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A state-space modeling of the information content of trading volume

Khaladdin Rzayev
University of Edinburgh, United Kingdom
London School of Economics and Political Science, United Kingdom

Gbenga Ibikunle*
University of Edinburgh, United Kingdom
Edinburgh Futures Institute, United Kingdom
European Capital Markets Cooperative Research Centre, Pescara, Italy

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Abstract We propose a state-space modeling approach for decomposing trading volume into its liquidity-driven and information-driven components. Using a set of high-frequency S&P 500 stock data, we show that informed trading is linked with a reduction in volatility, illiquidity, and toxicity/adverse selection. We observe that our estimated informed trading component of volume is a statistically significant predictor of one-second stock returns; however, it is not a significant predictor of one-minute stock returns. This disparity is explained by high-frequency trading activity, which eliminates pricing inefficiencies at low latencies.

JEL classification: G12; G14; G15

Keywords: trading volume; permanent component; transitory component; market quality; time series models; state-space modeling; high-frequency trading.

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*Corresponding author (Gbenga Ibikunle): University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh EH8 9JS, United Kingdom; e-mail: Gbenga.Ibikunle@ed.ac.uk; phone: +441316515186.
Khaladdin Rzayev: University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh EH8 9JS, United Kingdom; e-mail: Khaladdin.Rzayev@ed.ac.uk.

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1. Introduction

Trading in financial markets is driven either by information or by the search for liquidity (Admati and Pfleiderer, 1988). Liquidity traders do not trade on the basis of any specific information; their trading strategies are therefore not directly linked to future payoffs. The trading strategies of informed traders, on the other hand, are based on private information and are directly related to future payoffs. The activities of these two fundamental types of traders have been extensively analyzed in seminal papers in the larger financial markets literature, and more so in market microstructure papers. For example, Kyle (1985) predicts that the volatility of asset prices partially reflects inside information (informed trading) and is independent of liquidity-driven trading effects, while Glosten and Milgrom (1985) predict that the breadth of the bid-ask spread is primarily driven by informed trading, which incorporates adverse selection costs into the spread.[1]

More recently however, Kaniel and Liu (2006) have extended Glosten and Milgrom's (1985) model to show that informed traders with long-lived information are more likely to use limit orders than market orders. Therefore, informed traders' trading strategies, depending on the longevity of their information sets, may be negatively related to adverse selection. Using a comprehensive sample of trades from Schedule 13D filings by activist investors, Collin-Dufresne and Fos (2015) show that, consistent with Kaniel and Liu (2006), informed traders with long-lived information typically use limit orders, which leads to a negative correlation between adverse selection and informed trading (see also Collin-Dufresne and Fos, 2016).

In this paper, we build on the above predictions and findings by developing a general state-space-based methodology for decomposing trading volume into unobservable liquidity-driven and

[1] Consistent with Glosten and Milgrom (1985), Easley and O'Hara (1987) also suggest that stock illiquidity should increase in the presence of informed traders, as information asymmetry increases adverse selection, which widens the spread.

information-driven components. According to Hendershott and Menkveld (2014), state-space modeling is a natural tool for modeling an observed variable as the sum of two unobserved variables. While the application of state-space modeling for decomposing price, owing to its efficiency, is very common in the finance literature (e.g., Menkveld et al., 2007; Brogaard et al., 2014; Hendershott and Menkveld, 2014), the approach has thus far not been directly applied to trading volume.[2] This is surprising given the preponderance of literature on the strength of the relation between price and trading volume (e.g., Clark, 1973; Epps and Epps, 1976; Cornell, 1981; Harris, 1986; 1987; Karpoff, 1987).

The heavily evidenced relation shown in the literature is linked to the joint dependence of price and volume on an underlying or set of underlying variable(s); this is the mixture of distribution hypothesis (MDH) (Clark, 1973; Harris, 1986). Harris (1986) argues that the underlying variable is the rate of flow of information. Hence, as new information arrives, traders act on it by revising their positions and consequently increase trading volume. Harris (1987), using NYSE data, provides an empirical basis for the MDH. This implies that the theoretical basis for the application of state-space modeling to price (i.e., that price reflects both information and non-information components) holds for volume.[3] However, it is important to note that while the information component of price is its permanent component, the information component of volume is transitory. This is simply because, although new information implies a new permanent level of price, it will only affect trading volume temporarily, since once prices reflect this information,

[2] McCarthy and Najand (1993) apply state-space modeling to the analysis of price and volume dependence in currency futures.
[3] A second explanation for the existence of the price-volume relation is based on the sequential information models proposed by Copeland (1976), Jennings et al. (1981), and Smirlock and Starks (1984). The models suggest that volume improves the forecasts of price variability and vice versa.

informed traders will no longer hold an informational advantage and will therefore cease their trading based on the exploited information (Fama, 1970; Suominen, 2001; Chordia et al., 2002).

As discussed by Hendershott and Menkveld (2014), the state-space approach holds significant economic value over other methods that could be appropriated for variable decomposition, such as autoregressive models (e.g., Hasbrouck, 1991). Firstly, the estimation of the model using maximum likelihood is asymptotically unbiased and efficient. Secondly, maximum efficiency in dealing with missing values is achieved due to the use of the Kalman filter in the maximum likelihood estimation. The use of the Kalman filter accounts for level changes across periods with missing observations. This is a critical consideration in the use of state-space modeling for decomposing asset prices and trading volume in a high-frequency trading environment such as the one we examine, since standard estimation approaches do not deal with missing observations. For example, estimating a vector autoregression implies truncation of the lag structure. Although standard approaches to decomposing trading volume may work well in a low-frequency environment, information in today's markets travels at such ultra-high speeds that those standard approaches could potentially discard any additional information that could be obtained from high-frequency data. Thirdly, following estimation, the Kalman smoother, which is essentially a backward recursion after a forward recursion with the Kalman filter, facilitates a decomposition of any realized change in the series, such that the estimated permanent or transitory component at any interval is estimated using all past, present, and future observations in the series. Thus, the purpose of filtering is to ensure that estimates are updated with the introduction of every additional observation (see also Durbin and Koopman, 2012).

In line with the expectation that asset price (and by extension, volume) is driven by informed trading and can therefore be decomposed into permanent and transitory components

(Menkveld et al., 2007; Brogaard et al., 2014), we demonstrate that (observable) trading volume is the sum of two unobserved series. The first is a nonstationary series (the permanent component), and the second is a stationary series (the transitory component). We argue that the unobserved permanent component of trading volume is mainly driven by liquidity traders, whereas the unobserved transitory component is primarily driven by informed traders. The permanent component in the state-space model is a nonstationary series and follows a random walk. Consistent with the literature (e.g., Kyle, 1985), liquidity/uninformed traders trade randomly (i.e., the general reference to noise trading in the market microstructure literature), and thus we model the trading volume of liquidity traders as a random walk in the state-space framework. Consequently, the non-random walk component of trading volume is modeled as trading volume due to informed trading activity.

In a test of the validity of the proposed state-space-based volume decomposition approach, we use the estimated permanent and transitory components of trading volume to examine the impact of liquidity and informed trading on market quality metrics, such as volatility, liquidity, and toxicity. This part of our analysis serves as a joint test of the empirical relevance of our state-space model and the impact of informed and liquidity trading on market quality metrics. The relevance of our state-space approach is underscored as our empirical findings are in line with the model predictions in the relevant theoretical market microstructure literature. We examine the predictive power of the estimated information-driven/transitory component of trading volume on short-horizon returns. This analysis furthers demonstrates the relevance of the state-space approach to decomposing trading volume into proxies for informed and liquidity trading. It is also a direct test of the efficiency of the price discovery process (Chordia et al., 2005; 2008). Similar to the order imbalance metrics employed in Chordia et al. (2008), the transitory component, which we deem a proxy for informed trading, is expected to be a predictor of short-horizon returns.

All of our results are consistent with our expectations. Based on our state-space-estimated information and liquidity-driven components of trading volume, we find that after controlling for aggregate trading volume, stock price volatility and liquidity/toxicity are not driven by liquidity trading; however, it is impacted by informed trading. We also find that informed trading reduces price volatility and market toxicity, while enhancing liquidity. The results are robust to alternative estimation frequencies, approaches, and proxies for the market quality metrics. This finding is in line with the theoretical model developed by Collin-Dufresne and Fos (2016),[4] which predicts that the price volatility-informed trading relations is influenced by two effects. On the one hand, informed trading reveals information, which decreases uncertainty in financial markets, thereby reducing price volatility. On the other hand, aggressive trading behavior on the part of informed traders could increase volatility. Thus, the net impact of informed trading on stock price volatility depends on which effect dominates. Under normal trading conditions, the former effect would naturally dominate. Our results are also consistent with the empirical findings of Avramov et al. (2006) and Collin-Dufresne and Fos (2015), who find that price volatility and adverse selection are negatively correlated with informed trading. The negative relations of informed trading with order flow toxicity and illiquidity are linked to informed traders' use of limit orders rather than (aggressive) market orders.

Furthermore, we find that the transitory component, as estimated using our state-space approach, is a significant predictor of one-second stock returns. This implies that, although financial markets are efficient in the long-term, there are short-term inefficiencies in markets

[4] The rational expectation model developed by Wang (1993), via a different mechanism, also predicts a negative relation between informed trading and stock price volatility.

because investors need time to absorb new information (Chordia et al., 2008). However, we find that the horizon for short-term stock return predictability has decreased substantially since the five-minute window reported by Chordia et al. (2008). The predictability of short-horizon returns now only holds on a per-second basis, and no longer at the minutes-long threshold reported in earlier studies. We show that high-frequency trading is the driver of this sharp reduction in the length of short-term return predictability.

Several streams of the literature relate to this study. In some studies, traders are delineated into liquidity- and information-motivated traders (e.g., Avramov et al., 2006), while in others, the roles of the different types of traders are examined to see whether they impact price volatility and liquidity/toxicity (e.g., Daigler and Wiley, 1999; Van Ness et al., 2017). This paper differs from both streams in at least three respects. Firstly, the approach of decomposing trading volume using state-space modeling is fundamentally different than those employed in existing studies and holds noteworthy economic value/significance over other decomposition methods. Secondly, we examine the role of informed trading activity in the evolution of specific market quality metrics, including for a new market quality metric, market toxicity. Finally, and critically, we present new evidence on the speed of price adjustment in the presence of high-frequency trading (HFT)-driven informed order flow.

2. Trading volume and the state-space model

2.1 The application of state-space modeling to trading volume

State-space models are a natural tool for modeling an observed variable as the sum of two unobserved variables. The asymptotic unbiasedness and efficiency of their estimation, i.e., maximum likelihood via the Kalman filter (Brogaard et al., 2014; Hendershott and Menkveld, 2014), make them best suited to analyzing high-frequency time series.

In our setting, the state-space model decomposes trading volume into two parts: the permanent component of trading volume, which is driven by liquidity trading, and the transitory component of trading volume, which is driven by information-motivated trading. Thus, liquidity-motivated trading is expected to constitute the permanent part of trading volume, while informed order flow is expected to make up the transitory part. In other words, uninformed/liquidity order flow is necessary for trading, while informed order flow is not as critical. These expectations are consistent with the predictions of the models of Glosten and Milgrom (1985) and Suominen (2001).

Firstly, the Glosten and Milgrom (1985) model predicts a partial market breakdown if there is an excessive level of informed traders in the market relative to liquidity traders. This is simply because when there is a dearth of liquidity traders in the market, market makers will aim to protect themselves against being adversely selected by widening the spread. Wider spreads make order execution more difficult and trading less likely. As suggested by Glosten and Milgrom (1985), this prediction is congruous with the well-known lemons problems proposed by Akerlof (1970). It simply implies that trading relies on the *permanent* presence of liquidity traders in the market. The permanent character of liquidity order flow is underscored by the well-known "no trade" theorems. While trading may not be informationally efficient in the absence of informed trades, they can still occur because of the dispersion of beliefs inherent in uninformed order flow. This is not the case when liquidity-seeking order flow is unavailable in the market and informed order flow is. Specifically, high levels of informed orders relative to liquidity orders implies that an excessive number of orders will cluster on one side of the order book, leading to no trade scenarios (Brunnermeier, 2001), since there is no dispersion of belief in informed order flow. This is why Morris (1994) argues that no trade problems can be solved by adding liquidity traders to the market. Therefore, the permanent component of trading volume, as modeled using state-space modeling, can be characterized as the liquidity component of trading volume. In addition, generally, liquidity traders are modeled as random traders in the theoretical (e.g., Kyle, 1985). In line with this, in the state-space representation, the permanent component is modeled as a (nonstationary) random walk.

