Warp Speed Price Moves: Jumps after Earnings Announcements*

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Abstract

Corporate earnings announcements unpack large bundles of information that should, in efficient markets, trigger jumps in stock prices. Testing this implication is difficult in practice, as it requires noisy high-frequency data from after-hours markets, where most earnings announcements are released. With a unique dataset and a new microstructure noise-robust jump test, we show that earnings announcements almost always induce jumps in the stock price of announcing firms. They also significantly raise the probability of price co-jumps in non-announcing firms and the market. We find that returns from a post-announcement trading strategy are consistent with an efficient price formation after 2016.

JEL Classification: C10; C80.

Keywords: after-hours trading; earnings announcements; jump testing; spillover effects, high-frequency data; market efficiency; price discovery.

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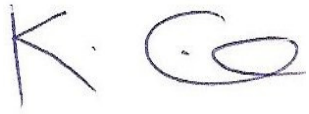
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1 Introduction

Earnings announcements constitute perhaps the single most important source of firm-level information for stock market investors and play an essential role in the price discovery process. They are the key occasions on which firms release audited results and communicate their views on economic prospects to investors. With several headline numbers being released simultaneously, earnings announcements can be thought of as points in time where draws from the news process have a very high variance which, in all likelihood, leads investors to materially revise their estimates of firm values.

In an efficient market where trading frictions are not prohibitively large, the widespread prevalence of high-frequency trading for the most liquid stocks means that earnings announcements should almost surely trigger jumps in prices. Effectively, a very high propensity of jumps in stock prices immediately after earnings announcements is a *necessary* condition for markets to efficiently incorporate the new information.[1]

Building on this idea, we propose to use jump tests based on high-frequency tick-by-tick price data as a new way to study market efficiency. Our theoretical framework is fundamentally different from conventional approaches. Indeed, existing work typically looks at return predictability, usually in terms of serial correlation, in one- or five-minute intervals after news announcements, see, e.g., Ederington and Lee (1993). While these time intervals are relatively short in an absolute sense, they are excessively long in a world with fast-paced high-frequency trading that can process thousands of orders in a matter of milliseconds after major news releases. In the presence of such high-frequency trading, jump tests conducted at the tick-by-tick level are arguably better suited to reveal whether markets react efficiently.

Testing for jumps in prices after earnings announcements creates special challenges, however. In recent years, the vast majority of publicly traded U.S. firms have made their earnings announcements in the after-hours market outside the regular trading session (9:30am–4:00pm).[2] After-hours trading on days with earnings announcements are therefore central to the price discovery process and it is important to understand price dynamics in these markets. We do so in this paper by studying transactions, bid-ask spreads, price discovery, and return predictability at a much higher tick-by-tick frequency than in previous studies. All told, we examine more than 89 billion after-hours quotes and nearly 8 billion after-hours transactions for 50 stocks over a 12-year sample. For these stocks, our analysis provides the most complete analysis of trades and price formation in the after-hours market to date.

[1] The condition that prices jump after earnings announcements is, however, not sufficient because the price could systematically over- or undershoot its new equilibrium level, thus introducing predictable dynamics in the post-announcement returns. We explore this issue in Section 6.

[2] Jiang, Likitapiwat, and McInish (2012), Lyle, Stephan, and Yohn (2021), and Michaely, Rubin, and Vedrashko (2013) report that more than 95% of US firms announce earnings outside the regular exchange trading session. This fraction is as high as 99.1% in the recent analysis by Grégoire and Martineau (2022) which studies companies belonging to the S&P 1500 stock index between 2011 and 2015.

Unfortunately, after-hours transaction prices are severely affected by market microstructure noise, which tends to distort standard jump tests. The irregular format of data from the after-hours trading sessions poses serious challenges to empirical work and has limited jump tests to focus on data recorded for the regular trading sessions.[3] To address these challenges, we develop a new jump test that is suitable for illiquid markets, by generalizing the classical bipower variation-based jump test of Barndorff-Nielsen and Shephard (2006). We construct a noise-robust test statistic that relies on a pre-averaging technique to lessen the detrimental impact of the noise (see, e.g., Aït-Sahalia, Jacod, and Li, 2012; Jacod, Li, Mykland, Podolskij, and Vetter, 2009; Lee and Mykland, 2012; Podolskij and Vetter, 2009a,b). We extend the existing theory by generalizing the microstructure noise to allow for heteroscedasticity and dependence and also show how to estimate the asymptotic variance of the test statistic, which is itself a non-trivial problem.[4] Through simulations and empirical results, we demonstrate that the conventional jump test is severely distorted by the type of market microstructure noise that is prevalent in after-hours markets, leading both to too many false positives and false negatives.

With our new noise-robust test statistic, we find strong empirical evidence in support of our hypothesis that earnings announcements trigger jumps in prices. Specifically, the probability that the stock price of the announcing firm jumps in after-hours sessions with earnings announcements exceeds 90% while the corresponding jump probabilities for the regular trading session and after-hours sessions without earnings announcements are 2.95% and 3.67%. In a nutshell, prices almost always jump after earnings announcements, but rarely jump otherwise.

If earnings announcements contain industry- and economy-wide news components, we should expect an increase in the jump probability of non-announcing firms' stock price as well as in the market index on announcement days. We test these implications and find compelling evidence for their presence. Jump spillover effects are strongly related to industry proximity and after-hours market liquidity with the probability of a price jump more than doubling for a high-liquidity, non-announcing firm within the industry of the announcing firm compared to a low-liquidity, non-announcing firm in unrelated businesses. The spillover effect is also much more important early in the earnings season than late in the earnings season, as consistent with Savor and Wilson (2016). Moreover, there is a big impact on the jump probability in the market index, which is stronger when many firms announce. This holds even after controlling for the mechanical price spillover effect that is a consequence of the announcing firms often being constituent members of the market index.

We next study whether prices adjust *sufficiently* fast and by an appropriate amount to efficiently incorporate the new information. Our analysis inspects all trades and quotes, using a more detailed and complete data set than that examined in previous studies. This means that we can pinpoint

[3]See, e.g., Aït-Sahalia and Jacod (2009b); Aït-Sahalia, Jacod, and Li (2012); Andersen, Bollerslev, and Dobrev (2007); Caporin, Kolokolov, and Renò (2017); Christensen, Oomen, and Podolskij (2014); Corsi, Pirino, and Renò (2010); Jiang and Oomen (2008).

[4]We propose an jump- and noise-robust version of the subsampling approach studied in Christensen, Podolskij, Thamrongrat, and Veliyev (2017), which delivers a consistent estimator with desirable finite sample properties.

exactly how long it takes for the price discovery process to incorporate new information as well as identify the factors—including earnings surprises, market liquidity and analyst coverage—that determine price movements in the immediate aftermath of earnings announcements.

We follow the approach of Patell and Wolfson (1984) by examining a simple trading rule based on return forecasts computed off the surprise component in earnings announcements. Over the 12-year sample (2008–2020) we find a highly significant mean return of 1.80% per transaction in a no-friction scenario where investors trade on the first transaction price after the announcement. Executing trades instead at the midquote of the bid-ask spread, mean returns drop to 1.50% per trade which remains highly significant. This finding continues to hold for trades executed at the actual spreads obtained from the bid-ask quotes after the announcement (mean return of 0.72%). Delaying trades by five seconds reduces mean returns to 0.41% per trade, which remains significant. Further delays beyond five seconds lead to mean returns that are no longer statistically significant.

To analyze whether market efficiency has changed over time, we split our data into two sub-samples chosen to reflect structural changes in market design due to the closure of the last electronic communication network (ECN) in 2015 which led to a rerouting of liquidity to alternative trading venues such as dark pools. In the early sub-sample (2008–2015), mean excess returns are a highly significant 2.30% and 2.00% per trade in the frictionless and midquote trading scenarios, respectively. Even with a trading delay of 10 seconds, mean returns remain significant and economically large (0.80% per trade). Conversely, in the second sub-sample (2016–2020), the only significant values for mean returns are obtained in the frictionless and midquote scenarios while mean returns become small and insignificant in the presence of bid-ask spreads, or even negative with timing delays. These findings suggest that the post-earnings announcement price discovery process in the after-hours market has become extremely fast and increasingly efficient over time for the most liquid U.S. stocks.

The noise-robust jump test is best suited for firms with a high trading volume in the after-hours market. This condition is not valid for smaller and more illiquid firms whose stocks are not traded frequently. To address this issue, we also propose a new close-to-open return-based test that relies solely on the change in the closing price prior to the announcement to the open price after the announcement. This test can be applied to any stock regardless of its after-hours activity, and while it does not possess the power of our noise-robust jump test based on tick-by-tick data, in practice we find that it identifies the majority of jumps and even has more power than conventional tests based on five-minute sampling.

Our analysis is related to a number of previous studies. Grégoire and Martineau (2022) examine how earnings announcement news get transmitted to stock prices in the after-hours market. They study a wider set of stocks than we do, but examine the dynamics of price formation for each firm in far less detail, aggregating instead price changes into five-minute intervals. They conclude that bid-ask spreads are so wide that investors could not cover their round-trip trading costs even if they

knew the post-announcement closing price.[5] We arrive at a very different conclusion for our sample of stocks, finding instead that post-announcement prices often move well outside the range covered by the pre-announcement bid-ask spread which remains relatively narrow.

Our analysis is also related to studies on price formation in the extended-hour trading session. In a seminal contribution, Barclay and Hendershott (2003) study price discovery and trading in the after-hours market, finding some evidence of inefficient price formation. Our results show that trading activity and price discovery in the after-hours market is a tale of two markets. Even for the most liquid stocks like those examined here, after-hours trading volume is almost entirely dormant on days without earnings announcements. In contrast, on days with earnings announcements, after-hours trading activity explodes. Average after-hours trading volume on days with earnings announcements exceeds its counterpart on days without earnings announcement by almost two full orders of magnitude.[6]

Another literature has examined jumps in stock prices and their relation to news effects on returns. Jeon, McCurdy, and Zhao (2022) examine the relation between news articles and price jumps. Their analysis is based on general news and daily data, whereas we look at earnings announcements and high-frequency data at a much higher level of granularity. Bollerslev, Li, and Todorov (2016) find significantly positive risk premia for jump and overnight market betas but not for continuous market betas. They find that stocks with higher jump and overnight market betas earn higher returns even when controlling for continuous market betas. This suggests that investors command a risk premium mainly for exposure to discontinuous variations in the aggregate market but not for exposure to continuous variations. Cremers, Halling, and Weinbaum (2015) find evidence of higher risk premia for exposure to changes in jump risk than for exposure to changes in volatility risk.

The outline of the paper is as follows. Section 2 establishes the link between price jumps and market efficiency before introducing our new noise-robust jump test statistic. Section 3 explains our data sources. Section 4 implements the jump test statistic on a unique set of high-frequency data that includes information about the transaction record from outside the official opening hours of the exchange. Section 5 examines jump spillover effects, and Section 6 studies price dynamics after earnings announcements and analyzes returns from a simple trading strategy. Section 7 concludes. Supplemental appendices at the back of the paper provide additional results and technical analysis.

2 Market efficiency and price jumps

We begin by motivating why, in efficient markets, we should expect stock prices to jump immediately after earnings announcements. Next, to test this implication we introduce a new jump test that is robust to the high levels of market microstructure noise that affect prices in after-hours trading sessions. We finish the section by reporting results from Monte Carlo simulations comparing the

[5] Specifically, Grégoire and Martineau (2022) write that "pre-announcement bid-ask spreads are wide enough to include the post-announcement closing price, eliminating the profits of informed liquidity takers."

[6] Averaged over firms and years, this ratio equals 93.57 over our sample.

performance of our new noise-robust test to existing jump tests.

2.1 Earnings announcements

Earnings announcements can be thought of as points in time where large bundles of information are disclosed simultaneously to all investors. Moreover, the timing of such information disclosures is typically known ahead of time, giving investors ample opportunity to prepare for the announcement and respond instantaneously.[7]

The asset pricing setup that most closely resembles earnings announcements is perhaps the continuous-time model with regime-switching dynamics and jumps developed by David and Veronesi (2014). In this model, discrete shifts between a set of unobserved regimes determine the drift of the fundamental variables. The real earnings process contains a Poisson jump component which also feeds into the pricing kernel and so is a source of systematic risk. Jumps in the earnings process therefore translate into jumps in stock prices. This is consistent with earnings announcements, which we can think of as discrete jumps in the earnings news process, inducing jumps in stock prices.[8]

Even in the absence of jumps in the earnings process, large revisions to investors' learning process about the underlying state can induce large, discrete changes to prices. For example, in the models developed by Veronesi (1999, 2000), the dividend growth process switches discretely between high-growth and low-growth states. Investors monitor dividends and infer the underlying state from news about dividends. A switch in the underlying dividend growth regime will generally lead to a significant revision in investors' dividend growth estimates and, in turn, the stock price. Assuming that the growth processes of dividends and earnings are correlated, a similar effect will emerge in a model in which investors observe earnings. Earnings announcements are events with significant releases of news about the earnings process at a single point in time. With a high likelihood, this triggers significant revisions to investors' beliefs about future earnings and, in turn, leads to large price movements at the time of the earnings announcement.

Accounting for risk aversion, prices could jump even when the earnings news does not surprise investors due to the uncertainty resolution effect from earnings announcements removing short-term uncertainty about firm earnings. Hence, stock prices are more likely to move up (due to the lower risk premium) than down following an earnings announcement that is close to investors' expectations.

In discrete-time models with disagreement among investors (heterogeneous priors) such as Banerjee and Kremer (2010), earnings announcements can be thought of as periods in which the variance

[7]Most large-cap companies inform markets in advance about their intention to release a financial report either Before Market Open (BMO), during Regular Trading Hours (RTH), or After Market Close (AMC), see, e.g., `https://www.nasdaq.com/market-activity/earnings`.

[8]David and Veronesi (2014) model the aggregate economy-wide earnings process, whereas we analyze earnings announcements at the firm level. However, as long as firms' earnings contain information about the economy-wide earnings process, firm-level prices should jump. Below, we show that this condition holds empirically.

of the public information signal is an order of magnitude bigger than normal. In these models, the revelation of big bundles of information is likely to cause investors to significantly revise their posteriors. Such revisions in beliefs will, in turn, typically trigger large changes in the underlying asset price whose variance is proportional to the variance of the public signal (see, e.g., Banerjee and Kremer, 2010, equation (10)).

Discrete-time asset pricing models tend to have a stylized time dimension and so do not directly spell out whether movements in asset prices take the form of rapid diffusion or discrete jumps. However, if markets are efficient, prices should adjust very quickly and are thus more likely to jump, i.e. move by a large amount more or less instantaneously, in the immediate aftermath of the release of large amounts of public information.

This discussion suggests the following hypothesis.

Hypothesis 1. *Necessary conditions for market efficiency after an earnings announcement include that, for the most liquid stocks,*

1. *The stock price of the announcing firm almost always jumps immediately after the earnings announcement.*

2. *Due to uncertainty resolution, the stock price of the announcing firm is more likely to jump up than down following an earnings announcement in line with analyst expectations.*

Earnings announcements may contain firm-, industry-, and market-wide components. Therefore, investors revise their expectations not only about the announcing firm's but also about the prospects of other firms and the broader economy. We therefore expect earnings announcements to induce spillover effects that increase the likelihood of jumps in the prices of non-announcing firms and the market index. This effect is arguably stronger for non-announcing firms with a closer industry proximity and high after-hours market trading activity, where the latter is required to facilitate the price discovery process. We also expect the information effect—and hence the jump spillover—to be enhanced for companies that announce their fiscal results early in the earnings season, since investors revise their beliefs the most in the beginning of the cycle (Savor and Wilson, 2016).

Hypothesis 2. *Information and learning-induced spillover effects in jump probabilities from the announcing to non-announcing firms and the broader market index imply that:*

1. *The prices of other (non-announcing) firms are more likely to jump on days with earnings announcements.*

2. *The increase in the jump probability for a non-announcing firm is higher if (i) the non-announcing firm is in the same industry as the announcing firm (industry proximity); (ii) the announcing firm is early in the news announcement cycle; and (iii) the announcing and non-announcing firm are more liquid with higher after-hours market trading activity.*

3. *The market index is more likely to jump on days with earnings announcements and the jump probability is higher on days where multiple firms announce their earnings.*

Higher jump probabilities in stock prices after an earnings announcement are a weak implication in the sense that it is a necessary but not sufficient condition for market efficiency. This holds because stock prices could over- or undershoot. For example, prices could jump too far, giving rise to a mean-reverting component that drifts towards the pre-announcement price in the aftermath of the jump. If instead prices do not jump far enough, we should expect to see post-announcement prices drift in the direction of the jump.

These examples suggest that a sufficient condition for market efficiency after earnings announcements is that investors cannot detect return predictability at any point on the post-announcement price path and exploit such predictability after accounting for trading costs and risk adjustments:[9]

Hypothesis 3. *A sufficient condition for market efficiency after an earnings announcement is that, at each point in time of the post-announcement price path:*

1. *Post-announcement returns of the announcing firm do not display any predictive patterns large enough to allow investors to earn abnormal returns after accounting for transaction costs and risk premia.*

2. *Post-announcement returns of the non-announcing firms and the market index do not display any predictive patterns large enough to allow investors to earn abnormal returns after accounting for transaction costs and risk premia.*

Hypothesis 3 does not mean that the price discovery process is settled instantaneously. We expect elevated volatility of the price process to last several minutes after the release of the news as information gets processed and trading positions are adjusted. However, the price discovery process should not leave any (local) biases allowing investors to predict future price movements.

The condition that return predictability should not be exploitable is important and goes back to Jensen (1978).[10] Trading costs and bid-ask spreads may induce negative autocorrelation in returns, but this should not generate abnormal profits after accounting for round-trip transaction costs. Time-varying risk premia may induce predictability in the price process but they are unlikely to matter at the high resolution studied here.

Testing the sufficient conditions in Hypothesis 3 is challenging because it has to hold for all possible trading rules that condition on the prevailing information. Short of inspecting the profitability of all possible trading and prediction rules based on the released information, it is difficult to conduct an exhaustive test of the condition. In practice, analysis typically examines simple

[9]Equilibrium prices are only determined up to the marginal cost of acquiring and processing information and implementing transactions (Grossman and Stiglitz, 1980; Pedersen, 2015).

[10]He defines market efficiency as follows: "A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t."

strategies based on news measures such as earnings surprises. Conclusions about market efficiency are therefore limited to the class of prediction and trading rules being examined.

2.2 Comparison to existing tests of market efficiency

Our approach to testing market efficiency by examining the presence of jumps after the disclosure of large information bundles is fundamentally different from common practice in the finance literature on testing market efficiency in the aftermath of macroeconomic news announcements (e.g., Ederington and Lee, 1993; Andersen, Bollerslev, Diebold, and Vega, 2003) or corporate earnings announcements (e.g., Beaver, 1968; Chambers and Penman, 1984; Jiang, Likitapiwat, and McInish, 2012; Grégoire and Martineau, 2022; Lyle, Stephan, and Yohn, 2021).

This literature typically studies predictability in post-announcement returns over fixed time intervals, such as one or five minutes. For example, Ederington and Lee (1993) conclude that "*Following an announcement, traders with immediate access to the market apparently form an estimate of the release's implication for market prices almost immediately, and the actual price adjusts to this level within one minute. The price level at the end of one minute of trading is a relatively unbiased estimate of the final equilibrium price.*" Andersen, Bollerslev, Diebold, and Vega (2003) observe that "*The general pattern is one of very quick exchange-rate conditional mean adjustment, characterized by a jump immediately following the announcement, and little movement thereafter.*" Importantly, the evidence of jumps presented by the latter relies on visual inspection of price movements over five-minute intervals and their sampling scheme does not allow them to formally test for instantaneous jumps in exchange rates.

In contrast, our hypotheses explicitly do *not* reference time intervals, such as one or five minutes. Rather, jumps must occur as close to instantaneously as trading technology allows (Hypotheses 1 and 2) and the sufficient conditions in Hypothesis 3 must hold at each point in time, i.e. on the entire price path, regardless of whether we are studying fixed or varying intervals in calendar or trading time. This is an important advantage because any choice of time interval used in conventional market efficiency tests is arbitrary.

More importantly, in the current fast-paced markets transactions can occur at high frequency, where it is possible to execute thousands of trades at very short intervals measured in milliseconds or less. The absence of serial correlation in, e.g., one-minute returns is therefore no guarantee that prices move efficiently. In a world dominated by algorithmic trading with latency delays shrinking ever closer to the lower bound imposed by the speed of light, ultimately only jump tests can reveal whether markets react efficiently to big news events.

To illustrate the extreme speed with which transactions occur in the immediate aftermath of an announcement, Panel A of Figure 1 shows tick-by-tick evidence on the price movement and transaction count from the announcement (time 0) to 60 seconds after Apple (AAPL) released its earnings report on 07/30/2020; Panel B zooms further in on the first 100 milliseconds. Transactions begin 15 milliseconds after the announcement and their toll exceeds more than 800 in the first post-

announcement second. The fastest trades can possibly be attributed to algorithmic traders sniping stale quotes in the limit order book, while the flat spots can appear when a large amount of passive resting volume (e.g, an iceberg order) is executed against a sequence of smaller trades. Trading activity then lies dormant for a few seconds before picking up significant steam again around the time where slower financial intermediaries are likely to have entered the market. On average, in the first ten seconds 300 trades execute per second, while in the one-minute post-announcement window more than 165 trades get executed per second.[11]

This example highlights the speed with which prices of the most liquid stocks adjust after earnings announcements. It also motivates the need for new market efficiency tests that account for such extremely fast trading, yet possess robustness to the high levels of noise typically encountered in after-hours markets. This is the topic we next turn to.

