Liquidity and the Strategic Value of Information

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Abstract

We offer a simple, intuitive and empirically useful expression quantifying the value of asset-specific information to a strategic trader. The value of information reflects the ratio of return volatility to price impact (Kyle's lambda). While volatility and illiquidity are highly correlated, their ratio fluctuates markedly giving rise to considerable variation in the value of information over time and across stocks. Using high frequency data on US stocks, we find that the value of information rises dramatically during crises and on earnings announcement days, and falls at calendar year ends. Furthermore, the value of information is higher for large, growth, and momentum stocks. The most dramatic spikes in the value of information occur at the start of the Covid-19 pandemic and the financial crisis of 2008, when the Fed announces novel liquidity facilities. Such policy interventions aimed at improving liquidity may unintentionally increase the private incentives to collect information.

Keywords: value of information, liquidity, strategic trading, Covid-19

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1 Introduction

What is the value of asset-specific information to a strategic trader? This is a question of paramount importance in security markets where investors, analysts, and professional money managers allocate their research capacity among a plethora of assets. Quantifying the amount investors would pay for information also has important practical implications such as determining the compensation for security analysts, pricing data services, and even penalizing insider trading.

Intuitively, the value of information to a speculator acting strategically depends on two components. On the one hand, information is more valuable when it offers the speculator a greater reduction in uncertainty. On the other hand, when the asset is more liquid, the acquired information can be used to trade quickly without adversely affecting the asset's price. Thus, the ratio of uncertainty about the asset's fundamentals and the asset's illiquidity should be associated with the value of acquiring information about the asset. In this paper, we formalize this intuition theoretically by providing a simple estimable expression for the value of asset-specific information. We then estimate the value of information on a daily basis for US-listed stocks, and study its cross-sectional and time-series properties.

We rely on the theoretical framework presented in Back (1992), who offers a continuous-time, log-normal version of the Kyle (1985) model. In the model, a risk-neutral informed trader possessing information on the fundamental value of an asset $\tilde{v}$ trades continuously over time in a market populated by noise traders. Prices are set by risk-neutral market makers as to break even. In equilibrium, the informed trader spreads her trades over time to camouflage them with the noise trading. By considering a continuous time model, we allow for the informed investor to break her orders into small pieces and spread the price impact over time.

Our aim is to advance an empirical literature that has thus far been mostly qualitative, by building on a quantitatively sound foundation where quantities can be easily interpreted. Considering a model with log-normally distributed fundamentals is empirically important, as it prevents the need to consider negative prices as in the original Kyle (1985) model, and it naturally leads to a price impact measure that considers returns rather than prices.[1] Recent empirical work has convincingly shown that private information is pervasive yet hardly reflected by equity prices (Collin-Dufrense and Fos 2015; Kacperczyk and Pagnotta 2019b; Akey, Gregoire, and Martineau 2020). Informed agents split and manage their trades in a manner consistent with the strategic considerations of the Kyle-Back model, in 18th-century markets (Koudijs 2015) and in modern ones (Kacperczyk and Pagnotta 2019a).

Using this framework, we show that the equilibrium ex-ante dollar expected profits of a trader informed about a specific asset is given by

$$\Omega = \frac{\sigma_v^2}{\lambda} P_0, \tag{1}$$

where σ_v is the volatility of the asset's returns, P_0 is the asset's current price, and λ is the sensitivity of the asset's return to share order flow. Thus, the value of information is proportional to the asset's return volatility and negatively proportional to a measure of the asset's illiquidity. This simple expression underscores the fundamental tension governing the value of information. Indeed, stocks that are associated with a high level of adverse selection are often also relatively illiquid. It is the ratio of these two that determines the profitability of investing in information acquisition for a specific asset. This ratio is proportional to the value of information in a fairly large class of models of strategic trading á-la Kyle (1985), including Back (1992), Caballé and Krishnan (1994), Back, Cao, and Willard (2000), and Collin-Dufresne and Fos (2016).

In our empirical analysis we estimate (1) on a daily basis using intraday data for US

1. Moreover, for many assets including stocks and equity options, prices are not stationary, which can lead to explosive behavior in price-based regressions, while returns are stationary (Cochrane 2005; Campbell 2017; Dávila and Parlatore 2018).

publicly-listed common stocks over the September 2003 to December 2020 period. The idea is to measure a daily value an investor would be willing to pay at the close of a trading day to learn the closing stock price at the end of the next trading day. We find that the average daily value of information is about $11,500, which annualizes to an average of $2.9 million for becoming informed on an average stock each day.

Our estimation approach allows us to answer fundamental questions regarding how the value of information varies cross-sectionally and over time. Is information more valuable during calm or turbulent times? Is gathering information more profitable for large or small firms? Does the value of information rise on scheduled corporate news releases like earnings announcements? The answers to these questions is not obvious because return volatility and liquidity are tightly linked (Nagel 2012; Drechsler, Moreira, and Savov 2018). For example, during turbulent times, one would expect uncertainty to rise, but also liquidity to fall, which would raise both numerator and denominator of (1). Whether the net effect on the value of information is positive is thus an empirical question.

We begin our analysis by considering time variation in the value of information. We find that the value of information rises dramatically during turbulent times. It is evident that the increase in uncertainty overshadows the rise in illiquidity during these times, leading to information becoming more valuable. The most dramatic increase in the value of information occurs during the Covid-19 pandemic of 2020. We observe nine of the ten highest value of information days in our sample in March 2020, when financial market participants fly to liquidity and the Federal Reserve intervenes at an unprecedented scale (Haddad, Moreira, and Muir 2020). We also observe notable spikes in the value of information during the financial crisis of 2008, several days after Lehman Brothers collapses, when the Fed announced several novel liquidity facilities. During both of these rare crises, it appears that the Fed, perhaps unintentionally, increases the value of information, by enhancing market liquidity. Such large rewards to collecting information can be beneficial if they encourage a more efficient capital allocation. But they can be harmful to short-term debt funded financial intermediaries, if they instigate coordinate failures and runs (He and Manela 2016).

We also document interesting seasonality patterns. The value of information increases monotonically during the work week, and drops markedly toward the end of the calendar year. Many of the lowest information value days in our sample occur between Christmas and New Year.

Cross-sectionally, one may argue that gathering information small stocks is more profitable, because such stocks are likely neglected by investors and analysts (e.g., Arbel, Carvell, and Strebel 1983; Hou and Moskowitz 2005). But, a countervailing argument is that trading on information discovered on small stocks is less profitable, because of their lack of liquidity. The expression in (1) encapsulates this trade-off. Empirically, we find that, perhaps surprisingly, information is significantly more valuable for large stocks as compared to small stocks. While it is certainly true that the adverse-selection associated with large stocks is smaller, this effect is being dwarfed by their superior liquidity. In fact, we document that volatility is significantly less sensitive to size than liquidity. Overall, information about large stocks is more valuable than information about small stocks. We further find that low book-to-market (growth) stocks and stocks that experienced high return over the past year (momentum), tend to have higher values of information.

As an example for valuing the information associated with a specific event type we consider the value of information during earning announcement days— days in which information is actively being released. Recent work finds that stock return anomalies are six times higher on earnings announcement days (Engelberg, Mclean, and Pontiff 2018) and that some investors trade on superior information around earnings (Hendershott, Livdan, and Schürhoff 2015; Huang, Tan, and Wermers 2020). One may expect that strategic traders would be willing to pay a higher amount to learn the end-of-day stock price at the beginning of such days in which firm-specific information is being released. But, market makers could simultaneously increase spreads to offset the cost of adverse selection

(Kim and Verrecchia 1994). Again, it is ex-ante unclear, whether the value of information increases or decreases on these days. Empirically, we find that the value of information rises dramatically during and around earning-announcement days. This increase in the value of information stems mainly from an increase in volatility during those days, when liquidity actually improves, reinforcing the increase in the value of information.

In our final analysis, we consider a model of strategic informed trading with multiple competing informed traders who receive imperfect private signals that may be correlated (Back, Cao, and Willard 2000). We show that in this case, the total value of information, to all informed traders combined, is proportional to the ratio of variance to price impact, the same ratio we use to measure the value of information in the monopolist informed trader case. We show that the constant of proportionality depends only on the number of informed traders and their signal correlation coefficient. Importantly, we prove that this constant of proportionality is bounded from below by 0.92. Thus, if one wishes to convert an estimate based on the simpler monopolist insider case to the competitive case, they know that the total value cannot fall below 0.92 times the original estimate. The lower bound on the per-capita value of information is that same number divided by the number of informed investors.

Our paper is the first to estimate the value of information to a strategic trader. The foundations for our analysis are set in the seminal work of Grossman and Stiglitz (1980) and Kyle (1985) who considered the value of information in a rational expectations setting. Their approach exploits a normal distribution, which does not lend itself naturally to empirical estimation. Ai (2007), Epstein, Farhi, and Strzalecki (2014), Croce, Marchuk, and Schlag (2019) and Kadan and Manela (2019) study the value of macro-level information in a setting employing Epstein and Zin (1989) preferences. This approach allows them to separate between the psychic and instrumental values of information. Hengjie Ai et al. (2019) augment the Kadan and Manela (2019) option-based approach to generalized risk preferences. Farboodi et al. (2021) compute the value of information implied by a structural noisy rational expectations model and find it is higher for large growth firms.[2] The high frequency nature of our measure allows us to document for the first time that the value of information rises during turbulent times and around earnings announcements, and falls at year and quarter ends.

The above papers consider the value of information to a small risk-averse agent having no effect on prices. The value of information is finite in these models because risk aversion prevents the informed agent from taking arbitrarily large positions in systematically risky assets, and prices therefore do not fully reveal their private information. By contrast, the essence of the value of information considered here is that it applies to a strategic investor whose trades affect prices, and liquidity plays a key role in our analysis. Here, the value of information is finite and prices are partially revealing because our agent internalizes its marginal effect on prices. Accordingly, we consider a risk-neutral trader and focus our attention on asset-specific as opposed to macro-level information. This approach complements the earlier work and may be more suitable in cases where systematic risk can be neutralized, for example by taking long-short positions that efficiently trade on asset-specific information, or when investment decisions are delegated to risk neutral money managers (Gârleanu and Pedersen 2018). The expression for the value of information that we derive (1) is also considerably simpler and has easy to interpret units.[3]

Our paper also relates to recent work that studies the informational efficiency of financial markets (Fama 1970). Bai, Philippon, and Savov (2016) document that price informativeness has increased since 1960, and that it is concentrated among growth stocks. Farboodi et al. (2021) show that this increase is driven by large, growth stocks, while the

2. A large literature on information choice studies the CARA-normal (mean-variance) noisy rational expectations framework. See Veldkamp (2011) for a survey, and see Malamud and Rostek (2017) and Dávila and Parlatore (forthcoming) for recent examples. Bringing such models to data is challenging because stock prices are neither stationary or Gaussian. Recent work suggests that moving beyond CARA utility can be important (Savov 2014; Breon-Drish 2015; Malamud 2015).

3. See Kyle and Obizhaeva (2016), Kyle and Obizhaeva (2018), Kyle, Obizhaeva, and Wang (2018), and Kyle and Obizhaeva (2019) for careful work on microstructure invariants and units of measurement.

informational efficiency of smaller assets' prices or prices of assets with less growth potential have been flat or declining. They argue that more data has been processed for large growth firms because the value of information for these firms has been higher. Dávila and Parlatore (2018) estimate price informativeness by regressing prices on fundamentals and find it is higher for stocks with greater size and trade volume. Kacperczyk, Sundaresan, and Wang (2019) find that greater foreign ownership increases stock price informativeness. We provide a simple measure of the value of information, which incentivizes market participants to seek private information and through their trades, improve capital allocation efficiency and managerial decisions (Bond, Edmans, and Goldstein 2012; Brogaard, Ringgenberg, and Sovich 2019).

The paper proceeds as follows. Section 2 develops the measure of the value of information. Section 3 discusses its estimation. The main empirical results are in Section 4. Section 5 reconsiders our estimates in the context of a multiple informed investors model. Section 6 concludes. Proofs and robustness tests are in the Online Appendix.

2 Theory

We build on a continuous-time version of the Kyle (1985) model as discussed in Back (1992). Consider an asset with value $\tilde{v}$ to be revealed at time 1 with cumulative distribution function $F(\cdot)$.[4] Trading of this asset and a risk free asset takes place continuously during the time interval $[0,1]$. There are three types of traders: (i) a risk neutral informed trader who learns v at time 0 and submits orders with cumulative number of shares described by an endogenous process X_t. We call this process the informed trader's trading strategy; (ii) noise traders submitting exogenous orders with cumulative number of shares described by the process $dZ_t = \sigma_z dB_t$, where B_t is a Brownian motion independent

4. One can think about $\tilde{v}$ as the price at which the asset will be traded at time 1, rather than the actual value of the asset at time 1.

of $\tilde{v}$; and (iii) risk neutral market makers who set prices to clear the market. Denote by $Y_t = X_t + Z_t$ the cumulative share order flow observed by market makers by time t.

Let $P_t = H(Y_t, t)$ describe the price process of the asset during $t \in [0, 1]$. Assuming $H(\cdot, \cdot)$ is strictly monotone in its first argument (order flow), the objective function of the informed trader can be written as[5]

$$W_1 = \int_0^1 (\tilde{v} - P_t)\, dX_t. \tag{2}$$

An equilibrium is defined as a pair (X_t, H_t) of a trading strategy for the informed trader and a price rule for the market maker such that (i) at each point in time the pricing rule is rational: $H(Y_t, t) = \mathrm{E}\left[\tilde{v} | (Y_s)_{s \le t}\right]$ given the trading strategy; and (ii) the trading strategy is optimal for the informed trader given the pricing rule, i.e, it maximizes her expected terminal wealth $\mathrm{E}[\tilde{W}_1 | v]$, where W_1 is given by (2).

Below we start by considering the original Kyle (1985) version of the model in which the fundamental value is normally distributed. We then explain why this specification does not lend itself naturally to empirical estimation, and then turn to the log-normal version of the model introduced in Back (1992), which is the version we use for estimating the value of information.