Secondly, Suominen (2001) shows that after trading reveals the private information held by informed traders, liquidity traders will inevitably revise their pricing and thus become more cautious. This may result in a reduction in informed trading in the market. Furthermore, according to the efficient market hypothesis, any new information is simultaneously absorbed by traders, and hence can only cause transitory (short-term) changes in trading volume (Fama, 1970). Similarly, Chordia et al. (2002) argue that private information impacts liquidity temporarily in financial markets. Thus any changes in the information-driven component of trading volume, while having a durable impact on price (Menkveld et al., 2007), should only affect trading volume temporarily. Consistent with this, in the state-space representation, the stationary and transitory component of trading volume, as modeled using state-space modeling, is adopted as a proxy for informed trading activity.

The above arguments provide a firm basis for our modeling approach. Additionally, it is useful to draw comparisons between our state-space modeling approach and a related methodological stream in the financial economics literature. When investigating trading behavior in financial markets, modeling may focus on the duration between transactions as a means of capturing trading intentions, such that the time stamp may be used as an explanatory variable in the mean function of durations. In addition, a cubic spline may be used to smooth out huge variations in the duration effects. Such a model is often regarded as a state-space counterpart of the autoregressive conditional duration (ACD) model of Engle and Russell (1998) (see also Durbin and Koopman, 2012).[5] The ACD is suitable for analyzing trading data with transactions at irregular intervals, and the model is extensively used in the market microstructure literature to test hypotheses about duration and transaction clustering. In our state-space representation, the permanent characteristics of the nonstationary series imply constant duration, whereas the transitory structure of the stationary series requires non-constant duration between transactions. Since the permanent and transitory components of trading volume are motivated by liquidity and informed trades respectively, there should be constant (non-constant) duration in liquidity (informed) trading activity. For example, as transaction duration decreases, we would expect an increase in the speed of price adjustment to new information (Dufour and Engle, 2000). Specifically, if indeed our state-space representation is empirically relevant, then we would expect that non-constant duration or duration clustering is driven by informed trading. The empirical findings in the literature (e.g., Dufour and Engle, 2000; Engle, 2000; Zhang et al., 2001; Russell and Engle, 2005) are in line with this expectation, and therefore provide an additional set of arguments that further underscore the empirical relevance of our state-space approach. However, ultimately, the ACD is an autoregressive model and consequently is less efficient for decomposing an observed variable into unobserved components than the state-space modeling approach using maximum likelihood estimation via the Kalman filter (Durbin and Koopman, 2012; Brogaard et al., 2014; Hendershott and Menkveld, 2014).

[5] Pacurar (2008) provides a review of the duration modeling literature.

2.2 The state-space equation

We model trading volume as the sum of a non-stationary permanent (liquidity-driven) component and a stationary transitory (information-driven) component.[6] In its simplest form, the structure of the state-space model for trading volume, a multiple of *I* stock prices, *T* intraday periods, and *D* intervals, can be expressed as:

$$v_{i,t,\tau} = m_{i,t,\tau} + s_{i,t,\tau} \tag{1}$$

and

$$m_{i,t,\tau} = m_{i,t,\tau-1} + u_{i,t,\tau}, \tag{2}$$

where

$$v_{i,t,\tau} = ln\left(TVolume_{i,t,\tau}\right), \tag{3}$$

for $i = 1,\ldots,I$, $\tau = 1,\ldots,T$, and $t = 1,\ldots,D$; both τ and t index event and calendar times respectively (Menkveld, 2013). $TVolume_{i,t,\tau}$ is the volume traded in stock *i* at interval *t* and period τ, $m_{i,t,\tau}$ is a non-stationary permanent component of the volume traded in stock *i* at interval *t* and period τ, $s_{i,t,\tau}$ is a stationary transitory component of the volume traded in stock *i* at interval *t* and period τ, and $u_{i,t,\tau}$ is an idiosyncratic disturbance error in stock *i* at interval *t* and period τ. $s_{i,t,\tau}$ and $u_{i,t,\tau}$ are assumed to be mutually uncorrelated and normally distributed. The structure of the model shows that only changes in $u_{i,t,\tau}$ affect trading volume permanently; $s_{i,t,\tau}$ is temporary because its effects are ephemeral. By using maximum likelihood (likelihood is constructed using the Kalman filter),[7] we can easily estimate $\sigma_{i,t}^{2u}$ and $\sigma_{i,t}^{2s}$, where *t* equals to one of one second, minute or hour.

[6] In addition to modeling the natural logarithm of trading volume as an observable variable in the state-space representation, for robustness, we also employ level trading volume, percentage changes in trading volume, and first difference of trading volume. Our inferences are unchanged irrespective of the approach we employ; indeed all the estimates obtained are qualitatively similar.

[7] We use the Kalman filter to evaluate the conditional mean and variances of the state vector $\boldsymbol{m_t}$ given past observations $V_{t-1} = \{\boldsymbol{v_1}, .., \boldsymbol{v_{t-1}}\}$: $\boldsymbol{a_{t|t-1}} = \mathrm{E}(\boldsymbol{m_t}|V_{t-1})$, $\boldsymbol{P_{t|t-1}} = \mathrm{var}(\boldsymbol{m_t}|V_{t-1})$, $\quad t = 1, .., N$.

Specifically, we first partition our sample into one second, minute, and hour intervals, then estimate $\sigma_{i,t}^{2u}$ and $\sigma_{i,t}^{2s}$ for these intervals by using trading volume at different periods (τ) during the intervals. This implies that, as in Menkveld et al. (2007), our permanent and transitory components ($\sigma_{i,t}^{2u}$ and $\sigma_{i,t}^{2s}$), as estimated using the state-space model, are time variant [see Table 4 in Menkveld et al. (2007: 220)]. We impose the time-variant structure, because we subsequently use the estimated components in multivariate predictive regressions. Brogaard et al. (2014) also compute time-variant permanent and transitory components of an observable variable (price).

According to the structure of the state-space model, the permanent component of trading volume is due to the activity of the fraction of the market populated by liquidity traders, while the other fraction of the market populated by informed traders reflects the transitory component of trading volume. It implies that our estimated coefficients, $\sigma_{i,t}^{2u}$ and $\sigma_{i,t}^{2s}$, modeled as variances of permanent and transitory trading volume respectively, can be used as proxies for the two fractions of trading volume, i.e., $\sigma_{i,t}^{2u}$ is a proxy for liquidity-motivated trading activity and $\sigma_{i,t}^{2s}$ is a proxy for information-motivated trading activity. Since informed trading occurs only occasionally relative to uninformed trading, which is more regular, we would expect $\sigma_{i,t}^{2s}$ to be higher than $\sigma_{i,t}^{2u}$.

Although a one-second interval is a suitable frequency to investigate HFT activity, it is a very short interval for trade-based measures such as trading volume; hence, we employ one-minute and one-hour interval analysis for robustness. Furthermore, any interval that has fewer than three transactions is excluded from the sample.

In order to initialize the Kalman filter, we also have $\boldsymbol{a_{1|0}} = \boldsymbol{a}$ and $\boldsymbol{P_{1|0}} = \boldsymbol{P}$, where $\boldsymbol{m_1} \sim N(\boldsymbol{a}, \boldsymbol{P})$. This initialization works only if $\boldsymbol{m_t}$ is a stationary process. However, as in our case, often $\boldsymbol{m_t}$ is not a stationary process. Hence, "diffuse initialization" is done and estimated by numerically maximizing the log-likelihood. This is evaluated by the Kalman filter due to prediction error decompositions. It can be shown that when the model is correctly specified, the standardized prediction errors are normally and independently distributed with a unit variance [see Durbin and Koopman (2012) for further details].

The value of our volume decomposition approach is inextricably linked to the relevance of the estimated transitory and permanent components as proxies for informed and liquidity trading respectively. Therefore, in order to test their empirical relevance, we employ a series of predictive multivariate regressions. Specifically, we test whether the estimated components of trading volume's impact on market quality proxies are consistent with the predicted and established patterns in the literature.

2.3 The empirical relevance of state-space decomposition of trading volume: theory and hypotheses

In this subsection, we develop three hypotheses to test the relevance of our state-space modeling approach.

2.3.1. Hypothesis I

Kyle (1985) presents a theoretical model for deriving equilibrium security prices when traders' information sets are asymmetric. The model predicts a constant volatility in a continuous auction system, reflecting information being incorporated into prices at a constant rate. Price volatility in part depends on the informed trader's information as incorporated into prices, and is "unaffected by the level of noise trading" (Kyle, 1985: 1319).[8] Degryse et al. (2013) extend Kyle's (1985) model by adding a large liquidity trader to the framework. They show that when a market maker perceives order flow as uninformed, she does not revise prices, such that the liquidity trader benefits from a lower price impact. This prediction also suggests an insignificant level of

[8] Kalotychou and Staikouras (2009), reviewing several market microstructure models, argue that, consistent with Kyle's (1985) model, only informed traders contribute to volatility in the long run.

uninformed trading-price volatility relation. Crucially, this relation relies on a risk neutrality assumption.

Hellwig (1980) takes a more apt approach by assuming that price reflects information derived from the auctioning activity of risk-averse agents. This assumption yields a prediction of a positive relation between liquidity trading and volatility (see also Daigler and Wiley, 1999; Collin-Dufresne and Fos, 2016). Considered together with the well-documented positive relation between aggregate trading volume and stock price volatility (e.g., Karpoff, 1987; Lamoureux and Lastrapes, 1990; Lee and Rui, 2002; Park, 2010), the implication of the above prediction is that, in a framework controlling for aggregate trading volume, the positive relation between volatility and liquidity trading activity dissipates. This is because, as argued by Daigler and Wiley (1999) and Collin-Dufresne and Fos (2016), the positive relation between trading volume and volatility is driven by liquidity trading. Furthermore, Hellwig (1980) shows that informed trading activity decreases volatility in financial markets (see also Wang, 1993; Avramov et al., 2006), implying a negative relation between volatility and informed trading activity.

We would therefore expect that the negative relation between informed trading and volatility will endure in a framework controlling for trading volume. Conversely, there should be no expectation of a statistically significant relation between liquidity trading and volatility once volume is controlled for, since liquidity trading is the main driver of the trading volume-volatility relation. We exploit these predicted relations in a test of the validity of our state-space modeling approach. Specifically, we test the following hypothesis:

Hypothesis I. The state-space model-estimated transitory component of trading volume reduces volatility.

2.3.2. Hypothesis II

In the market microstructure literature, the bid-ask spread holds economic significance for the market maker (e.g., Branch and Freed, 1977). Huang and Stoll (1997) show that the bid-ask spread incorporates three costs: the order processing cost, the inventory holding cost, and the adverse selection cost. Huang and Stoll (1997) and Bollen et al. (2004) argue that order processing and inventory holding costs respectively are not related to the type of traders active in the market, since a market maker incurs those costs irrespective of who they trade with. However, the adverse selection cost is trader type dependent. Glosten and Milgrom (1985) and Easley and O'Hara (1987) predict that the adverse selection cost is due to market makers facing adverse selection risk when they trade with informed traders. This means that the bid-ask spread is driven by informed trading activity. Order flow is considered toxic when market makers are adversely selected by informed traders in a high-frequency environment (Easley et al., 2011). Hence, market toxicity is seen as the high-frequency equivalent of adverse selection risk. We would therefore expect market toxicity to rise in line with increases in the adverse selection cost and the widening of the bid-ask spread. The widening of the bid-ask spread implies a reduction in liquidity.

While an increase in informed trading activity could lead to increased adverse selection risk for the market maker and induce a widening of the spread, this effect is often eclipsed by an overall increase in trading volume due to aggregate (uninformed and informed) trading activity. This is because informed trading mainly occurs in tandem with uninformed trading. According to Admati and Pfleiderer (1988), increases in uninformed/liquidity trading volume go hand in hand with induced informed trading volume, such that liquidity-seeking trading activity provides an opportunity for informed traders to camouflage their trades. This implies that informed traders would normally trade only when their trades could be disguised, and uninformed trading activity offers the opportunity for disguising informed trades. This is logical since if informed orders are identified ahead of execution, they would no longer be beneficial for informed traders and therefore could no longer be considered informed.

Kyle (1985) also states that an increase in noise trading induces a higher level of informed trading (see also Ibikunle, 2018). Ibikunle (2018) provides empirical evidence that informed traders increase their trading activity in the presence of higher trading volumes, which is shown to be dominated by uninformed trading activity. Increased trading activity has the effect of enhancing liquidity and therefore inducing a narrowing of the bid-ask spread [see Biais et al. (1999) and Barclay and Hendershott (2003) for further empirical evidence]. Hence, we would expect a positive relation between market liquidity and informed trading activity. This expectation is consistent with Kyle (1981; 1984; 1985; 1989) showing that informed trading activity is positively related to market liquidity (see also Collin-Dufresne and Fos, 2015). Improvements in liquidity imply a narrowing of the bid-ask spread and by extension a reduction in market toxicity.