2.3 A noise-robust jump test

The vast majority of corporate earnings announcements occur in the after-hours market where trading volume is typically far lower and bid-ask spreads much wider compared to the regular trading session.[12] As we demonstrate below, in the presence of such microstructure frictions, conventional jump tests tend to spuriously identify false jumps, while often failing to detect true jumps. This shortcoming makes it important to have tests that are robust to the noised-up features of high-frequency data from the after-hours market.[13]

Given the popularity in empirical work of the jump test of Barndorff-Nielsen and Shephard (2006), we develop a noise-robust generalization which retains the intuitive nature of their test. We provide the main results below with detailed definitions and formal proofs provided in Appendix A.

2.3.1 The efficient price

We start by introducing a general continuous-time setup for modeling noisy high-frequency data. Consider a security price observed on the time interval [0,1] which we interpret as a complete daily trading session as described in Section 3. The fundamental theorem of asset pricing implies that in an efficient market without frictions and no arbitrage the price process, $P = (P_t)_{t\geq 0}$, must be a semimartingale (e.g., Delbaen and Schachermayer, 1994). Starting with the log-price process $p = (p_t)_{t\geq 0}$, where $p_t = \log(P_t)$, we can decompose the cumulative intraday log-return at time t,

[11] Towards the end of our sample, overall trading activity in the after-hours market is much higher than in the early years with high-speed electronic trading often exceeding 200 trades per second right after earnings announcements.

[12] Empirical work based on high-frequency data from the regular trading session is inconclusive about the importance of jumps relative to the diffusive volatility (as often modeled by the inclusion of a Brownian motion in the price process), see, e.g., Christensen, Oomen, and Podolskij (2014).

[13] Aït-Sahalia, Jacod, and Li (2012) construct a noise-robust jump test from power variations sampled at different frequencies but it is unclear how to implement such sampling in the after-hours market that is typically quite illiquid with limited trading. Lee and Mykland (2008, 2012) construct a noise-robust point-in-time jump test, which employs high-frequency returns standardized by a localized bipower variation (see also Lee and Hannig, 2010) but requires that the exact timing of earnings announcements is known with certainty.

$r_t = p_t - p_0$, into a continuous part and a jump, or discontinuous, part:

$$r_t = r_t^c + r_t^d. \tag{1}$$

In Appendix A, we introduce a general but succinct mathematical definition of these two separate sources of risk. Our framework is nonparametric, since we do not constrain the dynamics of the efficient price process, and is compatible with salient features of high-frequency financial data such as time-varying expected returns, stochastic volatility, leverage effects, and jumps in the price and volatility. Furthermore, the price jump component can be infinitely active and of infinite variation.

The null hypothesis that we wish to test is that P is continuous. This can be formulated as $\mathcal{H}_0 : \omega \in \Omega_0$, where $\Omega_0 \subseteq \Omega$ is the subset:

$$\Omega_0 = \{\omega \in \Omega : t \longmapsto P_t(\omega) \text{ is continuous on } [0,1]\}. \tag{2}$$

We test this null, which is equivalent to the restriction $r_t^d = 0$ for all t, against the alternative $\mathcal{H}_a : \omega \in \Omega_1$ with $\Omega_1 = \Omega_0^{\complement}$, the complement of Ω_0.

To develop a test of $\mathcal{H}_0$, we examine the composition of the quadratic return variation:

$$[r]_1 = \int_0^1 \sigma_s^2 \mathrm{d}s + \sum_{0 \le s \le 1} (\Delta r_s^d)^2, \tag{3}$$

where σ_s is the instantaneous volatility at time s, $\Delta r_s^d = r_s^d - r_{s-}^d$ is the associated jump size, and $r_{s-}^d = \lim_{t \uparrow s} r_t^d$. The first term in (3) is the quadratic variation of the continuous log-return, also known as the integrated variance. The second term represents the quadratic variation of the jump process, which is zero under $\mathcal{H}_0$.

Quadratic variation can equivalently be defined as follows:

$$[r]_1 = \operatorname*{plim}_{n \to \infty} \sum_{i=1}^{n} r_i^2, \tag{4}$$

where $r_i = p_{t_i} - p_{t_{i-1}}$ is the log-return over $[t_{i-1}, t_i]$ and the convergence in probability holds for every partition $0 = t_0 < t_1 < \ldots < t_n = 1$ such that $\max_{1 \le i \le n}(t_i - t_{i-1}) \to 0$ as $n \to \infty$, motivating why tick-by-tick high-frequency data is used to estimate quadratic variation.

2.3.2 The observed price

In practice, the efficient market hypothesis is violated because of market frictions—or microstructure noise—such as price discreteness and bid–ask spreads. In addition, even though the price process evolves in continuous time, trading is discrete. For simplicity, suppose the observed log-price is recorded at equidistant time points $t_i = i\Delta_n$, for $i = 0, 1, \ldots, n$, where $\Delta_n = 1/n$ is the time gap, which we collect in $p^* = (p^*_{i\Delta_n})_{i=0}^n$. To account for microstructure noise, we follow Hasbrouck (1995) and model $p^*_{i\Delta_n}$ as

$$p^*_{i\Delta_n} = p_{i\Delta_n} + \epsilon_{i\Delta_n}, \tag{5}$$

where $\epsilon_{i\Delta_n}$ is the microstructure effect.

The key challenge is to draw inference about the presence of jumps in the efficient price from a high-frequency record of noisy prices. To see this, note from equation (5) that the observed log-return measures the efficient log-return with error due to the microstructure component:

$$r_i^* = p^*_{i\Delta_n} - p^*_{(i-1)\Delta_n} = r_i + \epsilon_{i\Delta_n} - \epsilon_{(i-1)\Delta_n}. \tag{6}$$

2.3.3 The pre-averaging approach

To mitigate the effect of microstructure noise, we adopt the pre-averaging procedure of Jacod, Li, Mykland, Podolskij, and Vetter (2009); Podolskij and Vetter (2009a,b). Specifically, we replace the observed noisy log-return by a pre-averaged log-return:

$$\bar{r}_i^* = \sum_{j=1}^{k_n-1} g_j^n r^*_{i+j}, \quad \text{for } i = 0, \ldots, n - 2k_n + 1, \tag{7}$$

where $g_j^n = g(j/k_n)$ is a weight function, $k_n = \theta\sqrt{n} + o\big(n^{-1/4}\big)$ is the pre-averaging horizon, and $\theta > 0$ is a tuning parameter.

The averaging in (7) attenuates the microstructure noise and enhances the efficient log-return. If k_n is even and $g(x) = \min(x, 1-x)$, (7) can be rewritten as

$$\bar{r}_i^* = \frac{1}{k_n} \sum_{j=k_n/2+1}^{k_n} p^*_{\frac{i+j}{n}} - \frac{1}{k_n} \sum_{j=1}^{k_n/2} p^*_{\frac{i+j}{n}}. \tag{8}$$

Thus, $(\bar{r}_i^*)_{i=1}^{n-k_n+2}$ constitutes a sequence of log-returns constructed by simple averaging of the noisy log-price. With minor modifications, standard estimators of quadratic variation can therefore be tweaked to exploit the pre-averaged log-return series. We next define the pre-averaged realized variance and pre-averaged bipower variation as follows:

$$\begin{aligned} RV_n^* &= c_1^n \sum_{i=0}^{n-2k_n+1} |\bar{r}_i^*|^2 - c_2^n \hat{\omega}_n^2, \\ BV_n^* &= c_1^n \frac{\pi}{2} \sum_{i=0}^{n-2k_n+1} |\bar{r}_i^*||\bar{r}^*_{i+k_n}| - c_2^n \hat{\omega}_n^2, \end{aligned} \tag{9}$$

where

$$\hat{\omega}_n^2 = -\frac{1}{n-1} \sum_{i=2}^{n} r_i^* r^*_{i-1}. \tag{10}$$

The scalars c_1^n and c_2^n are defined in Appendix A and depend on the weight function, g, and pre-averaging window, k_n.

Thus, RV_n^* is the sum of squared pre-averaged returns, whereas BV_n^* is based on cross-products that are k_n terms apart. As we prove in Theorem 1, the extra distancing ensures that BV_n^* is asymptotically jump-robust, whereas RV_n^* is not. Both estimators are normalized for the effect

induced by pre-averaging and bias-corrected for the residual microstructure noise.[14]

2.3.4 Asymptotic theory

We next develop the theoretical foundation for the construction of our noise-robust jump test procedure.

Theorem 1. *Assume that r follows the process in* (1) *and that Assumptions (V) and (N) in Appendix A hold. Then, as* $n \to \infty$*,*

$$RV_n^* \xrightarrow{p} [r]_1 \qquad \text{and} \qquad BV_n^* \xrightarrow{p} \int_0^1 \sigma_s^2 \mathrm{d}s. \tag{11}$$

Moreover, provided that $\mathcal{H}_0$ *is true, as* $n \to \infty$*,*

$$n^{1/4} \begin{pmatrix} RV_n^* - \int_0^1 \sigma_s^2 \mathrm{d}s \\ BV_n^* - \int_0^1 \sigma_s^2 \mathrm{d}s \end{pmatrix} \xrightarrow{d} N(0, \Sigma), \tag{12}$$

where Σ *is the* 2×2 *asymptotic covariance matrix, as presented in* (48) *in Appendix A.*

Theorem 1 establishes a weak law of large numbers for the pre-averaged realized variance and pre-averaged bipower variation in the noisy jump-diffusion model under $\mathcal{H}_a$. It shows that RV_n^* is consistent for the quadratic variation, including the jump part, while BV_n^* converges to the integrated variance, excluding the jump part. Their difference therefore estimates the quadratic jump variation, $RV_n^* - BV_n^* \xrightarrow{p} \sum_{0 \le s \le 1} (\Delta r_s^d)^2$ which is zero in the absence of jumps. The last part of Theorem 1 establishes a bivariate asymptotic normal distribution of RV_n^* and BV_n^* as estimators of integrated variance under $\mathcal{H}_0$.

Applying the delta rule to (12), it follows from Theorem 1 that, under $\mathcal{H}_0$,:

$$\mathcal{J}_n^{\text{inf.}} = \frac{n^{1/4}\big(RV_n^* - BV_n^*\big)}{\sqrt{v^\top \Sigma v}} \xrightarrow{d} N(0,1), \tag{13}$$

where $v = [1, -1]^\top$. In contrast, $\mathcal{J}_n^{\text{inf.}} \xrightarrow{p} \infty$ under the alternative, $\mathcal{H}_a$.

2.3.5 A noise- and jump-robust covariance estimator

The test statistic $\mathcal{J}_n^{\text{inf.}}$ is not feasible since it depends on the covariance matrix Σ, which is a function of the latent volatility and microstructure noise processes. We therefore next develop a noise- and jump-robust plug-in estimator of Σ.[15] Specifically, we propose to set

$$\Sigma_n^* = \frac{1}{L} \sum_{l=1}^{L} \left(\frac{n^{1/4}}{\sqrt{L}} \begin{bmatrix} \check{BV}_l^*(2,0) - \check{BV}_n^*(2,0) \\ \check{BV}_l^*(1,1) - \check{BV}_n^*(1,1) \end{bmatrix} \right) \left(\frac{n^{1/4}}{\sqrt{L}} \begin{bmatrix} \check{BV}_l^*(2,0) - \check{BV}_n^*(2,0) \\ \check{BV}_l^*(1,1) - \check{BV}_n^*(1,1) \end{bmatrix} \right)^\top, \tag{14}$$

[14] The bias-correction employs the jump-robust estimator in (10). It was proposed by Oomen (2006) and designed to estimate the variance of the noise in i.i.d. setting. We show in Appendix A that $\hat{\omega}_n^2$ remains consistent for the integrated time-varying noise variance under Assumption (N), which is in agreement with Kalnina (2011).

[15] In principle, we only need to estimate Σ given that $\mathcal{H}_0$ is true. However, by using a jump-robust estimator of the asymptotic covariance matrix we avoid losing power under $\mathcal{H}_a$.

where $B\check{V}_n^*(q,r)$ is a truncated pre-averaged bipower variation of Christensen, Hounyo, and Podolskij (2018). The details are in Appendix A.2.

Σ_n^* is the sample covariance matrix of truncated subsampled pre-averaged bipower variation estimators, $B\check{V}_l^*(q,r)$, calculated on small batches of high-frequency data covering blocks of length pk_n, for $l = 1, \ldots, L$, where $p \geq 2$ is an integer, and L is the number of subsamples. They are centered around the full sample statistic, $B\check{V}_n^*(q,r)$, and suitably normalized.

With this in place, we obtain the following result:

Theorem 2. *Assume that r follows the process in* (1)*, that Assumptions (V) and (N) in Appendix A hold, as do the conditions listed in Theorem 12 therein. Then, as* $n \to \infty$*,*

$$\Sigma_n^* \xrightarrow{p} \Sigma. \tag{15}$$

Theorem 2 shows that Σ_n^* is consistent both under the null (diffusion only) and under the alternative (diffusion and jumps). Our proof confines attention to jump processes of bounded variation, which is standard when inference is based on the continuous part of the process.

By Slutsky' theorem, we obtain the following feasible jump test that holds under the null $\mathcal{H}_0$:

$$\mathcal{J}_n = \frac{n^{1/4}\big(RV_n^* - BV_n^*\big)}{\sqrt{v^\top \Sigma_n^* v}} \xrightarrow{d} N(0,1). \tag{16}$$

In the presence of jumps, $\mathcal{J}_n \xrightarrow{p} \infty$, so large values of $\mathcal{J}_n$ are indicative of price jumps.

The finite sample properties of $\mathcal{J}_n$ under the alternative can be further improved if we also replace BV_n^* in the numerator of (16) with a truncated version:[16]

$$\mathcal{J}_n = \frac{n^{1/4}\big(RV_n^* - B\check{V}_n^*\big)}{\sqrt{v^\top \Sigma_n^* v}}, \tag{17}$$

where $B\check{V}_n^* \equiv B\check{V}_n^*(1,1)$. Exploiting that our test is asymptotically unbiased and consistent, we can compare the test statistic $\mathcal{J}_n$ against the standard normal distribution to test for jumps.

The final form of $\mathcal{J}_n$ in (17) serves as our noise-robust jump test statistic.[17] A one-sided test procedure is appropriate here so the decision rule is to reject $\mathcal{H}_0$ at significance level α if $\mathcal{J}_n > \Phi^{-1}(1-\alpha)$, where $\Phi(x)$ is the standard normal distribution function:

$$\mathbb{P}\Big(\mathcal{J}_n > \Phi^{-1}(1-\alpha)\Big) \to \begin{cases} \alpha, & \text{under } \mathcal{H}_0, \\ 1, & \text{under } \mathcal{H}_a. \end{cases} \tag{18}$$

[16] On the one hand, "big" jumps induce an upward bias in BV_n^* for realistic sample sizes, causing a downward bias in the estimated jump variation and reducing the power of the jump test. However, such biases can readily be handled through truncation. On the other hand, the bipower mechanism—multiplication of adjacent log-returns—is an effective tool to get rid of "small" jumps that survive any truncation. This approach of cracking down twice on the jump component was proposed by Corsi, Pirino, and Renò (2010) for bipower variation in the noise-free setting. In Appendix A, we show that the substitution of BV_n^* with $B\check{V}_n^*$ in the numerator does not alter the asymptotic theory in Theorem 1.

[17] Barndorff-Nielsen and Shephard (2006) advocate a log- and ratio-based transformation of the noise-free version of (17) via the delta method. We implemented both these alternative versions of the noise-robust jump test statistic, which does not impact any of our conclusions.

2.4 A close–to–open return-based test

Our noise-robust jump test requires a large number of high-frequency data points and so is best suited for assets that are actively traded in the after-hours market. For many assets, including individual stocks, this condition does not hold. We therefore propose an alternative inference strategy based on close-to-open returns which can be applied to a much broader cross-section of securities. Other advantages of this approach is that it (i) is suitable for both pre-market and after-hours releases, (ii) does not require knowledge of the exact announcement time, and (iii) is not impaired if trading is halted pending the announcement. The main idea is that the previous closing price and next opening price are proxies for the equilibrium value of the firm before and after an earnings report. In efficient markets, their difference therefore reflects the full pricing implications of the announcement.

The test can be seen as an adaptation of the Lee and Mykland (2008) jump test to low-frequency data. To explain how it is designed, let $r_t^{co} = p_t^o - p_{t-1}^c$ denote the close-to-open log-return of a stock on day t, where p_t^o (p_{t-1}^c) is the opening (closing) log-price on day t ($t-1$). We assume r_t^{co} follows a two-state process, where the state reflects whether there is an announcement during the overnight period as captured by the indicator variable EA_t:

$$r_t^{co} \mid EA_t \sim \begin{cases} N(0, \sigma^2), & EA_t = 0, \\ N(0, \sigma^2) + J_t, & EA_t = 1, \end{cases} \tag{19}$$

where $J_t \sim N(0, \sigma_{EA}^2)$ is an independent jump with $\sigma_{EA}^2 \geq 0$.

Conditional on no announcement ($EA_t = 0$), close-to-open returns are drawn from a centered normal distribution with variance σ^2 while conditional on an announcement ($EA_t = 1$), returns are further affected by a jump so that $r_t^{co} \mid EA_t = 1 \sim N(0, \sigma^2 + \sigma_{EA}^2)$.

To test the null hypothesis of no announcement effect, ($J_t = 0$ or $\sigma_{EA}^2 = 0$), we standardize the current close-to-open return with an estimator of the no-announcement standard deviation computed from the previous L close-to-open returns, $\hat{\sigma}^2 = L^{-1} \sum_{l=1}^{L} (r_{t-l}^{co})^2$:

$$Z_t = \frac{r_t^{co}}{\hat{\sigma}}. \tag{20}$$

Under the null hypothesis $\mathcal{H}_0 : \sigma_{EA}^2 = 0$, the distribution of Z_t approaches a standard normal as $L \to \infty$, i.e. $Z_t \xrightarrow{d} N(0,1)$. Under the alternative hypothesis $\mathcal{H}_a : \sigma_{EA}^2 > 0$, $Z_t \xrightarrow{d} N(0, 1 + \sigma_{EA}^2/\sigma^2)$, which is overdispersed compared to the standard normal. This implies that Z_t has a higher probability of rejecting the null hypothesis than the nominal level under the alternative. However, it does not define a consistent test, because power is not going to one.[18] Nonetheless, if σ_{EA}^2 is large compared to σ^2, we can get close.[19] Arguably, in practice the variance of the announcement effect

[18] In line with Lee and Mykland (2008), the time horizon has to shrink to zero to get a consistent test. In particular, assume that under the null the variance of r_t^{co} per unit of time is σ^2. Then, under the alternative, $Z_t \sim N(0, 1 + \sigma_{EA}^2/(\Delta\sigma^2))$, where $\Delta = t_{open} - t - 1_{close}$. Hence, $P(\text{reject } \mathcal{H}_0 \mid \mathcal{H}_a) \to 1$ as $\Delta \to 0$. In our context, this limit is not feasible, however, due to the fixed placement of the opening and closing.

[19] The power curve is readily calculated as $P(\text{reject } \mathcal{H}_0 \mid \mathcal{H}_a) = f(\sigma_{EA}^2/\sigma^2) = 1 - P(z_{\alpha/2} < N(0, 1 + \sigma_{EA}^2/\sigma^2) <$

is much bigger than the variance of the regular no-announcement news component, so the empirical rejection rate for Z_t across many announcement days may still serve as an effective indicator of a jump effect.

To get a consistent test, we conduct a two-sample test for equality of variance over announcement and no-announcement days. In essence, this amounts to testing whether the variance of the standardized announcement close-to-open returns is equal to one. Within our framework, this can be done with a textbook variance ratio statistic evaluated through an F-distribution. However, in keeping with the model-free approach, we switch to the Brown-Forsythe test in our application, which is a more robust alternative.[20]

2.5 Monte Carlo simulations

Appendix B conducts a thorough Monte Carlo study of the finite-sample properties of our noise-robust jump test which we compare to the noise-free test of Barndorff-Nielsen and Shephard (2006). We develop a general setting that examines levels of microstructure noise that match those seen in the after-hours trading sessions in our data.

Our key findings from these simulations can be summarized as follows.

1. Even when the observed price is affected by a very high level of noise, our jump test does not systematically over- or under-reject the null hypothesis of no jumps.

2. Our jump test has good power properties and correctly identifies jumps under the alternative in a variety of scenarios for the microstructure noise, pre-averaging, subsampling, and jump-truncation.

3. In sharp contrast, the performance of the conventional jump test based on 5-minute realized variance and bipower variation degrades in the presence of the levels of microstructure noise typical for after-hours trading. Under such noise, the classical test identifies too many spurious jumps, falsely rejecting the null when no jumps are present. Conversely, it frequently fails to identify true jumps when these are genuinely present.

In summary, our simulations demonstrate both the need for and benefits from utilizing our noise-robust jump test on the high-frequency after-hours transaction price data examined in our empirical application, which we next proceed to.

$z_{1-\alpha/2}$). For example, if $\sigma^2_{EA}/\sigma^2 = 1, 2, 3$, the probability of rejecting the null at the $\alpha = 1\%$ nominal level of significance is 19.78%, 39.06%, and 51.96%.

[20] In our implementation, we exclude previous announcement days from the calculation and employ the mean absolute deviation as a more robust estimator.

3 Data description

Earnings announcements should trigger jumps in stock prices if investors efficiently and instantaneously process the new earnings information. In this section, we introduce the data sources employed to study if this prediction is supported empirically.

3.1 Transaction and quotation data

Jump tests benefit crucially from having data at the highest possible resolution, so our analysis employs tick-by-tick transaction and quotation data on individual firms' stock prices to track their response to corporate earnings announcements.

U.S. stock exchanges are only open for trading on normal business days from 9:30am–4:00pm Eastern time.[21] On most days, official pre-market trading is available from 4:00am–9:30am, while the after-hours market runs from 4:00pm–8:00pm.[22] Orders can additionally be submitted and trades executed at any time via private trading systems such as electronic communication networks (ECNs) or dark pools. The consolidated tape collates such real-time tick-by-tick data, which is made available for purchase via the New York Stock Exchange (NYSE) Trade and Quote (TAQ) database. In practice, there is usually limited trading activity before 6:00am or after 6:30pm, so we exclude this part of the day.