2.1 Normally-Distributed Fundamental Values

Assume $\tilde{v} \sim N(\mu, \sigma_v^2)$, then, as shown in Kyle (1985) (see also Back (1992)), the equilibrium pricing rule is given by $H(y, t) = \mu + \lambda y$, where $\lambda = \frac{\sigma_v}{\sigma_z}$, and the informed trader's equilibrium strategy satisfies $dX_t = \frac{\tilde{v} - P_t}{\lambda(1-t)} dt$. Note that in this case,

$$dP_t = \lambda dY_t, \tag{3}$$

5. To be precise, the objective function also includes an additional term reflecting quadratic variation, but Back (1992) shows that under some continuity assumptions on H this term vanishes in equilibrium.

and thus Kyle's λ, should be interpreted as the marginal effect of share order flow on price — a measure of price impact. The ex-ante value of information in this case is the expected profit of the informed trader as given by Kyle (1985, p. 1330)

$$\Omega = \sigma_v \sigma_z = \frac{\sigma_v^2}{\lambda}, \tag{4}$$

that is, the ratio of price volatility to price impact.

The literature starting with Kyle (1985) emphasizes the first equality in (4), which says that the informed trader expects higher profits when fundamental volatility is higher or when prices are more noisy. We focus instead on the last expression because it is directly estimable, and turns out to hold quite generally. For example, we can show it holds even when noise trading volatility is stochastic, as in the Collin-Dufresne and Fos (2016) model.[6]

While the intuition here is appealing, this model does not translate naturally to realistic stock prices due to the normal distribution of the value, which allows for negative prices, even for limited liability assets like stocks. Another drawback of normality is that it is likely to be a poor approximation for the distribution of order flow (Hasbrouck 2007, p. 93). Moreover, σ_v^2 here is the volatility of prices rather than returns, which may be problematic to estimate due to lack of stationarity. For all these reasons, the empirical literature focusing on the estimation of price impact from intraday data considers versions of Kyle's lambda in which order flow affects returns rather than prices (e.g., Hasbrouck 2009; Holden and Jacobsen 2014).

Next, we consider a version of Kyle's model with a log-normal distribution for the fundamental value in which both volatility and price impact take more empirically-appealing forms.

6. It would be interesting to see if this expression still holds when the informed trader can affect the fundamental value of the asset as in Back et al. (2018).

2.2 Log-nomrally Distributed Fundamental Values

Assume $\tilde{v}$ is log-normally distributed with $\log \tilde{v} \sim N\left(\mu, \sigma_v^2\right)$. Under some technical restrictions on the set of trading strategies and pricing rules, Back (1992) solves for an equilibrium in which the pricing rule is given by $H\left(y,t\right) = \exp\left(\alpha + \lambda y + \sigma_v^2\left(1-t\right)/2\right)$, where $\lambda = \frac{\sigma_v}{\sigma_z}$. Thus, the marginal effect of share order flow on stock returns satisfies

$$\frac{dP_t}{P_t} = \lambda dY_t. \tag{5}$$

This is a useful deviation from the original Kyle (1985) model, in which λ measures the effect of order flow on price rather than the return. The equilibrium trading strategy satisfies $dX_t = \frac{\frac{\log \tilde{v}-\mu}{\lambda} - Y_t}{1-t} dt$.

Finally, for any given time $t \in [0,1]$ and current price p, the value function can be verified to be given by (see Back 2017, p. 650)

$$J\left(t,p,v\right) = \frac{p - v + v\left(\log v - \log p\right)}{\lambda} + \frac{1}{2}\sigma_v \sigma_z \left(1-t\right) v. \tag{6}$$

The price at time $t=0$ is

$$P_0 = \mathrm{E}\left[\tilde{v}\right] = e^{\mu + \frac{1}{2}\sigma_v^2} \equiv \bar{v}. \tag{7}$$

It follows that the ex-ante (time 0) value of information is given by $\Omega = \mathrm{E}J\left(0, \bar{v}, \tilde{v}\right)$. The next proposition establishes a simple expression for the value of information in the log-normal case.

Proposition 1 *The value of information in the version of the Kyle-Back model with a log-normal fundamental value distributed $\log \tilde{v} \sim N\left(\mu, \sigma_v^2\right)$, with percent price impact per share order flow λ, and with initial price P_0, is given by $\Omega = \frac{\sigma_v^2}{\lambda} P_0$.*

2.3 Discussion

The expression for information values Ω established in Proposition 1 is simple to estimate because unlike in the original Kyle model, the focus here is on returns rather than prices. In particular, σ_v is the volatility of returns and λ is the impact of share order flow on returns.[7] Importantly, the basic intuition from Kyle is preserved under the log-normal specification, as the value of information is still the ratio of uncertainty to illiquidity.

The expression for Ω is intriguing because uncertainty and illiquidity are known to be highly correlated.[8] In fact, the market microstructure literature traditionally considers asset volatility as a fundamental determinant of asset illiquidity (Stoll 1978; Copeland and Galai 1983; Admati and Pfleiderer 1988). And yet, the two are not perfectly correlated and, as we document below, their ratio fluctuates dramatically both cross-sectionally and over time. It is this ratio that determines the value of acquiring information on the asset.

The units of measurement of Ω are dollars (or whatever denominates prices). To see this, recall that $\lambda = \frac{\sigma_v}{\sigma_z}$ and that both σ_v and σ_z are unitless. Thus, the value of information, $\Omega = \frac{\sigma_v^2}{\lambda} P_0 = \sigma_v \sigma_z P_0$, inherits its units of measurement from P_0. It follows that the interpretation of Ω is the maximum dollar amount that an investor would be willing to pay ex-ante to become informed about v.

One caveat is that this setup assumes a monopolistic informed trader who obtains a perfect signal. In markets with multiple competing informed traders, each with an imperfect signal of the fundamental, the value of information could be different. In Section 5 below, we study a more general model along those lines and provide a link to interpret

7. To see that σ_v is the volatility of returns, note that in the log-normal fundamental model, (5) implies

$$\frac{dP_t}{P_t} = \lambda dX + \lambda dZ = \lambda dX + \frac{\sigma_v}{\sigma_z}\sigma_z dB_t = \lambda \frac{\frac{\log \tilde{v} - \mu}{\lambda} - Y_t}{1-t} dt + \sigma_v dB_t. \tag{8}$$

8. In our sample, the correlation between realized variance and price impact per dollar is 0.3. A univariate regression of log price impact per dollar on log realized variance estimates their elasticity at 0.9, or if we control for date and stock fixed effect, at 0.4.

the central ratio of Proposition 1 when there are multiple informed traders.

3 Estimation

Our goal is to estimate the value of information using Proposition 1 on a daily basis for stocks traded on US stock exchanges. To establish daily values of the value of information we rely on intraday data obtained from the NYSE TAQ database, which covers all US publicly traded stocks. Our sample includes 7,400 common stocks over the September 11, 2003 to December 31, 2020 sample period, which we could match by trading symbol and date to CRSP/Compustat. Following Amihud (2002) we drop all stocks with a previous-day closing stock price smaller than $5 to avoid market microstructure effects.[9] We then inflation-adjust all prices using the CPI to December 2020 values.

Empirically, we interpret the daily value of information for a particular stock as the dollar amount one would be willing to pay at the close of the trading day to learn the closing price at the end of the next trading day. As Back (1992) explains, because of risk neutrality, v in the model can be thought of as an unbiased signal of the end-of-period price. This price in turn, is an unbiased expectation of the next period's value. Thus, for each stock j on date t we estimate a daily value of information,

$$\hat{\Omega}_{jt} = \frac{\hat{\sigma}^2_{jt}}{\hat{\lambda}_{jt}} P_{jt-1}, \tag{9}$$

that is the ratio of realized log return variance $\hat{\sigma}^2_{jt}$ to price impact $\hat{\lambda}_{jt}$, both estimated from 1-minute log returns and order flow, times the previous day's closing price P_{jt-1}.

Specifically, let $p_{jt\tau} = \log P_{jt\tau}$ denote the log price of asset j on day t, at time $\tau \in [0, T]$. We observe equidistant observations over time intervals $\Delta = 1$ minute, so we estimate variance at time T based on $N + 1$ discrete observations recorded at times $\tau_0, \tau_1, \ldots, \tau_N =$

9. In the Online Appendix we show how our estimates change if we keep penny stocks

$N\Delta = T$. We annualize volatility (and the value of information), by setting $T = 1/252$. Let $r_{jti} = p_{jt\tau_i} - p_{jt\tau_{i-1}}$ be the log return of asset j on day t over interval $i = 1, \ldots, N$.

Following common practice (e.g., Aït-Sahalia, Mykland, and Zhang 2005), we estimate the intraday log return variance of stock j on day t as

$$\hat{\sigma}^2_{jt,\text{intraday}} = \frac{1}{T} \sum_{i=1}^{N} r^2_{jti}. \tag{10}$$

Recent work documents that a substantial amount idiosyncratic risk (Bogousslavsky 2019), as well as systematic risk (Hendershott, Livdan, and Rösch, forthcoming; Muravyev and Ni 2020) is resolved when stock markets are closed. We therefore augment this estimator with the squared overnight log return $r_{jt,\text{overnight}} = p_{jt\tau_0} - p_{jt-1\tau_N}$, properly scaled, to attain our estimator of annualized log return variance,

$$\hat{\sigma}^2_{jt} = \frac{1}{T} r^2_{jt,\text{overnight}} + \hat{\sigma}^2_{jt,\text{intraday}}. \tag{11}$$

Below we study both the total (overnight+intraday) value of information as well as the intraday-only value.

Let $Y_{jt\tau}$ denote cumulative signed order flow and let $y_{jti} = Y_{jt\tau_i} - Y_{jt\tau_{i-1}}$ be share order flow over intraday interval i. Several approaches to signing TAQ trades as buys $(+1)$ or sells (-1) have been proposed by prior work. Our baseline estimates are based on the Chakrabarty et al. (2007) approach, using the algorithms developed by Holden and Jacobsen (2014). In the Online Appendix we show that our qualitative and quantitative conclusions are not sensitive to this choice.

We estimate price impact λ_{jt}, defined in Equation (5), using a regression of 1-minute log returns on contemporaneous share order flow,

$$r_{jti} = \hat{\lambda}_{jt} y_{ijt} + \varepsilon_{ijt}. \tag{12}$$

Finally, we use the closing price of the preceding trading day, $P_{jt-1\tau_N}$ as the initial asset price P_0 in (9). We note that while in theory λ is positive, it could be negative in any finite sample. An alternative approach to estimating λ could be to take its theoretical definition (5) exactly, without error, and measure it as the ratio of mean returns to mean order flow. But because the latter is often close to zero, this alternative approach can produce many arbitrarily large price impact coefficients. Moreover, $\hat{\lambda}_{jt}$ could suffer from selection bias if traders employ price-dependent strategies and cancel expensive orders (Obizhaeva 2011). The are also other measures of price impact suggested by the large literature on its measurement (Holden and Jacobsen 2014). We prefer ours because it corresponds closely to the model we use to interpret the data, which means we can easily interpret the units of the value of information it yields.

The value of information (9) is a ratio of two random variables measured with error. Small or negative λ point estimates in particular can be problematic because they would result in arbitrarily large (or small) values of information. Therefore, sample means must be taken with care. Using the delta method it can be shown that a first-order approximation for the mean over a sample of observations s is just the ratio of the mean variance to mean price impact per dollar over that subsample.

Formally, let $\mu_{vs} = \frac{1}{|s|}\sum_{jt\in s}\hat{\sigma}^2_{jt}$ be an estimate of mean variance over subsample s, and let $\mu_{\lambda s} = \frac{1}{|s|}\sum_{jt\in s}\hat{\lambda}_{jt}/P_{jt-1}$ be an estimate of mean price impact per dollar.

Then by the delta method, a first-order estimator for the mean is

$$E\hat{\Omega}_s = \frac{\mu_{vs}}{\mu_{\lambda s}}. \tag{13}$$

To estimate the uncertainty about information value estimates, let $\Sigma_s = \begin{bmatrix} \Sigma_{vs} & \Sigma_{v\lambda s} \\ \Sigma_{v\lambda s} & \Sigma_{\lambda s} \end{bmatrix} = Cov([\hat{\sigma}^2_{jt}, \hat{\lambda}_{jt}/P_{jt-1}])$ be an estimate of the 2×2 variance-covariance matrix of variance and price impact over the same subsample. Using a second-order expansion yields the following estimator for the variance of the value of information:

$$Var\hat{\Omega}_s = \frac{1}{\mu_{\lambda s}^2}\left(\Sigma_{\lambda s}\frac{\mu_{vs}^2}{\mu_{\lambda s}^2} + \Sigma_{vs} - 2\Sigma_{v\lambda s}\frac{\mu_{vs}}{\mu_{\lambda s}}\right). \tag{14}$$

Naturally, the ratio is more variable when the mean price impact $\mu_{\lambda s}$ is small, but also when the covariance between return variance and price impact $\Sigma_{v\lambda s}$ is low. Below we rely on Σ_s estimates that allow for clustering over time (day) to estimate the variance of the value of information.

In some cases it is useful to consider the logarithmic version of (9), which allows for an additive interpretation. Denoting $\omega = \log \Omega$ we have

$$\omega = \log \sigma_v^2 - \log \frac{\lambda}{P_0}, \tag{15}$$

where the interpretation is that the log value of information equals the log of return variance less the log of percent price impact per dollar order flow. Of course, when we use this decomposition, we are restricted to observations where price impact is estimated to be positive. But an advantage of the logarithmic version is that its expectations are better behaved.

Before moving to the results, we note that the risk-neutral Kyle model is best suited for modeling information to a trader who receives idiosyncratic or stock-specific information and who can neutralize systematic risk from their portfolio. A reasonable objection in that case is that the estimate of variance reduction should be net of systematic risk. In the Online Appendix we redo our analysis with estimates of idiosyncratic variance. That analysis shows that the value of information in that case is slightly smaller and that its relation to the characteristics we study remains about the same. We also verify that this idiosyncratic value of information also generates similar peaks around turbulent times as reported below.