Furthermore, according to Collin-Dufresne and Fos (2015), informed traders with long-lived information mainly use limit orders. This helps them avoid detection and leads to a negative correlation between adverse selection and informed trading. Consequently, we test the following hypothesis:

Hypothesis II. The state-space model-estimated transitory component of trading volume enhances liquidity and reduces market toxicity.

2.3.3. Hypothesis III

According to Fama (1970), financial markets are largely informationally efficient over a daily horizon. Chordia et al. (2002; 2008), however, argue that there are inefficiencies in markets at shorter horizons because traders need time to act on new information. Motivated by this, Chordia et al. (2002; 2008) examine the predictability of short-term returns from lagged order imbalance and find that, indeed, markets are inefficient over short periods. They use order imbalance in their own regressions to investigate the predictability of short-horizon returns for two reasons. Firstly, order imbalance signals private information, which should result in a permanent price impact [this is also alluded to by Kyle (1985)]. Secondly, large order imbalances exacerbate the inventory problem faced by the market maker, leading to quote revisions and changes in the bid-ask spread. Similarly, we argue that our transitory component of trading volume signals private information, and thus we expect the component to be a significant predictor of short-horizon stock returns and, by extension, an inverse predictor of market efficiency (Chordia et al., 2008; Chung and Hrazdil, 2010).

The informative element of both Chordia et al.'s (2002; 2008) order imbalance measure and our own state-space-based transitory component of trading volume[9] measure make them suitable predictors in the short-horizon return predictive regressions. Consequently, our third hypothesis is as follows:

Hypothesis III. The state-space model-estimated transitory component of trading volume is a significant predictor of short-horizon returns.

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[9] In addition, the idea that returns depend on trading volume (or its components) is consistent with the literature. The relation between return and lagged trading volume is predicted by the sequential information arrival model developed by Copeland (1976) and Jennings et al. (1981). In this model, it is assumed that initially, new information is observed only by a trader, leading to her revising her beliefs and beginning to trade advantageously with the information. This informed trading activity generates a new equilibrium price, and therefore returns (price changes). Specifically, in sequential information flow models, contemporaneous absolute stock returns can be predicted by lagged trading volume [see also Hiemstra and Jones (1994)].

3. Data and measures

3.1 Data

We use two sets of data in this study. The first consists of ultra-high-frequency tick-by-tick data for the most active 100 S&P 500 stocks, as sourced from the Thomson Reuters Tick History (TRTH) database; trading activity is measured by dollar trading volume. The first dataset includes data for the trading days between October 2016 and September 2017. In the dataset, each message is recorded with a time stamp to the nearest millisecond, and the following variables are included: Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume, and ask volume. We apply Lee and Ready's (1991) algorithm to classify trades as buyer- or seller-initiated.[10] The final dataset after cleaning[11] contains about 216.37 million trades, out of which 106.89 million (109.48 million) are buyer- (seller-) initiated. The total value of all trades captured in the analysis equals US$3.28 trillion.

The second dataset is used to execute additional out-of-sample tests of the validity of our state-space modeling approach. It is a proprietary dataset obtained from NASDAQ, and contains transactions for 120 randomly selected NASDAQ and NYSE-listed stocks trading during all the trading days in 2009. The data are complementary to the first dataset we employ because it disaggregates transactions into those executed based on orders submitted by HFTs and non-HFTs. This is the same dataset described in detail by Brogaard et al. (2014). The dataset contains the following information on each transaction included in the sample: date, time (in milliseconds), transaction size (shares), price, buy-sell indicator, and liquidity nature of the two sides to each trade (HH, HN, NH, and NN). HH indicates a trade based on an HFT demanding liquidity and an

[10] Chakrabarty et al. (2015) compare the different trades classification methods and conclude that Lee and Ready's (1991) method is the most accurate.
[11] We follow Chordia et al. (2001) and Ibikunle (2015) in applying a standard set of exclusion criteria to the data, with the aim of eliminating inexplicable values due to erroneous data entry.

HFT supplying the required liquidity. HN implies that an HFT demands liquidity and a non-HFT supplies liquidity, while NH is the opposite. NN refers to trades where both counterparties are non-HFTs. We designate the sum of HH, HN, and NH as HFT volume. Based on this classification, HFTs are counterparties in about 71.30% of all trades in the sample. The NASDAQ-provided dataset is only used in Section 5, where further justification for its use is outlined.

3.2 Measures and descriptive statistics

In order to conduct a joint test of the empirical relevance of our state-space modeling approach and the impact of liquidity and informed trading on price volatility, liquidity, and market toxicity, we estimate a set of predictive regressions. Thus, apart from the state-space-estimated permanent and transitory components of trading volume, our volatility, liquidity, and market toxicity measures are the main variables of interest. Below we elaborate on how these and other relevant variables are computed.

3.2.1. Volatility measures

Consistent with the literature, we use the absolute value of price changes, $|\Delta p_{i,t}|$, as the main proxy for stock price volatility (Karpoff, 1987). $\Delta p_{i,t}$ is the difference in price change between the last transaction prices, p, for stock *i* at intervals *t* and *t*-1.

For robustness, we also proxy volatility using the standard deviation of stock returns $\sigma_{i,t}^{R}$ (Malceniece et al., 2019; Lamoureux and Lastrapes, 1990; Barclay and Hendershott, 2003; 2008), where R is the midpoint-to-midpoint return with each midpoint computed using the best bid and ask quotes corresponding to each transaction in stock *i* during interval *t*; R is thus defined in event/transaction time. The standard deviation of these returns within each interval *t* is our volatility measure. This midpoint-based approach is used to reduce the incidence of bid-ask bounce, which transaction prices are susceptible to (Avramov et al., 2006; Chordia et al., 2008). However, an alternative set of volatility estimates computed from transaction prices do not yield materially different results. Interval *t* corresponds to one of one second, minute or hour for both volatility proxies.

3.2.2. Liquidity measures

For robustness, we employ three spread measures as inverse proxies for liquidity; the spread metrics are the effective spread ($Espread_{i,t}$), quoted spread ($Qspread_{i,t}$), and relative spread ($Rspread_{i,t}$). The $Rspread_{i,t}$ is obtained by dividing the difference between interval *t*'s best ask and bid prices by the average of both the ask and bid prices for stock i, while the $Qspread_{i,t}$ is simply the difference between interval *t*'s best ask and bid prices for stock *i*. The $Espread_{i,t}$ is twice the absolute value of the difference between the last transaction price for stock *i* in interval *t* and the midpoint of the prevailing bid and ask prices when the transaction occurs for stock *i*. Interval *t* corresponds to one of one second, minute or hour for all liquidity proxies.

3.2.3. Market toxicity

We use the nominal order imbalance metric employed by Chordia et al. (2008) as a proxy for the level of order flow toxicity in the market; in this paper, we call the measure $MT_{i,t}$. This is because existing order toxicity measures, such as the volume synchronized probability of informed trading [VPIN; see Easley et al. (2012)], essentially capture the essence of order imbalance in the market, thus are highly correlated with $MT_{i,t}$. $MT_{i,t}$ is computed as the absolute value of the number of buyer-initiated trades minus the number of seller-initiated trades divided by the total number of trades for stock i during interval t, where t corresponds to one of one-minute or one-hour. We employ only minute and hour intervals because it is challenging to obtain enough trading volume for the lower volume stocks to compute unbiased order imbalance metrics within a one-second interval.

3.2.4. Volume measures

In our state-space model, trading volume is the observable variable, which is then decomposed into unobservable proxies of liquidity trading activity $\left(\sigma_{i,t}^{2u}\right)$ and informed trading activity $\left(\sigma_{i,t}^{2s}\right)$ in stock i at time t. Thus, the proxies could be mechanically correlated with trading activity and volume. In order to ascertain that the observed effects of the proxies are not due to aggregate trading volume, we need to include at least one proxy for trading volume/activity in our secondary models. This is particularly important in our framework since Andersen and Bondarenko (2014) show that the relation between VPIN, also estimated from trading volume, and future short-term volatility is trivial after controlling for mechanic correlation between VPIN and trading volume. Controlling for trading volume/activity in our secondary models addresses the Andersen and Bondarenko (2014) criticism. We employ the natural logarithm of trading volume for stock i at time t ($TV_{i,t}$) as a proxy for trading volume. A second trading activity-related proxy is also included in our models: $BSI_{i,t}$. $BSI_{i,t}$ is the absolute value of the difference between buyer- and seller-initiated trades for stock i during interval t. According to Chordia et al. (2002), the metric adequately proxies trading activity because it strongly influences prices and liquidity.

INSERT TABLE 1 ABOUT HERE

Table 1 presents the descriptive statistics for volatility, liquidity, market toxicity, and volume metrics. Midpoint return estimates for stock i at time t, $R_{i,t}$s, are also presented. All measures except that of market toxicity $\left(MT_{i,t}\right)$ are based on one-second computations; $MT_{i,t}$ is based on one-minute calculations. Consistent with recent evidence (e.g., Malceniece et al., 2019), the spread measures are tight, with the average $Espread_{i,t}$, $Rspread_{i,t}$, and $Qspread_{i,t}$ corresponding to 0.009, 0.0004, and 0.018, respectively. Average midpoint returns are weakly negative over our sample period. However, volatility is generally low irrespective of which proxy we focus on. The mean and median for $\left|\Delta p_{i,t}\right|$ are about 0.0092 and 0.009 respectively, while $\sigma_{i,t}^{R}$ is lower still at 0.00009.

4. Analysis of state-space decomposition of trading volume

4.1 State-space decomposition of trading volume: estimates

Table 2 presents the cross-sectional mean estimated values of the permanent (liquidity-driven) and transitory (information-driven) components of trading volume as decomposed using the state-space model. The mean estimates are based on one-second, one-minute, and one-hour estimations. For improved insight, we divide our sample into quartiles according to their level of trading activity; trading activity is measured by dollar trading volume. The stocks in Quartile 1 are the least active stocks, while Quartile 4 stocks are the most active. As expected, the mean $\sigma_{i,t}^{2s}$ is consistently higher than the mean $\sigma_{i,t}^{2u}$ across all quartiles, irrespective of the estimation frequency of the state-space model. This is consistent with the structure of our state-space modeling approach. Informed trades are modeled as transitory, occurring only when traders have an informational advantage in the market, while uninformed trades are a permanent fixture in markets. This implies a higher variance for informed trades, hence we would expect higher estimates for $\sigma_{i,t}^{2s}$ relative to $\sigma_{i,t}^{2u}$.

INSERT TABLE 2 ABOUT HERE

Informed traders are, strategically, more active when trading volume and liquidity trading are high, because higher trading volumes provide better "camouflage" for informed trades (Admati and Pfleiderer, 1988). The estimates in Table 2 are consistent with this widely-held view in the market microstructure literature. The mean $\sigma_{i,t}^{2u}$ estimate in the Quartile 4 stocks is higher than the mean $\sigma_{i,t}^{2u}$ in all of the other quartiles, and is lowest in the Quartile 1 stocks. This suggests that informed traders should be most active in Quartile 4 and least active in Quartile 1. The $\sigma_{i,t}^{2s}$ estimates in Table 2 are completely in line with this expectation. The mean $\sigma_{i,t}^{2s}$ in Quartile 4 are 1.51, 1.88, and 1.96 for the one-second, one-minute and one-hour estimations respectively. These estimates are 48%, 55.37%, and 46.27% larger than the one-second, one-minute, and one-hour frequencies mean estimated values for Quartile 1 stocks at 1.02, 1.21, and 1.34 respectively.

Inferring from the Kyle (1985) and Glosten and Milgrom (1985) models, when uninformed traders are scarce in the market, the price discovery process becomes impaired or even breaks down. This is because the prospect of compensation for gathering information is reduced in markets where uninformed traders are few, and this leads to fewer than optimal potential informed traders being incentivized to acquire information. The absence of informed traders impairs the price discovery process, since their trades convey information to the market. Thus, both liquidity and informed traders are critical to the price discovery process. An approach that allows us to directly estimate the proportion of trading volume that can be attributed to both types of traders is therefore valuable in several contexts, not least in market reporting activities, investment management, and policy/regulations development. For example, firm managers' responses to the so-called *speeding ticket* (price and volume query) often issued by some exchanges, such as the Australian Securities Exchange, focus mainly on explaining the evolution of trading volume.