As noted earlier, the vast majority of U.S. companies publish their financial results outside the regular trading session. They may prefer to announce at these times because these markets are mostly comprised of professional investors and informed traders, speeding up the price discovery process (see Jiang, Likitapiwat, and McInish, 2012). In Appendix D, we examine the trading activity in the pre-market (6:00am–9:30am) and after-hours market (4:00pm–6:30pm). We find that trading volume is much lower in the pre-market, even on announcement days. This impairs the implementation of our jump test so our analysis focuses on the after-hours market. Following Dubinsky, Johannes, Kaeck, and Seeger (2019), we look at the 50 firms with the largest after-hours trading volume on announcement days.[23] This is appropriate not only because individual transaction counts are prohibitively large, but also because liquidity evaporates fast as we descend to stocks with lower after-hours market liquidity. The selected stocks account for a sizeable fraction of trading activity in the after-hours market among all firms in the S&P 500 index during our sample (46.89% of the total transaction count vs. 21.31% in the regular trading session).

[21] The major national stock exchanges close at 1:00pm the day before big public holidays, such as July 4th, Thanksgiving, and Christmas.

[22] The trading schedule of NASDAQ- and NYSE-listed securities can be gauged at `https://www.nasdaq.com/stock-market-trading-hours-for-nasdaq` and `https://www.nyse.com/markets/nyse-arca/market-info`.

[23] To identify these firms, we sort the constituents of the S&P 500 index as of 12/31/2020 by their post-close (4:00pm–6:30pm) transaction volume on quarterly earnings announcement days, averaged over the five-year period from 01/01/2015–31/12/2019. We further require that the firms report at least 75% of their earnings announcements after the close of the regular trading session during our full sample period 06/02/2008–12/31/2020. We exclude Xilinx (XLNX, ranked 43th) from the original list since the analyst information is missing in the I/B/E/S database and replace it by CSX corporation (CSX).

We download high-frequency data from the NYSE TAQ database for the stocks over the sample period 06/02/2008 through 12/31/2020, a total of $T = 3{,}169$ business days. The data is cleaned using state-of-the-art procedures (e.g. Barndorff-Nielsen, Hansen, Lunde, and Shephard, 2009; Christensen, Oomen, and Podolskij, 2014). The main distinction here is that we retain observations with a timestamp outside the official exchange trading hours if they otherwise fulfill the conditions required to be tagged non-erroneous.[24] In total, we preserve almost ninety billion (89,640,467,708) quotations and nearly eight billion (7,985,202,326) transactions across stocks. We use tick-time sampling to remove transactions that merely repeat the previous price and aggregate remaining observations with identical timestamps. The latter are instead replaced with an average price, a procedure that is known to further alleviate microstructure noise.

Table 1 reports descriptive statistics about the after-hours trading volume of stock 1–25, while Table E.1 in Appendix E contains the information of stock 26–50.[25] We show the sample average, standard deviation, and the 25th, 50th, 75th and 99th percentiles of the transaction count distribution for days without earnings announcements (columns 2–8) and days with earnings announcements (columns 9–15). For many firms, the after-hours transaction count is two orders of magnitude larger on days with earnings announcements relative to days without them. For example, Facebook (FB) averaged 76,129 after-hours transactions on earnings announcement days, compared with only 891 transactions on days with no such announcements. It is clearly uncommon for individual firms to exhibit high transaction counts in the after-hours trading session on days without earnings announcements.

Transaction volume in the after-hours market has grown substantially between 2008 and 2020 with more than a ninefold increase for the stocks we analyze in our paper. The fraction of after-hours trading has grown even more, quadrupling from 0.17% to 0.71%, as a proportion of the total transaction volume (including trades from the regular trading session). On days with earnings announcements this fraction is substantially higher at the firm-level, frequently exceeding 10%. Appendix C summarizes trading volume and spreads in the after-hours market over time.

3.2 Close-to-open data

To illustrate the much broader usage of our close-to-open return-based jump test, we download from CRSP open and close price information from the full set of members of the S&P 500 index as of the redefinition on March 18, 2024. This list has 503 constituents, including the stocks analyzed above.[26] The series are corrected for dividend distributions, stock splits, and other corporate actions affecting

[24] A complete list of sale conditions that can be associated with a transaction is available in the documentation of the Daily TAQ Client Specification manual available for download at: `http://www.nyxdata.com/Data-Products/Daily-TAQ`. In particular, the label "T" identifies pre-market and after-hours trades. These are virtually always ignored in the high-frequency volatility literature, since the first rule of the widely used Barndorff-Nielsen, Hansen, Lunde, and Shephard (2009) filtering algorithm instructs researchers to "*P1. Delete entries with a time stamp outside the 9:30am–4:00pm window when the exchange is open.*"

[25] The corresponding table for the pre-market trading activity can be found in Appendix D.

[26] We remove GOOG since its earnings announcement dates are double-counted with GOOGL.

the price. We also obtain the placement of an earnings announcement either "Before Market Open", "During Regular Trading", or "After Market Close" from Zacks Investment Research. This suffices for the calculation of the close-to-open return test statistic which does not require knowledge about the exact timestamp. In addition, we obtain the individual S&P 500 index weights from Bloomberg. The sample period is January 1, 2012 to December 31, 2023. Our empirical analysis implements the close-to-open return-based jump test by calculating Z_t with $L = 22$, corresponding to estimating the standard deviation based on one month of previous close-to-open returns. However, our results are very robust to this choice.

3.3 Announcement timing

While most companies announce their financial results at a fixed time, for others the timing can vary quarter-by-quarter. Even slight inaccuracies in the recording of the announcement time can impede our calculation of the post-announcement price reaction, so accurate timing is imperative and we spend considerable effort on double checking the time stamps.

We begin by gathering announcement times from a data set provided by Wall Street Horizon (`https://www.wallstreethorizon.com/`) that offers a comprehensive suite of corporate events data, including detailed information on the timing of earnings announcements. Wall Street Horizon stores the timestamp included with the press release issued by the company when it publicly announces its quarterly results.[27]

As a double-check, we hand collect a separate set of announcement times from the Factiva news archive by searching on the announcement day for press releases marked with the company ticker code and a designated "Earnings" subject.[28]

Comparing the merged set of announcement times with the audit trail of the complete tick-by-tick transaction price history suggests that occasionally both Wall Street Horizon and Factiva get it wrong. To correct seemingly erroneous timestamps, we design a conservative screening algorithm that infers the announcement time based on the price volatility. In particular, we calculate the log-return for each minute from 4:00pm–6:30pm. If the largest absolute one-minute log-return exceeds 2.5% and precedes the announcement time from both Wall Street Horizon and Factiva, we assume the earnings were released at the earlier time. The filter affects only a very limited number of announcements (77 in total, or 3.5%). The median change is one minute, suggesting that the

[27] A publicly traded company with classes of securities registered in Section 12 or subject to Section 15(d) of the Securities Exchange Act of 1934 is legally required to file regular reports with the SEC, including an annual form 10-K and quarterly form 10-Q's, in addition to proxy reports and other reporting requirements. Most companies file form 10-Q either 40 or 45 days after the end of the fiscal quarter, but many large corporations choose to summarize their financial statements at an earlier date by issuing a press release and filing a form 8-K.

[28] A limitation of both data sets is that announcement times are rounded to the nearest minute. However, most of the earnings reports in our sample are released to the public through professional dissemination services, such as Business Wire or PR Newswire which are under strict requirements to ensure immediate and equal access to company information as noted by the SEC's Regulation Fair Disclosure. The audit-trail information left from the high-frequency data after each announcement suggests that the rounding effect is typically negligible.

algorithm primarily captures small rounding effects for some of the most important earnings reports that lead to substantial revisions of the security price.[29]

The third-to-last column in Table 1 shows the modal announcement time for each firm, which ranges from as early as 4:00pm for reports released immediately after the close of the regular exchange-trading session to as late as 4:30pm, with many firms announcing around 4:05pm.

3.4 Earnings surprises

Earnings announcements contain a wealth of information but the most important part is arguably the headline earnings figure. To compute the surprise element in earnings announcements, we employ the Institutional Brokers Estimate System (I/B/E/S) database available via subscription to Refinitiv (`https://www.refinitiv.com/`), formerly a part of Thomson Reuters. I/B/E/S aggregates earnings information for over 22,000 companies. In addition to storing the actual reported earnings per share (EPS), adjusted for non-recurring items and stock option expenses, prior to each announcement I/B/E/S surveys earnings forecasts from leading professional analysts covering individual companies. We compile this information into a consensus estimate (μ_{EPS}) and a standard deviation of that estimate calculated over the distribution of analyst expectations (σ_{EPS}). Following Berkman and Truong (2009), Michaely, Rubin, and Vedrashko (2013), among others, our measure of the standardized unexpected earnings is given by[30]

$$z_{\text{EPS}} = \frac{\text{Actual EPS} - \mu_{\text{EPS}}}{\sigma_{\text{EPS}}}. \tag{21}$$

We purge announcements with no analyst forecasts and those where σ_{EPS} is less than 0.001 (one tenth of a cent) which result in an unstable z_{EPS} measure. This removes five announcements from Ulta Beauty (ULTA) that was still a relatively overlooked small-cap stock with limited broker coverage at the beginning of our sample. A single announcement from Broadcom (AVGO) is also eliminated. We further exclude announcements where share trading was temporarily suspended by the exchange as it leads to a disconnected trade sequence.[31] Finally, following Grégoire and Martineau (2022) we discard announcements where z_{EPS} exceeds ten in absolute value. Such out-

[29] Importantly, our noise-robust jump test statistic does not depend on the announcement time and so is unaltered by the screening algorithm. Moreover, employing only Wall Street Horizon and Factive information does not cause any discernible change in the post-announcement return regression (Section 6.1). Only the returns from our trading strategy (Section 6.2) deteriorate slightly, but remain significant with the removal of the inferred announcement time.

[30] Some studies employ the median analyst estimate instead of the sample average (Dellavigna and Pollet, 2009; Grégoire and Martineau, 2022; Hartzmark and Shue, 2018). Others replace the standard deviation with the lagged closing price of the stock, e.g. from a week before the announcement or at the end of the previous quarter (Grégoire and Martineau, 2022; Lyle, Stephan, and Yohn, 2021). Our main findings are not altered by adopting these alternative ways of defining the standardized unexpected earnings.

[31] Trading halts are registered in the daily TAQ master files that contain static information for securities traded by participants of the Consolidated Tape Association (CTA), mainly stocks with NYSE as primary exchange, and Unlisted Trading Privileges (UTP), or NASDAQ-listed issues. The file has a letter code in the "Halt Delay Reason" if trading was paused (blank otherwise). Resumption of trading is flagged in the transaction data with a sale condition "5" defined as "Market Center Re-Opening Trade" (CTA) or "Re-opening Prints" (UTP).

liers are often caused by extraordinary items in the profit statement.[32] The last step removes 40 observations (about 1.7% of the sample).[33]

The number of quarterly earnings announcements retained for each company is shown in the fourth-to-last column in Table 1. We report summary statistics of z_{EPS} in the second-to-last column. Standardized unexpected earnings are substantially higher than zero on average, consistent with the notion that managers engage in earnings smoothing to avoid negative surprises.

4 Empirical results

We next proceed with our empirical investigation. Price dynamics and trading activity in the after-hours market is not as thoroughly studied and understood as that in the regular trading session and it has evolved significantly since the seminal analysis of Barclay and Hendershott (2003). We therefore begin by briefly summarizing some of the key features of the after-hours market, emphasizing the contrast between days with and without earnings announcements. We start by analyzing the pattern in trading volumes and bid-ask spreads in a short interval around earnings announcements before turning to the evidence on the presence of price jumps.

4.1 Trading volume and bid-ask spread

To get a broad picture of post-announcement trades, for each five-second interval in a one-hour window centered around the announcement time, we calculate transaction counts and bid-ask spreads (in basis points) relative to the midquote = (bid + ask)/2 as

$$\text{Spread} = 10000 \times \frac{\text{ask} - \text{bid}}{\text{midquote}}, \tag{22}$$

As a control sample, for each announcement we select a no-announcement date at random and calculate transaction counts and Spread on a corresponding window.

Panel A in Figure 2 reports the transaction count per five-second interval on days with and without earnings announcements. The modal announcement time across companies is 4:05pm so the market typically closes five minutes prior to the announcement (labeled time 0), as highlighted in the figure. The transaction volume right before the regular market close is notably higher on

[32] For example, on 08/25/2020 Salesforce (CRM) posted a quarterly EPS of \$1.44 after adjusting for non-recurrent items. With a consensus estimate of \$0.66 and a standard deviation of about four cents, this yields a twenty-sigma event. The surprise was motivated by mark-to-market accounting for the company's investments in nCino, which saw a \$617 million unrealized gain in the quarter.

[33] The I/B/E/S database incorrectly puts the EPS of Akamai Technologies (AKAM) as 0.31, 0.29, 0.28, and 0.34 for the Q1–Q4 earnings announcement of the fiscal year 2009. This induces a -9.64, -2.12, -8.86, and -7.80 unexpected standardized earnings surprise, despite the company meeting or beating expecations at all occasions. This is possibly caused by AKAM employing non-GAAP financial metrics in their accounting system, in particular a so-called normalized net income, which eliminates the effects of events that are either not part of the company's core operations or are non-cash. We replaced the wrong EPS numbers with the correct ones, i.e. 0.43, 0.40, 0.38, and 0.46, which were extracted directly from the PDF file containing the financial statement, available at the company's investor relations website (`www.ir.akamai.com`).

days with announcements than on days without announcements, but both drop sharply at the close. From this point onward, the graphs evolve very differently. Whereas the after-hours transaction count remains close to zero on no-announcement days, it spikes to more than five contracts shortly after the announcement time on days with earnings announcements before gradually tailoring off over the next 30 minutes.

In Panel B of Figure 2, we compare bid-ask spreads in the after-hours market on days with and without earnings announcements. Again, we see distinct differences. On no-announcement days, the median quoted spread starts at 5 bps at the end of the regular trading session before rising to 30–35 bps within the first five minutes of the post-trading session. It then gradually inclines for the duration of the after-hours session as we approach the overnight period. On announcement days, the median quoted spread goes from 5 bps at close (4:00pm) before quickly rising to 60 bps at the time of the announcement, then drops to 30 bps within 10–20 minutes of the announcement.

For comparison, the average quoted spread during post-close trading is 58.1 bps, while the average spread in regular trading equals 8.4 bps, implying that the bid-ask spread on average is about seven times greater in the after-hours session compared with the regular trading session.[34]

4.2 Jump proportion

The theoretical analysis in Section 2 highlights that jumps in prices increase the realized variance without affecting the bipower variation. This insight suggests an intuitive way to check whether earnings announcements cause jumps.

First, since earnings announcements almost exclusively fall outside the hours of the exchange-traded session, in Panel A of Figure 3 we plot the pre-averaged realized variance computed for the regular trading session (9:30am–4:00pm) against its corresponding value computed for the extended trading session (9:30am–6:30pm), both converted to annualized standard deviations. Their difference measures the incremental volatility observed in the after-hours market (4:00pm–6:30pm). On no-announcement days (indicated by a red dot) the extra volatility during after-hours trading is typically minuscule and has a negligible impact on the cumulative pre-averaged realized variance measure. Except for a few outliers, the vast majority of these observations form a cloud close to the 45-degree line. Conversely, on days with a quarterly earnings announcement (indicated by a blue cross), differences are much greater with the extended trading session pre-averaged realized variance substantially exceeding its corresponding value from the regular trading session. Earnings releases clearly trigger substantial price volatility in the after-hours market, which is otherwise dormant.

Second, and more directly related to our jump test, in Panel B of Figure 3 we plot the pre-averaged bipower variation against the pre-averaged realized variance, both based on high-frequency data from the extended trading session (9:30am-6:30pm). Realized variance less bipower variation isolates the contribution of jumps to return variation, which is zero (up to sampling error) if the price path is continuous but is strictly positive if there are price jumps. Hence, the farther to the

[34]See Appendix C, which reports summary statistics on the after-hours trading volume and bid-ask spreads.

right of the 45-degree line a data point is, the more it indicates the presence of jumps. Consistent with this interpretation, the pre-averaged realized variance and bipower variation are more or less perfectly aligned on no-announcement days. Conversely, on days with earnings announcements we observe large differences indicating jumps in price movements at these times. Table 2 provides further stock-level details on realized variance and bipower variation for the regular and extended trading session broken into days with and without earnings announcements. Appendix F provides an even more detailed analysis for Apple which is perhaps the most prominent stock in our sample.

An alternative approach to gauge the relative importance of jumps is to examine the jump proportion which estimates the fraction of the return variation originating from the jump component. Following Christensen, Oomen, and Podolskij (2014), this is defined as[35]

$$\text{Jump proportion} = 1 - \frac{\text{Bipower variation}}{\text{Realized variance}}. \tag{23}$$

Figure 4 plots kernel density estimates of the distribution of the jump proportion. As indicated by the peak near zero for the graphs based on our noise-robust pre-averaging estimators, on most days without announcements (Panel A) the jump component accounts for none of the variation in the stock price. Note that small negative numbers can be observed due to estimation error. Conversely, on days with earnings announcements (Panel B) more than fifty percent of the total variation in price movements stems from the jump component.[36]

In contrast, the jump proportion extracted with five-minute sampling peaks near 10%, regardless of whether there is an announcement or not. Although the jump proportion for the five-minute measure is slightly more right-skewed on days with announcements, in general it overestimates the importance of jumps on days with no announcements and underestimates it on days with announcements. These findings are consistent with the biases in the conventional jump measure documented in our Monte Carlo simulation results.

4.3 Jump frequency

Figure 4 shows that the jump component is important in after-hours trading sessions on days with earnings announcements but largely absent on days without announcements. To examine this point more closely, we compute the jump indicator:

$$J_{it} = \begin{cases} 1, & \mathcal{J}_{n,it} > q, \\ 0, & \text{otherwise.} \end{cases} \tag{24}$$

where $\mathcal{J}_{n,it}$ is the noise-robust jump test statistic in (17) for company i on day t. We set the critical value q in a way that reduces the likelihood of identifying false jumps by applying a Bonferroni

[35]The jump proportion is computed without pre-averaging if sampling at a 5-minute frequency or with pre-averaging if sampling at the tick-by-tick frequency.

[36]The slight attenuation observed with $\theta = 1$ is consistent with our Monte Carlo evidence in Appendix B, where we note that excessive pre-averaging tends to deflate the power of our microstructure noise-robust jump test.

correction to account for multiple testing and keep the family-wise error rate at 1%.[37]

Table 2 reports the jump frequency for stock 1–25 in our sample, while Table E.2 in Appendix E contains the information for stock 26–50. Panel A is for the regular trading session, while Panel B is for the extended trading session. The sample is further split into days with and without an earnings announcement. For the regular trading session, we estimate a jump frequency of 2.95%. While jumps do occur at a higher frequency than expected by random chance, they are relatively rare during the regular trading session. This result is consistent with Christensen, Oomen, and Podolskij (2014). For after-hours trading sessions without earnings announcements, we obtain a slightly higher jump frequency of 3.67%. Finally, for after-hours trading sessions with earnings announcements, our jump frequency estimate is 91.06% which is far higher than the previous values. Moreover, though very high on average, the jump frequency is even higher after 2016 (95.84%) versus before 87.49%.

In essence, while it is rare to identify a jump during regular trading sessions or in extended trading sessions with no announcements, it is rare *not* to find a jump in extended sessions with earnings announcements. This finding provides strong empirical support for Hypothesis 1.1.

The corresponding jump frequency rates for the five-minute jump test statistic of Barndorff-Nielsen and Shephard (2006) are 5.46% in regular trading sessions, 14.38% in extended trading sessions without earnings announcements, and 40.40% in extended trading sessions with earnings announcements. Recall that our simulations in Appendix B show that the five-minute jump test overrejects in the presence of little or no microstructure noise (as in the regular trading sessions) but lacks power (underrejects) in the presence of high levels of noise contamination (as in the after-hours market). Hence, our estimates illustrate that the conventional jump test identifies too many jumps (false positives) during regular trading sessions and extended trading sessions without earnings announcements but too few jumps (false negatives) during extended trading with earnings announcements.

Table 2 suggests that failure to find jumps after earnings announcements is associated with the trading activity in the after-hours market. As this has increased over time, the lower average jump frequency prior to 2016 is therefore largely a result of fewer trades and weaker power in detecting jumps. If trading is too sparse, there are often relatively few post-announcement observations to base the analysis on, rendering it problematic for our noise-robust test statistic to work as intended. The other main reason why we sometimes fail to detect a post-announcement price jump is that although our jump test has excellent power, it is not bullet proof. This is particularly relevant for announcements that are succeeded by severe whipsawing in the price. Intuitively, a jump is less likely to be detected when it is surrounded by extremely high diffusive volatility which reduces the relative contribution of the jump to return variation.

[37] Bajgrowicz, Scaillet, and Treccani (2016) report that up to 90% of jumps identified with the five-minute jump test are spurious due to multiple hypothesis testing.

4.4 The close-to-open return-based jump test

Figure 5 reports the outcome for our close-to-open return-based jump test. In Panel A, we plot the test statistic over time for Apple (AAPL), highlighting earnings announcement days with circles. At the 1% level of significance, the close-to-open test flags 74.47% of these announcements as containing a jump, as indicated with a crossed circle. This compares to 100% detected by the noise-robust test using high-frequency data, thus demonstrating the lower power of the close-to-open jump test. In Panel B, we plot the average jump frequency across the members of the S&P 500, sorted in descending order by index weight and separately for announcement and no-announcement days. Overall, the rejection rate on no-announcement days is 3.68% which is indistinguishable from the 3.67% reported for the pre-averaging jump test during after-hours trading sessions without announcements. Conversely, on announcement days the jump frequency is 52.86%, notably lower than the 91.06% obtained from our tick-by-tick jump test during after-hours trading sessions with announcements, but notably higher than the 40.40% jump frequency reported by the 5-minute jump test.

