3.74)	0.013 (3.21)	0.005 (1.17)	0.006 (1.47)	0.006 (1.54)
RET_12	-0.011 (-6.49)	-0.011 (-6.85)	-0.013 (-7.80)	-0.010 (-6.53)	-0.010 (-6.15)	-0.011 (-6.99)
Firm and time fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.227	0.228	0.228	0.187	0.188	0.189

Table V Regressions of stock returns on earnings surprises and HFT

The dependent variable is either contemporaneous stock returns (RET_t) or future stock returns (RET_{t+1}). *HFT* is high-frequency trading volume. ΔE is earnings surprises. *SIZE* is firm size. *BM* is the book to market ratio. *ERET_12* is the past 12-month stock returns with respect to earnings surprises. Please see appendix for detailed variable definitions. The sample consists of 289,246 firm-quarter observations between 1995Q1 and 2009Q2 with non-missing value of *HFT* and ΔE. For other variables, I set the missing values to their means in the regressions. All variables are winsorized at 1% and 99%, except for RET_t and RET_{t+1}. The regressions are pooled regressions with firm- and year-quarter fixed effects. Standard errors are clustered at the firm level.

	Dep. Var. = RET_t			Dep. Var. = RET_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔE	0.357 (21.88)	0.354 (21.81)	0.378 (26.71)	-0.022 (-1.39)	-0.019 (-1.24)	-0.007 (-0.49)
HFT		0.041 (6.96)	0.041 (6.89)		-0.022 (-5.90)	-0.022 (-6.01)
ΔE*HFT*		0.250 (2.96)	0.282 (3.17)		-0.220 (-3.69)	-0.189 (-3.13)
ΔE*SIZE*			-0.053 (-2.00)			-0.058 (-2.29)
ΔE*BM*			-0.048 (-1.28)			-0.026 (-0.78)
ΔE*ERET_12*			0.095 (3.97)			0.084 (3.65)
SIZE	-0.085 (-53.85)	-0.089 (-50.73)	-0.088 (-50.75)	-0.083 (-53.51)	-0.082 (-51.38)	-0.081 (-51.18)
BM	0.012 (3.57)	0.011 (3.02)	0.010 (2.79)	0.006 (1.99)	0.008 (2.25)	0.007 (2.13)
ERET_12	0.001 (0.80)	0.000 (0.23)	-0.000 (-0.10)	-0.010 (-7.47)	-0.010 (-7.12)	-0.010 (-7.33)
Firm and time fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.153	0.154	0.154	0.146	0.147	0.147

Table VI The effect of measurement error in HFT in the price discovery test

The dependent variable is either contemporaneous stock returns (RET_t) or future stock returns (RET_{t+1}). *HFT* is high-frequency trading volume. *REV* is analyst forecast revision. ΔE is earnings surprises. *SIZE* is firm size. *BM* is the book-to-market ratio. *RET_12* is the past 12-month stock returns. *ERET_12* is the past 12-month stock returns with respect to earnings surprises. Please see the appendix for detailed variable definitions. The sample period is from 1985 to 1994. The sample consists of 102,625 firm-quarter observations with non-missing value of *HFT* and *REV* in Panel A and 134,804 firm-quarter observations with non-missing value of *HFT* and ΔE in Panel B. For other variables, I set the missing values to their means in the regressions. All variables are winsorized at 1% and 99%, except for RET_t and RET_{t+1}. The regressions are pooled regressions with firm- and year-quarter fixed effects. Standard errors are clustered at the firm level.