4.2 State-space decomposition of trading volume: analysis of empirical relevance

4.2.1 *Hypothesis I: State-space model-estimated components of trading volume and volatility*

We estimate the multivariate predictive model presented in equation (4) to examine the relation between the state-space estimated proxies of liquidity $\left(\sigma_{i,t}^{2u}\right)$ and informed $\left(\sigma_{i,t}^{2s}\right)$ trading on the one hand and volatility on the other. This is a direct test of Hypothesis I.

$$\left|\Delta p_{i,t}\right| = \alpha + \beta_1 Espread_{i,t-1} + \beta_2 TV_{i,t-1} + \beta_3 BSI_{i,t-1} + \beta_4 \sigma_{i,t-1}^{2s} + \beta_5 \sigma_{i,t-1}^{2u} + \varepsilon_{i,t}, \quad (4),$$

where all variables are as defined in Subsection 3.2. Equation (4) is estimated at one-second, one-minute, and one-hour intervals. $\sigma_{i,t-1}^{2s}$ and $\sigma_{i,t-1}^{2u}$, the proxies for informed and uninformed/liquidity trading respectively, are estimated from trading volume. Multicollinearity may therefore be of potential concern, since we include two proxies of trading activity ($TV_{i,t-1}$ and $BSI_{i,t-1}$) in the model. However, as shown in Table 3, this is not the case. Note that our state-space representation models, we model informed and uninformed trading volume as variances of transitory and permanent trading volume. We employ these variance measures as proxies of informed and uninformed trading volume in equation (4), and subsequent models. Therefore, collinearity is not expected in the regression framework. Consistent with this view, the correlation coefficient estimates in Table 3 show that there are no multicollinearity issues in our empirical models.

INSERT TABLE 3 ABOUT HERE

As stated in Subsection 3.2.1, for robustness, we employ a second volatility proxy (i.e., the standard deviation of midpoint returns). Consistent with the literature, we include the proxy's lagged value as an additional explanatory variable (e.g., Schwert, 1989; Justiniano and Primiceri, 2008) in equation (5):

$$\sigma_{i,t}^{R} = \alpha + \beta_1 \sigma_{i,t-1}^{R} + \beta_2 Espread_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5 \sigma_{i,t-1}^{2s} + \beta_6 \sigma_{i,t-1}^{2u} + \varepsilon_{i,t},$$

(5)

where all variables are as previously defined. Equations (4) and (5) are estimated using pooled least squares with panel corrected standard errors. For robustness, we also include stock and date fixed effects both separately and jointly. All of the estimation approaches yield qualitatively similar results.

Both of the volatility proxies we employ encapsulate all variation in stock prices; no distinction is made between permanent and temporary price changes. This approach is based on the extensive market microstructure literature stream reporting the impact of various market phenomena on market quality proxies (e.g., Malceniece et al., 2019; Buti et al., 2011; Comerton-Forde and Putniņš, 2015). The purpose of this analysis is to test the empirical relevance of our state-space modeling approach by verifying whether the estimated components of trading volume affect market quality variables as predicted in the literature (see Subsection 2.3), hence our adoption of the volatility measures developed in the literature.

The results obtained from the estimation of equations (4) and (5) are in Table 4.

INSERT TABLE 4 ABOUT HERE

The inferences drawn from the estimates in Table 4 are consistent across all frequency estimations. The coefficient estimates show that lagged $\sigma_{i,t}^{2s}$ is a significant predictor of the absolute value of price changes, $\left|\Delta p_{i,t}\right|$, and the standard deviation of stock returns, $\sigma_{i,t}^{R}$; the $\sigma_{i,t}^{2s}$ coefficients are negative and statistically significant at the 0.01 level. The estimates indicate that increases in information-motivated trading reduce price volatility in financial markets. This result is consistent with the findings of Avramov et al. (2006), who find that stock price volatility is negatively correlated with informed trading activity (see also Hellwig, 1980; Wang, 1993). Hypothesis I is therefore upheld.

In contrast, $\sigma_{i,t}^{2u}$ is not a significant predictor of volatility once we control for volume. This is because the positive relation between trading volume and volatility is driven by trading volume due to liquidity trading (Daigler and Wiley, 1999; Collin-Dufresne and Fos, 2016).[12] The significant negative $\sigma_{i,t}^{2s}$ and the insignificant $\sigma_{i,t}^{2u}$ coefficient estimates imply a validation of our state-space approach to decomposing trading volume into informed and liquidity-driven components.

We note that while the coefficient estimates are consistent for all estimation frequencies across both panels, the impact of $\sigma_{i,t}^{2s}$ is stronger for lower frequencies. For example, in Panel A (B) of Table 4, the effect of $\sigma_{i,t}^{2s}$ on volatility proxies for the one-hour frequency estimation is 6.65 (124.28) and 98.80 (1,249) times larger than that of the one-minute and one-second frequency estimations respectively. These differences are due to more information being typically released over longer intervals. It is plausible that the market learns more about the developments relevant to an instrument over an hour than over a second or a minute, or at the very least, comes to terms more with new information over a longer time horizon. The estimated coefficients for all the remaining variables are consistent with the literature.

The explanatory powers of the one-second regressions are low, with the $\overline{R^2}$ being only about 0.40% for $|\Delta p_{i,t}|$ in Panel A and 0.92% for $\sigma_{i,t}^{R}$ in Panel B. This is unsurprising and is because we estimate the models at a one-second frequency, with very little information being released

[12] For robustness and in a test of the arguments presented by Collin-Dufresne and Fos (2016) and Daigler and Wiley (1999), i.e., that a positive volume-volatility relation is driven by liquidity trading, we exclude the trading volume proxy from a follow-up model. We find that once trading volume is not controlled for, the liquidity trading proxy becomes a positive and statistically significant predictor of volatility. For parsimony, we do not show this result in the paper, however it is available upon request.

during the very narrow window (Chordia et al., 2008). Consequently, the $\overline{R^2}$ estimates are larger for the one-minute and one-hour frequencies, which are 1.71% and 5.27% respectively in Panel B.

4.2.2 *Hypothesis II: State-space model-estimated components of trading volume, liquidity and market toxicity*

We next test Hypothesis II. Specifically, we investigate the nature of the relation between our state-space model-estimated components of trading volume on the one hand, and liquidity and market toxicity on the other. For this purpose, we estimate the following multivariate predictive models:

$$Spread_{i,t} = \alpha + \beta_1\sigma^{p}_{i,t-1} + \beta_2 TV_{i,t-1} + \beta_3 BSI_{i,t-1} + \beta_4\sigma^{2s}_{i,t-1} + \beta_5\sigma^{2u}_{i,t-1} + \varepsilon_{i,t} \quad (6),$$

$$MT_{i,t} = \alpha + \beta_1\sigma^{p}_{i,t-1} + \beta_2 TV_{i,t-1} + \beta_3 BSI_{i,t-1} + \beta_4\sigma^{2s}_{i,t-1} + \beta_5\sigma^{2u}_{i,t-1} + \varepsilon_{i,t}, \quad (7),$$

where $Spread_{i,t}$ corresponds to one of $Espread_{i,t}$, $Qspread_{i,t}$, and $Rspread_{i,t}$. All variables are as previously defined. Equation (6) is estimated at one-second, one-minute, and one-hour frequencies, while equation (7) is estimated at one-minute and one-hour frequencies only. This is because trading activity during a one-second interval is minimal and not substantial enough to compute $MT_{i,t}$ within the interval in an unbiased manner.

INSERT TABLE 5 ABOUT HERE

Panels A, B, and C of Table 5 show the results for equation (6), where $Rspread_{i,t}$, $Qspread_{i,t}$, and $Espread_{i,t}$ correspond to $Spread_{i,t}$ respectively. The negative and statistically significant (*p*-value = <0.01) $\sigma^{2s}_{i,t-1}$ coefficient estimates show that, consistent with Hypothesis II and the predictions of Kyle (1981; 1984; 1985; 1989), informed trading activity is positively linked to liquidity. By contrast, $\sigma^{2u}_{i,t-1}$'s coefficient estimates are not statistically significant, suggesting that $\sigma_{i,t}^{2u}$ is not a significant predictor of liquidity once we control for volume and order flow dynamics. This is in line with the estimates for equation (5). The results are also consistent with the empirical findings of Collin-Dufresne and Fos (2015) and suggest that, as predicted by Kaniel and Liu (2006), informed traders use limit orders rather than market orders. The coefficients of all of the control variables are in line with the literature. The consistency of the results with previous studies emphasize the relevance of our state-space modeling approach. Similar to the price volatility model, $\overline{R^2}$ values in Panels A, B, and C are generally small for the one-second and one-minute high-frequency estimations, with estimates ranging from 0.37% to 1.45%. The low $\overline{R^2}$ values are due to the estimation frequencies. Hence, the one-hour frequency models have much higher explanatory power. In Panels A, B, and C, the $\overline{R^2}$ values are 14.01%, 11.15%, and 10.18% respectively for the one-hour frequency estimations.

INSERT TABLE 6 ABOUT HERE

Table 6 presents the estimated coefficients for the model estimated at one-minute and one-hour frequencies. Consistent with the results in Tables 4 and 5, $\sigma_{i,t-1}^{2s}$ is negatively and statistically significantly related to $MT_{i,t}$ at the 0.01 level of statistical significance; however, $\sigma_{i,t-1}^{2u}$ is not, once volume and order flow dynamic are controlled for. The inverse relation between the $MT_{i,t}$ and $\sigma_{i,t-1}^{2s}$ suggests that information-motivated trading volume reduces order flow toxicity in financial markets, even after controlling for the overall impact of trading volume and volatility. This is in line with the arguments that informed trading, which is dependent on uninformed trading activity, enhances liquidity (Kyle, 1981; 1984; 1985; 1989). Another explanation for the ameliorating effect of informed trading on market toxicity is presented by Admati and Pfleiderer (1988), who show that when informed traders observe the same information signal (a plausible scenario), they compete against each other to exploit the signal. This competition may lead to the market maker facing reduced adverse selection risk. When faced with reduced adverse selection risk, market makers will respond with tighter spreads, implying a reduction in toxic order flow.

Although all other control variables are significant in the one-minute frequency model estimation, the explanatory power of the regression is small, with the $\overline{R^2}$ being only about 0.14%, again owing to the high frequency of the model estimation. This view is underscored by the larger $\overline{R^2}$ value for the one-hour frequency estimation at 2.85%.

4.2.3. *Hypothesis III: State-space model-estimated components of trading volume and short-horizon returns*

As outlined in Subsection 2.3.3, Hypothesis III suggests that $\sigma_{i,t}^{2s}$ is a significant predictor of short-horizon stock returns. In a test of this hypothesis, we estimate the following regression model:

$$R_{i,t} = \alpha + \beta_1\sigma_{i,t-1}^{p} + \beta_2 Espread_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5\sigma_{i,t-1}^{2s} + \varepsilon_{i,t}, \qquad (8)$$

where all of the variables are as previously defined. All variables are computed over a one-second frequency.

INSERT TABLE 7 ABOUT HERE

Table 7 presents the estimated coefficients for equation (8). All of the coefficients, except β_1 (for $\sigma_{i,t-1}^{R}$), are statistically significant at the 0.01 level. These results are a validation of Hypothesis III and thus further emphasizes the empirical relevance of our state-space modeling approach. The statistically significant relation between $\sigma_{i,t-1}^{2s}$ and one-second $R_{i,t}$ implies that $\sigma_{i,t}^{2s}$, as obtained using the state-space modeling approach, signals private information similar to the order imbalance metrics used by Chordia et al. (2008). The $\sigma_{i,t-1}^{2s}$ coefficient estimate is negative, suggesting that an increase in the level of informed trading eliminates/reduces return predictability/arbitrage (Hellwig, 1980; Wang, 1993). The $\overline{R^2}$ is 0.06%. The low $\overline{R^2}$ is linked to the estimation frequency of the regression model, which is one second in this case.

An estimation of the model over a lower frequency, such as the one-minute interval, could also prove insightful. This is because the trading volume in our sample appears to be mainly driven by HFTs, given the sample period and market we focus on (Brogaard et al., 2014). Thus, if HFTs are responsible for driving a substantial portion of the informed trading volume, the predictability of stock return should be greatly diminished over a one-minute interval, since a one-minute interval cannot be considered a short-horizon in an HFT-driven market. We estimate the following regression at a one-minute frequency; the only difference to equation (8) is the addition of $MT_{i,t}$, which can only be validly computed at a minimum frequency of about one minute:

$$R_{i,t} = \alpha + \beta_1\sigma_{i,t-1}^{p} + \beta_2 Espread_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5\sigma_{i,t-1}^{2s} + \beta_6 MT_{i,t-1} + \varepsilon_{i,t.} \tag{9}$$

In this model, we expect that the coefficients for the two information signal proxies, i.e., $MT_{i,t-1}$ and $\sigma_{i,t-1}^{2s}$, will not be statistically significant at the one-minute interval because of the superfast trading systems of HFTs trading in S&P 500 stocks.