Table 1: Information values and other summary statistics

variable	Mean	Std	Min	q25	Median	q75	Max	Obs
Information value, $M	2.91	86.61	-322.61	3.22	12.03	46.57	2,184.51	11,857,178
Information value (intraday), $M	2.50	70.04	-271.61	2.95	10.97	41.14	1,561.07	11,857,178
Volatility	0.50	0.36	0.09	0.26	0.39	0.60	2.12	11,857,178
Volatility (intraday)	0.46	0.33	0.06	0.25	0.37	0.57	1.91	11,857,178
Price impact per $M	0.13	0.43	-0.09	0.00	0.01	0.06	3.35	11,857,178
Stock price	42.48	113.81	5.00	14.90	27.92	49.60	251,980.93	11,857,178
Size (lnME)	13.97	1.78	10.29	12.68	13.86	15.12	18.60	11,857,178
Book-to-market ratio	0.61	0.45	0.03	0.29	0.51	0.80	2.57	11,857,178
Momentum	0.17	0.47	-0.64	-0.10	0.10	0.33	2.31	11,857,178
Earnings	0.01	0.11	0.00	0.00	0.00	0.00	1.00	11,857,178
Analysts	16.67	11.01	3.00	8.00	14.00	23.00	84.00	4,845,755
Analyst Dispersion	0.31	48.20	0.00	0.00	0.00	0.00	15,384.08	3,105,277

Notes: Daily common stocks panel from NYSE TAQ, CRSP, and Compustat, September 2003 to December 2020. The value of information is annualized variance divided by price impact and reported in millions of dollars. Dollar figures are CPI adjusted to December 2020 values. Volatility is the square root of the annualized sum of squared one-minute log returns. Price impact is estimated by regressing one-minute log returns on contemporaneous share order flow and divided by the previous trading day's closing stock price. The intraday value of information is based on intraday volatility alone (excluding overnight returns). Size is log market equity over the previous month. Momentum is the return over the prior 2–12 months. Book-to-market is book equity as of last June divided by market equity as of last December (Fama-French conventions). Earnings indicates an earnings announcement day. All variables are 1% winsorized.

4 Empirical Analysis of the Value of Information

4.1 Estimated information values and other summary statistics

Table 1 reports sample moments of the value of information as well as summary statistics for the sampled firms. The mean and standard deviation of the value of information are estimated using the delta method as described in Section 3 above. While our estimates pertain to the value from acquiring information to be realized over one day, because our measure of return volatility is annualized, so is the value of information we report throughout. Thus, reported values of information correspond to the maximal amount an investor would be willing to pay to receive daily information on a stock over a year. The average annualized value of information in our sample is \$2.9 million (\$11,500 per day). The value of information is highly variable, with a standard deviation of about \$87 million.

The median annualized intraday return volatility is 37%, and the median volatility accounting for overnight returns is 39%. As a result, about 6 percent of the median volatility accrues overnight. The median price impact (λ divided by stock price) is 0.01, reflecting that \$1 million of order flow changes prices by 1 percent.[10] About 4 percent of the observations have a negative price impact (and thus information value) estimate. These observations are included when we report information value in levels, but omitted whenever we report results in logs below. The median market capitalization of firms in the sample is \$1 billion, the median book-market ratio is 51 percent. Median momentum shows that the median stock appreciated by 10 percent over the preceding 11 months. Firms reported earnings on about 1 percent of the days in the sample.

4.2 Time Trends in the Value of Information

Figure 1 describes how the value of information changes over time. Panel (a) reports the value of information Ω in levels, averaged over stocks and days each month. Panel (b) reports a decomposition into log volatility and log price impact, which sum up to the value of information in logs. Recession periods are shaded in the graph. The figure shows that during turbulent times, when volatility goes up, and in particular during recessions, stocks become less liquid as reflected in an increased price impact. Thus, as expected, a high level of uncertainty goes hand-in-hand with low market liquidity. However, the figure demonstrates that the increase in volatility during turbulent times is far steeper than the increase in price impact, leading to an increase in the value of information. This pattern is particularly stark during the financial crisis of 2007–2009 and the Covid-19 pandemic of

10. Our estimate of median price impact is similar to that of Hasbrouck (2009, Table II), where a \$1 million order would move the log price by 0.7%.

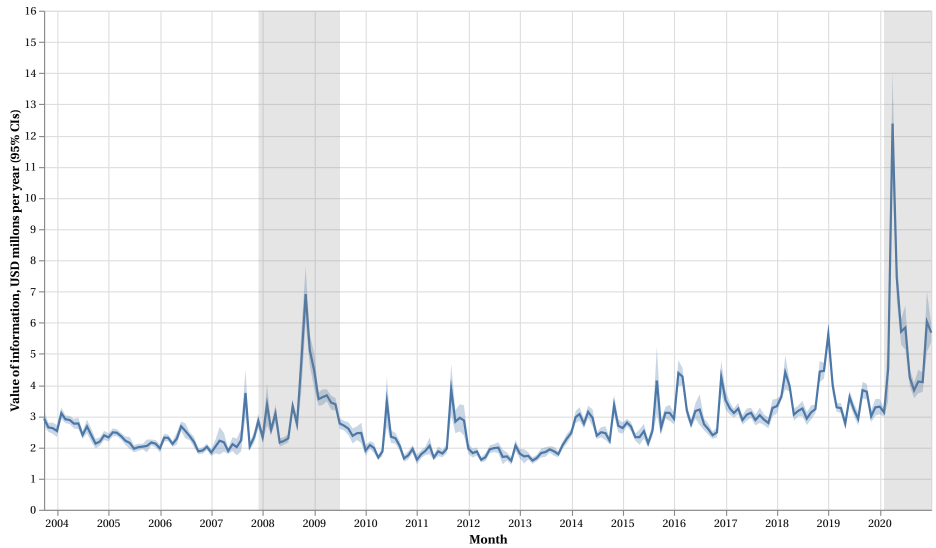
2020. In both cases, both volatility and illiquidity increase dramatically, but the increase in volatility is much steeper, leading to a spike in the value of information.

Figure 2a zooms in on the value of information during the recent Covid-19 pandemic period. The two highest value of information days in our sample are Monday, March 16, 2020, when the annualized value of information reaches \$19.3 million (\$76k per day), and Friday, March 20, 2020 with an information of value of \$19.6 million (\$78k per day). During that week it became clear that the virus has been spreading in the US for quite some time, and New York City schools, restaurants and bars shut down. The Federal Reserve slashed interest rates to near-zero and unveiled a remarkable set of programs to backstop the US economy (Smialek and Irwin 2020). The heightened uncertainty coupled with the Fed's interventions to increase market liquidity made information more valuable than on any other time in our sample. In fact, nine of the ten highest values of information during our sample all occur during March 2020 (see Table OA.1), as financial market participants fled to liquidity and the Fed continued to intervene at an unprecedented scale (Haddad, Moreira, and Muir 2020). The only other day to make the top 10 is Monday, November 9, 2020—the first trading day after the 2020 US election results became clear and when news arrived that Pfizer's Covid-19 vaccine is highly effective.

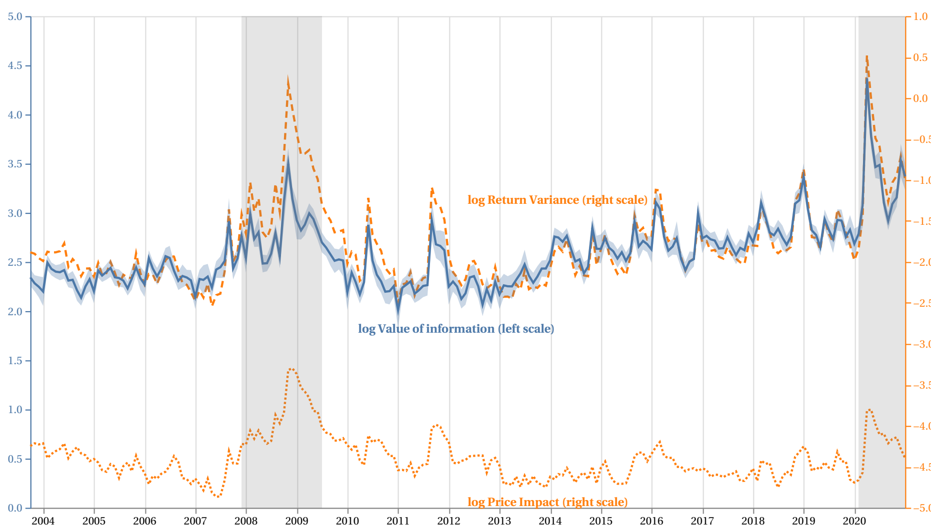
Figure 2b focuses on the financial crisis of 2007–2009. It shows that the value of information peaked on September 19, 2008, just a few days after the collapse of Lehman Brothers. Volatility increases that day by 0.50 log points at the same time that market liquidity improves, with price impact declining by 0.76 log points relative to the previous day's values. On this day the Fed announced new asset-backed commercial paper and money market mutual fund liquidity facilities, and that it will purchase mortgage-backed securities from primary dealers.[11] The combined spike in volatility and improved market liquidity lead to a dramatic increase in the value of information.

11. Federal Reserve Bank of St. Louis' Financial Crisis Timeline. https://fraser.stlouisfed.org/timeline/financial-crisis, accessed on June 10, 2020.

Figure 1: Value of information over time



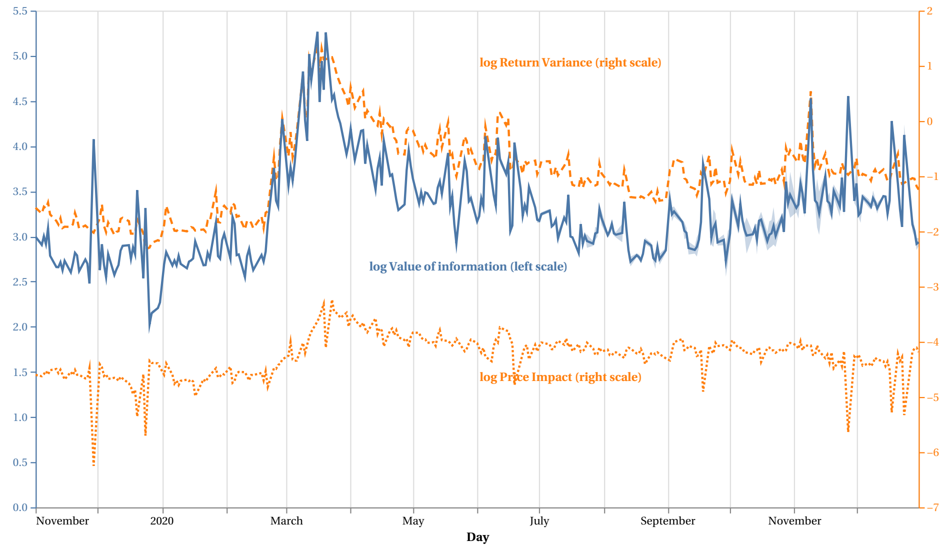
(a) Value of information in levels



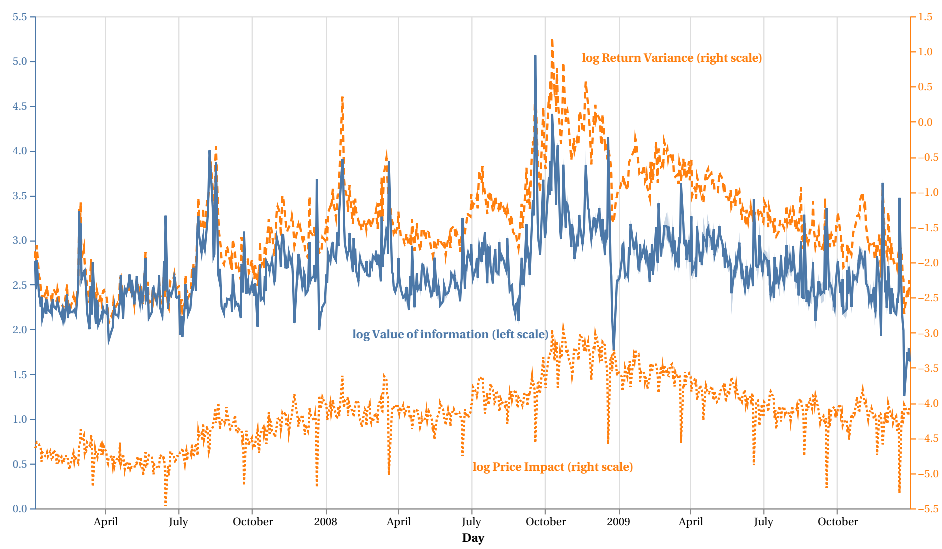
(b) Value of information in logs and its components

Notes: The solid line is the monthly information value averaged over stocks and days surrounded by its 95 percent confidence interval, based on time-clustered variance estimates. The value of information is annualized variance divided by price impact and reported in millions of dollars. The log information value equals log annualized return variance less log price impact, so we also report the mean of log annualized return variance (dashed line) and the mean of log price impact (dotted line). Shades indicate recessions.

Figure 2: Value of information rises sharply at the onset of crises



(a) Covid-19 pandemic: November 2019 to December 2020



(b) Financial crisis: November 2007 to December 2009

Notes: Solid lines are daily information values averaged over stocks surrounded by their 95 percent confidence interval, based on time-clustered variance estimates. The value of information is annualized variance divided by price impact and reported in millions of dollars. The log information value equals log annualized return variance less log price impact, so we also report the mean of log annualized return variance (dashed line) and the mean of log price impact (dotted line).

These two turbulent episodes are rare, so learning from them is subject to caveats about small sample inference. That said, it appears that the Fed, perhaps unintentionally, tends to increase the value of information during crises, by enhancing market liquidity. Such large rewards to collecting information can be beneficial if investors learn about solvency by facilitating a more efficient capital allocation. But they can be harmful if investors reap these rewards by researching funding liquidity, which can instigate coordination failures and debt runs (He and Manela 2016).