Panel A: Analyst forecast revision to proxy for fundamental news

	Dep. Var. = RET_t			Dep. Var. = RET_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
REV	1.433 (42.97)	1.427 (43.18)	1.493 (40.98)	-0.003 (-0.08)	-0.011 (-0.32)	-0.005 (-0.15)
HFT		-0.004 (-0.52)	-0.004 (-0.49)		-0.044 (-6.29)	-0.044 (-6.40)
*REV*HFT*		0.353 (1.46)	0.391 (1.59)		0.024 (0.09)	0.077 (0.29)
*REV*SIZE*			0.132 (1.69)			-0.212 (-2.36)
*REV*BM*			-0.251 (-2.34)			0.129 (1.24)
*REV*RET_12*			0.070 (0.91)			0.283 (3.55)
SIZE	-0.084 (-36.35)	-0.084 (-36.00)	-0.084 (-35.96)	-0.070 (-32.21)	-0.069 (-31.65)	-0.069 (-31.48)
BM	0.010 (2.37)	0.011 (2.41)	0.009 (2.08)	0.014 (3.21)	0.016 (3.73)	0.017 (3.84)
RET_12	-0.012 (-5.55)	-0.012 (-5.53)	-0.013 (-6.05)	0.001 (0.31)	0.001 (0.55)	0.000 (0.09)
Firm and time fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.260	0.260	0.261	0.226	0.226	0.227

Panel B: Earnings surprises to proxy for fundamental news

	Dep. Var. = RET_t			Dep. Var. = RET_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔE	0.458 (25.79)	0.457 (25.88)	0.463 (25.65)	0.040 (2.48)	0.039 (2.39)	0.044 (2.79)
HFT		-0.029 (-4.34)	-0.029 (-4.35)		-0.035 (-6.65)	-0.035 (-6.64)
*ΔE*HFT*		0.017 (0.12)	0.018 (0.12)		0.086 (0.95)	0.082 (0.90)
*ΔE*SIZE*			-0.003 (-0.07)			0.021 (0.67)
*ΔE*BM*			-0.035 (-0.77)			-0.004 (-0.12)
*ΔE*ERET_12*			0.004 (0.11)			-0.008 (-0.23)
SIZE	-0.079 (-36.10)	-0.078 (-35.37)	-0.078 (-35.38)	-0.077 (-37.79)	-0.075 (-37.15)	-0.075 (-37.18)
BM	0.016 (3.77)	0.018 (4.04)	0.018 (4.05)	0.001 (0.26)	0.002 (0.70)	0.002 (0.69)
ERET_12	0.000 (0.02)	0.000 (0.05)	0.000 (0.01)	-0.001 (-0.64)	-0.001 (-0.62)	-0.001 (-0.65)
Firm and time fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.189	0.189	0.189	0.171	0.172	0.172

Table VII Regressions of HFT on individual holdings

The dependent variable is high-frequency trading volume (*HFT*). *INDIV* is individual holdings. *SIZE* is firm size. *BM* is the book-to-market ratio. *RET_12* is the past 12-month stock returns. *sdΔROE* is earnings surprise volatility. *sdSGR* is sales growth volatility. *DISP* is analyst forecast dispersion. *LEV* is market leverage. 1/*P* is the inverse of stock price. Please see the appendix for detailed variable definitions. All variables are winsorized at 1% and 99%. Standard errors are clustered at the firm level.

	(1)	(2)	(3)
INTERCEPT	0.277 (61.82)	0.031 (2.92)	-0.012 (-0.79)
INDIV	-0.373 (-61.91)	-0.273 (-37.21)	-0.342 (-35.17)
SIZE		0.028 (23.04)	0.036 (20.33)
BM		0.014 (5.39)	-0.009 (-1.62)
RET_12		0.021 (11.25)	0.034 (11.46)
sdROE			0.057 (5.39)
sdSGR			0.006 (5.39)
DISP			10.61 (21.37)
LEV			0.011 (5.12)
1/P			-0.024 (-1.18)
R^2	0.097	0.148	0.186
# of observations	391,013	307,535	144,259

Table VIII The effect of trading volume on price discovery

The dependent variable is either contemporaneous stock returns (RET_t) or future stock returns (RET_{t+1}). *TO* is trading volume as a percentage of outstanding shares. *REV* is analyst forecast revision. ΔE is earnings surprises. *SIZE* is firm size. *BM* is the book-to-market ratio. *RET_12* is the past 12-month stock returns. Please see the appendix for detailed variable definitions. All variables are winsorized at 1% and 99%, except for RET_t and RET_{t+1}. The regressions are pooled regressions with firm- and year-quarter fixed effects. Standard errors are clustered at the firm level.