The final column of Table 7 presents the estimated coefficients for equation (9). As predicted, $\sigma_{i,t-1}^{2s}$'s coefficient is not statistically significant, owing to the lack of return predictability over a time period stretching into a minute. However, the $\overline{R^2}$ coefficient at 0.09% is larger than for the one-second frequency estimation from equation (8). The lack of statistical significance for $\sigma_{i,t-1}^{2s}$'s coefficient in the one-minute frequency regression model is due to the prevalence of HFT activity in the data we use, and the ability of HFTs to absorb and act on new information at a fast pace, which eliminates arbitrage opportunities. This leads to the elimination of return predictability at less than ultra-high frequencies. $MT_{i,t-1}$ is an information signal based on the order imbalance metric used by Chordia et al. (2008); however, in contrast to the results presented by Chordia et al. (2008), the metric is not statistically significant here. This shows that while one-second stock returns are predictable from lagged metrics that signal private information, one-minute stock returns are not predictable in financial markets dominated by HFTs.

A key finding here is that although $\sigma_{i,t}^{2s}$ is a lag predictor of one-second stock returns, one-minute stock returns are not predictable using either $\sigma_{i,t}^{2s}$ or the order imbalance metric $MT_{i,t}$ inspired by Chordia et al. (2008). Thus, the latter part of the findings is not consistent with the results presented by Chordia et al. (2008), who show that even five-minute stock returns can be predicted from past order imbalance. The inconsistency here is linked to the data period employed by both studies. While Chordia et al. (2008) employ a dataset covering the years 1993 to 2002, when HFTs were not the main drivers of trading in financial markets, the analysis in this section is based on a much more recent dataset from 2016 to 2017. In Section 5, we show that, based on 2009 data, 71% of the NASDAQ and NYSE trading volume is linked to HFT activity. It is therefore not surprising to find that in recent years, the speed of price adjustment through the incorporation of new information has become much higher.

5. High-frequency trading and return predictability[13]

In Subsection 4.2.3, we argue that the lack of a statistically significant relation between $\sigma_{i,t}^{2_s}$ and one-minute $R_{i,t}$ is due to HFTs driving a faster incorporation of information into prices. In this subsection, we substantiate this theory by addressing the role of HFTs in the elimination of return predictability. In comparison with non-HFTs, HFTs could be viewed as being informed, simply on the basis that they trade with either private or public information (e.g., the sudden arrest of a firm's CEO for fraudulent activities) at a faster pace than non-HFTs. This is referred to as latency arbitrage; it involves the exploitation of a trading time disparity between fast and slow traders, when that trade is executed solely because of a speed advantage. Ibikunle (2018) argues that this speed advantage is tantamount to an informational advantage when traders trade at different speeds, since the end result remains the same—a set of traders exploit information (whether private or public) ahead of a different set of traders. Thus, exchanges with infrastructures that especially accommodate HFTs tend to display efficient prices ahead of others when instruments are traded simultaneously across those exchanges. This is the case with the analysis of price leadership in the London equity market conducted by Ibikunle (2018). Brogaard et al. (2014) and Chaboud et al. (2014) show that HFTs enhance informational efficiency by speeding up price discovery and eliminating arbitrage opportunities.

In order to capture the transitory nature of informed trading volumes linked to HFT activity, we design a test that reflects the extent of transitory informed trading in the market when arbitrageurs observe that the instruments' prices have deviated from their underlying values. We note that, while HFTs could be considered informed in comparison with non-HFTs, not all HFTs employ arbitrage strategies. Hagströmer and Nordén (2013) and Menkveld (2013) show that the

[13] We are grateful to an anonymous referee for suggesting this analysis.

majority of HFTs (about 80%) typically apply market making strategies. Furthermore, in a market dominated by HFTs, the speed advantage will not consistently confer appreciable advantages over their competitors, who are also fast. Thus, our test is designed to capture the changes in HFT volumes attributable to informed HFT activity.

For the test, we use the transactions dataset for 120 NASDAQ and NYSE stocks obtained from the NASDAQ. Employing the dataset, we re-estimate equations (8) and (9) by adding the new variable, $D_{HFT,i,t-1} * \sigma^{2s}_{i,t-1}$ and substituting $Espread_{i,t-1}$ for $Illiq_{i,t-1}$:

$$R_{i,t} = \alpha + \beta_1 \sigma^{p}_{i,t-1} + \beta_2 Illiq_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5 \sigma^{2s}_{i,t-1} + \beta_6 D_{HFT,i,t-1} * \sigma^{2s}_{i,t-1} + \varepsilon_{i,t} \quad (10)$$

$$R_{i,t} = \alpha + \beta_1 \sigma^{p}_{i,t-1} + \beta_2 Illiq_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5 \sigma^{2s}_{i,t-1} + \beta_6 MT_{i,t-1} + \beta_7 D_{HFT,i,t-1} * \sigma^{2s}_{i,t-1} + \varepsilon_{i,t}. \quad (11)$$

$D_{HFT,i,t-1} * \sigma^{2s}_{i,t-1}$ is obtained by interacting a new variable, $D_{HFT,i,t-1}$, with the lag transitory component variable, $\sigma^{2s}_{i,t-1}$. $D_{HFT,i,t-1}$ is a dummy variable equaling one for stock *i* for interval *t*-1 during periods of high HFT activity. In order to determine the intervals of high HFT activity, we compute the proportion of HFT trades to non-HFT trades using the designations (HFT/non-HFT) for the transactions in the NASDAQ data. A one-second or one-minute interval is designated as an interval of high HFT activity if the fraction of HFT trades for that interval is one standard deviation higher than the mean for the surrounding -60, +60 corresponding intervals. Intervals correspond to one-second or one-minute. No other interval is considered because the literature (e.g., Chordia et al., 2008) shows that short-horizon predictability is eliminated within a few minutes. All HFT trades may not be identifiable in the NASDAQ dataset, as pointed out by Brogaard et al. (2014). Hence, for robustness, we employ an alternative measure of HFT activity in our analysis; this is the widely deployed proxy based on the ratio of messages to the number of transactions (e.g., Malceniece et al., 2019; Boehmer et al., 2012). $Illiq_{i,t-1}$ is a proxy for one period lag illiquidity and corresponds to one of either the Amihud (2002) illiquidity ratio or $Espread_{i,t}$. As for equations (8) and (9), equations (10) and (11) are estimated at one-second and one-minute frequencies respectively.

If $D_{HFT,i,t-1} * \sigma^{2s}_{i,t-1}$'s coefficient is negative and statistically significant, it implies that a transitory rise in HFT activity is informed and reduces return predictability. This conclusion will be especially strengthened if $\sigma^{2s}_{i,t-1}$ is not statistically significant in equations (10) and (11), since it would imply that the reduction in return predictability is primarily driven by transitory HFT volume. A result of this nature would be in line with one of the assumptions underlying our state-space modeling approach, i.e., informed trading volume is transitory and only arises to exploit deviations in the price of an instrument from its fundamental value.

INSERT TABLE 8 ABOUT HERE

In Table 8, we present the results based on the two approaches to computing D_{HFT}; Panel A shows the results using the NASDAQ-defined HFT/non-HFT transactions, while Panel B shows the results using the ratio of messages to transactions HFT proxy. $Illiq_{i,t}$ corresponds to the Amihud (2002) illiquidity ratio and $Espread_{i,t}$ in Panels A and B respectively. Contrary to the results in Table 7, although it remains negative, $\sigma^{2s}_{i,t-1}$'s coefficients for the one-second frequency estimation in both panels are not statistically significant. However, when the transitory component variable is interacted with $D_{HFT,i,t-1}$, it becomes highly statistically significant, while also retaining its negative sign. This implies that the reduction in the return predictability observed in the earlier analysis is driven by informed HFT activity. Consistent with the assumption underlying our state-space modeling approach, the transitory component of trading volume, i.e., an increase in HFT volume above the mean, aids the speedy incorporation of information into instruments' prices and leads to the elimination of arbitrage opportunities. With this analysis, we ascertain that the transitory trading volume component relevant to eliminating return predictability in today's financial markets is the HFT kind.

6. Conclusion

In this paper, we conduct a state-space decomposition of trading volume into its liquidity-driven (permanent) and information-driven (transitory) components. We argue that the permanent component of trading volume is driven by liquidity-seeking order flow, while the transitory component is driven by information-motivated order flow. In addition to providing a robust set of arguments grounded in the literature to support our hypotheses, we further develop a set of multivariate regression models to formally test them. Firstly, we find that the transitory component of trading volume obtained from our state-space model has a statistically significantly relation with volatility, liquidity, and market toxicity/adverse selection, even after controlling for volume. Specifically, informed trading is linked with a reduction in volatility, illiquidity, and market toxicity/adverse selection. There is no such relation observed for the permanent component once volume is controlled for. These results are consistent with an extensive stream of theoretical and empirical studies on the relation of the informed and liquidity trading activity with volatility, liquidity, and market toxicity. The consistency therefore implies that the permanent and transitory components, estimated using our state-space modeling approach, can be viewed as encapsulating liquidity- and information-motivated trades, respectively.

We also demonstrate that the transitory component is a significant predictor of short-horizon returns. This underscores the argument that the transitory component is a proxy for private information. However, in contrast to Chordia et al. (2008), we find that one-minute returns cannot be predicted using either the state-space-estimated transitory component or the minute(s)-long order imbalance metrics employed by Chordia et al. (2008). This implies that in today's high-frequency trading environment, arbitrage opportunities are eliminated at a much faster rate than in the early 2000s period examined in earlier studies. We show that this sharp decline in the window for return predictability is driven by HFT activity.

References

Admati AR, Pfleiderer P. A Theory of Intraday Patterns: Volume and Price Variability. The Review of Financial Studies, 1 (1) (1988), 3-40.

Akerlof GA. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. The Quarterly Journal of Economics, 84 (3) (1970), 488-500.

Amihud Y. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, 5 (1) (2002), 31-56.

Andersen T, Bondarenko O. VPIN and the flash crash. Journal of Financial Markets, 17 (2014), 1-46.

Avramov D, Chordia T, Goyal A. The Impact of Trades on Daily Volatility. The Review of Financial Studies, 19 (4) (2006), 1241-1277.

Barclay MJ, Hendershott T. Price Discovery and Trading After Hours. The Review of Financial Studies, 16 (4) (2003), 1041-1073.

Barclay MJ, Hendershott T. A comparison of trading and non-trading mechanisms for price discovery. Journal of Empirical Finance, 15 (5) (2008), 839-849.

Biais B, Hillion P, Spatt C. Price Discovery and Learning during the Preopening Period in the Paris Bourse. Journal of Political Economy, 107 (6) (1999), 1218-1248.

Boehmer E, Fong KYL, Wu J. International evidence on algorithmic trading. (2012) Working paper.

Bollen NPB, Smith T, Whaley RE. Modeling the bid/askspread: measuring the inventory-holding premium. Journal of Financial Economics, 72 (1) (2004), 97-141.

Branch B, Freed W. Bid-Asked Spreads on the AMEX and the Big Board. The Journal of Finance, 32 (1) (1977), 159-163.

Brogaard J, Hendershott T, Riordan R. High-Frequency Trading and Price Discovery. The Review of Financial Studies, 27 (8) (2014), 2267-2306.

Brunnermeier MK. Asset Pricing Under Asymmetric Information: Bubbles, Crashes, Technical Analysis, and Herding. Oxford University Press (2001).

Buti S, Rindi B, Werner IM. Diving into Dark Pools. (2011) Working paper.

Chaboud AP, Chiquoine B, Hjalmarsson E, Vega C. Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market. The Journal of Finance, 69 (5) (2014), 2045-2084.

Chakrabarty B, Moulton P, Shkilko A. Evaluating Trade Classification Algorithms: Bulk Volume Classification versus the Tick Rule and the Lee-Ready Algorithm. Journal of Financial Markets, 25 (2015), 52-79.

Chordia T, Roll R, Subrahmanyam A. Market Liquidity and Trading Activity. The Journal of Finance, 56 (2) (2001), 501-530.