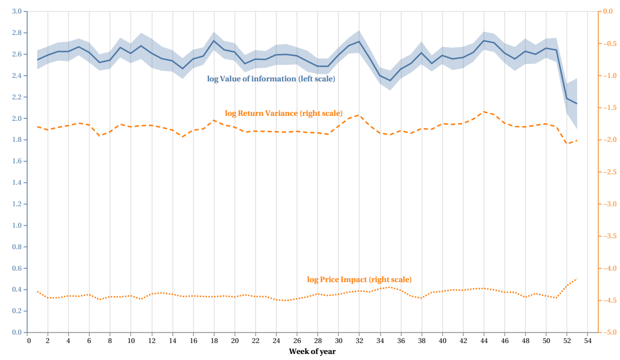
The only other event to make the top 20 days list is the stock market crash of August 24, 2015. This global market price drop has been attributed to concerns about China's economy (Driebusch 2015) and to the Fed beginning to raise short-term interest rates (Feldstein 2015) after years near the zero lower bound following the 2008 crisis.

Figure 3 documents seasonality patterns of the value of information over the year, over the quarter, and over the trading week. Two main patterns emerge. First, the value of information drops sharply toward the end of the year, and second, the value of information increases gradually during the work week. A potential explanation for the end-of-year drop is that when traders work less during the holiday period volatility drops because less information is being generated, and at the same time market makers are supplying less liquidity. This can be seen from Panel 3a, where volatility drops and price impact rises during the last weeks of the average year.

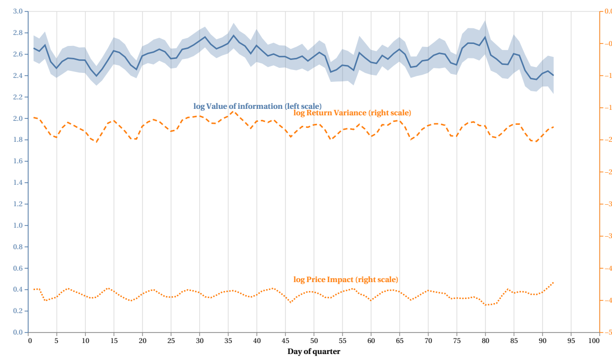
4.3 The Value of Information in the Cross-section of Stocks

We next turn to studying how the value of information varies cross-sectionally. We begin by considering firm size. It is often argued that the value of acquiring information is higher for small stocks. Such stocks are more likely to be neglected (Arbel, Carvell, and Strebel 1983) and they suffer from frictions preventing information from being fully incorporated into their price (Hou and Moskowitz 2005). These arguments, however, do not account

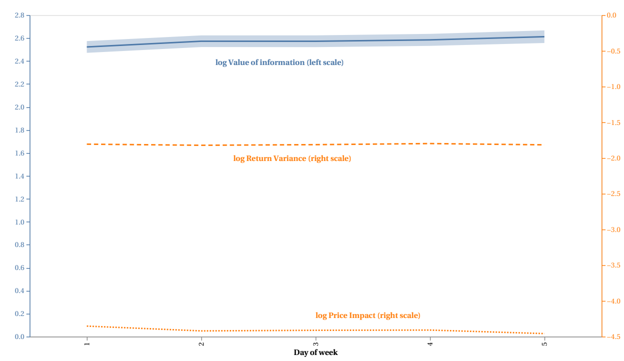
Figure 3: Seasonality in the Value of information



(a) Year-end decline



(b) Quarter-end decline



(c) Gradual rise over the trading week

Notes: Solid lines are daily information values averaged over stocks surrounded by their 95 percent confidence interval, based on time-clustered variance estimates. The value of information is annualized variance divided by price impact and reported in millions of dollars. The log information value equals log annualized return variance less log price impact, so we also report the mean of log annualized return variance (dashed line) and the mean of log price impact (dotted line).

for the fact that small stocks are typically illiquid, and thus, trading on the information acquired on such stocks is associated with significant price impact. Thus, a priori, it is not obvious whether the value of information is higher for large or small stocks.

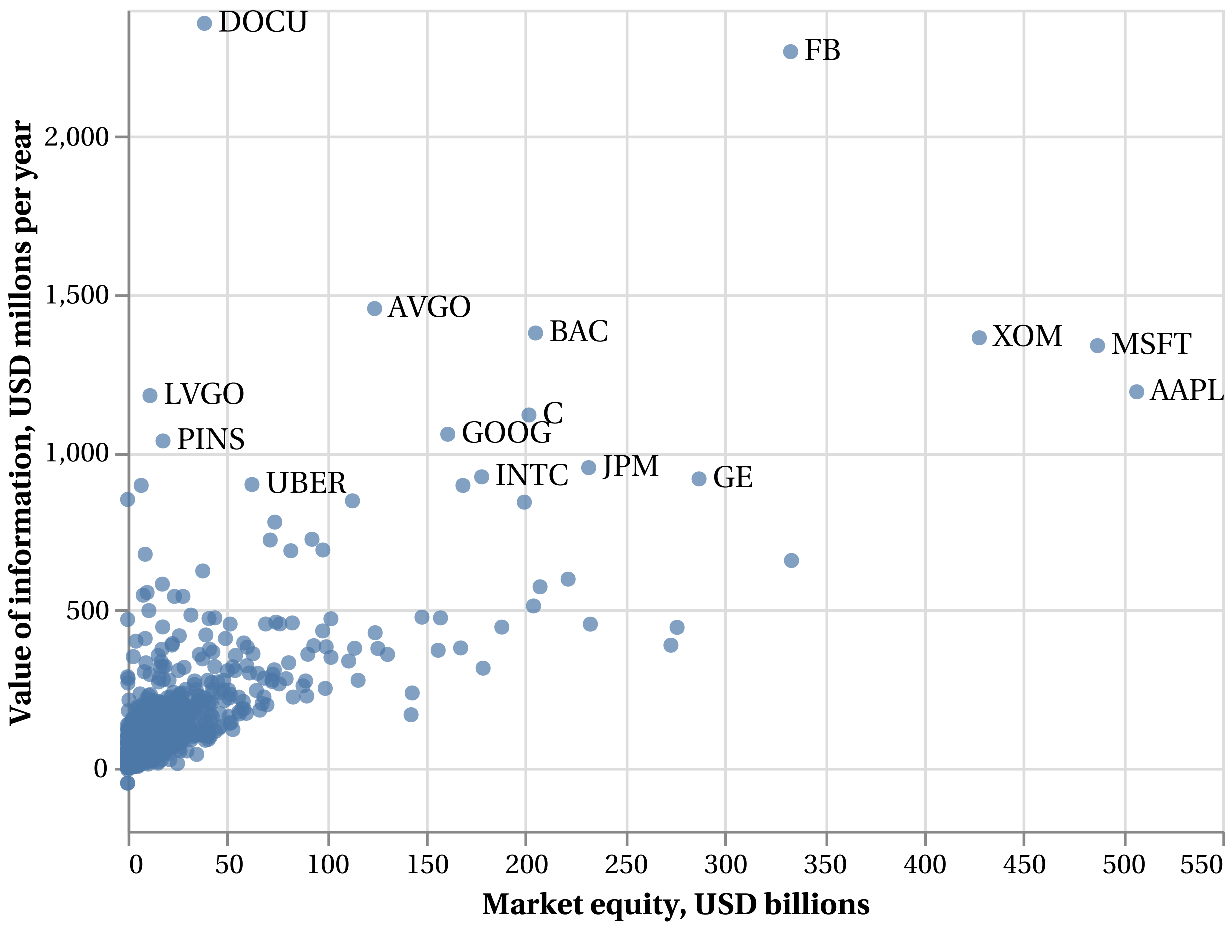
Figure 4 shows that for some stocks, the value of information is considerably larger than the $2.9 million for the average firm reported in Table 1. For example, the value for information on Google is about a $1 billion a year. From the scatter plot we can see that size explains some but not all of this variation.

Figure 5 shows that, perhaps surprisingly, the value of information is consistently higher for large stocks than it is for small stocks. While the uncertainty associated with large stocks is lower, their illiquidity as measured by price impact is much lower to an extent that makes investment in acquiring information on such stocks more valuable. Note that the higher value of information for large stocks is consistent throughout our sample period. The spread between the value of information for large/small stocks widens during turbulent times, as stock volatility of small stocks is much more sensitive to macroeconomic shocks that the volatility of large stocks.

To formally test the hypothesis that the value of information is higher for large stocks, we regress the value of information on stock size (measured as log of market equity) as well as stock and day fixed effects. The results reported in Table 2a show a strong positive association between firm size and the value of information for all specifications. The coefficients can be interpreted as elasticities with respect to size. Specification (1) implies that the value of information rises by 0.81% when market equity rises by 1%. Before adding any fixed effects, the large R-squared in this univariate regression means size explains a substantial share of the variation in information values. Specifications (2) through (4) show that these conclusions are quite robust to controlling for firm-specific and time-specific heterogeneity. Specifications (5) through (8) show that the intraday value of information, which is somewhat smaller on average (Table 1), has a higher size elasticity.

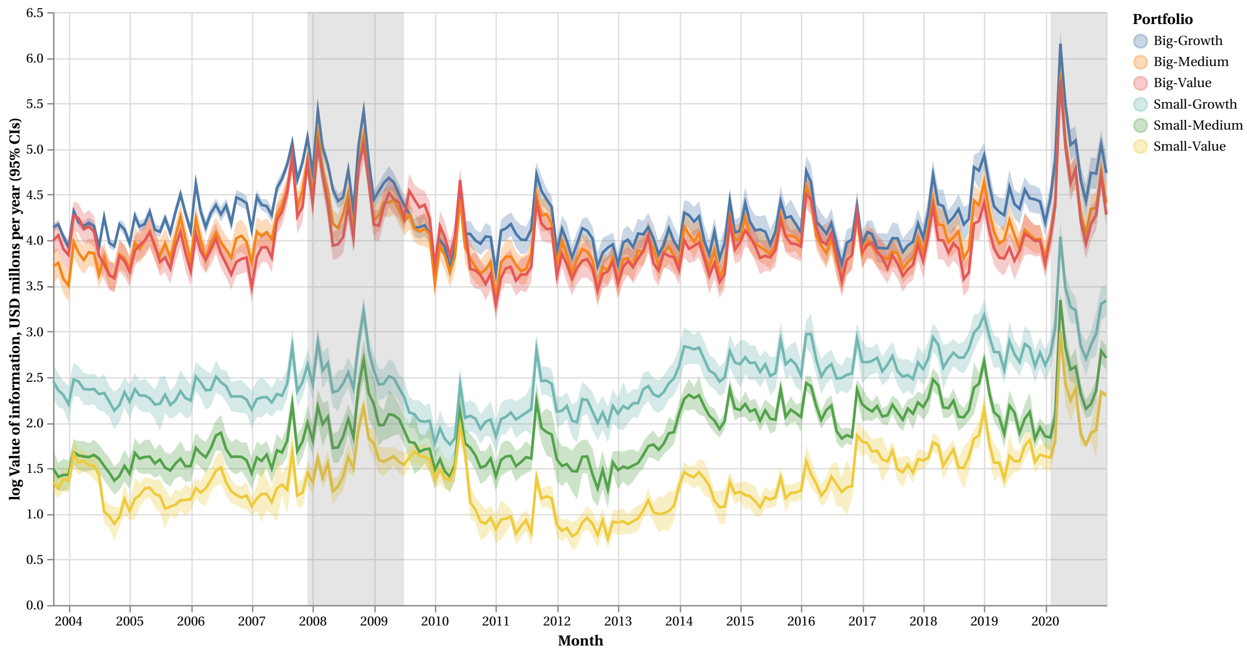
Table 2b shows that the main reason for the higher value of information for large stocks

Figure 4: Value of information by stock



Notes: Mean value of information plotted against mean market equity for each specific stock (permno). The value of information is annualized variance divided by price impact and reported in millions of dollars. We label the 15 most information valuable stocks with their latest ticker symbols.

Figure 5: Information on large growth stocks is more valuable



Notes: Monthly log information value averaged over stocks and days surrounded by their 95 percent confidence interval for stocks sorted to size and book-to-market portfolios. Following Fama-French conventions for constructing size-based portfolios, big stocks have market equity greater than the median NYSE stock over the previous month, and the rest are defined as small. Value stocks have a book-to-market equity ratio greater than the 70th percentile NYSE stock, growth stocks below the 30th percentile, and the rest are classified as medium. The value of information is annualized variance divided by price impact and reported in millions of dollars. Shades indicate recessions.

Table 2: Information on large stocks is more valuable

	log Information value				log Information value (intraday)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.81***	0.81***	0.69***	0.71***	0.82***	0.82***	0.72***	0.72***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	11,431,389	11,431,389	11,431,344	11,431,344	11,431,389	11,431,389	11,431,344	11,431,344
R^2	0.46	0.50	0.57	0.60	0.46	0.49	0.58	0.61

(a) Size explains a substantial share of information value variation

	log Return variance				log Price impact			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.32***	-0.33***	-0.34***	-0.34***	-1.12***	-1.13***	-1.04***	-1.05***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	11,431,389	11,431,389	11,431,344	11,431,344	11,431,389	11,431,389	11,431,344	11,431,344
R^2	0.20	0.40	0.36	0.54	0.68	0.70	0.72	0.74

(b) Larger stocks have lower volatility, but even lower price impact

Notes: Panel (a) shows regressions of the log value of information and its components on size. The log information value equals log annualized return variance less log price impact, so in Panel (B) we regress log return variance and log price impact on the same variables. Volatility is the square root of the annualized sum of squared one-minute log returns. Price impact is estimated by regressing one-minute log returns on contemporaneous share order flow and divided by the previous trading day's closing stock price. Size is log market equity over the previous month. The intraday value of information is based on intraday volatility alone (excluding overnight returns). Observations with negative price impact are omitted. Standard errors clustered by date and stock are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

is that price impact is more sensitive than volatility to size. The see this, we regress both log variance and log price impact on log market capitalization. Comparing, for example, specifications (1) and (5) we find that a 1% increase in size reduces variance by about 0.32% but it reduces price impact by about 1.12%.

Table 3 studies the extent to which the value of information can be explained by commonly studied characteristics: size, book-to-market, and momentum. Panel 3a shows that growth and momentum stocks have higher values of information. Unlike book-to-market, which is subsumed by the inclusion of both stock and day fixed effects, stocks that appreciated over the preceding year (high momentum stocks) have higher values of information regardless of the regression specification.

Comparing the R-squares in Table 2 to those in Table 3 we can see that size explains most of the variation in information values. By contrast, the increase in explanatory power from the addition of book-to-market ratios and momentum is quite modest.