The robust Brown-Forsythe test of equality of variance is firmly rejected. Across the board, the P-values are no larger than 0.0001. Thus, the close-to-open analysis provides compelling evidence of an announcement jump effect. We should note that there is no discernible serial correlation in the first or second moments of the close-to-open return-based jump test statistic. This is important since the variance ratio test presumes random sampling.

4.5 Determinants of the jump probability

To more formally test Hypothesis 1, we next develop a regression framework to examine the determinants of price jumps. We begin by inspecting the role of earnings surprises since this is the measure most directly related to earnings announcements.

To capture the relation between the jump probability versus the sign and magnitude of earnings surprises, we sort announcements by the value of the earnings surprise, form decile portfolios, and plot the corresponding average jump frequencies implied by our noise-robust jump test in Panel A of Figure 6. The jump probability mostly exceeds 90% across deciles, and does not depend systematically on the size of the earnings surprise.

Our finding that prices jump even when investors are not surprised by the reported earnings per share is consistent with Hypothesis 1.2 and can be explained as follows. First, information other than the headline earnings figure is typically released (e.g., forward guidance on future earnings) and this may trigger a jump.[38] While this helps explain why prices *can* jump even on days where markets do not get surprised by the earnings figure, we would still expect a lower *average* jump probability on such days. This points to the second explanation, namely that prices jump because

[38]For example, on 10/24/2011 Netflix (NFLX) reported third-quarter EPS of $1.16 which beat the consensus expectation of $0.94, corresponding to a modest 1.6 standard deviation surprise. However, the company also significantly lowered its forward guidance, and the stock crashed more than 20% in after-hours trading.

of the resolution of uncertainty associated with the earnings announcement (Banerjee and Kremer, 2010). An implication of this story is that prices are more likely to move up (due to the lower post-announcement risk premium) than down following an earnings announcement that is close to investor expectations. We explore this prediction in Section 6.1.

To establish a more formal connection between price jumps and earnings announcements and examine whether other factors affect jump probabilities, we next estimate logit regressions. Our analysis includes up to five regressors. To estimate the effect of an earnings announcement on the jump probability and test Hypothesis 1.1, we consider an announcement dummy variable:

$$EA_{it} = \begin{cases} 1, & \text{on announcement days,} \\ 0, & \text{otherwise.} \end{cases} \tag{25}$$

Since z_{EPS} proxies for the magnitude of the news component in the announcement, we expect this to matter for the jump probability, even though the evidence from Panel A of Figure 6 is a bit weak. As our second and third covariates, we therefore include the absolute value of the earnings surprise, measured separately for positive and negative surprises, i.e., we define $z^{+}_{\text{EPS},it} = z_{\text{EPS},it} EA^{+}_{it}$ and $z^{-}_{\text{EPS},it} = z_{\text{EPS},it} EA^{-}_{it}$, where $EA^{+}_{it} = \mathbb{1}(z_{\text{EPS},it} > 0)$ and $EA^{-}_{it} = \mathbb{1}(z_{\text{EPS},it} < 0)$ are indicator variables that capture the direction of the earnings surprise.

Fourth, to see whether high volatility in prices prior to the announcement makes it more or less likely to find jumps, we include the pre-averaged realized volatility, $\sqrt{RV^{*}_{n}}$, computed over the regular trading session from 9:30am–4:00pm on the day of the announcement. We expect to find a negative effect since high volatility makes it harder for our noise-robust jump test to detect jumps.

Fifth, as a measure of the resources available to facilitate the price discovery process, we include the number of analysts covering the stock, N_A.[39] We would expect to find a positive coefficient since the price discovery process, and thus the speed of price adjustments, should be more efficient for stocks with the greatest analyst coverage.

In summary, we estimate the logit model using observations for stock i on day t:

$$P(J_{it} = 1) = F(a + b_1 EA_{it} + b_2 |z^{+}_{\text{EPS},it}| + b_3 |z^{-}_{\text{EPS},it}| + b_4 \sqrt{RV^{*}_{n,it}} + b_5 N_{A,it}), \tag{26}$$

where F is the logistic distribution function.[40]

Table 3 reports estimation results for the logit regression applied to the extended trading session.[41] The estimated intercept in column (2) with only the announcement dummy yields a jump probability on days without announcements ($EA = 0$) of 3.67% compared to 91.06% for announce-

[39] We also considered the dispersion in EPS forecasts across analysts, σ_{EPS}, to get a measure of subjective uncertainty surrounding a particular earnings announcement. However, this measure fails to be significant in our logit regression.

[40] The coefficients in (26) are estimated on the entire sample of days with and without earnings announcements. Hence, the extra explanatory variables in the model should implicitly be understood as being interacted with the EA variable and assume a value of zero on no-announcement days. With this design, all covariates measure the marginal effect (or the logarithm of the odds ratio) on the jump probability *conditional* on an announcement.

[41] The results of our logistic jump probability regressions and the linear return regression in the next subsection are robust to the inclusion of stock fixed effects.

ment days ($EA = 1$), which agrees with the results in Section 4.3. Further, and consistent with Hypothesis 1.1 and Figure 6, the earnings announcement dummy is highly statistically significant and positive, showing that the likelihood of a jump increases by a huge amount and is near unity in the wake of an earnings announcement.

As reported in column (3), the estimated coefficients on both positive ($|z^+_{\text{EPS}}|$) and negative ($|z^-_{\text{EPS}}|$) earnings surprises are positive. While the former is small and insignificant, the much larger coefficient estimate for negative surprises is significant, suggesting that disappointing earnings news is particularly likely to trigger a jump.

The effect of $\sqrt{RV^*_n}$ is significantly negative so higher pre-announcement return volatility reduces the jump probability. For example, setting the pre-averaged realized volatility at its 10th and 90th percentiles while keeping the number of analysts fixed at its average value our coefficient estimates imply a conditional jump probability of 98.46% and 97.49% (93.97% and 88.52%) for an average negative (positive) announcement. A plausible explanation is that it is harder to detect a post-announcement price jump amid high levels of volatility which weakens the testing power. Moreover, a high level of volatility can act as a substitute for price jumps, since it widens the dispersion of the return distribution and enables the price to move rapidly, albeit continuously, in response to earnings announcements.

The effect of the number of analysts covering a stock, N_A, is significantly positive, so jumps are more likely on earnings announcement days for those stocks covered by the largest number of analysts. For example, the coefficient estimates imply a conditional jump probability of 94.86% and 99.37% (79.18% and 97.77%) for an average negative (positive) announcement when the number of analysts is at its 10th and 90th percentiles while keeping pre-averaged realized volatility fixed at its average value. Broader analyst coverage may speed up the price discovery process and increase the chance of observing jumps.

5 Jump spillover effects

Earnings announcements reveal important information about the cash flow prospects of the announcing firm, but it may also affect other firms or even the broader economy. Patton and Verardo (2012) and Savor and Wilson (2016) develop a theoretical model in which investors use earnings of announcing firms (AFs) to revise their expectations of earnings for non-announcing firms (NAFs), generating a covariance between firm-specific and market-wide cash flow news. It is natural to hypothesize that such learning effects can induce spillovers in the form of an earnings announcement from the AF triggering co-jumps in the prices of NAFs and the market portfolio.[42] In this section,

[42]Existing empirical work on co-jumps include Bollerslev, Law, and Tauchen (2008), Caporin, Kolokolov, and Renò (2017), and Li, Todorov, and Tauchen (2017a). However, these studies mainly examine jump dependence between individual equity prices and the stock index around macroeconomic announcements, where systematic news are expected to arrive. Bibinger and Winkelmann (2015) propose a co-jump test based on spectral analysis, while Ding, Li, Liu, and Zheng (2023) construct a co-jump network model.

we examine if these predictions hold true and test Hypothesis 2.

5.1 Jump spillover frequency

We begin by matching announcement days for the AFs with no-announcement days in the NAFs. Any evidence of co-jump spillover effects should show up as a higher conditional jump probability for the NAFs, given an earnings release from the AF, compared to the jump probability when no firms announce.

Table 4 reports the proportion of extended trading sessions with a jump in the NAF (listed in columns) when the individual AFs (in rows) report their financial results. To preserve space, we narrow down our examination to the 25 most liquid stocks. This suffices to highlight the importance of industry proximity and differences in the size of firms' idiosyncratic and market-wide earnings components.

We find compelling evidence that industry proximity plays a crucial role in determining the co-jump probability. For example, conditional on a Facebook (FB) announcement, the price of Apple (AAPL), Amazon (AMZN), and Google (GOOG) jump on 13.3%, 25.8%, and 28.1% of their no-announcement days. Thus, conditional on the AF being a tech firm the jump frequency generally rises for companies within that sector and is much lower for companies from other sectors. This is consistent with the presence of a common jump factor for the tech industry. Moreover, on days where Intel (INTC) is the AF, we record a conditional jump frequency of 20.0%, 44.0%, and 30.0% in the price of Nvidia (NVDA), Advanced Micro Devices (AMD), and Micron Technology (MU), pointing to a common jump component tracking the microconductor industry. These numbers are much higher than the common no-announcement jump frequency of 4.18%, calculated as the average jump frequency on days where there are no announcements among any of our firms.[43] Our analysis therefore provides strong support for Hypothesis 2.1.

Conversely, there is scant evidence of spillover effects from some of the other companies in our sample without obvious industry peers. For example, conditional on an announcement from Walt Disney (DIS), the jump frequency in the other stocks is always less than 10% and often close to zero, which suggests that the jump component is tracking idiosyncratic news.

In the right-most column of Table 4, we compute the jump frequency in the S&P 500 index (proxied by the SPDR S&P 500 ETF Trust, SPY) over the extended trading session in which the firm announces its earnings. This can be interpreted as the conditional jump probability in the market index given that a particular firm releases its financial statement. If earnings announcements contain systematic news, we should expect this number to be higher than the comparable jump frequency in the S&P 500 in the absence of any earnings announcement.[44] Furthermore, we expect

[43]The conditional jump frequency on common no-announcement days is slightly lower than the conditional no-announcement day jump frequency reported in Table 2, since the latter does not discriminate between days where other firms are or are not announcing.

[44]To rule out that an accompanying jump in the S&P 500 is a mechanical effect following from the AF being an index constituent, we remove the AF's price effect from the index by subtracting its price times its weight in the

the effect to be stronger for businesses that are more central to the economy.

The table offers strong backing for the presence of a systematic "market" factor in individual stocks' price jumps. For instance, the frequency of jumps in the S&P 500 index is very high conditional on an announcement from important stocks such as Apple (AAPL), Facebook (FB), Amazon (AMZN), Microsoft (MSFT), Oracle (ORCL), and Starbucks (SBUX). Notably, the market index jumps 30% of the time Apple makes its earnings announcements, which is an order of magnitude higher than the jump probability in the market index on common no-announcement days (3.60%). By contrast, the market jump probability is much lower when firms such as Tesla (TSLA) and Salesforce (CRM) announce earnings, suggesting that price movements in both of these stocks are to a larger extent driven by idiosyncratic news unrelated to the broader economy.

In our sample, there are between a minimum of zero and a maximum of nine earnings announcements on any given day. The conditional jump frequency in the market index is increasing in the number of announcements. On average, the rate at which the market index jumps rises from the 3.60% on common no-announcement days [0 announcements] to 4.82% [1–2 announcements], 3.02% [3–4 announcements], 12.28% [5–6 announcements], and 21.05% [7–9 announcements]. These observations are consistent with Hypothesis 2.3.

5.2 Determinants of the jump spillover probability

Our empirical results on co-jump frequencies are particularly interesting because it is often difficult to detect jumps in the market index even when the price of the underlying stocks jump. This is because individual firms typically only take up a small part of the index basket, so their price jumps are attenuated. Our findings point towards an information channel that leads investors to revise their earnings expectations for the broader economy after individual firms' earnings announcements. We next examine key determinants of this transmission mechanism and estimate their importance for jump spillover effects.

5.2.1 Estimates based on after-hours trading activity

We start by reporting results for the 50 firms with the largest after-hours trading volume. For this subset of firms, we can use our high-frequency jump estimator and compute estimates of after-hours trading volume. Let J_{jt}^{NAF} be an indicator variable that equals one if the price of NAF j jumps on day t, zero otherwise. We then estimate a logit model for the conditional jump probability of stock j's price, given that AF i releases its fiscal results on day t ($i \neq j$ by construction):

$$P\left(J_{jt}^{\text{NAF}} = 1 \mid EA_{it} = 1\right) = F\left(a + b_1 IP_{ij} + b_2 \ln(V_{jt}^{\text{NAF}}) + b_3 \ln(V_{it}^{\text{AF}}) + b_4 D_{it}^{\text{EARLY}} + b_5 D_{it}^{\text{LATE}}\right). \tag{27}$$

S&P 500 index from the SPY before we implement the jump test. We are grateful to Andrew Patton for raising this point.

We include an intercept, a measure of industry proximity, IP, the logarithm of the transaction volume of the AF and NAF, $\ln(V^{\text{NAF}})$ and $\ln(V^{\text{AF}})$, and indicator variables for whether the AF is disclosing its fiscal statement early or late in the earnings season, D^{EARLY} and D^{LATE}.[45] Following Wang and Zajac (2007), we define industry proximity as the proportion of common consecutive digits (starting with leading digit and going down) in their SIC code shown in Table 1.[46] V^{NAF} and V^{AF} are the average number of transactions in the NAF and AF in the after-hours market in the month prior to t. We log-transform the latter to make them less right-skewed and closer to Gaussian. Following Savor and Wilson (2016), we define early (late) announcers as those firms that release their financial results in the 1st (4th) quartile of the earnings season. The latter is assumed to start two weeks and stop two months after the end of a quarter (e.g., the earnings season for Q1 starts on April 15 and ends on May 31).

The results are reported in Panel A of Table 5. We expect a positive relationship with the first three covariates since greater industry proximity should induce a positive jump spillover effect, higher liquidity facilitates a bigger and more rapid transmission of information from the AF to the NAF, and companies that announce early in the cycle are more likely to disclose new information relevant to other companies. This is confirmed by the fitted model. Industry proximity is associated with a positive and highly significant marginal effect on the jump spillover probability (t-statistic of 7.16). The liquidity of both the NAF and AF in the after-hours market are also positive and significant with the coefficient estimate on V^{NAF} being twice as large and significant as that on V^{AF} (t-statistics of 7.16 and 14.56). In addition, the spillover from early announcers is positive and significant (t-statistic of 3.28), and vice versa for late announcers (t-statistic of -10.11). These findings are consistent with Hypothesis 2.2.

To convert these estimates into an implied co-jump probability, we again change the covariates one at a time, while holding the others fixed. For example, early in the earnings cycle ($D^{\text{EARLY}} = 1$) and for firms with no industry overlap ($IP = 0$), the coefficient estimates imply that the conditional jump probability for the NAF is 4.02% and 7.19% (4.96% and 5.80%) when V^{NAF} (V^{AF}) is assumed to be at its 10th and 90th percentile while holding V^{AF} (V^{NAF}) fixed at its average value. Late in the earnings cycle ($D^{\text{LATE}} = 1$), those numbers drop notably to 2.39% and 4.34% (2.97% and 3.48%). Furthermore, early in the earnings cycle and for firms with identical industry classification ($IP = 1$), the conditional jump probability for the NAF is shifted up to 5.70% and 10.06% (7.01% and 8.17%) when V^{NAF} (V^{AF}) is at its 10th and 90th percentile while holding V^{AF} (V^{NAF}) fixed at its average value. Those numbers again drop late in the earnings cycle to 3.42% and 6.15% (4.23% and 4.96%).

[45] We also included the jump indicator of the AF, J_{it}^{AF}, as a covariate. However, since the probability of a jump for an AF is near unity and varies little over our sample, this variable has little-to-no explanatory power.

[46] IP_{ij} is discrete with range 0.00, 0.25, 0.50, 0.75, 1.00, where $IP_{ij} = 0$ means no industry overlap (leading digit in SIC code differs), while $IP_{ij} = 1$ is perfect overlap (SIC codes are identical).

To uncover any jump spillover effects on the market portfolio, we estimate the following model:

$$P\left(J_t^{\text{SPY}} = 1 \mid \#\text{AF}_t \geq 1\right) = F\left(a + b_1 D_t^{\#\text{AF}} + b_2 \ln\left(CV_t^{\text{AF}}\right)\right), \tag{28}$$

where

$$D_t^{\#\text{AF}} = \begin{cases} 1, & \text{if } \#\text{AF}_t \geq 5, \\ 0, & \text{otherwise.} \end{cases} \tag{29}$$

and $\#\text{AF}_t = \sum_i EA_{it}$ is the number of AFs on a given day. The dummy variable separates days with "few" or "many" announcements. We further include the logarithm of the cumulative average number of transactions in the AFs in the after-hours market in the month prior to day t, $CV_t^{\text{AF}} = \sum_{i\,:\,EA_{it}=1} V_{it}^{\text{AF}}$.

Panel B of Table 5 shows that the jump probability for the market portfolio is significantly higher on days where many firms announce their results. Moreover, there is also a positive relationship with the after-hours liquidity of the AFs, CV_t^{AF}. These findings make sense because a larger pool of company announcements implies that more market-related information is being released to investors and larger liquidity among the AFs facilitates a faster price discovery process, which feeds into the market index, consistent with Hypothesis 2.3.[47]

5.2.2 Estimates based on close-to-open information

We next turn to the logit regression that employs our close-to-open return-based jump test statistic. We proceed as above by defining a jump indicator

$$J_{it}^{oc} = \begin{cases} 1, & Z_{it} > q, \\ 0, & \text{otherwise.} \end{cases} \tag{30}$$

We then estimate the model in (27) with J_{it}^{oc} as dependent variable, but because information about after-hours trading activity is missing in the CRSP database, we exclude the variables $\ln(V^{\text{NAF}})$ and $\ln(V^{\text{AF}})$ from the analysis and only employ the remaining three covariates:

$$P\left(J_{jt}^{oc,\text{NAF}} = 1 \mid EA_{it} = 1\right) = F\left(a + b_1 IP_{ij} + b_2 D_{it}^{\text{EARLY}} + b_3 D_{it}^{\text{LATE}}\right). \tag{31}$$

The results are reported in Panel C of Table 5. They are entirely consistent with the results based on after-hours high-frequency data. In particular, industry proximity has a positive and significant spillover effect on the co-jump probability. Moreover, the coefficients on the early and late dummy variables are both significant with the correct positive and negative signs.

6 Price dynamics after earnings announcements

Our results so far provide insights into price jump dynamics in the immediate aftermath of earnings announcements. However, they do not address if the jumps in prices over- or undershoot. In this

[47] Again, we account for the mechanical effect of a constituent members' price jump on the market index by subtracting its price component from the SPY.

section, we explore whether post-announcement returns are predictable and whether this can be exploited in simple trading strategies to generate abnormal returns. Both points help us better understand the efficiency of the post-announcement price formation and test the "sufficiency" part of conditions for market efficiency in Hypothesis 3.

6.1 Determinants of the jump size

While our noise-robust jump test statistic speaks to the presence (or absence) of a jump, it does not reveal by how much the price jumps. We therefore next construct a proxy for the jump size based on returns measured over a small time interval following the earnings announcement. In particular, we compute the one-minute post-announcement return (r_{1m}^{EA}) as the log-price a minute after the earnings release less the latest log-price just prior to the announcement.

The last column of Table 1 reports summary statistics for the one-minute post-announcement returns for each company. While the cross-sectional sample average of 0.15% is rather large, the standard deviation of 3.50% is even bigger, indicating that one-minute post-announcement returns, while positive on average, are highly dispersed. One-minute returns are slightly negatively skewed (-0.48), although this is mainly driven by a few extremely negative return observations in our sample as evidenced by a large coefficient of kurtosis (5.76).

In Panel B of Figure 6, we plot the average one-minute post-announcement return against the standardized earnings surprise. We observe a near-monotonic relationship between the sign and magnitude of earnings surprises and subsequent returns. Specifically, large negative (positive) earnings surprises are associated with large negative (positive) post-announcement returns.

More than 85% of earnings announcements surprise positively in our sample, so firms are expected to beat consensus estimates. The average value of the standardized unexpected earnings is $\bar{z}_{\text{EPS}} = 1.73$ (median value of 1.37), which is located in the sixth decile in Figure 6. The average one-minute post-announcement return in that decile is 0.46% (median value of 0.37%), which is consistent with Hypothesis 1.2, that earnings announcements in line with expectations generate positive returns due to uncertainty resolution.

We next examine the determinants of the change in stock prices in the aftermath of earnings announcements. To understand which factors drive post-announcement returns, we estimate a regression model that includes the predictor variables from the logit model in (26) except the EA dummy variable, which is captured by the intercept here. In addition, we add the cumulative net order imbalance, which we construct following Grégoire and Martineau (2022):

$$OI_{it} = \frac{B_{it} - S_{it}}{B_{it} + S_{it}}, \tag{32}$$

where B_{it} and S_{it} correspond to the buyer- and seller-initiated trading volume over the one-minute post-announcement window. To get signed trade volume, we assign an aggressiveness indicator to each transaction based on whether it was buyer- or seller-initiated. We employ a "level-1 algorithm"

known as the tick rule (e.g. Chakrabarty, Pascual, and Shkilko, 2015).[48] Note that in contrast to the other variables, the net order imbalance is not known ahead of the announcement.