Chordia T, Roll R, Subrahmanyam A. Order imbalance, liquidity, and market returns. Journal of Financial Economics, 65 (1) (2002), 111-130.

Chordia T, Roll R, Subrahmanyam A. Evidence on the speed of convergence to market efficiency. Journal of Financial Economics, 76 (2) (2005), 271-292.

Chordia T, Roll R, Subrahmanyam A. Liquidity and market efficieny. Journal of Financial Economics, 87 (2) (2008), 249-268.

Chung D, Hrazdil K. Liquidity and market efficiency: A large sample study. Journal of Banking & Finance, 34 (10) (2010), 2346-2357.

Clark PK. A subordinated stochastic process model with finite variance for speculative prices. Econometrica, 41 (1) (1973), 135-155.

Collin-Dufresne P, Fos V. Do Prices Reveal the Presence of Informed Trading? The Journal of Finance, 70 (4) (2015), 1555-1582.

Collin-Dufresne P, Fos V. Insider Trading, Stochastic Liquidity, and Equilibrium prices. Econometrica, 84 (4) (2016), 1441-1475.

Comerton-Forde C, Putniņš TJ. Dark trading and price discovery. Journal of Financial Economics, 118 (1) (2015), 70-92.

Copeland TE. A Model of Asset Trading Under the Assumption of Sequential Information Arrival. The Journal of Finance, 31 (4) (1976), 1149-1168.

Cornell B. The Relationship between Volume and Price Variability in Futures Markets. Journal of Futures Markets, 1 (3) (1981), 303-316.

Daigler RT, Wiley MK. The Impact of Trader Type on the Futures Volatility-Volume Relation. The Journal of Finance, 54 (6) (1999), 2297-2316.

Degryse H, de Jong F, van Kervel V. Does order splitting signal uninformed order flow? (2013) Working paper.

Dufour A, Engle RF. Time and the impact of a trade. The Journal of Finance, 55 (6) (2000), 2467–2498.

Durbin J, Koopman S. Time Series Analysis by State Space Models. Oxford University Press (2012).

Easley D, De Prado M, O'Hara M. The microstructure of the "flash crash": flow toxicity, liquidity crashes, and the probability of informed trading. Journal of Portfolio Management, 37 (2) (2011), 118-128.

Easley D, De Prado M, O'Hara M. Flow Toxicity and Liquidity in a High-frequency World. The Review of Financial Studies, 25 (5) (2012), 1457-1493.

Easley D, O'Hara M. Price, trade size, and information in securities markets. Journal of Financial Economics, 19 (1) (1987), 69-90.

Engle RF. The econometrics of ultra-high frequency data. Econometrica, 68 (1) (2000), 1–22.

Engle RF, Russell JR. Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data. Econometrica, 66 (5) (1998), 1127-1162.

Epps TW, Epps ML. The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distributions Hypothesis. Econometrica, 44 (2) (1976), 305-321.

Fama E. Efficient capital markets: a review of theory and empirical work. The Journal of Finance, 25 (2) (1970), 383-417.

Glosten L, Milgrom P. Bid, ask, and transaction prices in a specialist market with heterogeneously informed agents. Journal of Financial Economics, 14 (1) (1985), 71-100.

Hagströmer B, Nordén L. The diversity of high-frequency traders. Journal of Financial Markets, 16 (4) (2013), 741-770.

Harris L. Cross-security Tests of the Mixture of Distributions Hypothesis. Journal of Financial and Quantitative Analysis, 21 (1) (1986), 39-46.

Harris L. Transactions Data Tests of the Mixture of Distributions Hypothesis. Journal of Financial and Quantitative Analysis, 22 (2) (1987), 127-141.

Hasbrouck J. Measuring the Information Content of Stock Trades. The Journal of Finance, 46 (1) (1991), 179-207.

Hellwig MF. On the Aggregation of Information in Competitive Markets. Journal of Economic Theory, 22 (3) (1980), 477-498.

Hendershott T, Menkveld AJ. Price pressures. Journal of Financial Economics, 114 (3) (2014), 405-423.

Hiemstra C, Jones JD. Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. The Journal of Finance, 49 (5) (1994), 1639-1664.

Huang RD, Stoll HR. The Components of the Bid-Ask Spread: A General Approach. The Review of Financial Studies, 10 (4) (1997), 995-1034.

Ibikunle G. Opening and closing price efficiency: Do financial markets need the call auction? Journal of International Financial Markets, Institutions & Money, 34 (2015), 208-227.

Ibikunle G. Trading places: Price leadership and the competition for order flow. Journal of Empirical Finance, 49 (2018), 178-200.

Jennings RH, Starks LT, Fellingham JC. An Equilibrium Model of Asset Trading with Sequential Information Arrival. The Journal of Finance, 36 (1) (1981), 143-161.

Justiniano A, Primiceri GE. The Time-Varying Volatility of Macroeconomic Fluctuations. American Economic Review, 98 (3) (2008), 604-641.

Kalotychou E, Staikouras SK. Stock Market Volatility. Taylor & Francis Group (2009).

Kaniel R, Liu H. So What Orders Do Informed Traders Use? The Journal of Business, 79 (4) (2006), 1867-1913.

Karpoff JM. The Relation Between Price Changes and Trading Volume: A Survey. Journal of Financial and Quantitative Analysis, 22 (1) (1987), 109-126.

Kyle AS. An Equilibrium Model of Speculation and Hedging. (1981). University of Chicago PhD Thesis.

Kyle AS. Market Structure, Information, Futures Markets, and Price Formation. Westview Press (1984).

Kyle AS. Continuous Auctions and Insider Trading. Econometrica, 53 (6) (1985), 1315-1336.

Kyle AS. Informed Speculation with Imperfect Competition. The Review of Economic Studies, 56 (3) (1989), 317-355.

Lamoureux CG, Lastrapes WD. Heteroskedasticity in Stock Return Data: Volume versus GARCH effects. The Journal of Finance, 45 (1) (1990), 221-229.

Lee BS, Rui OM. The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. Journal of Banking & Finance, 26 (1) (2002), 51-78.

Lee C, Ready M. Inferring Trade Direction from Intraday Data. The Journal of Finance, 46 (2) (1991), 733-746.

Malceniece L, Malcenieks K, Putniņš TJ. High Frequency Trading and Co-Movement in Financial Markets. Journal of Financial Economics, Forthcoming (2019).

McCarthy J, Najand M. State Space Modeling of Price and Volume Dependence: Evidence from Currency Futures. Journal of Futures Markets, 13 (4) (1993), 335-344.

Menkveld AJ. High frequency trading and the new market makers. Journal of Financial Markets, 16 (4) (2013), 712-741.

Menkveld AJ, Koopman SJ, Lucas A. Modeling Around-the-Clock Price Discovery for Cross-Listed Stocks Using State Space Methods. Journal of Business & Economic Statistics, 25 (2) (2007), 213-225.

Morris S. Trade with Heterogeneous Prior Beliefs and Asymmetric Information. Econometrica, 62 (6) (1994), 1327-1347.

Pacurar M. Autoregressive conditional duration models in finance: A survey of the theoretical and empirical literature. Journal of Economic Surveys, 22 (4) (2008), 711-751.

Park B. Surprising information, the MDH, and the relationship between volatility and trading volume. Journal of Financial Markets, 13 (3) (2010), 344-366.

Russell JR, Engle RF. A discrete-state continous-time model of financial transactions prices and times: the autoregressive conditional multinomialautoregressive conditional duration model. Journal of Business and Economic Statistics, 23 (2) (2005), 166–180.

Schwert GW. Why Does Stock Market Volatility Change Over Time? The Journal of Finance, 44 (5) (1989), 1115-1153.

Smirlock M, Starks L. A Transactions Approach to Testing Information Arrival Models. Washington University (1984).

Suominen M. Trading Volume and Information Revelation in Stock Markets. the Journal of Financial and Quantitative Analysis, 36 (4) (2001), 545-565.

Van Ness BF, Van Ness RA, Yildiz S. The role of HFTs in order flow toxicity and stock price variance, and predicting changes in HFTs' liquidity provisions. Journal of Economics and Finance, 41 (4) (2017), 739-762.

Wang J. A Model of Intertemporal Asset Prices Under Asymmetric Information. The Review of Economic Studies, 60 (2) (1993), 249-282.

Zhang MY, Russell JR, Tsay RS. A nonlinear autoregressive conditional duration model with applications to financial transaction data. Journal of Econometrics, 104 (1) (2001), 179–207.

Table 1. Definitions of variables and descriptive statistics

In this table, we define the variables calculated for each stock-interval, *i*, *t*, and report the descriptive statistics. All variables, except $MT_{i,t}$, are computed at a one-second frequency (t equals one-second). $MT_{i,t}$ is computed at a one-minute frequency. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on the NYSE and the NASDAQ.

Variable	Description	Mean	Median	Std. Dev.
$Espread_{i,t}$	Effective spread for stock *i* at interval *t*. Computed as twice the absolute value of the difference between the last execution price and the midpoint of the prevailing bid and ask prices at interval *t*.	0.0091	0.0100	0.0463
$Rspread_{i,t}$	Relative spread for stock *i* at interval *t*. Computed as the difference between the best ask and bid prices divided by the midpoint of both prices during interval *t*.	0.0004	0.0003	0.0009
$Qspread_{i,t}$	Quoted spread for stock *i* at interval *t*. Computed as the difference between the best ask and bid prices during interval *t*.	0.0186	0.0100	0.0564
$BSI_{i,t}$	Absolute difference between buyer- and seller-initiated trades for stock *i* during interval *t*.	1584.05	424.00	35771
$\|\Delta p_{i,t}\|$	Absolute value of price change for stock *i* during interval *t*. Computed as the absolute value of the differences between last prices at intervals *t* and *t*-1.	0.0092	0.0090	0.0671
$R_{i,t}$	Midpoint-to-midpoint return for stock *i* during interval *t*. Computed as the difference between the midpoints corresponding to the last transactions at intervals *t* and *t*-1 divided by the midpoint corresponding to the last transaction at interval *t*-1	-0.412×10^{-6}	0.00	0.0014
$\sigma_{i,t}^{R}$	Standard deviation of midpoint-to-midpoint returns for stock *i* during interval *t*; each midpoint during the interval *t* corresponds to a transaction occurring during the interval.	0.92×10^{-4}	0.59×10^{-4}	0.0009
$MT_{i,t}$	Market toxicity for stock *i* for interval *t*. Computed as the absolute value of the difference between the numbers of buy and sell trades divided by the sum of the numbers of buy and sell trades occurring during interval *t*.	0.5407	0.50375	0.3419

Table 2. State-space estimates

The table shows the mean cross-sectional estimates of transitory (information-driven) and permanent (liquidity-driven) components of trading volume for the most active 100 S&P 500 stocks trading between October 1, 2016 and September 30, 2017. Stocks are divided into quartiles according to their level of trading activity; trading activity is based on trading volume. Quartile 1 contains the least active companies, while Quartile 4 contains the most active stocks. The estimates are based on the following state-space model for decomposing trading volume into its transitory and permanent components:

$v_{i,t,\tau} = m_{i,t,\tau} + s_{i,t,\tau}$; $m_{i,t,\tau} = m_{i,t,\tau-1} + u_{i,t,\tau}$.,where $v_{i,t,\tau} = ln(TVolume_{i,t,\tau})$, i = 1,…,*I (stocks)*, t = 1,...,D *(intervals)*, τ = 1,...,T *(periods)*, $TVolume_{i,t,\tau}$ corresponds to the trading volume of stock *i* at interval *t* and period τ, $m_{i,t,\tau}$ is a non-stationary permanent component of stock *i* at interval t, and period τ, $s_{i,t,\tau}$ is a stationary transitory component for stock *i* at interval *t* and period τ and $u_{i,t,\tau}$ is an idiosyncratic disturbance error for stock *i* at interval t and period τ. $\sigma_{i,t}^{2_s}$ and $\sigma_{i,t}^{2_u}$ are the respective estimates of the transitory and permanent components of trading volume for stock i and interval t, estimated by maximum likelihood (constructed using the Kalman filter). Estimations are presented for one-second, one-minute, and one-hour frequencies (t equals one-second, one-minute, and one-hour).