Overall, our results show that, while small stocks may sound appealing for research, the value of information is actually higher for large stocks. The higher liquidity of large stocks more than makes up for the reduced uncertainty associated with their cash flows.

4.4 The Value of Information around Earning Announcement Days

We next turn to studying how the value of information changes on dates in which major pieces of information are released. Intuitively, a strategic trader should be willing to pay a higher amount to learn the end-of-day stock price at the beginning of days in which information is scheduled to be released. To this end, we focus our attention on the most prominent information release dates in the life of a firm—earnings announcement dates.

We collect earnings announcement dates from the Compustat quarterly database. Given that firms often report earnings after hours, we follow Engelberg, Mclean, and Pontiff (2018) and define the earnings announcement date as the date in which the trading vol-

Table 3: Value of information and stock characteristics

	log Information value				log Information value (intraday)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	0.79***	0.79***	0.68***	0.68***	0.80***	0.80***	0.70***	0.68***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Book-to-market	-0.27***	-0.24***	-0.05***	-0.01	-0.30***	-0.28***	-0.05***	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Momentum	0.20***	0.32***	0.05***	0.17***	0.21***	0.34***	0.05***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	11,431,389	11,431,389	11,431,344	11,431,344	11,431,389	11,431,389	11,431,344	11,431,344
R^2	0.47	0.50	0.57	0.60	0.47	0.50	0.58	0.61

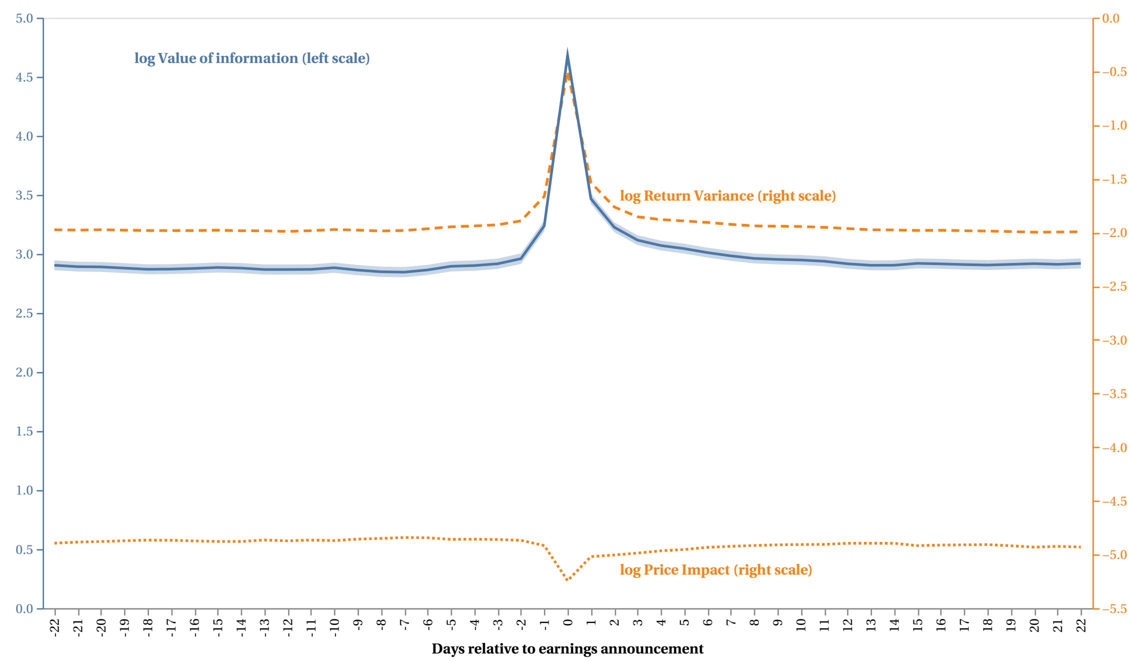
(a) Information values are higher for growth and momentum stocks

	log Return variance				log Price impact			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size	-0.33***	-0.34***	-0.31***	-0.35***	-1.11***	-1.12***	-1.00***	-1.03***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Book-to-market	-0.18***	-0.16***	0.05***	0.04***	0.07***	0.06***	0.09***	0.04***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Momentum	0.01	0.24***	-0.11***	0.12***	-0.18***	-0.08***	-0.16***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	11,431,389	11,431,389	11,431,344	11,431,344	11,431,389	11,431,389	11,431,344	11,431,344
R^2	0.20	0.41	0.36	0.54	0.68	0.70	0.72	0.74

(b) Momentum stocks are more volatile and more liquid

Notes: Panel (a) shows regressions of the log value of information and its components on stock characteristics. The log information value equals log annualized return variance less log price impact, so in Panel (B) we regress log return variance and log price impact on the same variables. Size is log market equity over the previous month. Momentum is the return over the prior 2–12 months. Book-to-market is book equity as of last June divided by market equity as of last December (Fama-French conventions). The intraday value of information is based on intraday volatility alone (excluding overnight returns). Observations with negative price impact are omitted. Standard errors clustered by date and stock are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 6: Value of information rises when firms report earnings



Notes: Solid line is the daily information value averaged over stocks surrounded by its 95 percent confidence interval, based on time-clustered variance estimates. The value of information is annualized variance divided by price impact and reported in millions of dollars. The log information value equals log annualized return variance less log price impact, so we also report the mean of log annualized return variance (dashed line) and the mean of log price impact (dotted line).

ume in the firm scaled by market volume is the highest among the official earnings date and the days just before/after it.

Figure 6 plots the value of information averaged across stocks and dates during a 45 trading day window around the earnings announcement date (day 0). The figure shows a dramatic increase in the value of information on days in which earnings are announced. This increase stems primarily from a spike in volatility on these days whereas liquidity appears to be actually mildly improving.

Table 4a provides more formal evidence supporting this conclusion. We regress the log of the value of information for each firm and day during our sample on firm size, book-to-market, momentum, date and stock fixed effects as well as an indicator variable for earning-announcement dates. The coefficient of the earnings indicator is positive and statistically significant in all specifications, indicating that the value of information rises on earning-announcement days. From an economic perspective, this effect is quite large, and implies that the value of information increases more than five-fold on the mean earnings release ($e^{1.74} > 5$).

Table 4b sheds further light on the increase in the value of information on earning announcement days. Here, we regress log variance and log price impact on the earnings-day indicator and control variables. In all specifications, we find a significant increase in volatility and a decrease in price impact on earning announcement days. These two effects reinforce each other, and jointly lead to the stark increase in the value of information on these days.

That the value of information rises on earnings announcement days is interesting in its own right. But it can also serve to explain the previously documented fact that investor attention spikes around these events. Ben-Rephael, Da, and Israelsen (2017) and Liu, Peng, and Tang (2019) find that both institutional and retail investor attention rises on earnings days, and that this effect is stronger for institutional investors. This fact is consistent with institutional investors superior ability to gather and exploit private information.

5 Multiple Informed Traders

Until this point, we have assumed that there is only one informed trader who possesses a perfect signal on the fundamental value. In practice, there may be multiple informed traders each of whom possesses an imperfect signal, and the signals may have different correlation structures. To study the robustness of our results to such a setting, we

Table 4: Information about earnings is highly valuable

	log Information value				log Information value (intraday)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings	1.83***	1.81***	1.76***	1.74***	1.57***	1.55***	1.49***	1.46***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	0.78***	0.79***	0.68***	0.68***	0.79***	0.80***	0.70***	0.68***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Book-to-market	-0.27***	-0.24***	-0.05***	-0.01	-0.30***	-0.28***	-0.05***	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Momentum	0.20***	0.32***	0.05***	0.17***	0.21***	0.34***	0.05***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	11,431,389	11,431,389	11,431,344	11,431,344	11,431,389	11,431,389	11,431,344	11,431,344
R^2	0.48	0.51	0.58	0.61	0.47	0.50	0.59	0.61

(a) Value of information is higher on earnings announcement days

	log Return variance				log Price impact			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings	1.45***	1.43***	1.44***	1.41***	-0.42***	-0.42***	-0.37***	-0.37***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.33***	-0.34***	-0.31***	-0.35***	-1.11***	-1.12***	-1.00***	-1.03***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Book-to-market	-0.18***	-0.16***	0.05***	0.04***	0.07***	0.06***	0.09***	0.04***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Momentum	0.01	0.24***	-0.11***	0.12***	-0.18***	-0.08***	-0.16***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	11,431,389	11,431,389	11,431,344	11,431,344	11,431,389	11,431,389	11,431,344	11,431,344
R^2	0.22	0.42	0.38	0.56	0.68	0.70	0.72	0.74

(b) Volatility is higher and price impact is lower on earnings announcement days

Notes: Panel (a) shows regressions of the log value of information and its components on size, book-to-market, and an earnings indicator. The log information value equals log annualized return variance less log price impact, so in Panel (B) we regress log return variance and log price impact on the same variables. Earnings indicates an earnings announcement day. Observations with negative price impact are omitted. Standard errors clustered by date and stock are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

rely on the model introduced in Back, Cao, and Willard (2000, hereafter BCW).[12] This model offers a generalization of the Kyle (1985) continuous-time model along two dimensions. First, it allows for $n \geq 1$ risk-neutral informed agents, and second, whenever $n \geq 2$, the signal received by each informed agent is imperfect. For tractability, we focus on the normally-distributed fundamental case (as opposed to log-normal case studied above). Specifically, consider a time period $[0, 1]$ and let $\tilde{v}$ be the expected value of the asset at time 1. Assume that the value at the end of the trading day is

$$\tilde{v} = \sum_{i=1}^{n} \tilde{s}^i,$$

where $\tilde{s}^i$ is the signal obtained by informed trader i, and $(\tilde{s}^1, ..., \tilde{s}^n)$ are symmetrically joint-normally distributed, with correlation coefficient $0 \leq \rho < 1$ between $\tilde{s}^i$ and $\tilde{s}^j$ for $\bar{\imath} \neq j$.[13] The cumulative noise trading process is given by

$$dZ\left(t\right) = \sigma_z dW\left(t\right),$$

where W_t is a Wiener process.[14] BCW show the existence of equilibria in this game that are linear in price $P\left(t\right)$ and signal s^i. That is, there are functions $\alpha\left(t\right), \beta\left(t\right),$ and $\lambda\left(t\right)$ such that the rate of trade of each informed trader i at time t is given by

$$\alpha\left(t\right) P\left(t\right) + \beta\left(t\right) \tilde{s}^i$$

12. Foster and Viswanathan (1996) study a dynamic model with multiple informed traders holding imperfect signals in discrete time. We rely on BCW because their continuous-time approach simplifies some of the analysis.

13. BCW show that in the case $\rho = 1$ an equilibrium fails to exist. We thus do not consider this case.

14. Note that BCW assume $\sigma_z = 1$ saying "We could easily make this an arbitrary constant σ_z. However, this parameter will affect market depth, the profits of informed traders, and so on." In the context of our paper, we cannot assume that $\sigma_z = 1$ because the value of information is affected by this parameter.

and the price set by the market maker follows the process

$$dP(t) = \lambda(t)\left\{dZ(t) + \sum_{i=1}^{n}\left[\alpha(t)P(t) + \beta(t)\tilde{s}^i\right]dt\right\}.$$

Similar to BCW, denote

$$\phi(n,\rho) = \frac{var(\tilde{v})}{var(n\tilde{s}^i)} = \frac{1}{n} + \frac{n-1}{n}\rho, \tag{16}$$

and

$$\zeta(n,\rho) = \frac{1-\phi(n,\rho)}{n\phi(n,\rho)}. \tag{17}$$

For brevity, we will often omit the arguments of $\phi(n,\rho)$ and $\zeta(n,\rho)$ and will refer to them as ϕ and ζ. Denote also

$$\kappa = \int_1^\infty x^{\frac{2(n-2)}{n}} e^{-2x\zeta} dx.$$

Theorem 1 in BCW (generalized slightly to allow for arbitrary σ_z) establishes the existence of a unique linear equilibrium satisfying:

$$\beta(t) = \sigma_z\left(\frac{\kappa}{\Sigma(0)}\right)^{\frac{1}{2}}\left(\frac{\Sigma(t)}{\Sigma(0)}\right)^{\frac{n-2}{n}}\exp\left[\zeta\frac{\Sigma(0)}{\Sigma(t)}\right],$$

$$\alpha(t) = -\beta(t)/n,$$

and

$$\lambda(t) = \frac{\beta(t)\Sigma(t)}{\sigma_z^2},$$

where $\Sigma(t)$ is the conditional variance of $\tilde{v}$ given the market maker's time t information.

Denote by Ω the value of information to all informed traders combined, which is equal to the expected loss of noise traders. We have

$$\begin{aligned}\Omega &= \int_0^1 dP(t)\, dZ(t) = \int_0^1 \lambda(t)\, dZ(t)\, dZ(t) = \sigma_z^2 \int_0^1 \lambda(t)\, dt \\ &= \sigma_z^2 \int_0^1 \frac{\beta(t)\,\Sigma(t)}{\sigma_z^2} dt = \int_0^1 \beta(t)\,\Sigma(t)\, dt.\end{aligned}$$

Corollary 3 in BCW (allowing for an arbitrary σ_z) establishes that the total value of information is given by

$$\Omega = \sigma_z \left(\frac{var(\tilde{v})}{\kappa}\right)^{\frac{1}{2}} \int_1^\infty x^{-\frac{2}{n}} \exp[-\zeta x]\, dx.$$

It follows that,

$$\begin{aligned}\Omega\lambda(0) &= \sigma_z \left(\frac{var(\tilde{v})}{\kappa}\right)^{\frac{1}{2}} \int_1^\infty x^{-\frac{2}{n}} \exp[-\zeta x]\, dx \cdot \frac{\beta(0)\,\Sigma(0)}{\sigma_z^2} \\ &= \frac{1}{\sigma_z} \left(\frac{var(\tilde{v})}{\kappa}\right)^{\frac{1}{2}} \int_1^\infty x^{-\frac{2}{n}} \exp[-\zeta x]\, dx \cdot (var(\tilde{v}))^{\frac{1}{2}} \cdot \sigma_z \kappa^{\frac{1}{2}} e^{\zeta} \\ &= var(\tilde{v})\, e^{\zeta} \int_1^\infty x^{-\frac{2}{n}} \exp[-\zeta x]\, dx.\end{aligned}$$

We thus have the following corollary of BCW.