We then estimate a pooled panel regression for the one-minute post-announcement return for stock i on day t, $r^{\text{EA}}_{1m,it}$:

$$r^{\text{EA}}_{1m,it} = a + b_1 z^{+}_{\text{EPS},it} + b_2 z^{-}_{\text{EPS},it} + b_3 \sqrt{RV^{*}_{n,it}} D_{it} + b_4 N_{A,it} D_{it} + b_5 OI_{it} + \epsilon_{it}, \tag{33}$$

where $D_{it} = \text{sign}(z_{\text{EPS},it})$ is the sign function. We interact the sign of z_{EPS} with pre-averaged realized volatility and the number of analysts because the latter are strictly positive and merely capture the speed with which information gets impounded into stock prices whereas earnings surprises are directional. The bigger the return volatility and number of analysts, the more we expect positive news (a positive sign indicator) to move returns upwards and negative news (a negative sign indicator) to move returns downwards. A priori, we therefore expect all coefficients to be positive in (33).

Table 6 reports our estimation results. In the restricted model in column (2) with only z^{+}_{EPS} and $z^{-}_{\text{EPS},it}$ but no additional controls, the estimates of b_1 and b_2 are both positive, implying that larger earnings surprises translate into larger announcement returns. The marginal effect of negative earnings surprises is more than twice as large as that of positive earnings surprises. Negative earnings surprises thus trigger a much larger drop in the stock price than the rise in prices for comparable positive surprises. In this regression, the coefficients are also significantly different from each other (P-value of 0.0016). Adding controls in column (3) and (4), the estimates of b_1 and b_2 remain positive and $b_2 > b_1$, but they are nearly identical and the hypothesis $H_0 : b_1 = b_2$ is no longer rejected.

The slope estimate on the pre-averaged realized volatility, $\sqrt{RV^{*}_{n}}$, is positive and borderline statistically significant. Higher volatility is therefore weakly associated with wider dispersion in returns as post-announcement prices move further away from their initial value during periods of higher volatility.

The coefficient estimate on the number of analysts, N_A, is positive and significant. Hence, a larger number of analysts monitoring a company leads to larger one-minute post-announcement returns following positive surprises and smaller (more negative) returns for negative surprises.

Finally, we consider the order imbalance variable, OI. While the other variables in the regression are known ex-ante (at or before the earnings announcement), order imbalance is only known ex-post. Bearing this in mind, our estimates on OI are positive and highly significant for both positive and negative earnings surprises, implying that larger net order imbalances are associated with bigger movements in returns. Intuitively, buying pressure (positive OI) pushes prices up, while selling

[48] Quoting from their paper: *"The tick rule classifies a trade as buyer-initiated if the trade price is above the preceding trade price (an uptick trade) and as seller-initiated if the trade price is below the preceding trade price (a downtick trade). If the trade price is identical to the previous trade price (a zero-tick trade), the rule looks for the closest prior price that differs from the current trade price. Zero-uptick trades are classified as buys, and zero-downtick trades are classified as sells."*

pressure (negative OI) reduces prices.[49]

We conclude from this evidence that both small and large earnings surprises almost always trigger a jump in the stock price. However, while small earnings surprises are associated with small returns, large earnings surprises tend to move prices by a bigger amount in a direction that is consistent with the sign of the earnings surprise. This effect is stronger for negative earnings surprises. Moreover, prices move by more, the more analysts cover a given stock and the magnitude of price movements is also affected by the pre-announcement price volatility.[50]

6.2 Trading strategy

We next examine if the one-minute post-announcement return can be predicted and, if so, whether the resulting forecasts can be exploited in a simple trading strategy. We employ the parsimonious earnings response model of Ball and Brown (1968) by using the pooled panel regression in (33) based on the standardized earnings surprise as the only conditioning information:

$$r^{\text{EA}}_{1m,it} = a + b_1 z^{+}_{\text{EPS},it} + b_2 z^{-}_{\text{EPS},it} + \epsilon_{it}. \tag{34}$$

We recursively estimate the parameters in (34) using an initial warm-up sample of one month of announcement days, adding new data as it becomes available. This ensures our forecasts are available in real time and do not suffer from look-ahead bias.

Our trading strategy follows Patell and Wolfson (1984). It opens a long (short) position if the predicted return in (34) is positive (negative). In our baseline scenario the position is held until the end of the trading day (6:30pm, or EOD) and closed at the last observation. In contrast to Patell and Wolfson (1984), there is little evidence of elevated returns during the overnight period following the release or at the opening of trading on the next day, see Appendix C.3. Thus, our results are robust to leaving the position on the book until the exchange opens the next morning. To avoid chasing too small profits, we set an entrance barrier of 0.75% in absolute value for the predicted return, which is a 25% markup of the immediate post-announcement bid-ask spread observed in Panel B of Figure 2. However, our results are robust to using a range of other threshold values. With a 0.75% required return, the strategy generates 826 trading signals from 2,193 earnings announcements, of which 664 are long and 162 are short.

To gauge the importance of transaction costs, we implement four versions of our trading strategy. The first sets the entry level of the trade equal to the first post-announcement transaction price (Trade). Our second approach employs the midquote (Midquote). We expect the transaction price to be in the direction of the announcement surprise, but it is possible that it is on the other side of the strategy (e.g., a sale following a positive announcement surprise, or vice versa). Moreover,

[49] As a robustness check, we reestimated the return regression in (33) based on 5-, 10-, 30-, and 60-minute post-announcement returns. Although some of the marginal effects were found to be larger simply because the longer-horizon returns tend to be larger than one-minute returns, none of the conclusions regarding the sign and significance of the coefficient estimates changed.

[50] We also examined our data for a pre-earnings announcement drift but failed to identify any significant effect.

whereas the Trade strategy can snipe stale quotes resting in the limit order book prior to the announcement, the Midquote strategy employs an updated quote that incorporates the information from the announcement.[51] Trading at the midquote is often possible for large institutional traders, but may not be feasible for other entities. Our third strategy therefore incorporates the quoted bid-ask spread (Best Bid and Offer, or BBO). It initiates a buy order at the prevailing best ask, whereas a sell order is initiated at the prevailing best bid. The latter therefore incorporates a full spread in the returns generated from the trading strategy.[52] Finally, our fourth approach makes the odds even more unfavorable by introducing a latency delay, which is the minimum number of seconds an investor must wait before entering a position (BBO+Xs). Such trading delays cause investors to miss out on the initial reaction in the stock price. In principle, it could be beneficial to wait a few seconds before starting a trade because spreads narrow following an announcement.

Figure 7 shows the evolution over time in the cumulative returns based on payoffs from individual trades. The slope of the graph reflects the rate at which returns accrue: The steeper the curve, the larger the returns. Conversely, flat spots or a declining curve indicate that the trading strategy fails to earn, or outright loses, money.

The figure highlights that the transaction price and midquote approaches yield positive returns throughout our sample with no notable periods of inferior performance (full blue and dashed red lines). As expected, introducing execution costs or latency delays reduces the rate of accumulation. In particular, from 2016 onward the strategy that pays the bid-ask spread (dashed-dotted line) is flatlining. Adding a further 5- or 10-second latency delay (dashed lines) reduces returns even more and the strategy loses money after 2016. This indicates that the speed with which earnings announcement information gets incorporated into prices has increased in the second part of our sample.

To inspect the profitability of our trading strategy, Figure 7 also reports (in parenthesis) the sample average return and a test statistic examining if the mean return is different from zero. In frictionless markets where investors can enter the position at the first post-announcement transaction price, a highly significant return of 1.80% per trade (t-statistic of 8.88) is earned over the full sample. Trading at the midquote, the average return drops to a highly significant 1.50% per trade (t-statistic of 7.67). Even if trading is executed at the bid-ask spreads, the average return of 0.72% continues to be significant (t-statistic of 3.68). A 5-second latency delay reduces the return to 0.41% per trade, which is only borderline significant (t-statistic of 2.18). Forcing a 10-second delay on trade entrance, the average return is still positive at 0.28% per trade, which is now insignificant (t-statistic of 1.51).[53]

[51] Baldauf and Mollner (2022) document the importance of stale quotes in generating jumps in the transaction price.

[52] We do not control for market impact since our data is not rich enough to include such information. Hence, our results are mostly relevant for small trading sizes.

[53] We can estimate how much money investors leave on the table after an earnings announcement using transaction information between the announcement and 6:30pm. Denote by $P^j_{t,i}$ and $n^j_{t,i}$ the price and number of shares of the ith transaction in stock j after the announcement at time t. Also, let $P^j_{t,6:30}$ be the price at 6:30pm. The

Panel A of Table 7 reports a more comprehensive set of summary statistics. On top of the full sample (2008–2020) results, we also do the analysis separately for the period 2008–2015 and 2016–2020. In this way, we can examine if the price discovery process has changed over time. We choose the subsample splits based on major structural changes in market design. First, the last electronic communication network (ECN) in the U.S., as defined by Rule 600(b)(23) of Regulation NMS, closed in 2015. The disappearance of ECNs implies that during our sample an increased amount of liquidity has been rerouted to alternative after-hours trading venues, such as dark pools.[54] The latter provide anonymous trading and, in general, do not display quotes to the public. On the one hand, this can impede price discovery, because order flow contains valuable information.[55] On the other hand, less pre-trade transparency can facilitate price discovery because investors can conceal their trading activity, which increases the incentive to collect private information. Moreover, as earnings announcement news is arguably short-lived, it encourages faster and more aggressive trading on such information (e.g. Brogaard and Pan, 2021; Flood, Huisman, Koedijk, and Mahieu, 1999). Second, stricter legislation approved by the SEC means that from April 4, 2016 a greater number of broker-dealers are required to disclose stock-by-stock aggregate volume and transaction count information to the Financial Industry Regulatory Authority (FINRA) on a weekly basis.[56] Post-trade transparency helps investors locate more liquid platforms, which accelerates the matching process. Furthermore, the reduction in the number of trading venues makes the market less fragmented, which further enhances this process.

Across the board, average returns are both larger and more significant in the first subsample (2008–2015) compared to the full sample. For example, the average return per trade in the transaction price setting is 2.30% (t-statistic of 8.77) over 2008–2015 but only 1.11% (t-statistic of 3.49) over 2016–2020. Moreover, the average return inferred from the midquote strategy drops to 0.80% (t-statistic of 2.65) in the second subsample – more than a full percentage point lower than its early subsample counterpart (2.00%). Trading at the bid-ask spread further reduces the average return and adding a latency delay even renders them slightly negative, though not significant, in the second subsample. These findings are consistent with a more efficient price discovery process over time with average returns declining to the point where they are no longer significantly different from zero after accounting for bid-ask spreads or latency delay.

Patell and Wolfson (1984) found that excess returns in their sample ceased to exist within 10- to 15-minutes following an earnings announcement. In Panel B of Table 7, we show the effect of

dollar profit made by an investor buying in the ith post-announcement trade and closing it out at 6:30pm is then $\pi^j_{t,i} = n^j_{t,i}(P^j_{t,6:30} - P^j_{t,i})$. Cumulative dollar profits across the whole sample are $\pi^{\$} = \sum_j \sum_{\#EA_j} \sum_i \pi^j_{t,i}\mathcal{I}^j_{t,i}$, where $\mathcal{I}^j_{t,i}$ is the signal from the trading strategy (1 = long, -1 = short, 0 = no position). We estimate a total profit of \$418,783,007, or 0.3209% of turnover. The average profit is \$507,001 with a standard deviation of \$189,115, or a z-score of 2.68. We thank Lasse Heje Pedersen for suggesting this calculation.

[54]Traditional floor trading is available, but it is not anonymous and probably also not fast enough.

[55]Hendershott and Jones (2003) find evidence of a deterioration in price discovery, when the Island ECN transitioned into a dark pool following stricter display requirements pursuant of Regulation ATS.

[56]See, for example, `https://www.finra.org/sites/default/files/NoticeDocument/p446087.pdf` and `https://www.finra.org/sites/default/files/Regulatory-Notice-15-48.pdf`.

changing the investment horizon with more recent data. Instead of closing positions at 6:30pm, the duration of the position is now measured either in minutes (physical time) or by the number of tick updates (tick time) after the announcement.[57]

In Panels B.1–B.5, we maintain the position from 30 seconds to 5 minutes. In the full sample, average returns from the no-friction strategy based on transaction prices increase monotonically from 0.74% (t-statistic of 8.28) for positions closed after 30 seconds to 1.58% (t-statistic of 10.82) per trade for positions closed after five minutes. In the midquote strategy, the average return is slightly compressed but continues to be positive and statistically significant. Trades executed at the BBO reduce the average return which becomes slightly negative at -0.47% (t-statistic of -4.75) for the 30-second termination rule but rises to 0.41% at the 5-minute mark (t-statistic of 2.81). Latency delays lead to further reductions in trading performance as none of the approaches generate positive *and* significant average returns. Once again the results change meaningfully between the first and second subsamples. As the price discovery process improves, average returns become lower and less significant in the second subsample compared to the earlier subsample. Interestingly, the average return over the 2016–2020 sample for the baseline scenario in Panel A is close to the corresponding value for the 5-minute stopping rule in Panel B.5. This suggests that, in the most recent subsample, the price discovery process has more or less been completed at that time.

Next, we consider what happens to trading performance in transaction time if we close the position after between 50 and 1,000 tick updates. As shown in Panels B.6–B.10, we continue to generate positive and significant average returns for trades executed at the transaction price or midquote. However, executing at the BBO again produces insignificant mean returns in the latest subsample. Interestingly, trades stopped after 1,000 tick updates in Panel B.10 yield mean returns nearly identical to those from the positions held until 6:30pm (Panel A) in the first subsample, but not in the second. This reflects the lower trading activity in the early parts of our sample, which means that 1,000 tick updates cover a much longer time interval.

Figure 8 summarizes these results by plotting the cumulative return from trading strategies that close out the position after a fixed number of tick updates (Panels A–C) or after a fixed number of seconds (Panels D–F), employing either the transaction price, midquote, or BBO. The figure illustrates both how fast the price adjusts in the very short period after an earnings announcement (both in trade time and in physical time) and also that the price settles at its new level even faster in the second subsample.

Overall, our results demonstrate that price discovery in the post-announcement window has gotten far speedier during our twelve-year sample. Prior to 2016, investors were able to reap significant

[57]We also estimated the predictive return regression with the post-announcement return (dependent variable) measured over a 5-, 10-, 30-, and 60-minute horizon. Average trading returns decline monotonically as the length of the measurement window is extended, suggesting that the price response to earnings surprises is very rapid and the "signal" is strongest for the one-minute post-announcement return. For example, compared to the number in Table 7, moving from a one-minute to a 60-minute horizon causes a decline of 48 basis points in average return for the transaction price approach.

profits from post-earnings announcement trades executed at the BBO even with a latency delay of 10 seconds. In contrast, during the last subsample, after-hours prices move so fast after earnings announcements that it is no longer possible to generate significant outperformance after accounting for bid-ask spreads. This suggests that the positive effects of decreased pre-trade transparency and improved post-trade transparency outweigh the negative effects of decreased pre-trade transparency, leading to better price discovery around corporate earnings announcements.

Proving that the sufficiency condition for market efficiency holds ultimately requires us to inspect a much broader class of trading strategies. However, the evidence presented here for the most recent subsample is consistent with Hypothesis 3.1 and with trading in the after-hours market becoming notably more efficient over time.

6.3 Risk-adjusted return performance

Large average returns on some of the trading strategies may reflect a risk premium, i.e. exposure to the market or other priced risk factors. To examine this, we create a monthly return series by summing daily trading strategy log-returns within a given month. On days without active trading signals, we assume a risk-free rate is earned, which is proxied through the yield-to-maturity of a one-month T-bill converted into a continuously compounded daily interest rate. This yields the monthly log-return:

$$r_m = (N_m - \#\mathrm{EA}_m) r_{f,d} + \sum_{t=1}^{\#\mathrm{EA}_m} r_t^{\mathrm{EA}}, \quad \text{for } m = 1, \ldots, M, \tag{35}$$

where $\#\mathrm{EA}_m$ is the number of announcement days with trading signals in month m, r_t^{EA} is the return generated from trading on day t, $r_{f,d}$ is the daily risk-free rate, N_m is the number of days in month m, and M is the number of months.

The first row in Panel A of Table 8 reports the sample mean of the raw monthly returns series computed under our different trading scenarios. For trades executed at the transaction price (column 1 labeled "Trade"), the mean return is 10.35% per month. This figure is both economically large and highly statistically significant. In the same vein, executing at the midquote earns a mean return of 8.61% per month. Trading at the best bid or offer reduces the mean return to 4.15% per month, which remains highly significant. Introducing latency of five or ten seconds brings it further down to 2.34% and 1.62% per month with only the former being significant at the 5% level, however. These results are in close alignment with our trading strategy results from Table 7, so aggregation to the monthly horizon does not affect our conclusions.

We also compute the Sharpe ratio as the average monthly excess returns divided by the sample standard deviation of the monthly return series, both converted to annualized figures. The Sharpe ratio (shown in the third row) follows the pattern of the mean (excess) returns, starting out at 2.26 for the transaction price and 1.90 for midquote setting. It then drops to 0.97, 0.59 and 0.41 for the BBO scenarios with a zero, five and ten second latency delay.

Panels B and C in Table 8 show subsample results with the top row reporting average raw returns and the third row showing the Sharpe ratio. The results are distinctly different. The mean return in the scenario with no trading frictions (12.75% per month) is almost twice as high in the 2008–2015 period as compared to the 2016–2020 subsample (6.68%). Moreover, the mean return in the early subsample is statistically significant across all trading scenarios even after accounting for bid-ask spreads and a 10-second latency delay. In contrast, in the late subsample the mean return is only 0.057% per month in the BBO scenario, which is statistically insignificant. Our estimated Sharpe ratios are also much smaller, in some cases even negative, in the second subsample as compared to the first period. These results are again consistent with our daily returns analysis.

To adjust for risk exposure, we next subtract the monthly risk-free rate, $r_{f,m}$, from r_m and regress the resulting excess return on an intercept, the five factors from the extended Fama and French (2015) model, and the momentum factor of Carhart (1997):

$$r_m - r_{f,m} = \alpha + \beta_{\text{MKT}} r_m^{\text{MKT}} + \beta_{\text{HML}} r_m^{\text{HML}} + \beta_{\text{SMB}} r_m^{\text{SMB}} + \beta_{\text{RMW}} r_m^{\text{RMW}} + \beta_{\text{CMA}} r_m^{\text{CMA}} + \beta_{\text{MOM}} r_m^{\text{MOM}} + \epsilon_m, \tag{36}$$

where r_m^{MKT} is the monthly excess return on the market portfolio (MKT), and the remaining covariates are excess returns on the factor-mimicking portfolios, where r_m^{HML} is High Minus Low (HML), r_m^{SMB} is Small Minus Big (SML), r_m^{RMW} is Robust Minus Weak (RMW), r_m^{CMA} is Conservative Minus Aggressive (CMA), and r_m^{MOM} is Momentum (MOM).[58]

Our trading strategies generate slightly negative market betas with values ranging from -0.454 to -0.267, though none of these estimates are statistically different from zero. The only risk factor that our trading strategy returns load marginally significantly on is the profitability factor, RMW, which generates negative estimates around -1.1 to -1.6. Since earnings announcements contain information that is relevant to profitability, it is not surprising that the RMW factor stands out in terms of significance. Our trading rule goes long in stocks whose actual earnings numbers surprise analysts the most while it shorts stocks whose earnings disappoint. The negative loadings on the RMW factor is therefore consistent with firms with relatively weak profitability outperforming analyst expectations the most, whereas companies with relatively robust earnings disappoint the most. However, the relationship is weak.

The monthly alpha estimates from the risk-adjustment regression in (36) are bigger than the corresponding mean raw returns. The alpha estimate is positive (at 2.37% per month) and statistically significant even for the BBO strategy with a 10-second latency delay in the full sample. Turning to the subsample analysis, Panels B and C show that alpha estimates are far bigger, and always statistically significant in the early period (2008–2015) as compared to the later sample (2016–2020). Conversely, in the second subsample alpha estimates are only statistically significant under the no-friction and midquote scenarios.

We conclude from these findings that while risk-adjusting the returns from our trading strategy

[58]The data are downloaded from Kenneth French's website: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`. The one-month T-bill rate is from Ibbotson Associates.

slightly strengthens our performance results, the basic conclusions from the earlier analysis remain unaltered. In the early subsample, there is strong evidence that information on earnings surprises could have been exploited to generate significantly positive mean returns both on a raw and risk-adjusted basis. Conversely, market efficiency seems to have improved after 2016 to the point where our trading strategy is no longer generating significantly positive raw or risk-adjusted returns after accounting for transaction costs.

6.4 Spillover effects on returns of non-announcing firms

Our jump spillover analysis shows that the release of financial statements by an announcing firm (AF) increases the likelihood of jumps in a non-announcing firm (NAF), particularly when the two firms have a close industry proximity and high after-hours trading volumes. These results do not, however, show the extent to which earnings surprises of AFs affect the returns of NAFs and whether the information dissemination is fully efficient as stipulated by Hypothesis 3, part (ii).

To shed light on this, we estimate a return regression equivalent to (33):

$$r_{1m,jt}^{\text{NAF}} = a + b_1 z_{\text{EPS},it}^{+} IP_{ij} + b_2 z_{\text{EPS},it}^{-} IP_{ij} + b_3 D_{it} \ln(V_{jt}^{\text{NAF}}) + b_4 D_{it} \ln(V_{it}^{\text{AF}}) + \epsilon_{jt}, \tag{37}$$

where $r_{1m,jt}^{\text{NAF}}$ is the one-minute post-announcement return of NAF j after the announcement of AF i on day t. The other variables are unchanged. The industry proximity interaction terms allow us to attenuate the effect of earnings surprises on the post-announcement return of NAFs in more distant industries. Similarly, we interact the sign of z_{EPS} with $\ln(V_{jt}^{\text{NAF}})$ and $\ln(V_{it}^{\text{AF}})$, allowing the liquidity measures to reinforce an expected negative price movement after a bad announcement. We find that none of the estimated coefficients in (37) are statistically significant and their explanatory power is close to zero.