	Stock quartiles			
Variable	Least active	2	3	Most active
One-second frequency (*t* equals one-second)				
$\sigma_{i,t}^{2_s}$	1.02	1.24	1.37	1.51
$\sigma_{i,t}^{2_u}$	0.46	0.49	0.53	0.78
One-minute frequency (*t* equals one-minute)				
$\sigma_{i,t}^{2_s}$	1.21	1.36	1.63	1.88
$\sigma_{i,t}^{2_u}$	0.49	0.55	0.72	0.85
One-hour frequency (*t* equals one-hour)				
$\sigma_{i,t}^{2_s}$	1.34	1.65	1.77	1.96
$\sigma_{i,t}^{2_u}$	0.51	0.59	0.76	0.97

Table 3. Correlation matrix for variables

The table shows the correlation matrix of the variables. One-second frequency (t equals one-second) is used to compute all variables. $Qspread_{i,t}$ is the quoted spread for stock i for interval t and is computed as the difference between the best ask and bid prices for interval t. $Rspread_{i,t}$ is the relative spread for stock i and interval t and is computed as the difference between the best ask and bid prices divided by the midpoint of both prices for interval t. $Espread_{i,t}$ is the effective spread for stock i for interval t and computed as twice the absolute value of the difference between the last execution price and the midpoint of the prevailing bid and ask prices for interval t, $TV_{i,t}$ is the natural logarithm of trading volume for stock i for interval t, while $BSI_{i,t}$ is the absolute difference between buyer- and seller-initiated traders for stock i for interval t. $\sigma_{i,t}^{2_s}$ is the state-space model-estimated transitory component of trading volume and is the proxy for informed trading in stock i during interval t, while $\sigma_{i,t}^{2_u}$ is the state-space model-estimated permanent component of trading volume and is the proxy for liquidity trading in stock i during interval t. $|\Delta p_{i,t}|$ is the absolute value of price change for stock i for interval t and is computed as the absolute value of the differences between the last prices at intervals t and t-1, while $\sigma_{i,t}^{R}$ is the standard deviation of midpoint-to-midpoint returns for stock i during interval t; each midpoint corresponds to a transaction. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on NYSE and NASDAQ.

	$Qspread_{i,t}$	$Rspread_{i,t}$	$Espread_{i,t}$	$TV_{i,t}$	$BSI_{i,t}$	$\sigma_{i,t}^{2_s}$	$\sigma_{i,t}^{2_u}$	$\|\Delta p_{i,t}\|$	$\sigma_{i,t}^{R}$
$Qspread_{i,t}$	1								
$Rspread_{i,t}$	0.7991	1							
$Espread_{i,t}$	0.9072	0.7248	1						
$TV_{i,t}$	-0.0414	-0.0626	-0.0167	1					
$BSI_{i,t}$	0.0013	0.0127	0.0028	0.1109	1				
$\sigma_{i,t}^{2_s}$	0.0000	0.0001	0.0001	0.0033	0.4434	1			
$\sigma_{i,t}^{2_u}$	0.0000	-0.0000	0.0001	0.0002	-0.0000	-0.0000	1		
$\|\Delta p_{i,t}\|$	0.0862	0.0505	0.0679	0.0190	0.0110	0.0000	0.0001	1	
$\sigma_{i,t}^{R}$	0.1238	0.1638	0.1148	0.0170	0.0105	0.0000	0.0000	0.4291	1

Table 4. Predictive regressions of market volatility on lagged components of trading volume

The table shows the results for the estimation of the predictive power of state-space estimated one-second/minute/hour permanent and transitory components of trading volume using the following models:

$$\left|\Delta p_{i,t}\right| = \alpha + \beta_1 Espread_{i,t-1} + \beta_2 TV_{i,t-1} + \beta_3 BSI_{i,t-1} + \beta_4 \sigma^{2s}_{i,t-1} + \beta_5 \sigma^{2u}_{i,t-1} + \varepsilon_{i,t}$$

$$\sigma^{R}_{i,t} = \alpha + \beta_1 \sigma^{p}_{i,t-1} + \beta_2 Espread_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5 \sigma^{2s}_{i,t-1} + \beta_6 \sigma^{2u}_{i,t-1} + \varepsilon_{i,t},$$

where $\left|\Delta p_{i,t}\right|$ is the absolute value of price change for stock *i* and interval *t* and computed as the absolute value of the differences between last prices at intervals *t* and *t*-1, $Espread_{i,t-1}$ is the effective spread for stock *i* for interval *t*-1 and computed as twice the absolute value of the difference between the last execution price and the midpoint of the prevailing bid and ask prices for interval *t*-1. $\sigma^{R}_{i,t-1}$ is the standard deviation of midpoint-to-midpoint returns for stock *i* during interval *t*-1; each midpoint corresponds to a transaction. $TV_{i,t-1}$ is the natural logarithm of trading volume for stock *i* and interval *t*-1, and $BSI_{i,t-1}$ is the absolute difference between buyer- and seller-initiated traders for stock *i* and interval *t*-1. $\sigma^{2s}_{i,t-1}$and $\sigma^{2u}_{i,t-1}$ are state-space model-estimated proxies (estimated using Kalman filter constructed maximum likelihood) for informed and uninformed trading activity respectively for stock *i* and interval *t*-1. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on NYSE and NASDAQ. ***, **, and * correspond to statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A. The effects of lagged components of trading volume on the absolute value of price change

	Dependent Variable: $\lvert\Delta p_{i,t}\rvert$		
	One-second frequency	One-minute frequency	One-hour frequency
$Intercept$	$0.847\text{x}10^{-2***}$ (681.52)	$0.198\text{x}10^{-1***}$ (138.29)	$0.110\text{x}10^{-1***}$ (26.05)
$Espread_{i,t-1}$	$0.742\text{x}10^{-1***}$ (280.32)	$0.457\text{x}10^{-1***}$ (76.42)	$0.287\text{x}10^{-1***}$ (15.34)
$TV_{i,t-1}$	$0.967\text{x}10^{-3***}$ (14.98)	$0.410\text{x}10^{-2***}$ (6.45)	$0.177\text{x}10^{-2***}$ (4.07)
$BSI_{i,t-1}$	$0.100\text{x}10^{-6***}$ (152.25)	$0.134\text{x}10^{-6***}$ (130.21)	$0.758\text{x}10^{-6***}$ (13.66)
$\sigma^{2s}_{i,t-1}$	$-0.334\text{x}10^{-4***}$ (-12.89)	$-0.496\text{x}10^{-3***}$ (-7.95)	$-0.330\text{x}10^{-2***}$ (-4.87)
$\sigma^{2u}_{i,t-1}$	$0.842\text{x}10^{-5}$ (0.15)	$-0.211\text{x}10^{-4}$ (-0.07)	$-0.863\text{x}10^{-4}$ (-0.03)
Sample size *(n)*	29959938	8880028	204354
$\overline{R^2}$	0.40 %	0.86 %	3.17 %

Panel B. The effects of lagged components of trading volume on the standard deviation of midpoint-to-midpoint returns

	Dependent Variable: $\sigma^{R}_{i,t}$		
	One-second frequency	One-minute frequency	One-hour frequency
$Intercept$	$0.741\text{x}10^{-4***}$ (426.41)	$0.740\text{x}10^{-4***}$ (256.55)	$0.789\text{x}10^{-4***}$ (14.75)
$\sigma^{R}_{i,t-1}$	$0.133\text{x}10^{-1***}$ (86.44)	$0.377\text{x}10^{-1***}$ (50.32)	0.6191^{***} (86.09)
$Espread_{i,t-1}$	$0.147\text{x}10^{-2***}$ (394.72)	$0.158\text{x}10^{-2***}$ (59.77)	$0.414\text{x}10^{-4}$ (1.50)
$TV_{i,t-1}$	$0.839\text{x}10^{-5***}$ (9.30)	$0.865\text{x}10^{-5***}$ (8.83)	$0.115\text{x}10^{-4***}$ (5.55)
$BSI_{i,t-1}$	$0.221\text{x}10^{-8***}$ (265.98)	$0.222\text{x}10^{-8***}$ (135.22)	$0.204\text{x}10^{-8***}$ (29.48)
$\sigma^{2s}_{i,t-1}$	$-0.721\text{x}10^{-6***}$ (-19.92)	$-0.725\text{x}10^{-5***}$ (-16.76)	$-0.901\text{x}10^{-3***}$ (-12.71)
$\sigma^{2u}_{i,t-1}$	$0.761\text{x}10^{-7}$ (0.01)	$0.687\text{x}10^{-6}$ (0.03)	$-0.575\text{x}10^{-3}$ (-0.01)
Sample size *(n)*	29959938	8880028	204354
$\overline{R^2}$	0.92%	1.71%	5.27%

Table 5. Predictive regressions of market liquidity on lagged components of trading volume

The table shows the results for the estimation of the predictive power of the state-space-estimated lagged permanent and transitory components of trading volume using the following model:

$$Spread_{i,t} = \alpha + \beta_1 \sigma^R_{i,t-1} + \beta_2 TV_{i,t-1} + \beta_3 BSI_{i,t-1} + \beta_4 \sigma^{2_s}_{i,t-1} + \beta_5 \sigma^{2_u}_{i,t-1} + \varepsilon_{i,t}$$

where $Spread_{i,t}$ corresponds to one of $Espread_{i,t}$, $Qspread_{i,t}$ and $Rspread_{i,t}$. $Espread_{i,t}$ is the effective spread for stock *i* at interval *t* and is computed as twice the absolute value of the difference between the last execution price and the midpoint of the prevailing bid and ask prices for interval *t*, $Rspread_{i,t}$ is the relative spread for stock *i* at interval *t* and is obtained by dividing the difference between the best ask and bid prices by the midpoint of both prices for interval t, $Qspread_{i,t}$ is the quoted spread for stock *i* for interval *t* and computed as the difference between the best ask and bid prices for interval *t*. $\sigma^R_{i,t-1}$ is the standard deviation of mid-price returns for stock *i* during interval *t*-1 and calculated as the standard deviation of midpoint-to-midpoint returns during interval *t*-1; each midpoint corresponds to a transaction. $TV_{i,t-1}$ is the natural logarithm of trading volume for stock *i* during interval *t*-1 and $BSI_{i,t-1}$ is the absolute difference between buyer- and seller-initiated traders for stock *i* during interval *t*-1. $\sigma^{2_s}_{i,t-1}$ and $\sigma^{2_u}_{i,t-1}$ are state-space model-estimated proxies (estimated using Kalman filter constructed maximum likelihood) for informed and uninformed trading activity respectively for stock *i* and interval *t*-1. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on NYSE and NASDAQ. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. The effects of lagged components of trading volume on relative spread

Dependent Variable: $RSpread_{i,t}$			
	One-second frequency	One-minute frequency	One-hour frequency
$Intercept$	$0.385\text{x}10^{-3***}$	$0.435\text{x}10^{-3***}$	$0.497\text{x}10^{-3***}$
	(240.73)	(181.54)	(47.93)
$\sigma^R_{i,t-1}$	$0.608\text{x}10^{-1***}$	$0.199\text{x}10^{-3***}$	$0.203\text{x}10^{-1***}$
	(241.98)	(57.72)	(71.57)
$TV_{i,t-1}$	$0.677\text{x}10^{-5}$	$0.927\text{x}10^{-4}$	$-0.492\text{x}10^{-4}$
	(0.80)	(1.41)	(-0.12)
$BSI_{i,t-1}$	$0.252\text{x}10^{-8***}$	$0.246\text{x}10^{-8***}$	$0.825\text{x}10^{-8***}$
	(387.31)	(231.72)	(61.22)
$\sigma^{2_s}_{i,t-1}$	$-0.902\text{x}10^{-5***}$	$-0.979\text{x}10^{-4***}$	$-0.349\text{x}10^{-4***}$
	(-26.48)	(-15.25)	(-12.23)
$\sigma^{2_u}_{i,t-1}$	$-0.352\text{x}10^{-6}$	$-0.258\text{x}10^{-4}$	$-0.615\text{x}10^{-4}$
	(-0.05)	(-0.08)	(-0.08)
Sample size *(n)*	29959938	8880028	204354
$\overline{R^2}$	1.09%	1.45%	14.01%

Panel B. The effects of lagged components of trading volume on quoted spread

Dependent Variable: $QSpread_{i,t}$			
	One-second frequency	One-minute frequency	One-hour frequency
$Intercept$	$0.182\text{x}10^{-1***}$	$0.179\text{x}10^{-1***}$	$0.230\text{x}10^{-1***}$
	(181.80)	(93.45)	(31.74)
$\sigma^R_{i,t-1}$	2.767^{***}	2.24^{***}	128^{***}
	(230.62)	(101.94)	(55.54)
$TV_{i,t-1}$	$-0.918\text{x}10^{-3*}$	$-0.145\text{x}10^{-3}$	$-0.385\text{x}10^{-2}$
	(-1.74)	(-0.35)	(-1.37)
$BSI_{i,t-1}$	$0.921\text{x}10^{-7***}$	$0.968\text{x}10^{-7***}$	$0.352\text{x}10^{-7***}$
	(182.69)	(143.04)	(37.42)
$\sigma^{2_s}_{i,t-1}$	$-0.329\text{x}10^{-4***}$	$-0.386\text{x}10^{-4***}$	$-0.155\text{x}10^{-3***}$
	(-15.50)	(-9.44)	(-6.22)
$\sigma^{2_u}_{i,t-1}$	$0.116\text{x}10^{-6}$	$0.310\text{x}10^{-6}$	$-0.284\text{x}10^{-5}$
	(0.03)	(0.02)	(-0.05)
Sample size *(n)*	29959938	8880028	204354
$\overline{R^2}$	0.49%	1.08%	11.15%