Corollary 2 *The total value of information to all informed traders can be written as*

$$\Omega = c(n,\rho)\, \frac{var(\tilde{v})}{\lambda(0)}, \tag{18}$$

where the coefficient of proportionality $c(n,\rho) > 0$ does not depend on σ_z and is given by

$$c(n,\rho) = e^{\zeta} \int_1^\infty x^{-\frac{2}{n}} e^{-x\zeta} dx. \tag{19}$$

Expression (18) is similar to (4) as the value of information is once again proportional to the variance of the fundamental value divided by Kyle's lambda measured at the beginning of the trading period. A key to estimating the value of information then becomes the magnitude of the coefficient of proportionality $c(n, \rho)$, which only depends on the number of informed traders n and the correlation between signals, ρ. When $n = 1$, we have $c = 1$, which is the case studied in Section 2. The next proposition establishes that the case $n = 2$ and $\rho = 0$ provides a lower bound on $c(n, \rho)$ for any $n \geq 1$ and $\rho \geq 0$. One can calculate that $c(2, 0) \approx 0.9229$. We thus have,

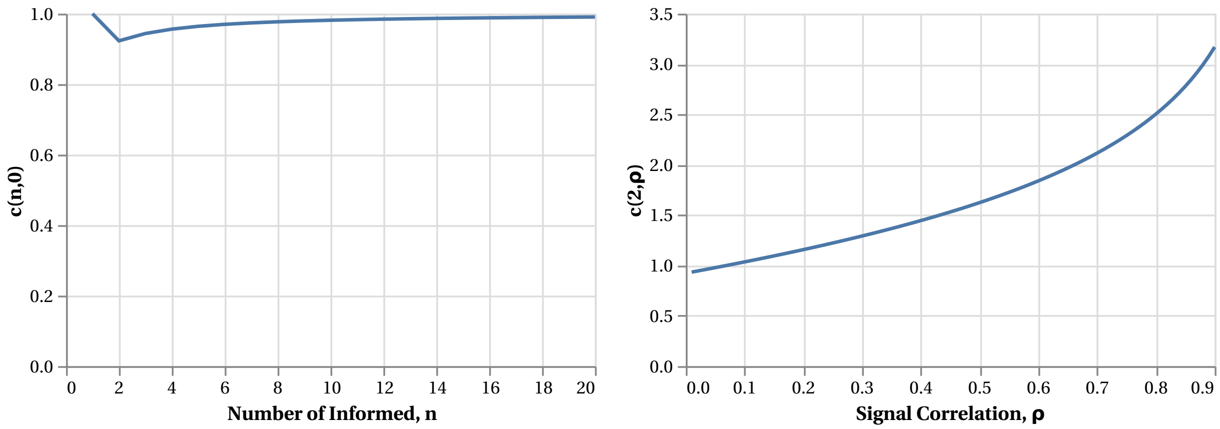
Proposition 3 *For any $n \geq 1$ and $\rho \geq 0$, $c(n, \rho) \geq 0.92$, and the total value of information satisfies*

$$\Omega \geq 0.92 \frac{var(\tilde{v})}{\lambda(0)}.$$

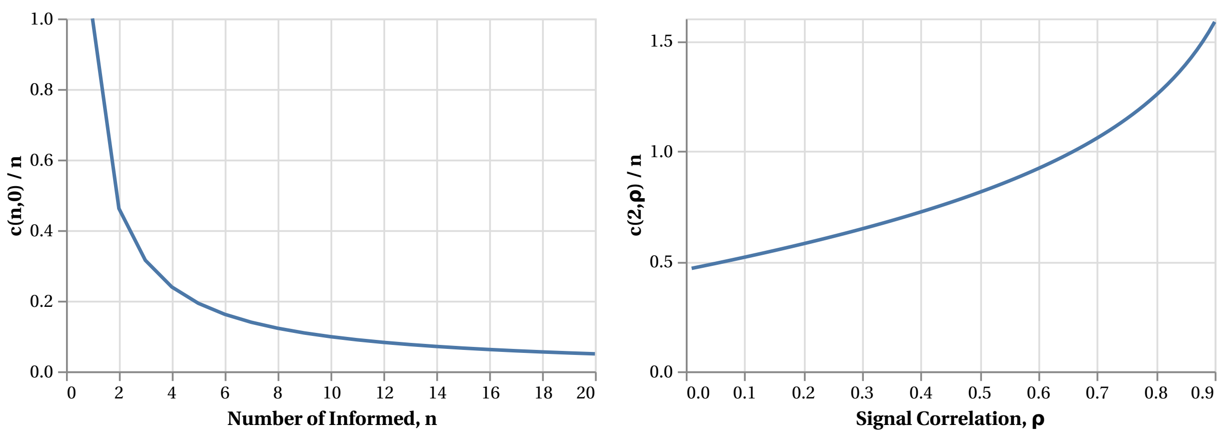
The importance of Proposition 3 is in establishing the robustness of our previous results. It ensures that, regardless of the degree of competition among informed traders and the extent to which their imperfect signals are correlated, the total value of information cannot be lower than 92% of the ratio of fundamental variance to initial price impact.

Figure 7 illustrates this proposition. It shows that $c(n, \rho)$ grows quickly and exceeds 0.92 even for relatively low values of n. The top-right plot shows that for $n = 2$, $c()$ is increasing in signal correlation ρ. In the bottom two plots, we divide further by n to get the constant of proportionality per informed trader. Because $c(n, 0)$ is approximately 1, the per-capita value of information with uncorrelated signals is essentially that of the monopolist informed trader split equally among all the informed traders, as shown in the bottom-left plot. The bottom-right plot, shows that even when there are only two informed traders, the per-capita value of information can exceed that of the monopolist insider case. When the private signals are sufficiently positively correlated, the value of information to each individual trader is greater than we would estimate based on the single insider model. For example, with $n = 6$ informed traders and correlation coefficient $\rho = 0.8$, the value to each trader is roughly 2 times the ratio of variance to price impact.

Figure 7: Lower bounds on the value of information with multiple informed investors



(a) Constant of proportionality for the total value of information



(b) Constant of proportionality for the per-capita value of information

Notes: Panel (a) plots the constant of proportionality $c(n, \rho)$ defined in Corollary 2. Multiplying this constant by the value of information estimated under the Kyle (1985) model with a single monopolist informed investor, yields the total value of information with n informed investors whom signals are ρ correlated. The plots show that $c(n, \rho) \geq c(2, 0) > 0.92$ as proved in Proposition 3. In Panel (b) we divide further by number of informed investors to get per-capita values of information.

Corollary 2 also implies that the effects on the value of information of the different stock characteristics and events studied thus far may be biased because the number of informed investors and the correlation in their signals are omitted from the regression.

Following Pasquariello and Vega (2007) and Di Mascio, Lines, and Naik (2017), we use analyst coverage as a proxy for the number of informed investors n, and use the dispersion in analyst earning forecasts as a proxy for the correlation in their signals ρ. Table 5 shows that including these controls hardly changes the point estimates or the conclusions we draw from the regressions. We suspect that most of the difference relative to Table 4 is due to the restricted sample for which analyst coverage is available. The more saturated fixed effects specifications in particular, show that analyst coverage and dispersion are largely absorbed by stock fixed effects as they are highly persistent characteristics.

6 Conclusion

In this paper we offer a simple, intuitive, and empirically useful expression quantifying the value of gathering firm-specific information to a strategic informed trader. The value of information is the ratio of return variance to price impact measured using a version of Kyle's lambda. While volatility and illiquidity are known to be correlated, we find that the ratio of the two varies markedly both over time and in the cross section, giving rise to interesting patterns in the value of information.

In the time series, we find that the value of information rises in turbulent times and during recessions. In particular, the value of information spikes dramatically during both the great recession of 2007–2009 and the Covid-19 crisis of 2020. During these times, stock volatility increases more steeply than illiquidity, and information becomes much more valuable. In the cross section, we find that information on large stocks is consistently more valuable than information on small stocks, despite informational frictions that are known to be associated with the latter. This follows from the lack of liquidity in small

Table 5: Controlling for analyst coverage and forecast dispersion

	log Information value				log Information value (intraday)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings	1.78***	1.75***	1.79***	1.75***	1.49***	1.44***	1.50***	1.45***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	0.50***	0.49***	0.53***	0.56***	0.48***	0.48***	0.53***	0.56***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Book-to-market	-0.18***	-0.11***	-0.10***	0.02	-0.20***	-0.13***	-0.10***	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Momentum	0.17***	0.31***	0.01	0.14***	0.18***	0.32***	0.01	0.13***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Analysts	0.03***	0.03***	0.00	0.01***	0.03***	0.03***	0.00	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Analyst Disp.	0.00**	0.00**	0.00	-0.00	0.00**	0.00**	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	3,026,000	3,026,000	3,025,992	3,025,992	3,026,000	3,026,000	3,025,992	3,025,992
R^2	0.41	0.48	0.50	0.56	0.41	0.47	0.50	0.56

(a) Value of information is higher on earnings announcement days

	log Return variance				log Price impact			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Earnings	1.53***	1.52***	1.54***	1.52***	-0.36***	-0.33***	-0.36***	-0.33***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Size	-0.43***	-0.45***	-0.31***	-0.32***	-0.94***	-0.95***	-0.86***	-0.89***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Book-to-market	-0.12***	-0.05***	0.05*	0.12***	0.07***	0.07***	0.14***	0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Momentum	0.01	0.26***	-0.15***	0.10***	-0.16***	-0.06***	-0.16***	-0.04***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Analysts	0.02***	0.02***	-0.01***	0.00	-0.02***	-0.02***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Analyst Disp.	0.00***	0.00***	-0.00	0.00	0.00	0.00***	-0.00***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Date (day) FE		Yes		Yes		Yes		Yes
Stock FE			Yes	Yes			Yes	Yes
N	3,026,000	3,026,000	3,025,992	3,025,992	3,026,000	3,026,000	3,025,992	3,025,992
R^2	0.29	0.57	0.44	0.69	0.64	0.67	0.69	0.71

(b) Volatility is higher and price impact is lower on earnings announcement days

Notes: Panel (a) shows regressions of the log value of information and its components on size, book-to-market, and an earnings indicator. The log information value equals log annualized return variance less log price impact, so in Panel (B) we regress log return variance and log price impact on the same variables. Earnings indicates an earnings announcement day. Observations with negative price impact are omitted. Standard errors clustered by date and stock are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

stocks, which makes it harder to exploit information associated with them. Finally, we find that the value of information rises on earning announcement days, when significant firm-specific information is revealed.

Our measure of the value of information has a variety of potential applications–both in academic work and in practice. Future empirical work could use our approach to rank information sources such as analysts, news letters, and alternative data. It can also be used to rank and evaluate the degree to which different types of corporate announcements add value to investors. And, our measure can be employed by the courts to assess penalties in cases of insider trading.

References

Admati, Anat R., and Paul Pfleiderer. 1988. "A Theory of Intraday Patterns: Volume and Price Variability." *Review of Financial Studies* 1 (1): 3–40.

Ai, Hengjie. 2007. *Information Quality and Long-Run Risks: Asset Pricing and Welfare Implications.* Wokring Paper.

Aït-Sahalia, Yacine, Per A. Mykland, and Lan Zhang. 2005. "How Often to Sample a Continuous-Time Process in the Presence of Market Microstructure Noise." *Review of Financial Studies* 18 (2): 351–416. ISSN: 0893-9454.

Akey, Pat, Vincent Gregoire, and Charles Martineau. 2020. *Price Revelation from Insider Trading: Evidence from Hacked Earnings News.* SSRN Scholarly Paper ID 3365024. Rochester, NY: Social Science Research Network, May 28.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5 (1): 31–56. ISSN: 1386-4181.

Arbel, Avner, Steven Carvell, and Paul Strebel. 1983. "Giraffes, Institutions and Neglected Firms." *Financial Analysts Journal.*

Back, Kerry. 1992. "Insider Trading in Continuous Time." *Review of Financial Studies* 5 (3): 387–409. ISSN: 0893-9454.

———. 2017. *Asset Pricing and Portfolio Choice Theory.* 2nd ed. Oxford University Press. ISBN: 978-0-19-024114-8.

Back, Kerry, C. Henry Cao, and Gregory A. Willard. 2000. "Imperfect Competition among Informed Traders." *The Journal of Finance* 55, no. 5 (October): 2117–2155. ISSN: 00221082.

Back, Kerry, Pierre CollinDufresne, Vyacheslav Fos, Tao Li, and Alexander Ljungqvist. 2018. "Activism, Strategic Trading, and Liquidity." *Econometrica* 86 (4): 1431–1463. ISSN: 1468-0262.

Bai, Jennie, Thomas Philippon, and Alexi Savov. 2016. "Have Financial Markets Become More Informative?" *Journal of Financial Economics* 122, no. 3 (December 1): 625–654. ISSN: 0304-405X.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen. 2017. "It Depends on Where You Search: Institutional Investor Attention and Underreaction to News." *The Review of Financial Studies* 30, no. 9 (September 1): 3009–3047. ISSN: 0893-9454.

Bogousslavsky, Vincent. 2019. *The Cross-Section of Intraday and Overnight Returns.* Working Paper ID 2869624. Rochester, NY: SSRN.

Bond, Philip, Alex Edmans, and Itay Goldstein. 2012. "The Real Effects of Financial Markets." *Annual Review of Financial Economics* 4, no. 1 (October 1): 339–360. ISSN: 1941-1367.

Breon-Drish, Bradyn. 2015. "On Existence and Uniqueness of Equilibrium in a Class of Noisy Rational Expectations Models." *Review of Economic Studies:* rdv012.

Brogaard, Jonathan, Matthew C. Ringgenberg, and David Sovich. 2019. "The Economic Impact of Index Investing." *Review of Financial Studies* 32 (9): 3461–3499. ISSN: 0893-9454.

Caballé, Jordi, and Murugappa Krishnan. 1994. "Imperfect Competition in a Multi-Security Market with Risk Neutrality." *Econometrica* 62 (3): 695–704. ISSN: 0012-9682.