Figure 9 explains this finding. In the left panel, we show a box plot of the distribution of one-minute returns of NAFs in three settings: (i) NAFs on common non-announcement days; (ii) NAFs in other industries ($IP_{ij} = 0$); and (iii) NAFs in the same industry ($IP_{ij} = 1$). Results in (ii) and (iii) are based on days with at least one announcement.[59]

While the median one-minute return is close to zero and nearly identical across the three distributions, there is a clear ranking of their spread. The dispersion is smallest on common no-announcement days, where the one-minute return mostly reflects the bid-ask spread since no information is being released. The spread is slightly wider on announcement days for NAFs in other industries and much wider for NAFs in the same industry as the AF. However, the spillover effects on the NAFs pale in comparison to the impact of the AF on itself shown in the right panel. Thus, although we can detect co-jump spillover effects, the magnitude of the price impact is much smaller than the impact on the announcing firm itself.

[59] We construct (i) by taking for each announcement of an AF a common no-announcement day at random and measuring the stock price movement of the AF over the one-minute window aligned with its associated announcement time.

We next implement the earlier trading strategies on the post-announcement returns of NAFs. Absent any trading frictions, and assuming we do not impose a threshold on the magnitude of the predicted return, the trading strategy produces a small, positive, and marginally significant average return on the order of 3–4 bps per trade.[60] This is consistent with the volatility of NAF returns being minuscule. Indeed, any profits completely vanish and turn into severe losses once trading frictions and latency delays are introduced.

We also inspect whether AFs affect one-minute returns on the market index, $r^{\text{SPY}}_{1m,t}$, again after correcting for the mechanical price impact from the announcement, through the regression:

$$r^{\text{SPY}}_{1m,t} = a + b_1 \sum_{i\,:\,EA_{it}=1} w_i z_{\text{EPS},it} + b_2 \bar{D}_{it} \sum_{i\,:\,EA_{it}=1} \ln(V^{\text{AF}}_{it}) + \epsilon_t, \tag{38}$$

where

$$\bar{D}_{it} = \text{sign}\left(\sum_{i\,:\,EA_{it}=1} w_i z_{\text{EPS},it} \right) \quad \text{and} \quad w_i = \frac{\ln(V^{\text{AF}}_{it})}{\sum_{i\,:\,EA_{it}=1} \ln(V^{\text{AF}}_{it})}. \tag{39}$$

In this model, when more than one firm is announcing on a given day, we weight the earnings surprises by the respective after-hour trading volume of the companies.

The coefficient estimates are both significant and of the correct sign, i.e $100 \times \hat{b}_1 = 0.15$ (t-statistic of 2.26) and $100 \times \hat{b}_2 = 0.09$ (t-statistic of 2.49), but the predictive power of the regression is very small. Moreover, the slope estimates are economically small with a marginal effect around one-tenth of a basis point for a unit change in the explanatory variables. Consequently, the predicted market return only rarely exceeds a full basis point which cannot be exploited in practice.

Taken together, the analysis in this subsection is consistent with Hypothesis 3.2.

7 Conclusion

High-frequency trading is widespread in today's financial markets. This suggests that, at least for the most liquid stocks, information from public announcements should be incorporated into prices almost instantaneously after the news release. In an efficient market without large trading frictions, stock prices should therefore jump, almost surely, in the immediate aftermath of releases of large bundles of information such as firms' earnings announcements. This suggests employing jump tests on highly granular tick-by-tick data as a way to test a necessary (but not sufficient) condition for market efficiency. This strategy is very different from the conventional practice of scrutinizing post-announcement returns defined over a fixed time intervals, such as one or five minutes, which can be almost an eternity in a modern fast-paced market environment.

However, the vast majority of earnings announcements occur outside the regular exchange trading hours, so such an analysis of the post-announcement price discovery process requires that we examine a relatively unexplored set of high-frequency data that includes quotation and transaction

[60] The return forecasts of NAFs rarely exceed more than a few basis points, so imposing a threshold on expected return often prevents the trading strategy from entering a position, which renders the mean return insignificant.

records from the after-hours trading session. The irregular trading activity combined with pronounced levels of microstructure noise in this market pose serious challenges to conventional jump tests that can severely distort the inference.

To address these critical shortcomings, we develop a new jump test that is robust to the unusually noisy price data observed in after-hours markets. Our noise-robust generalization extends the classical bipower variation-based jump test of Barndorff-Nielsen and Shephard (2006) to a pre-averaged version that can be implemented on noisy high-frequency data. Moreover, we develop a subsample estimator of the asymptotic variance-covariance matrix that is jump-robust under the alternative, extending earlier work of Christensen, Podolskij, Thamrongrat, and Veliyev (2017). Equipped with these tools, we show that prices of the stocks with the highest after-hours trading volume almost always jump after earnings announcements. Conversely, jumps in stock prices are rare both during the regular trading session and during after-hours trading sessions without earnings announcements.

We document a strong jump spillover effect. Conditional on an announcement from a firm, there is a significantly higher probability that prices of non-announcing firms, both within and outside the industry of the announcing firm, as well as the market index, jumps in the same after-hours trading session. The effect is larger for companies with a closer industry proximity to the announcing firm. Moreover, early announcers induce a much stronger spillover effect than late announcers. This finding is consistent with investors learning about industry- and economy-wide news components from earnings announcements.

That stock prices in the after-hours market nearly always jump after the release of earnings announcements is indicative of a very rapid price discovery process and, thus, consistent with efficient markets. However, the price jump in the immediate aftermath of an earnings release may be too big or too small, potentially introducing profitable trading opportunities. We examine if in fact prices are unbiased predictors of their future steady-state values by studying the performance of a trading rule subject to different degrees of trading frictions.

In the absence of transaction costs, we find that investors could have earned highly significant, positive risk-adjusted mean returns in the early years of our sample (2008–2015). Conversely, in the second part of our sample (2016–2020), even minor trading frictions such as bid-ask spreads reduce average raw and risk-adjusted returns to the point where they are no longer statistically significant. We conclude from this analysis that the after-hours market incorporates information on the earnings announcements of the largest US firms extremely fast, particularly after 2016.

References

Aït-Sahalia, Y., and J. Jacod, 2009a, "Estimating the degree of activity of jumps in high frequency data," *Annals of Statistics*, 37(5), 2202–2244.

——— , 2009b, "Testing for jumps in a discretely observed process," *Annals of Statistics*, 37(1), 184–222.

Aït-Sahalia, Y., J. Jacod, and J. Li, 2012, "Testing for jumps in noisy high frequency data," *Journal of Econometrics*, 168(2), 207–222.

Aït-Sahalia, Y., and R. Kimmel, 2007, "Maximum likelihood estimation of stochastic volatility models," *Journal of Financial Economics*, 83(2), 413–452.

Andersen, L. B. G., 2008, "Simple and efficient simulation of the Heston stochastic volatility model," *Journal of Computational Finance*, 11(3), 1–42.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega, 2003, "Micro effects of macro announcements: Real-time price discovery in foreign exchange," *American Economic Review*, 93(1), 38–62.

Andersen, T. G., T. Bollerslev, and D. Dobrev, 2007, "No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications," *Journal of Econometrics*, 138(1), 125–180.

Baeumer, B., and M. M. Meerschaert, 2010, "Tempered stable Lévy motion and transient superdiffusion," *Journal of Computational and Applied Mathematics*, 233(10), 2438–2448.

Bajgrowicz, P., O. Scaillet, and A. Treccani, 2016, "Jumps in high-frequency data: Spurious detections, dynamics, and news," *Management Science*, 62(8), 2198–2217.

Baldauf, M., and J. Mollner, 2022, "Fast traders make a quick buck: The role of speed in liquidity provision," *Journal of Financial Markets*, 58(100621), 1–22.

Ball, R., and P. Brown, 1968, "An empirical evaluation of accounting income numbers," *Journal of Accounting Research*, 6(2), 159–178.

Bandi, F. M., and J. R. Russell, 2008, "Microstructure noise, realized variance, and optimal sampling," *Review of Economic Studies*, 75(2), 339–369.

Banerjee, S., and I. Kremer, 2010, "Disagreement and learning: Dynamic patterns of trade," *Journal of Finance*, 65(4), 1269–1302.

Barclay, M. J., and T. Hendershott, 2003, "Price discovery and trading after hours," *Review of Financial Studies*, 16(4), 1041–1073.

Barclay, M. J., and J. B. Warner, 1993, "Stealth trading and volatility: Which trades move prices?," *Journal of Financial Economics*, 34(3), 281–305.

Barndorff-Nielsen, O. E., S. E. Graversen, J. Jacod, M. Podolskij, and N. Shephard, 2006, "A central limit theorem for realized power and bipower variations of continuous semimartingales," in *From Stochastic Calculus to Mathematical Finance: The Shiryaev Festschrift*, ed. by Y. Kabanov, R. Lipster, and J. Stoyanov. Springer, Heidelberg, pp. 33–68.

Barndorff-Nielsen, O. E., P. R. Hansen, A. Lunde, and N. Shephard, 2009, "Realized kernels in practice: trades and quotes," *Econometrics Journal*, 12(3), 1–32.

Barndorff-Nielsen, O. E., and N. Shephard, 2006, "Econometrics of testing for jumps in financial economics using bipower variation," *Journal of Financial Econometrics*, 4(1), 1–30.

Beaver, W. H., 1968, "The information content of annual earnings announcements," *Journal of Accounting Research*, 6, 67–92.

Berkman, H., and C. Truong, 2009, "Event day 0? After-hours earnings announcements," *Journal of Accounting Research*, 47(1), 71–103.

Bibinger, M., and L. Winkelmann, 2015, "Econometrics of co-jumps in high-frequency data with noise," *Journal of Econometrics*, 184(2), 361–378.

Blumenthal, R. M., and R. K. Getoor, 1961, "Sample functions of stochastic processes with stationary independent increments," *Journal of Mathematics and Mechanics*, 10(3), 493–516.

Bollerslev, T., T. H. Law, and G. Tauchen, 2008, "Risk, jumps, and diversification," *Journal of Econometrics*, 144(1), 234–256.

Bollerslev, T., S. Z. Li, and V. Todorov, 2016, "Roughing up beta: Continuous versus discontinuous betas and the cross section of expected stock returns," *Journal of Financial Economics*, 120(3), 464–490.

Bollerslev, T., and V. Todorov, 2011, "Tails, fears and risk premia," *Journal of Finance*, 66(6), 2165–2211.

Brogaard, J., and J. Pan, 2021, "Dark pool trading and information acquisition," *Review of Financial Studies*, 35(5), 2625–2666.

Caporin, M., A. Kolokolov, and R. Renò, 2017, "Systemic co-jumps," *Journal of Financial Economics*, 126(3), 563–591.

Carhart, M. M., 1997, "On persistence in mutual fund performance," *Journal of Finance*, 52(1), 57–82.

Chakrabarty, B., R. Pascual, and A. Shkilko, 2015, "Evaluating trade classification algorithms: Bulk volume classification versus the tick rule and the Lee-Ready algorithm," *Journal of Financial Markets*, 25(1), 52–79.

Chambers, A. E., and S. H. Penman, 1984, "Timeliness of reporting and the stock price reaction to earnings announcements," *Journal of Accounting Research*, 22(1), 21–47.

Christensen, K., U. Hounyo, and M. Podolskij, 2018, "Is the diurnal pattern sufficient to explain intraday variation in volatility? A nonparametric assessment," *Journal of Econometrics*, 205(2), 336–362.

Christensen, K., S. Kinnebrock, and M. Podolskij, 2010, "Pre-averaging estimators of the ex-post covariance matrix in noisy diffusion models with non-synchronous data," *Journal of Econometrics*, 159(1), 116–133.

Christensen, K., R. C. A. Oomen, and M. Podolskij, 2014, "Fact or friction: Jumps at ultra high frequency," *Journal of Financial Economics*, 114(3), 576–599.

Christensen, K., R. C. A. Oomen, and R. Renò, 2022, "The drift burst hypothesis," *Journal of Econometrics*, 227(2), 461–497.

Christensen, K., M. Podolskij, N. Thamrongrat, and B. Veliyev, 2017, "Inference from high-frequency data: A subsampling approach," *Journal of Econometrics*, 197(2), 245–272.

Corsi, F., D. E. Pirino, and R. Renò, 2010, "Threshold bipower variation and the impact of jumps on volatility forecasting," *Journal of Econometrics*, 159(2), 276–288.

Cox, J. C., J. E. Ingersoll, and S. A. Ross, 1985, "A theory of the term structure of interest rates," *Econometrica*, 53(2), 385–407.

Cremers, M., M. Halling, and D. Weinbaum, 2015, "Aggregate jump and volatility risk in the cross-section of stock returns," *Journal of Finance*, 70(2), 577–614.

David, A., and P. Veronesi, 2014, "Investors' and central bank's uncertainty embedded in index options," *Review of Financial Studies*, 27(6), 1661–1716.

Delbaen, F., and W. Schachermayer, 1994, "A general version of the fundamental theorem of asset pricing," *Mathematische Annalen*, 300(1), 463–520.

Dellavigna, S., and J. M. Pollet, 2009, "Investor inattention and Friday earnings announcements," *Journal of Finance*, 64(2), 709–749.

Ding, Y., Y. Li, G. Liu, and X. Zheng, 2023, "Stock co-jump networks," *Journal of Econometrics*, (Forthcoming).

Dubinsky, A., M. Johannes, A. Kaeck, and N. J. Seeger, 2019, "Option pricing of earnings announcement risks," *Review of Financial Studies*, 32(2), 646–687.

Ederington, L. H., and J. H. Lee, 1993, "How markets process information: News releases and volatility," *Journal of Finance*, 48(4), 1161–1191.

Fama, E. F., and K. R. French, 2015, "A five-factor asset pricing model," *Journal of Financial Economics*, 116(1), 1–22.

Flood, M. D., R. Huisman, K. G. Koedijk, and R. J. Mahieu, 1999, "Quote disclosure and price discovery in multiple-dealer financial markets," *Review of Financial Studies*, 12(1), 37–59.

Grégoire, V., and C. Martineau, 2022, "How is earnings news transmitted to stock prices," *Journal of Accounting Research*, 60(1), 261–297.

Grossman, S. J., and J. E. Stiglitz, 1980, "On the impossibility of informationally efficient markets," *American Economic Review*, 70(3), 393–408.

Hartzmark, S. M., and K. Shue, 2018, "A tough act to follow: Contrast effects in financial markets," *Journal of Finance*, 73(4), 1567–1613.

Hasbrouck, J., 1995, "One security, many markets: Determining the contributions to price discovery," *Journal of Finance*, 50(4), 1175–1199.

Hendershott, T., and C. M. Jones, 2003, "Island goes dark: Transparency, fragmentation, and regulation," *Review of Financial Studies*, 18(3), 743–793.

Heston, S. L., 1993, "A closed-form solution for options with stochastic volatility with applications to bond and currency options," *Review of Financial Studies*, 6(2), 327–343.

Jacod, J., Y. Li, P. A. Mykland, M. Podolskij, and M. Vetter, 2009, "Microstructure noise in the continuous case: The pre-averaging approach," *Stochastic Processes and their Applications*, 119(7), 2249–2276.

Jacod, J., Y. Li, and X. Zheng, 2017, "Statistical properties of microstructure noise," *Econometrica*, 85(4), 1133–1174.

Jacod, J., and P. E. Protter, 2012, *Discretization of Processes*. Springer, Berlin, 2nd edn.

Jacod, J., and A. N. Shiryaev, 2003, *Limit Theorems for Stochastic Processes*. Springer, Berlin, 2nd edn.

Jensen, M. C., 1978, "Some anomalous evidence regarding market efficiency," *Journal of Financial Economics*, 6(2–3), 95–101.

Jeon, Y., T. H. McCurdy, and X. Zhao, 2022, "News as sources of jumps in stock returns: Evidence from 21 million news articles for 9000 companies," *Journal of Financial Economics*, 145(2), 1–17.

Jiang, C. X., T. Likitapiwat, and T. McInish, 2012, "Information content of earnings announcements: Evidence from after-hours trading," *Journal of Financial and Quantitative Analysis*, 47(6), 1303–1330.

Jiang, G. J., and R. C. A. Oomen, 2008, "Testing for jumps when asset prices are observed with noise – A "swap variance" approach," *Journal of Econometrics*, 144(2), 352–370.

Kalnina, I., 2011, "Subsampling high frequency data," *Journal of Econometrics*, 161(2), 262–283.

Kalnina, I., and O. Linton, 2008, "Estimating quadratic variation consistently in the presence of endogenous and diurnal measurement error," *Journal of Econometrics*, 147(1), 47–59.

Lee, S. S., and J. Hannig, 2010, "Detecting jumps from Lévy jump diffusion processes," *Journal of Financial Economics*, 96(2), 271–290.

Lee, S. S., and P. A. Mykland, 2008, "Jumps in financial markets: A new nonparametric test and jump dynamics," *Review of Financial Studies*, 21(6), 2535–2563.

——— , 2012, "Jumps in equilibrium prices and market microstructure noise," *Journal of Econometrics*, 168(2), 396–406.

Li, J., V. Todorov, and G. Tauchen, 2017a, "Jump regressions," *Econometrica*, 85(1), 173–195.

——— , 2017b, "Robust jump regressions," *Journal of the American Statistical Association*, 112(517), 332–341.

Lyle, M. R., A. Stephan, and T. L. Yohn, 2021, "The differential market reaction to pre-open versus post-close earnings announcements," Working paper, Northwestern University.

Mancini, C., 2009, "Non-parametric threshold estimation for models with stochastic diffusion coefficient and jumps," *Scandinavian Journal of Statistics*, 36(2), 270–296.

Michaely, R., A. Rubin, and A. Vedrashko, 2013, "Corporate governance and the timings of earnings announcements," *Review of Finance*, 18(6), 2003–2044.

Mykland, P. A., and L. Zhang, 2017, "Assessment of uncertainty in high frequency data: The observed asymptotic variance," *Econometrica*, 85(1), 197–231.

Oomen, R. C. A., 2006, "Comment on 2005 JBES invited address "Realized variance and market microstructure noise" by Peter R. Hansen and Asger Lunde," *Journal of Business and Economic Statistics*, 24(2), 195–202.

Patell, J. M., and M. A. Wolfson, 1984, "The intraday speed of adjustment of stock prices to earnings and dividend announcements," *Journal of Financial Economics*, 13(2), 223–252.

Patton, A. J., and M. Verardo, 2012, "Does beta move with news? Firm-specific information flows and learning about profitability," *Review of Financial Studies*, 25(9), 2789–2839.

Pedersen, L. H., 2015, *Efficiently Inefficient – How Smart Money Invests and Market Prices Are Determined*. Princeton University Press, Princeton, 1st edn.

Podolskij, M., and M. Vetter, 2009a, "Bipower-type estimation in a noisy diffusion setting," *Stochastic Processes and their Applications*, 119(9), 2803–2831.

——— , 2009b, "Estimation of volatility functionals in the simultaneous presence of microstructure noise and jumps," *Bernoulli*, 15(3), 634–658.

Politis, D. N., J. P. Romano, and M. Wolf, 1999, *Subsampling*. Springer, Berlin, 1st edn.

Santosh, S., 2019, "The path of price discovery: Trade time vs clock time," Working paper, University of Maryland.

Savor, P., and M. Wilson, 2016, "Earnings announcements and systematic risk," *Journal of Finance*, 71(1), 83–138.

Todorov, V., G. Tauchen, and I. Grynkiv, 2014, "Volatility activity: Specification and estimation," *Journal of Econometrics*, 178(1), 180–193.

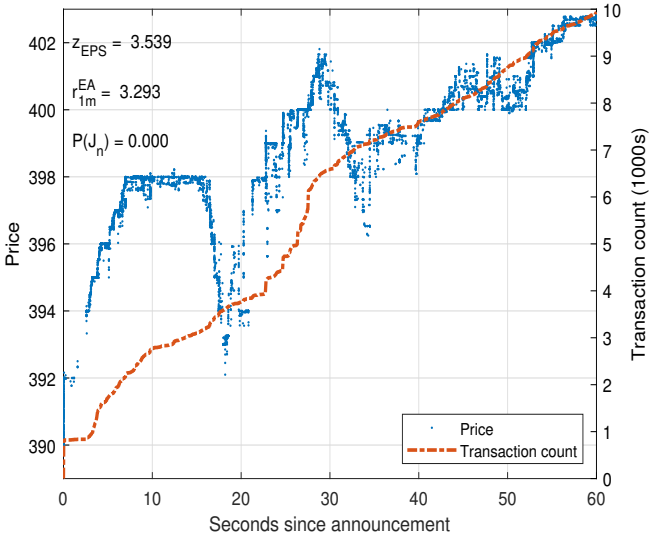
Veronesi, P., 1999, "Stock market overreaction to bad news in good times: A rational expectations equilibrium model," *Review of Financial Studies*, 12(5), 975–1007.

——— , 2000, "How does information quality affect stock returns?," *Journal of Finance*, 55(2), 807–837.

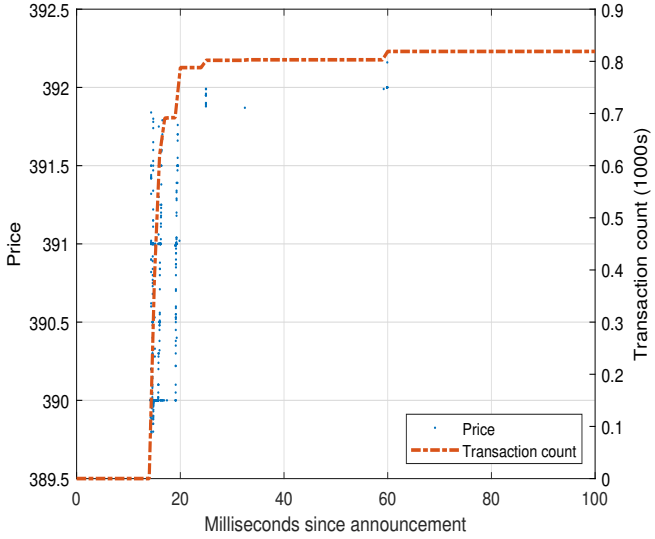
Wang, L., and E. J. Zajac, 2007, "Alliance or acquisition? A dyadic perspective on interfirm resource combinations," *Strategic Management Journal*, 28(13), 1291–1317.