Panel A: Analyst forecast revision to proxy for fundamental news

	1977–1984		1985–1994		1995–2009	
	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. Var. = RET_t					
REV	0.887 (26.93)	0.846 (25.01)	1.220 (41.88)	1.237 (42.14)	1.813 (69.64)	1.787 (69.68)
TO		0.460 (16.22)		0.206 (18.14)		0.128 (22.46)
*REV*TO*		2.122 (4.23)		2.714 (9.92)		1.239 (14.05)
SIZE	-0.092 (-28.08)	-0.092 (-21.43)	-0.084 (-36.33)	-0.089 (-33.42)	-0.094 (-54.89)	-0.103 (-52.87)
BM	0.009 (2.33)	0.012 (2.97)	0.027 (7.43)	0.026 (7.08)	0.032 (8.80)	0.034 (9.31)
RET_12	0.021 (9.19)	0.009 (3.38)	0.015 (8.86)	0.004 (2.31)	0.008 (6.58)	0.003 (2.43)
R^2	0.320	0.356	0.261	0.278	0.225	0.235
	Dep. Var. = RET_{t+1}					
REV	0.168 (4.89)	0.173 (4.90)	0.130 (4.12)	0.124 (3.92)	-0.102 (-2.94)	-0.101 (-2.75)
TO		-0.073 (-5.49)		-0.070 (-11.46)		-0.028 (-7.77)
*REV*TO*		-0.209 (-0.58)		-0.394 (-1.89)		-0.224 (-2.14)
SIZE	-0.087 (-26.01)	-0.087 (-25.21)	-0.069 (-34.60)	-0.068 (-34.48)	-0.079 (-48.42)	-0.077 (-46.03)
BM	0.004 (0.88)	0.001 (0.26)	0.022 (6.32)	0.022 (6.29)	0.028 (7.57)	0.028 (7.42)
RET_12	0.015 (6.68)	0.015 (6.16)	0.014 (7.83)	0.017 (9.48)	0.001 (0.55)	0.002 (1.45)
R^2	0.290	0.290	0.215	0.216	0.188	0.188

Panel B: Earnings surprises to proxy for fundamental news

	1977–1984		1985–1994		1995–2009	
	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. Var. = RET_t					
ΔE	0.364 (19.10)	0.365 (18.52)	0.327 (22.13)	0.338 (22.29)	0.304 (23.05)	0.326 (23.87)
TO		0.631 (22.41)		0.380 (27.65)		0.222 (28.52)
$\Delta E*TO$		0.541 (1.93)		1.115 (5.64)		0.630 (7.86)
SIZE	-0.068 (-29.88)	-0.076 (-29.63)	-0.075 (-35.95)	-0.088 (-37.40)	-0.090 (-55.93)	-0.105 (-55.68)
BM	0.029 (9.44)	0.031 (9.71)	0.031 (8.83)	0.029 (8.20)	0.029 (9.22)	0.030 (9.06)
RET_12	0.001 (0.65)	-0.012 (-5.53)	0.005 (3.31)	-0.005 (-3.02)	0.007 (6.48)	0.000 (0.37)
R^2	0.220	0.273	0.162	0.188	0.147	0.168
	Dep. Var. = RET_{t+1}					
ΔE	0.110 (6.84)	0.103 (6.46)	0.078 (5.80)	0.077 (5.72)	0.039 (3.12)	0.039 (2.98)
TO		-0.073 (-5.51)		-0.063 (-9.08)		-0.028 (-7.36)
$\Delta E*TO$		-0.091 (-0.61)		-0.067 (-0.70)		-0.123 (-2.63)
SIZE	-0.070 (-29.96)	-0.069 (-29.51)	-0.079 (-38.68)	-0.077 (-37.35)	-0.085 (-53.92)	-0.083 (-51.32)
BM	0.018 (5.55)	0.018 (5.36)	0.014 (4.08)	0.014 (4.05)	0.022 (7.51)	0.022 (7.38)
RET_12	-0.004 (-2.10)	-0.003 (-1.55)	0.002 (1.66)	0.004 (2.68)	-0.001 (-1.23)	-0.000 (-0.38)
R^2	0.204	0.205	0.145	0.146	0.142	0.144