Campbell, John Y. 2017. *Financial Decisions and Markets: A Course in Asset Pricing.* Princeton University Press.

Chakrabarty, Bidisha, Bingguang Li, Vanthuan Nguyen, and Robert A. Van Ness. 2007. "Trade Classification Algorithms for Electronic Communications Network Trades." *Journal of Banking & Finance* 31 (12): 3806–3821. ISSN: 0378-4266.

Chiccoli, C., S. Lorenzutta, and G. Maino. 1990. "Recent Results for Generalized Exponential Integrals." *Computers & Mathematics with Applications* 19 (5): 21–29. ISSN: 0898-1221.

Cochrane, John H. 2005. *Asset Pricing.* Revised. Princeton University Press, June.

Collin-Dufrense, Pierre, and Vyacheslav Fos. 2015. "Do Prices Reveal the Presence of Informed Trading?" *Journal of Finance* 70 (4): 1555–1582. ISSN: 1540-6261.

Collin-Dufresne, Pierre, and Vyacheslav Fos. 2016. "Insider Trading, Stochastic Liquidity, and Equilibrium Prices." *Econometrica* 84 (4): 1441–1475. ISSN: 1468-0262.

Copeland, Thomas E., and Dan Galai. 1983. "Information Effects on the Bid-Ask Spread." *Journal of Finance* 38 (5): 1457–1469. ISSN: 0022-1082.

Croce, Mariano (Max) Massimiliano, Tatyana Marchuk, and Christian Schlag. 2019. *The Leading Premium.* Working Paper ID 2692892. Rochester, NY: SSRN.

Dávila, Eduardo, and Cecilia Parlatore. 2018. *Identifying Price Informativeness* w25210. Cambridge, MA: National Bureau of Economic Research, November.

———. Forthcoming. "Trading Costs and Informational Efficiency." *Journal of Finance:* 79.

Di Mascio, Rick, Anton Lines, and Narayan Y. Naik. 2017. *Alpha Decay.* SSRN Scholarly Paper ID 2580551. Rochester, NY: Social Science Research Network, November 21.

Drechsler, Itamar, Alan Moreira, and Alexi Savov. 2018. "Liquidity Creation As Volatility Risk." *SSRN Electronic Journal.* ISSN: 1556-5068.

Driebusch, Corrie. 2015. "Investors Grasp for Answers Amid Wild Stock Rout." *Wall Street Journal: Markets,* August 25. ISSN: 0099-9660.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara. 2000. "The Accuracy of Trade Classification Rules: Evidence from Nasdaq." *Journal of Financial and Quantitative Analysis* 35 (4): 529–551. ISSN: 0022-1090.

Engelberg, Joseph, R. David Mclean, and Jeffrey Pontiff. 2018. "Anomalies and News." *Journal of Finance* 73 (5): 1971–2001. ISSN: 1540-6261.

Epstein, Larry G, and Stanley E Zin. 1989. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework." *Econometrica:* 937–969.

Epstein, Larry G., Emmanuel Farhi, and Tomasz Strzalecki. 2014. "How Much Would You Pay to Resolve Long-Run Risk?" *American Economic Review* 104 (9): 2680–2697.

Fama, Eugene F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25, no. 2 (May): 383–417.

Farboodi, Maryam, Adrien Matray, Laura Veldkamp, and Venky Venkateswaran. 2021. "Where Has All the Data Gone?" *The Review of Financial Studies* (hhab110). ISSN: 0893-9454.

Feldstein, Martin. 2015. "The Feds Stock-Price Correction." *Wall Street Journal: Opinion,* August 24. ISSN: 0099-9660.

Foster, F. Douglas, and S. Viswanathan. 1996. "Strategic Trading When Agents Forecast the Forecasts of Others." *The Journal of Finance* 51 (4): 1437–1478. ISSN: 1540-6261.

Gârleanu, Nicolae, and Lasse Heje Pedersen. 2018. "Efficiently Inefficient Markets for Assets and Asset Management." *Journal of Finance* 73 (4): 1663–1712. ISSN: 1540-6261.

Grossman, Sanford J., and Joseph E. Stiglitz. 1980. "On the Impossibility of Informationally Efficient Markets." *American Economic Review* 70 (3): 393–408. ISSN: 00028282.

Haddad, Valentin, Alan Moreira, and Tyler Muir. 2020. *When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Feds Response.* Working Paper.

Hasbrouck, Joel. 2007. *Empirical Market Microstructure: The Institutions, Economics, and Econometrics of Securities Trading.* Oxford University Press.

———. 2009. "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data." *Journal of Finance* 64 (3): 1445–1477. ISSN: 1540-6261.

He, Zhiguo, and Asaf Manela. 2016. "Information Acquisition in Rumor-Based Bank Runs." *Journal of Finance* 71 (3): 1113–1158. ISSN: 1540-6261.

Hendershott, Terrence, Dmitry Livdan, and Dominik Rösch. Forthcoming. "Asset Pricing: A Tale of Night and Day." *Journal of Financial Economics.*

Hendershott, Terrence, Dmitry Livdan, and Norman Schürhoff. 2015. "Are Institutions Informed about News?" *Journal of Financial Economics* 117, no. 2 (August): 249–287. ISSN: 0304405X.

Hengjie Ai, Bansal, Ravi, Guo, Hongye, and Yaron, Amir. 2019. *Identifying Preference for Early Resolution from Asset Prices.* Wokring Paper.

Holden, Craig W., and Stacey Jacobsen. 2014. "Liquidity Measurement Problems in Fast, Competitive Markets: Expensive and Cheap Solutions." *Journal of Finance* 69 (4): 1747–1785. ISSN: 1540-6261.

Hou, Kewei, and Tobias J. Moskowitz. 2005. "Market Frictions, Price Delay, and the Cross-Section of Expected Returns." *Review of Financial Studies* 18 (3): 981–1020. ISSN: 0893-9454.

Huang, Alan Guoming, Hongping Tan, and Russ Wermers. 2020. "Institutional Trading around Corporate News: Evidence from Textual Analysis." *Review of Financial Studies.*

Kacperczyk, Marcin, and Emiliano Pagnotta. 2019a. *Becker Meets Kyle: Inside Insider Trading.* Wokring Paper ID 3142006. Rochester, NY: Social Science Research Network.

———. 2019b. "Chasing Private Information." *Review of Financial Studies* 32 (12): 4997–5047. ISSN: 0893-9454.

Kacperczyk, Marcin, Savitar Sundaresan, and Tianyu Wang. 2019. *Do Foreign Institutional Investors Improve Price Efficiency?* Wokring Paper ID 3141866. Rochester, NY: Social Science Research Network.

Kadan, Ohad, and Asaf Manela. 2019. "Estimating the Value of Information." *Review of Financial Studies* 32 (3): 951–991. ISSN: 0893-9454.

Kim, Oliver, and Robert E. Verrecchia. 1994. "Market Liquidity and Volume around Earnings Announcements." *Journal of Accounting and Economics* 17 (1): 41–67. ISSN: 0165-4101.

Koudijs, Peter. 2015. "Those Who Know Most: Insider Trading in Eighteenth-Century Amsterdam." *Journal of Political Economy* 123 (6): 1356–1409.

Kyle, Albert S. 1985. "Continuous Auctions and Insider Trading." *Econometrica* 53 (6): 1315–1335. ISSN: 00129682.

Kyle, Albert S., and Anna A. Obizhaeva. 2016. "Market Microstructure Invariance: Empirical Hypotheses." *Econometrica* 84 (4): 1345–1404.

———. 2018. "The Market Impact Puzzle." *Anna A., The Market Impact Puzzle (February 4, 2018).*

———. 2019. "Market Microstructure Invariance: A Dynamic Equilibrium Model." *Anna A., Market Microstructure Invariance: A Dynamic Equilibrium Model (January 31, 2019).*

Kyle, Albert S., Anna A. Obizhaeva, and Yajun Wang. 2018. "Smooth Trading with Overconfidence and Market Power." *Review of Economic Studies* 85 (1): 611–662.

Lee, Charles M. C., and Mark J. Ready. 1991. "Inferring Trade Direction from Intraday Data." *Journal of Finance* 46 (2): 733–746. ISSN: 1540-6261.

Liu, Hongqi, Lin Peng, and Yi Tang. 2019. *Retail Attention, Institutional Attention.* SSRN Scholarly Paper ID 3370683. Rochester, NY: Social Science Research Network, April 12.

Malamud, Semyon. 2015. *Noisy Arrow-Debreu Equilibria.* Working Paper.

Malamud, Semyon, and Marzena Rostek. 2017. "Decentralized Exchange." *American Economic Review* 107, no. 11 (November): 3320–3362. ISSN: 0002-8282.

Muravyev, Dmitriy, and Xuechuan (Charles) Ni. 2020. "Why Do Option Returns Change Sign from Day to Night?" *Journal of Financial Economics* 136, no. 1 (April 1): 219–238. ISSN: 0304-405X.

Nagel, Stefan. 2012. "Evaporating Liquidity." *Review of Financial Studies* 25, no. 7 (July 1): 2005–2039. ISSN: 0893-9454.

Obizhaeva, Anna A. 2011. "Selection Bias in Liquidity Estimates." *University of Maryland Working.*

Pasquariello, Paolo, and Clara Vega. 2007. "Informed and Strategic Order Flow in the Bond Markets." *The Review of Financial Studies* 20, no. 6 (November 1): 1975–2019. ISSN: 0893-9454.

Savov, Alexi. 2014. "The Price of Skill: Performance Evaluation by Households." *Journal of Financial Economics* 112 (2): 213–231. ISSN: 0304-405X.

Smialek, Jeanna, and Neil Irwin. 2020. "Fed Slashes Rates to Near-Zero and Unveils Sweeping Program to Aid Economy." *The New York Times: Business,* March 15. ISSN: 0362-4331.

Stoll, Hans R. 1978. "The Supply of Dealer Services in Securities Markets." *Journal of Finance* 33 (4): 1133–1151. ISSN: 0022-1082.

Veldkamp, Laura. 2011. *Information Choice in Macroeconomics and Finance.* Princeton, NJ: Princeton University Press.

A Online Appendix

A.1 Proofs

Proof of Proposition 1. We first argue that for log-normally distributed $\tilde{v}$ with $\log \tilde{v} \sim N\left(\mu, \sigma_v^2\right)$

$$\mathrm{E}\left[\tilde{v} \log \tilde{v}\right] = e^{\mu + \frac{\sigma^2}{2}} \left(\mu + \sigma_v^2\right). \tag{OA.20}$$

To see this, let $\tilde{w} = \log \tilde{v}$. Then, $\tilde{w} \sim N\left(\mu, \sigma_v^2\right)$ and we have,

$$\begin{aligned}
\mathrm{E}\left[\tilde{v} \log \tilde{v}\right] &= \mathrm{E}\left[e^{\tilde{w}} \tilde{w}\right] \\
&= \frac{1}{\sqrt{2\pi}\sigma_v} \int_{-\infty}^{\infty} e^w w e^{-\frac{(w-\mu)^2}{2\sigma_v^2}} dw \\
&= \frac{1}{\sqrt{2\pi}\sigma_v} \int_{-\infty}^{\infty} w e^{-\frac{w^2 - 2\mu w - 2\sigma_v^2 w + \mu^2}{2\sigma_v^2}} dw \\
&= \frac{1}{\sqrt{2\pi}\sigma_v} \int_{-\infty}^{\infty} w e^{-\frac{w^2 - 2w\left(\mu + \sigma_v^2\right) + \mu^2}{2\sigma_v^2}} dw \\
&= e^{\mu + \frac{\sigma_v^2}{2}} \left[\frac{1}{\sqrt{2\pi}\sigma_v} \int_{-\infty}^{\infty} w e^{-\frac{\left(w - \left(\mu + \sigma_v^2\right)\right)^2}{2\sigma_v^2}} dw\right] \\
&= e^{\mu + \frac{\sigma_v^2}{2}} \left(\mu + \sigma_v^2\right),
\end{aligned}$$

where the last equality follows because the term in brackets is the expectation of a random variable distributed $N\left(\mu + \sigma_v^2, \sigma_v^2\right)$.[15]

Now, the value of information is given by

$$\begin{aligned}
\mathrm{E}J\left(0, \bar{v}, \tilde{v}\right) &= \frac{\mathrm{E}\left[\bar{v} - \tilde{v}\right] + \mathrm{E}\left[\tilde{v}\left(\log \tilde{v} - \log \bar{v}\right)\right]}{\lambda} + \frac{1}{2}\frac{\sigma_v^2}{\lambda}\bar{v} \\
&= \frac{e^{\mu + \frac{1}{2}\sigma_v^2}\left(\mu + \sigma_v^2\right) - e^{\mu + \frac{1}{2}\sigma_v^2}\left(\mu + \frac{1}{2}\sigma_v^2\right)}{\lambda} + \frac{1}{2}\frac{\sigma_v^2}{\lambda}\bar{v}
\end{aligned}$$

15. An alternative approach to establishing (OA.20) is to apply the well-known expression for the moment-generating function $E[e^{tw}]$ for a normally distributed w, and differentiating at $t = 1$. We thank Nicolae Garleanu for pointing this out to us.

$$= \frac{\sigma_v^2}{\lambda} P_0,$$

where the first equality follows from (6), the second from (7) and (OA.20), and the third from (7). ■

Proof of Proposition 3: When $n = 1$, $c(1, \rho) = 1$ and we are done. Thus, assume $n \geq 2$, From (19), we have that

$$c(n, \rho) = e^{\zeta} E_{\frac{2}{n}}(\zeta), \tag{OA.21}$$

where $E_p(z)$ is the generalized exponential integral defined as

$$E_p(z) = \int_1^{\infty} x^{-p} e^{-xz} dx.$$

To show that $c(n, \rho) \geq c(2, 0) \approx 0.92$, we establsih 3 claims.

Claim 1: For any $n \geq 2$ and $\rho \geq 0$, $\frac{\partial \zeta(n,\rho)}{\partial \rho} < 0$. Thus, for any $n \geq 2$, $\zeta(n, \rho)$ is maximized at $\rho = 0$, where the maximal value is $\zeta(n, 0) = \frac{n-1}{n}$.

The proof of this claim follows from direct differentiation of (17).