Figure 1: Apple's third-quarter 2020 earnings announcement on 07/30/2020.

Panel A: 60-second horizon.



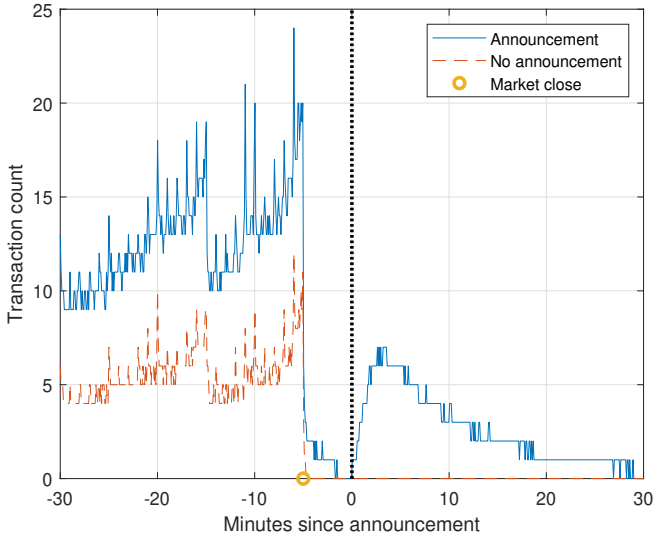
Panel B: 100-millisecond horizon.



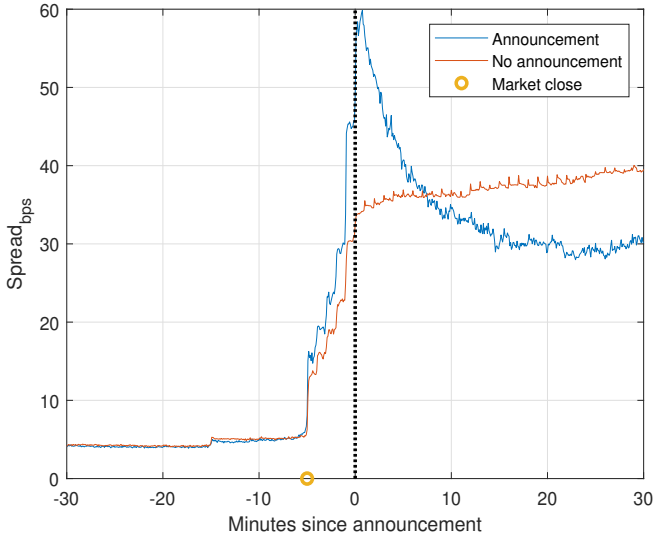
Note. The figure shows the post-announcement price (left y-axis) and cumulative transaction count in 1000s (right y-axis) for Apple's third-quarter 2020 earnings announcement, which was released at 4:30pm on 07/30/2020. In Panel A, we plot the data from the first 60 seconds since the announcement, whereas Panel B zooms further in on the first 100 milliseconds since the announcement.

Figure 2: Trading volume and bid-ask spread in the after-hours market.

Panel A: Transaction count.



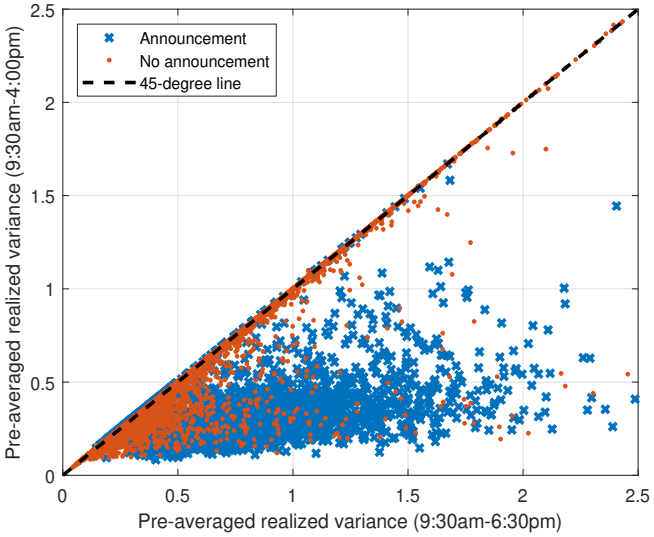
Panel B: Bid-ask spread (in bps).



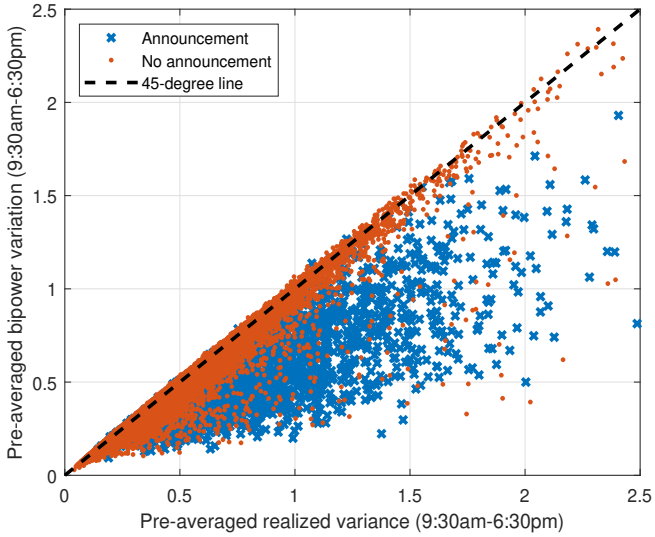
Note. In Panel A, we show the cross-sectional sample average trading volume (measured by transaction counts) for each five-second interval in a one-hour window centered around the earnings announcement, which occurs at time 0. In Panel B, we report the associated median bid-ask spread (in basis points), which is computed as $\text{Spread}_{\text{bps}} = 10000 \times (\text{ask} - \text{bid})/\text{midquote}$, where $\text{midquote} = (\text{bid} + \text{ask})/2$. As a control sample, for each announcement we select a random no-announcement date without replacement and calculate trading volume and $\text{Spread}_{\text{bps}}$ on the corresponding time interval. The modal announcement time across companies is 4:05pm. Hence, the exchange typically closes five minutes prior to an announcement (highlighted by an orange circle).

Figure 3: Pre-averaged realized variance and bipower variation.

Panel A: Incremental return variation.

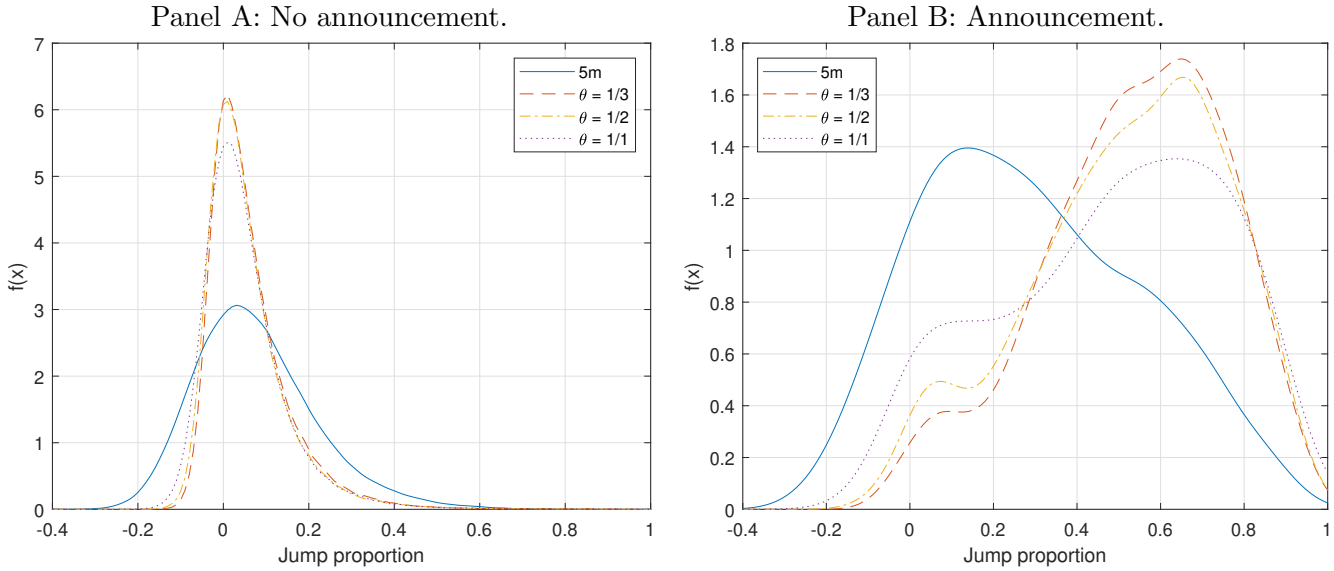


Panel B: Incremental jump variation.



Note. We show point estimates of the pre-averaged realized variance and pre-averaged bipower variation, converted to an annualized standard deviation. The axis label shows which estimator is plotted. In parenthesis, we further indicate for which part of the day high-frequency data are employed to calculate the estimate.

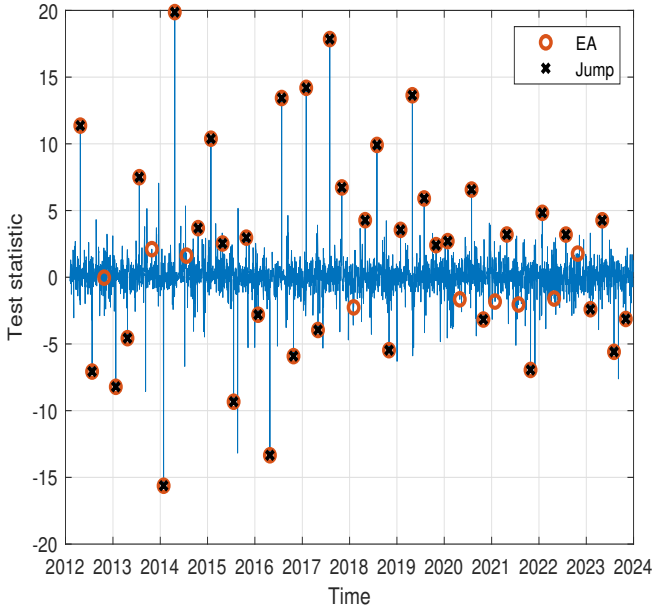
Figure 4: Distribution of the estimated jump proportion.



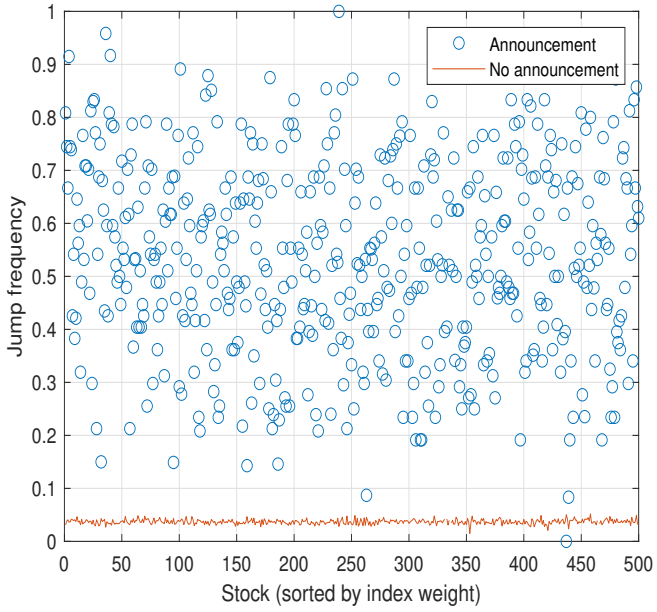
Note. This figure shows kernel smoothed densities of the proportion of quadratic return variation from the jump component, which is estimated by: Jump proportion = 1 - Bipower variation / Realized variance. The latter are computed without pre-averaging if sampling at a 5-minute frequency (5m) or with pre-averaging if sampling at the tick-by-tick frequency (rest). θ controls the size of the pre-averaging horizon $k_n = \lfloor \theta\sqrt{n} \rfloor$ for calculating pre-averaged returns. n is the number of tick-by-tick data. The sample is split into days without (in Panel A) and with earnings announcements (in Panel B).

Figure 5: Close-to-open return-based jump test.

Panel A: Test statistic (AAPL).

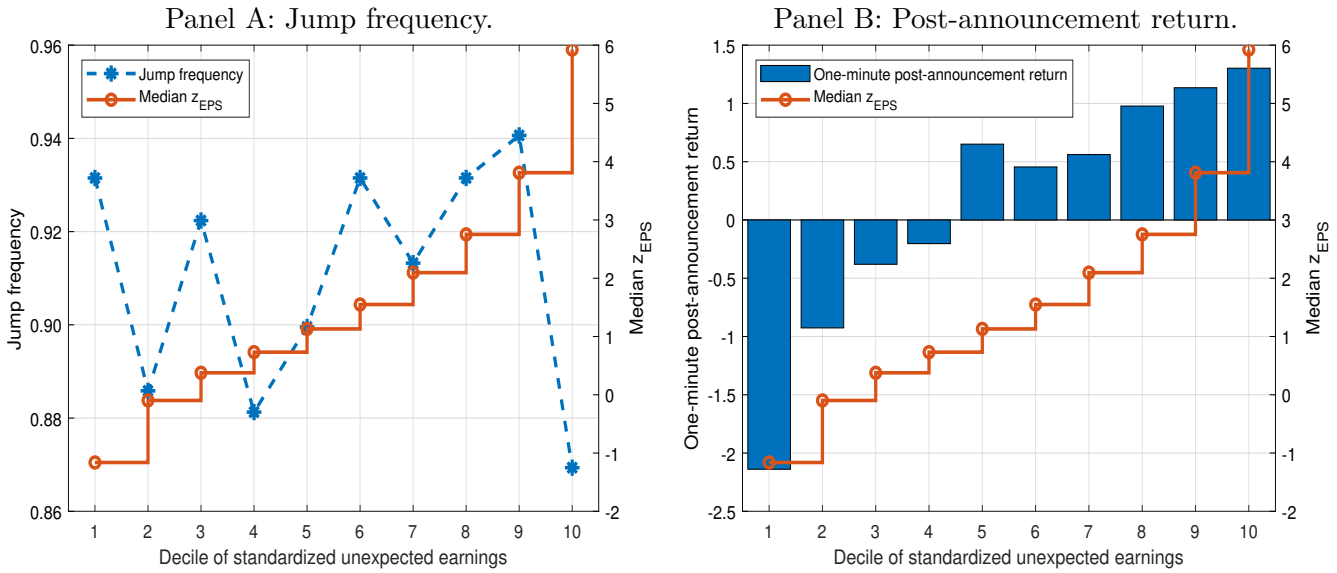


Panel B: Jump frequency.



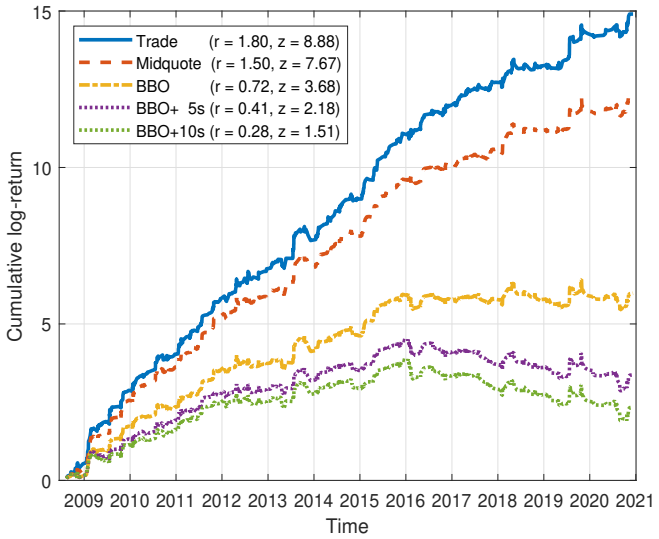
Note. We report some properties of the close-to-open return-based jump test statistic. In Panel A, we plot the test statistic for Apple. An announcement date is highlighted with a circle (a significant test is further indicated with a cross). In Panel B, we show the rejection rate for announcement and no-announcement days across companies in the S&P 500, sorted in descending order by index weight.

Figure 6: Jump frequency and post-announcement return against standardized earnings surprise.



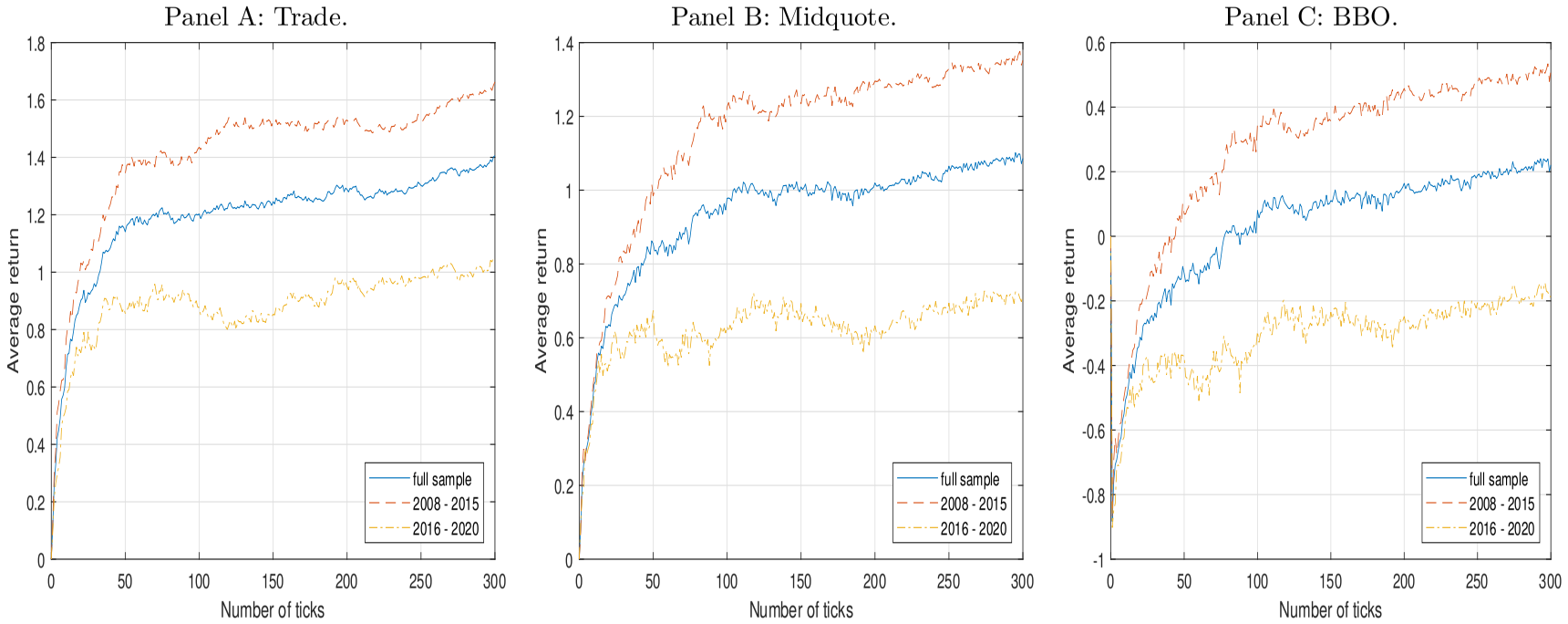
Note. We sort our earnings announcements by the value of the standardized unexpected earnings, z_{EPS}, and form decile portfolios from lowest to highest values of the earnings surprise. In Panel A, we then plot the corresponding announcement jump frequency implied by our noise-robust jump test (averaged within decile). In Panel B, we report the one-minute post-announcement return (averaged within decile). The median value of z_{EPS} within each decile is plotted against the right-hand y-axis.

Figure 7: Cumulative return from trading strategy.



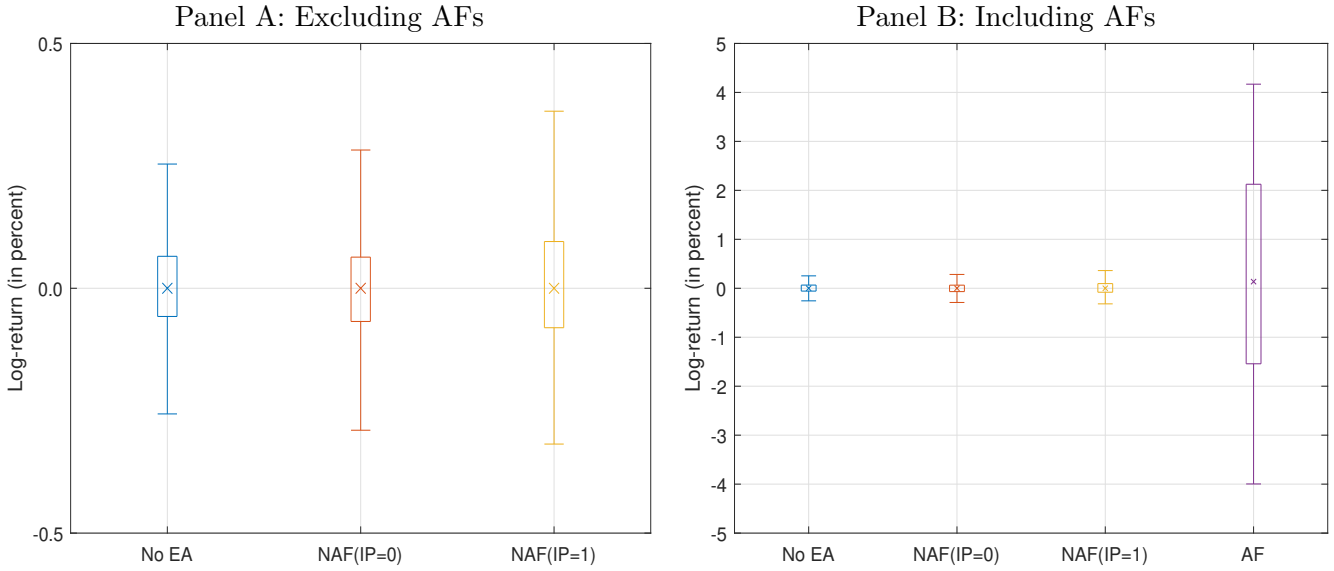
Note. The figure shows the cumulative return from a trading strategy that employs the standardized earnings surprise to predict the one-minute post-announcement return: $r^{\text{EA}}_{1m,it} = a + b_1 z^{+}_{\text{EPS},it} + b_2 z^{-}_{\text{EPS},it} + \epsilon_{it}$. A long (short) position in the stock is entered if the predicted return is greater (smaller) than 0.5% (-0.5%) and held until 6:30pm. The sample average return and test statistic for testing that the mean return is zero, based on robust standard errors, is reported in parenthesis. "Trade" employs the transaction price, "Midquote" the midquote, and "BBO" the best bid and offer. "+Xs" enforces a latency delay of X seconds before entrance.