Panel C. The effects of lagged components of trading volume on effective spread

Dependent Variable: $ESpread_{i,t}$			
	One-second frequency	One-minute frequency	One-hour frequency
$Intercept$	$0.874\text{x}10^{-2***}$	$0.882\text{x}10^{-2***}$	$0.981\text{x}10^{-2***}$
	(107.46)	(67.52)	(15.54)
$\sigma_{i,t-1}^{R}$	2.009^{***}	13.34^{***}	107.66^{***}
	(127.41)	(71.03)	(14.92)
$TV_{i,t-1}$	$-0.160\text{x}10^{-3***}$	$-0.102\text{x}10^{-3}$	$-0.197\text{x}10^{-2}$
	(-3.74)	(-0.28)	(-0.80)
$BSI_{i,t-1}$	$0.604\text{x}10^{-7***}$	$0.634\text{x}10^{-7***}$	$0.240\text{x}10^{-6***}$
	(118.35)	(89.80)	(29.34)
$\sigma_{i,t-1}^{2_s}$	$-0.216\text{x}10^{-4***}$	$-0.254\text{x}10^{-4***}$	$-0.107\text{x}10^{-3***}$
	(-12.55)	(-11.23)	(-12.80)
$\sigma_{i,t-1}^{2_u}$	$-0.758\text{x}10^{-4}$	$-0.186\text{x}10^{-4}$	$-0.208\text{x}10^{-4}$
	(-0.20)	(-0.11)	(-0.04)
Sample size *(n)*	29959938	8880028	204354
$\overline{R^2}$	0.37%	1.09%	10.18%

Table 6. Predictive regressions of market toxicity on lagged components of trading volume

The table shows the results for the estimation of the predictive power of the state-space-estimated lagged permanent and transitory components of trading volume using the following model:

$$MT_{i,t} = \alpha + \beta_1\sigma^R_{i,t-1} + \beta_2 TV_{i,t-1} + \beta_3 BSI_{i,t-1} + \beta_4\sigma^{2_s}_{i,t-1} + \beta_5\sigma^{2_u}_{i,t-1} + \varepsilon_{i,t}$$

where $MT_{i,t}$ is the proxy for market toxicity for stock *i* and interval *t* and is calculated as the absolute value of the difference between the numbers of buy and sell trades divided by the sum of the numbers of buy and sell trades occurring during interval *t*. $\sigma^R_{i,t-1}$ is the standard deviation of mid-price returns for stock *i* during interval *t*-1 and calculated as the standard deviation of midpoint-to-midpoint returns during interval *t*-1; each midpoint corresponds to a transaction. $TV_{i,t-1}$ is the natural logarithm of trading volume for stock *i* during interval *t*-1 and $BSI_{i,t-1}$ is the absolute difference between buyer- and seller-initiated traders for stock *i* during interval *t*-1. $\sigma^{2_s}_{i,t-1}$and $\sigma^{2_u}_{i,t-1}$ are state-space model-estimated proxies (estimated using Kalman filter constructed maximum likelihood) for informed and uninformed trading activity respectively for stock *i* and interval *t*-1. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on NYSE and NASDAQ. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

	Dependent Variable: $MT_{i,t}$	
	One-minute frequency	One-hour frequency
$Intercept$	0.526***	0.538***
	(451.44)	(117.92)
$\sigma^R_{i,t-1}$	1.564***	1.633***
	(62.19)	(42.33)
$TV_{i,t-1}$	0.119x10^{-3}***	0.356x10^{-2}
	(9.72)	(1.55)
$BSI_{i,t-1}$	0.188x10^{-6}***	0.222x10^{-6}***
	(53.27)	(51.48)
$\sigma^{2_s}_{i,t-1}$	-0.549x10^{-2}***	-0.159x10^{-2}***
	(-4.23)	(-20.19)
$\sigma^{2_u}_{i,t-1}$	-0.253x10^{-3}	-0.733x10^{-3}
	(-0.79)	(-0.66)
Sample size *(n)*	8880028	204354
$\overline{R^2}$	0.14%	2.85%

Table 7. Predictive regressions of short-horizon stock returns on lagged transitory component of trading volume

The table shows the results for the estimation of the predictive power of the state-space-estimated lagged permanent and transitory components of trading volume using the following model:

$$R_{i,t} = \alpha + \beta_1 \sigma^R_{i,t-1} + \beta_2 Espread_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5 \sigma^{2s}_{i,t-1} + \beta_6 MT_{i,t-1} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the midpoint-to-midpoint return for stock *i* during interval *t* and is computed as the difference between the midpoints corresponding to the last transactions at intervals *t* and *t*-1 divided by the midpoint corresponding to the last transaction at interval *t*-1. $\sigma^R_{i,t-1}$ is the standard deviation of mid-price returns for stock *i* during interval *t*-1 and calculated as the standard deviation of midpoint-to-midpoint returns during interval *t*-1; each midpoint corresponds to a transaction. $Espread_{i,t-1}$ is the effective spread for stock *i* and interval *t*-1 and computed as twice the absolute value of the difference between the last execution price and the midpoint of the prevailing bid and ask prices for interval *t*-1. $TV_{i,t-1}$ is the natural logarithm of trading volume for stock *i* during interval *t*-1 and $BSI_{i,t-1}$ is the absolute difference between buyer- and seller-initiated traders for stock *i* during interval *t*-1. $MT_{i,t-1}$ is a proxy for market toxicity for stock *i* and interval *t*-1 and calculated as the absolute value of the difference between the numbers of buy and sell trades divided by the sum of the numbers of buy and sell trades for interval *t*-1. $\sigma^{2s}_{i,t-1}$ is a state-space model-estimated proxy (estimated using Kalman filter constructed maximum likelihood) for informed trading activity for stock *i* and interval *t*-1. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on the NYSE and NASDAQ. ***, ** and * correspond to statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Dependent Variable: $R_{i,t}$	
	One-second frequency	One-minute frequency
$Intercept$	-0.535x10^{-5***} (-20.14)	-0.774x10^{-4***} (-8.19)
$\sigma^R_{i,t-1}$	0.524x10^{-3**} (2.22)	-0.106x10^{-4} (-1.30)
$ESpread_{i,t-1}$	0.440x10^{-3***} (77.59)	0.871x10^{-3***} (59.59)
$TV_{i,t-1}$	0.108x10^{-6***} (7.89)	0.838x10^{-5***} (7.75)
$BSI_{i,t-1}$	0.540x10^{-9***} (51.12)	0.123x10^{-8***} (47.22)
$\sigma^{2s}_{i,t-1}$	-0.153x10^{-6***} (-27.71)	-0.417x10^{-4} (-1.52)
$MT_{i,t-1}$		0.265x10^{-5} (0.69)
Sample size *(n)*	29959938	8880028
$\overline{R^2}$	0.06%	0.09%

Table 8. Predictive regressions of short-horizon stock returns on lagged components of HFT-driven volume

The table shows the results for the estimation of the predictive power of the state-space-estimated lagged transitory component of trading volume (interacted with a dummy variable for high-frequency trading activity) using the following model:

$$R_{i,t} = \alpha + \beta_1\sigma^R_{i,t-1} + \beta_2 Illiq_{i,t-1} + \beta_3 TV_{i,t-1} + \beta_4 BSI_{i,t-1} + \beta_5\sigma^{2_s}_{i,t-1} + \beta_6 MT_{i,t-1} + \beta_7 D_{HFT,i,t-1} * \sigma^{2_s}_{i,t-1} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the midpoint-to-midpoint return for stock *i* during interval *t* and is computed as the difference between the midpoints corresponding to the last transactions at intervals t and t-1 divided by the midpoint corresponding to the last transaction at interval t-1. $\sigma^R_{i,t-1}$ is the standard deviation of mid-price returns for stock *i* during interval t-1 and calculated as the standard deviation of midpoint-to-midpoint returns during interval t-1; each midpoint corresponds to a transaction. $Illiq_{i,t-1}$ is a proxy for one period lag illiquidity and corresponds to one of the Amihud (2002) illiquidity ratio ($Amihud_{i,t-1}$) or $Espread_{i,t}$. $Amihud_{i,t-1}$ is computed as absolute return divided by trading volume for stock *i* during interval t-1. $Espread_{i,t-1}$ is the effective spread for stock *i* and interval t-1 and computed as twice the absolute value of the difference between the last execution price and the midpoint of the prevailing bid and ask prices for interval t-1. $TV_{i,t-1}$ is the natural logarithm of trading volume for stock *i* during interval t-1 and $BSI_{i,t-1}$ is the absolute difference between buyer- and seller-initiated traders for stock *i* during interval t-1. $MT_{i,t-1}$ is a proxy for market toxicity for stock *i* and interval t-1 and calculated as the absolute value of the difference between the numbers of buy and sell trades divided by the sum of the numbers of buy and sell trades for interval t-1. $\sigma^{2_s}_{i,t-1}$is a state-space model-estimated proxy (estimated using Kalman filter constructed maximum likelihood) for informed trading activity for stock i and interval t-1. $D_{HFT,i,t-1}$ is a dummy variable equaling one during periods of high HFT activity for stock *i* and interval *t*-1. A one-second or one-minute interval is designated as an interval of high HFT activity if HFT trades for that interval is one standard deviation higher than the mean for the surrounding -60, +60 corresponding intervals. The sample contains the most active 100 S&P 500 stocks traded between October 1, 2016 and September 30, 2017 on the NYSE and NASDAQ. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.10 levels, respectively.

Panel A. The effects of lagged components of NASDAQ-defined high-frequency trading volume on short-horizon stock returns

	Dependent Variable: $R_{i,t}$	
	One-second frequency	One-minute frequency
$Intercept$	-0.311x10^{-3***} (-6.76)	0.423x10^{-2**} (2.06)
$\sigma^R_{i,t-1}$	0.630*** (8.86)	0.049x10^{-1} (1.64)
$Amihud_{i,t-1}$	-3.668*** (-4.60)	-1.405 (-0.25)
$TV_{i,t-1}$	0.240x10^{-4***} (3.96)	0.385x10^{-3**} (2.52)
$BSI_{i,t-1}$	0.01x10^{-9*} (1.74)	0.01x10^{-6*} (1.85)
$\sigma^{2_s}_{i,t-1}$	-0.097x10^{-6} (-1.58)	0.556x10^{-4} (1.49)
$D_{HFT,i,t-1} * \sigma^{2_s}_{it-1}$	-0.346x10^{-4***} (-3.38)	-0.170x10^{-3} (-1.51)
$MT_{i,t-1}$		-0.153x10^{-2} (-1.32)
Sample size *(n)*	8291971	2069787
$\overline{R^2}$	0.09%	0.25%

Panel B. The effects of lagged components of order-to-trade ratio-defined high-frequency trading volume on short-horizon stock returns

	Dependent Variable: $R_{i,t}$	
	One-second frequency	One-minute frequency
$Intercept$	-0.258×10^{-5}*** (-3.19)	-0.107×10^{-4}* (-1.85)
$\sigma^{R}_{i,t-1}$	0.242×10^{-2}** (2.45)	-0.650×10^{-4} (-1.02)
$ESpread_{i,t-1}$	0.287×10^{-3}*** (17.44)	0.566×10^{-3}*** (2.99)
$TV_{i,t-1}$	0.234×10^{-6}** (2.07)	0.217×10^{-5}*** (11.17)
$BSI_{i,t-1}$	0.264×10^{-10} (0.87)	0.492×10^{-8}*** (13.49)
$\sigma^{2_s}_{i,t-1}$	-0.284×10^{-8} (-0.01)	-0.267×10^{-7} (-1.08)
$D_{HFT,i,t-1} * \sigma^{2_s}_{i,t-1}$	-0.264×10^{-5}*** (-3.51)	-0.128×10^{-10} (-1.45)
$MT_{i,t-1}$		0.114×10^{-5} (0.29)
Sample size *(n)*	29959938	8880028
$\overline{R^2}$	0.04%	0.11%