Claim 2: For any $n \geq 2$ and $\rho \geq 0$, $c(n, \rho) \geq c(n, 0)$.

To prove this, we fix $n \geq 2$ and differentiate $c(n, \rho)$ by ρ applying (OA.21):

$$\begin{aligned} \frac{\partial}{\partial \rho} c(n, \rho) &= e^{\zeta} \frac{\partial \zeta}{\partial \rho} E_{\frac{2}{n}}(\zeta) + e^{\zeta} \left(\frac{\partial}{\partial \zeta} E_{\frac{2}{n}}(\zeta) \frac{\partial \zeta}{\partial \rho} \right) \\ &= e^{\zeta} \frac{\partial \zeta}{\partial \rho} \left(E_{\frac{2}{n}}(\zeta) + \frac{\partial}{\partial \zeta} E_{\frac{2}{n}}(\zeta) \right). \end{aligned}$$

From Eq. (3) in Chiccoli, Lorenzutta, and Maino (1990),

$$\frac{\partial}{\partial \zeta} E_{\frac{2}{n}}(\zeta) = -E_{\frac{2}{n}-1}(\zeta).$$

It follows that

$$\frac{\partial}{\partial \rho} c(n, \rho) = e^{\zeta} \frac{\partial \zeta}{\partial \rho} \left(E_{\frac{2}{n}}(\zeta) - E_{\frac{2}{n}-1}(\zeta) \right).$$

Now, $\frac{\partial \zeta}{\partial \rho} < 0$ (from Claim 1), and $E_{\frac{2}{n}}(\zeta) - E_{\frac{2}{n}-1}(\zeta) < 0$ (from Eq. (8) in Chiccoli, Lorenzutta, and Maino (1990)). It follows that $\frac{\partial}{\partial \rho} c(n, \rho) > 0$, and thus $c(n, \rho) \geq c(n, 0)$.

Claim 3: We now show that $c(n, \rho) \geq 0.92$ for all $n \geq 2$ and $\rho \geq 0$.

By Claim 2, it is sufficient to show that $c(n, 0) \geq c(2, 0) \approx 0.92$ for all $n \geq 2$. For $n = 2, ..., 11$, we calculate that $c(n, 0) = e^{\zeta(n,0)} E_{\frac{2}{n}}(\zeta(n, 0)) > 0.92$. For $n \geq 12$, we apply Eq. (13) in Chiccoli, Lorenzutta, and Maino (1990), which (using Claim 1) implies that

$$c(n, 0) = e^{\zeta(n,0)} E_{\frac{2}{n}}(\zeta(n, 0)) > \frac{1}{\frac{2}{n} + \frac{n-1}{n}} = \frac{n}{n+1} \geq \frac{12}{13} > 0.92.$$

This concludes the proof. ■

A.2 Robustness

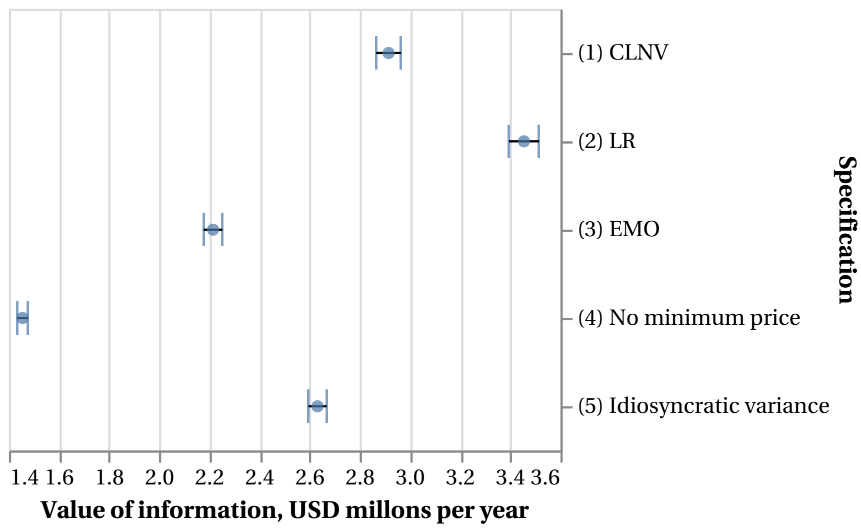
Here we include some additional results that are not meant for print publication.

Table OA.1: Extreme value of information days

Date	Information value, $M	Return variance	Price impact per $M
2020-03-20	19.65	3.34	0.17
2020-03-16	19.26	4.08	0.21
2020-03-12	18.38	3.30	0.18
2020-03-18	17.77	3.87	0.22
2020-03-09	16.85	2.68	0.16
2020-11-09	15.21	2.22	0.15
2020-03-13	14.62	2.76	0.19
2020-03-19	14.51	3.36	0.23
2020-03-24	14.06	3.17	0.23
2020-03-25	13.25	2.83	0.21
2020-03-23	13.09	3.44	0.26
2020-03-17	13.04	2.77	0.21
2015-08-24	12.92	1.94	0.15
2020-03-26	12.77	2.53	0.20
2008-09-19	12.30	2.46	0.20
2008-10-10	11.97	3.66	0.31
2020-02-28	11.33	1.38	0.12
2020-06-05	10.87	1.37	0.13
2020-04-01	10.61	2.22	0.21
2020-04-07	10.35	2.17	0.21
⋮			
2005-11-25	1.23	0.16	0.13
2013-04-12	1.23	0.16	0.13
2012-04-12	1.23	0.16	0.13
2013-02-12	1.22	0.14	0.11
2012-10-08	1.21	0.16	0.13
2012-05-25	1.21	0.18	0.15
2012-10-12	1.20	0.15	0.13
2010-10-11	1.20	0.17	0.14
2010-11-26	1.20	0.15	0.13
2012-08-28	1.19	0.16	0.13
2010-12-23	1.18	0.13	0.11
2012-08-24	1.18	0.16	0.14
2010-12-27	1.17	0.13	0.11
2010-12-29	1.17	0.12	0.10
2010-12-28	1.14	0.12	0.11
2010-12-30	1.09	0.12	0.11
2013-01-16	1.08	0.13	0.12
2012-08-30	1.05	0.14	0.13
2010-12-31	1.05	0.13	0.13
2009-12-24	0.96	0.16	0.16

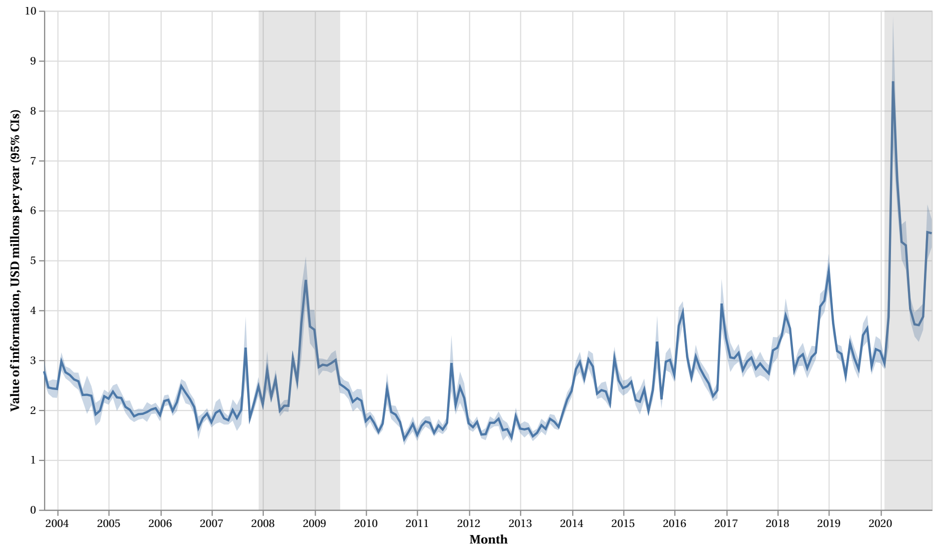
Notes: The 20 highest and lowest information value days, September 2003 to December 2020.

Figure OA.1: Robustness: Mean value of information

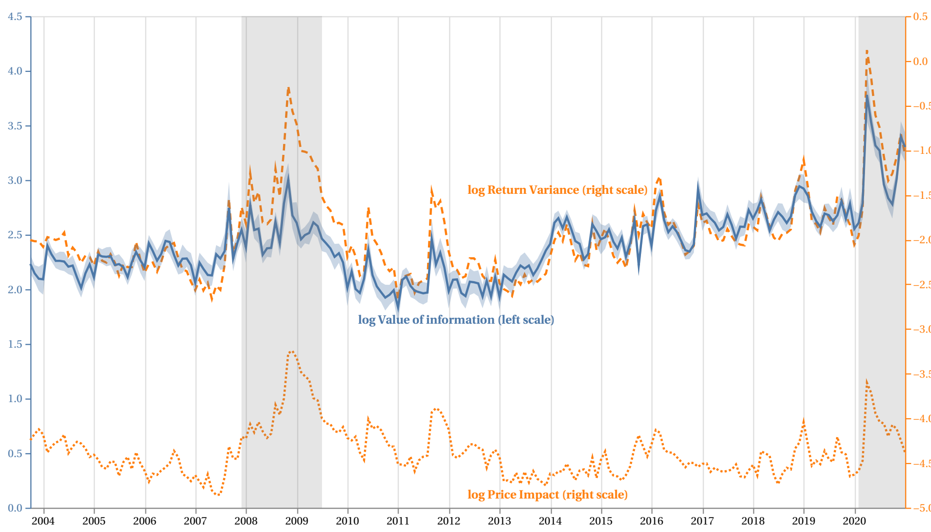


Notes: Reported is the mean value of information across days and stocks for three different algorithms for signing trades as buys or sells: Chakrabarty et al. (2007, CLNV), Lee and Ready (1991, LR), and Ellis, Michaely, and O'Hara (2000, EMO). No minimum price shows the effect of including stocks with nominal price below $5. Idiosyncratic variance shows the effect of subtracting market variance from stock-specific variance to measure the values of idiosyncratic information. The value of information is annualized variance divided by price impact and reported in millions of dollars. All variables are 1% winsorized.

Figure OA.2: Value of idiosyncratic information over time



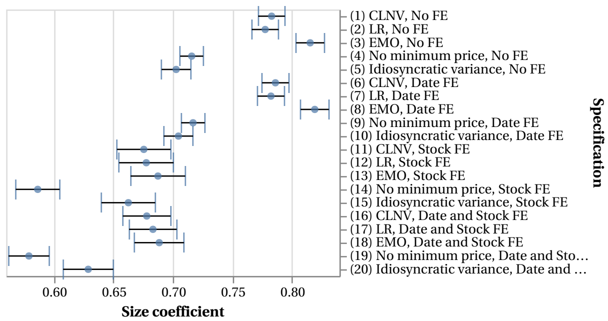
(a) Value of information in levels



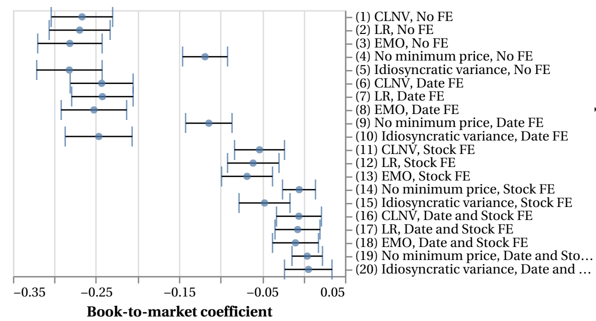
(b) Value of information in logs and its components

Notes: The solid line is the monthly information value averaged over stocks and days surrounded by its 95 percent confidence interval, based on time-clustered variance estimates. The idiosyncratic value of information is annualized idiosyncratic variance divided by price impact and reported in millions of dollars, where idiosyncratic variance is stock-specific variance less market (SPY) variance. The log information value equals log annualized return variance less log price impact, so we also report the mean of log annualized return variance (dashed line) and the mean of log price impact (dotted line). Shades indicate recessions.

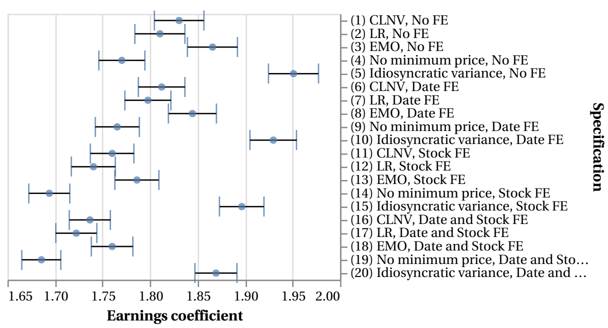
Figure OA.3: Robustness: Value of information and stock characteristics



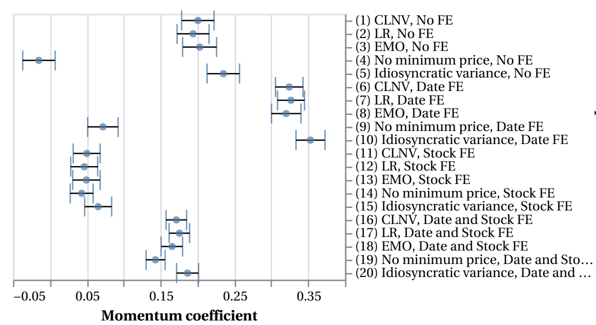
(a) Size



(b) Book-to-market



(c) Earnings



(d) Momentum

Notes: Reported are coefficients from regressions of the log value of information on stock characteristics. We evaluate several fixed effect specifications and three different algorithms for signing trades as buys or sells: Chakrabarty et al. (2007, CLNV), Lee and Ready (1991, LR), and Ellis, Michaely, and O'Hara (2000, EMO). No minimum price shows the effect of including stocks with nominal price below $5. Idiosyncratic variance shows the effect of subtracting market variance from stock-specific variance to measure the values of idiosyncratic information. The log information value equals log annualized return variance less log price impact, so in Panel (B) we regress log return variance and log price impact on the same variables. Size is log market equity over the previous month. Momentum is the return over the prior 2–12 months. Book-to-market is book equity as of last June divided by market equity as of last December (Fama-French conventions). Observations with negative price impact are omitted. Standard errors clustered by date and stock are used to construct the 95% errors bars.