Figure 8: Cumulative returns from trading strategy.



Note. The figure shows the cumulative return in percent from a trading strategy that employs the standardized earnings surprise to predict the one-minute post-announcement return: $r^{\text{EA}}_{1m,it} = a + b_1 z^{+}_{\text{EPS},it} + b_2 z^{-}_{\text{EPS},it} + \epsilon_{it}$. A long (short) position in the stock is entered if the predicted excess return is greater (smaller) than 0.5% (-0.5%). The cumulative return is based on closing out the position after a fixed number of tick updates. "Trade" employs the transaction price, "Midquote" the midquote, and "BBO" the best bid and offer.

Figure 9: One-minute return distribution.



Note. The box plots in the left panel show the one-minute return distribution of (i) non-announcing firms (NAFs) on common non-announcement days (no EA), (ii) NAFs outside the industry of the announcing firm (AF), NAF(IP = 0), and (iii) NAFs within the industry of the AF, NAF(IP = 1). The cross measures the median, the box is the interquartile range, and the whisker marks the 0.10 (lower) and 0.90 (upper) percentile. While (i) is based on days when none of our firms are announcing, (ii) and (iii) are based on days with at least one announcement. We construct (i) by taking for each announcement of an AF a common no-announcement day at random and measuring the stock price movement of the AF over the one-minute window aligned with its associated announcement time. In Panel B, we add the one-minute post-announcement return distribution of the AFs in our sample.

Table 1: S&P 500 companies by after-hours (4:00pm–6:30pm) trading activity.

		Conditional on no announcement							Conditional on announcement							Announcement information			
					Quantile							Quantile							
Ticker	SIC	Mean	Fraction	Std.	0.25	0.50	0.75	0.99	Mean	Fraction	Std.	0.25	0.50	0.75	0.99	#EA	Time	z_{EPS}	r_{1m}^{EA}
FB	7370	891	0.52	1,258	307	526	1,000	5,380	76,129	20.80	29,991	59,075	70,024	88,936	211,431	34	4:05pm	1.750	0.336
																		(1.252)	(4.446)
AAPL	3571	1,552	0.61	3,950	386	649	1,235	18,311	51,346	15.94	29,927	32,891	44,509	56,832	194,220	40	4:30pm	1.669	0.806
																		(1.584)	(3.395)
NFLX	7841	367	0.55	606	52	128	434	2,732	33,328	20.89	26,447	14,460	25,303	46,619	122,817	47	4:05pm	1.028	−0.236
																		(1.621)	(6.769)
AMZN	5961	808	0.82	1,442	74	152	866	6,751	33,612	22.16	18,872	22,063	28,423	38,523	94,020	50	4:01pm	0.687	−0.369
																		(1.790)	(5.714)
NVDA	3674	405	0.36	860	39	74	428	3,912	16,909	8.45	20,656	1,903	4,456	36,972	68,790	48	4:20pm	1.626	0.714
																		(1.787)	(3.988)
TSLA	3711	2,156	0.86	10,399	25	195	824	32,536	27,210	15.41	35,016	1,287	15,304	30,270	139,936	40	4:05pm	0.355	1.248
																		(1.696)	(3.422)
AMD	3674	579	0.38	1,486	40	80	612	5,722	15,417	7.37	21,607	1,711	4,849	25,714	86,880	47	4:15pm	0.746	−0.859
																		(1.342)	(4.201)
MU	3674	251	0.21	480	53	102	280	1,959	13,508	6.89	13,340	1,990	11,078	21,868	59,740	50	4:01pm	0.262	0.196
																		(1.259)	(2.927)
MSFT	7372	609	0.27	1,425	112	195	479	6,460	20,152	7.31	17,196	9,919	16,144	24,788	104,119	46	4:03pm	2.257	−0.148
																		(2.698)	(1.787)
GOOG	7370	198	0.60	370	61	100	201	1,524	15,221	20.81	7,253	9,630	14,043	19,716	30,074	49	4:01pm	0.930	0.347
																		(1.849)	(2.973)
INTC	3674	278	0.20	549	92	159	281	2,029	22,705	9.72	17,642	12,198	17,908	27,180	102,918	42	4:01pm	2.320	−0.034
																		(2.250)	(2.425)
DIS	7990	328	0.38	898	26	57	276	3,666	10,043	7.87	12,298	2,116	5,545	11,760	56,136	48	4:15pm	1.263	−0.194
																		(2.192)	(2.200)
CRM	7372	102	0.24	296	18	34	90	1,066	10,131	12.71	13,701	4,216	6,285	10,431	86,704	46	4:05pm	1.761	0.874
																		(1.728)	(3.484)
NKE	3021	98	0.23	171	16	33	120	715	7,339	10.79	6,527	2,679	5,947	9,337	36,950	48	4:15pm	2.309	0.421
																		(2.632)	(2.903)
CSCO	3576	194	0.17	239	74	124	219	1,210	20,912	10.00	16,488	11,140	17,694	24,999	91,696	50	4:05pm	2.331	−0.109
																		(1.428)	(2.588)
SBUX	5810	145	0.24	314	39	61	153	1,269	6,607	7.46	4,012	3,670	5,691	9,331	16,886	50	4:05pm	1.126	−0.347
																		(1.872)	(2.998)
IBM	3570	79	0.21	124	30	49	87	469	8,385	11.85	5,432	5,161	7,474	9,924	30,725	48	4:08pm	1.203	0.030
																		(1.337)	(2.058)
CMG	5812	47	0.45	157	9	24	53	263	4,695	18.30	4,002	1,222	3,821	7,024	16,027	48	4:10pm	1.231	−0.443
																		(2.324)	(4.224)
PYPL	7389	205	0.28	273	51	125	216	1,297	10,836	8.74	10,650	4,104	6,680	13,351	47,021	21	4:15pm	2.159	0.116
																		(1.944)	(2.525)
ORCL	7372	102	0.11	554	39	61	96	612	8,994	6.34	5,863	4,131	8,979	11,217	26,529	49	4:00pm	1.757	−0.220
																		(2.804)	(2.402)
ADBE	7372	84	0.24	202	26	40	81	624	5,389	9.51	4,273	2,675	4,628	6,477	23,037	49	4:05pm	2.235	0.102
																		(2.084)	(2.856)
QCOM	3663	145	0.18	581	49	74	130	947	9,695	8.21	7,473	5,000	7,594	12,302	33,231	49	4:00pm	1.355	0.500
																		(1.444)	(2.639)
EBAY	7389	77	0.13	86	38	55	85	374	8,664	8.15	7,007	4,180	7,488	11,404	42,753	49	4:15pm	1.624	−0.489
																		(1.518)	(3.514)
GILD	2836	208	0.23	2,014	46	69	112	1,685	4,125	4.07	5,449	566	1,830	7,064	25,630	48	4:05pm	0.671	0.081
																		(1.703)	(1.362)
AMAT	3674	88	0.15	106	37	59	101	476	3,368	3.85	3,221	666	2,268	4,998	12,834	48	4:01pm	1.573	0.324
																		(1.878)	(2.278)

Note. In the left-hand side, we show descriptive statistics of the most liquid companies from the S&P 500 index based on their after-hours market (4:00pm–6:30pm) trading volume, which is separated into no announcement days (columns 2–8) and announcement days (columns 9–15). Ticker is the stock listing symbol. SIC is the standard industrial classification code. Mean and Std. are the transaction count sample average and standard deviation. Quantile are selected quantiles from the empirical transaction count distribution. Fraction is the number of transactions executed in the after-hours session divided by the total transaction count for the extended trading session from 9:30am–6:30pm. In the right-hand side, we report announcement information. #EA is the number of earnings announcements. Time is the modal announcement time (Eastern Standard Time). z_{EPS} and r_{1m}^{EA} are the sample average standardized unexpected earnings and one-minute post-announcement return (standard deviation across announcements reported below in parenthesis).

Table 2: Sample average of realized variance, bipower variation, and jump proportion.

	Panel A: Regular trading session (9:30am–4:00pm)								Panel B: Extended trading session (9:30am–6:30pm)							
	no EA				EA				no EA				EA			
	RV	BV	JP	JF	RV	BV	JP	JF	RV	BV	JP	JF	RV	BV	JP	JF
FB	17.1	16.9	0.6	1.0	26.8	26.6	1.6	0.0	17.3	17.1	1.6	3.1	97.0	71.0	42.6	97.1
AAPL	21.4	21.1	1.6	1.6	20.4	20.0	4.1	5.0	21.7	21.3	2.2	3.3	63.4	42.0	51.7	100.0
NFLX	35.6	35.3	0.8	1.3	38.8	38.6	0.9	2.1	35.9	35.4	1.2	2.4	143.0	89.2	57.3	97.9
AMZN	25.5	25.4	0.0	0.5	28.9	28.7	1.2	0.0	25.7	25.5	0.7	2.4	110.1	72.6	50.4	100.0
NVDA	33.1	32.5	3.8	1.9	37.6	37.1	3.4	2.1	33.5	32.6	4.5	3.5	101.5	65.5	54.2	97.9
TSLA	33.4	33.2	0.2	0.5	42.4	42.1	0.2	5.0	34.0	33.7	0.9	2.0	111.4	86.2	37.7	90.0
AMD	43.0	39.1	14.8	10.9	44.7	39.5	16.7	19.1	43.6	39.4	15.3	12.6	106.0	71.1	49.0	93.6
MU	40.2	38.4	7.6	4.5	44.8	42.4	7.8	2.0	40.6	38.5	8.4	6.3	93.1	70.7	40.7	96.0
MSFT	20.0	19.5	6.4	5.3	22.0	21.4	6.1	4.3	20.2	19.6	6.9	7.0	57.9	40.0	49.8	100.0
GOOG	19.8	19.7	0.6	0.8	22.0	22.0	0.4	0.0	20.0	19.8	1.1	2.2	75.7	50.4	51.1	93.9
INTC	22.2	21.5	7.8	6.4	25.8	25.1	7.1	0.0	22.5	21.6	8.4	8.3	70.8	49.0	50.6	100.0
DIS	19.5	19.1	4.3	2.7	23.8	23.2	5.9	4.2	19.6	19.1	4.5	3.0	56.5	34.0	61.6	97.9
CRM	28.3	27.8	3.7	1.5	36.2	35.3	5.0	2.2	28.5	27.8	4.0	2.1	92.3	57.3	59.0	95.7
NKE	20.5	20.0	4.5	2.1	23.8	23.2	5.3	8.3	20.5	20.1	4.5	2.2	68.1	39.1	63.5	100.0
CSCO	20.5	19.6	9.9	8.7	23.5	22.4	9.9	14.0	20.7	19.7	10.3	9.9	71.8	51.1	47.5	100.0
SBUX	22.3	21.7	4.6	2.6	26.3	25.5	6.5	2.0	22.4	21.8	4.9	3.3	69.5	45.8	52.7	100.0
IBM	16.8	16.5	3.2	1.6	18.8	18.5	2.9	2.1	16.8	16.5	3.3	1.8	52.0	30.6	62.5	100.0
CMG	26.7	26.2	2.7	1.6	29.2	28.7	3.1	0.0	26.8	26.2	2.8	1.8	96.0	54.7	60.5	87.5
PYPL	10.8	10.6	3.7	1.1	26.5	26.1	3.0	0.0	10.8	10.6	4.1	1.6	84.4	55.9	53.5	90.5
ORCL	19.9	19.2	7.7	5.2	25.5	24.1	9.5	10.2	19.9	19.2	7.7	5.3	66.8	39.8	60.2	93.9
ADBE	23.5	23.0	3.8	1.9	27.2	26.6	4.0	2.0	23.7	23.1	4.0	2.4	78.2	49.7	54.2	98.0
QCOM	22.8	22.2	5.2	3.5	25.0	24.3	5.7	4.1	23.0	22.3	5.6	4.5	76.3	47.4	58.2	95.9
EBAY	24.6	23.8	7.0	3.9	30.5	29.4	7.2	4.1	24.7	23.8	7.0	4.0	91.9	56.6	57.5	95.9
GILD	23.6	22.9	5.1	3.6	27.4	26.7	6.0	4.2	23.7	23.0	5.4	4.4	51.2	35.1	46.7	81.2
AMAT	27.2	26.2	7.8	4.2	29.7	28.6	8.7	4.2	27.3	26.2	8.1	4.7	64.7	45.0	46.9	83.3
Average	24.7	24.1	4.7	3.2	29.1	28.2	5.3	4.0	24.9	24.2	5.1	4.2	82.0	54.0	52.8	95.4

Note. This table reports the pre-averaged realized variance (RV) and pre-averaged bipower variation (BV). We also construct the jump proportion (JP), which is defined as Jump Proportion = 1 - Bipower variation/Realized Variance. We further compute the jump frequency (JF), which is derived from the jump indicator in (24). The realized variance and bipower variation are converted to annualized standard deviation in percent for convenience. The full sample is split into days without (no EA) and with (EA) earnings announcements. The measures are then averaged across subsamples by company. In Panel A, we report the analysis for the regular trading session (9:30am–4:00pm), whereas Panel B displays the associated results for the extended trading session (9:30am–6:30am). The bottom row reports the grand mean ("Average") over all stock-days.

Table 3: Logit estimates for the stock price jump probability.

Variable	(1)	(2)	(3)
Intercept	−2.970	−3.268	−3.268
	(0.012)	(0.013)	(0.013)
EA		5.589	3.586
		(0.076)	(0.345)
$\lvert z^{+}_{\text{EPS}}\rvert$			0.052
			(0.042)
$\lvert z^{-}_{\text{EPS}}\rvert$			0.647
			(0.235)
$\sqrt{RV^{*}_{n}}$			−0.254
			(0.060)
N_A			0.102
			(0.011)
Pseudo R^2		0.1831	0.1854

Note. We estimate the logit regression: $P(J_{it}=1) = F(a + b_1 EA_{it} + b_2|z^{+}_{\text{EPS},it}| + b_3|z^{-}_{\text{EPS},it}| + b_4\sqrt{RV^{*}_{n,it}} + b_5 N_{A,it})$, where F is the logistic distribution function. J_{it} is equal to one if there is a jump in the price of company i's stock on day t, zero otherwise. EA_{it} is equal to one if there is an earnings announcement for company i on day t, zero otherwise. $z^{+}_{\text{EPS},it}$ ($z^{-}_{\text{EPS},it}$) is the standardized unexpected earnings for positive (negative) announcements, $\sqrt{RV^{*}_{n,it}}$ is the pre-averaged realized volatility calculated over the regular trading session on the announcement day, and $N_{A,it}$ is the number of analyst earnings forecasts for the announcement. The other covariates are interacted with EA and take a value of zero on no-announcement days. The table reports parameter estimates of the full model in column (3) and of restricted versions in column (1)–(2). Standard errors are shown in parenthesis below the parameter estimate. The number of observations is 158,279 of which 156,086 are no-announcement days and 2,193 are announcements days. Pseudo R^2 is the likelihood ratio index, $R^2 = 1 - L_1/L_0$, where L_0 is the log-likelihood of the constant model in (1) and L_1 is the log-likelihood of the models in (2)–(3).

Table 4: Co-jump analysis.

Announcing firm (AF)	Non-announcing firm (NAF)																									
	Fb	Aapl	Nflx	Amzn	Nvda	Tsla	Amd	Mu	Msft	Goog	Intc	Dis	Crm	Nke	Csco	Sbux	Ibm	Cmg	Orcl	Adbe	Qcom	Ebay	Gild	Amat	Ulta	MKT
Fb		16.1	3.0	25.8	17.6	0.0	12.5	8.8	10.3	28.1	5.9	0.0	0.0	0.0	17.6	0.0	2.9	0.0	5.9	2.9	16.7	0.0	10.7	8.8	2.9	14.7
Aapl	24.3		2.6	19.4	15.0	2.5	17.6	20.0	18.4	5.4	12.8	0.0	2.5	5.0	20.0	5.9	5.0	2.9	2.5	5.0	23.1	8.6	16.1	7.5	5.0	30.0
Nflx	13.0	6.7		33.3	6.4	2.1	15.6	8.5	8.9	19.1	15.2	0.0	2.1	4.3	19.1	6.8	2.6	2.3	4.3	2.1	7.0	2.4	10.9	6.4	0.0	6.4
Amzn	17.0	6.5	12.5		12.0	0.0	20.0	18.0	11.1	35.1	11.9	6.0	2.0	0.0	16.0	5.7	6.0	2.4	2.0	8.0	16.3	4.0	2.5	8.0	2.0	12.0
Nvda	0.0	6.2	2.1	0.0		2.2	35.4	10.4	0.0	0.0	10.4	2.6	0.0	4.2	8.9	4.3	0.0	0.0	2.1	0.0	4.3	4.2	0.0	2.8	0.0	2.1
Tsla	6.1	5.0	0.0	12.5	10.5		15.4	5.0	6.1	7.5	15.0	5.0	0.0	2.5	16.2	0.0	0.0	2.7	2.5	0.0	2.9	0.0	2.5	10.3	0.0	5.0
Amd	13.3	9.8	2.2	12.8	19.1	2.2		19.1	15.8	6.7	19.1	2.1	0.0	0.0	10.6	4.9	0.0	0.0	6.4	2.1	6.7	4.7	4.8	0.0	6.4	8.5
Mu	0.0	2.0	2.0	0.0	8.0	2.0	20.0		8.0	0.0	12.0	2.0	4.0	2.5	10.0	2.0	2.0	2.0	10.2	4.0	0.0	4.0	6.0	16.0	0.0	6.0
Msft	17.1	6.8	4.5	31.2	6.5	0.0	13.5	15.2		20.0	17.1	6.5	2.2	0.0	13.0	2.6	2.3	5.6	2.2	2.2	7.0	2.3	0.0	13.0	2.2	10.9
Goog	31.9	17.4	2.0	27.8	8.2	2.0	15.6	10.2	10.5		13.6	8.2	0.0	0.0	8.2	4.8	4.8	0.0	6.1	8.2	8.2	2.0	2.3	2.0	4.1	8.2
Intc	9.5	7.3	4.9	5.9	11.9	2.4	38.1	26.2	24.3	10.8		2.4	4.8	2.4	9.5	5.9	2.7	0.0	2.4	2.4	10.0	2.6	5.0	14.3	0.0	7.1
Dis	4.2	0.0	2.1	0.0	0.0	0.0	8.3	4.2	4.2	0.0	6.2		2.1	2.1	8.5	2.1	0.0	0.0	2.1	0.0	2.1	2.1	6.8	10.4	0.0	2.1
Crm	2.2	2.2	0.0	0.0	4.3	4.3	10.9	8.7	2.2	0.0	8.7	6.5		0.0	13.3	2.2	2.2	0.0	4.3	0.0	2.2	6.5	2.2	0.0	0.0	2.2
Nke	2.1	6.2	4.2	0.0	4.2	2.1	14.6	7.9	8.3	4.2	8.3	0.0	4.2		16.7	8.3	6.2	2.1	13.3	2.1	6.2	6.2	10.4	4.2	4.2	6.2
Csco	0.0	4.0	0.0	2.0	0.0	4.3	18.0	2.0	8.0	0.0	4.0	4.1	0.0	4.0		4.0	4.0	0.0	6.0	2.0	2.0	2.0	4.0	2.4	0.0	4.0
Sbux	13.0	4.5	4.3	8.6	10.2	0.0	22.7	22.0	9.5	11.6	9.5	2.0	4.0	2.0	8.0		0.0	0.0	0.0	4.0	15.2	2.3	4.3	6.0	2.0	10.0
Ibm	4.2	8.3	2.6	14.6	6.2	2.1	7.3	18.8	15.2	7.3	16.3	0.0	4.2	2.1	18.8	0.0		0.0	2.1	0.0	8.5	2.3	2.1	4.2	4.2	4.2
Cmg	13.0	14.0	11.1	25.6	8.3	0.0	21.1	18.8	18.4	9.5	19.1	4.5	0.0	0.0	16.7	4.4	4.3		4.2	4.2	4.8	4.5	0.0	10.4	2.1	6.2
Orcl	2.0	6.1	2.0	2.0	0.0	2.0	8.2	10.4	4.1	2.0	10.2	10.2	4.1	4.3	8.2	6.1	8.2	2.0		7.3	6.1	6.1	10.2	6.1	0.0	12.8
Adbe	4.1	10.2	4.1	0.0	0.0	2.0	6.1	8.2	6.1	0.0	10.2	4.1	0.0	4.1	8.2	2.0	2.0	4.1	4.9		2.0	12.2	2.0	4.1	2.2	4.3
Qcom	0.0	8.3	4.4	12.5	6.2	2.3	10.6	12.2	10.9	12.2	12.8	2.1	4.1	2.0	4.2	0.0	2.1	2.3	2.0	2.0		2.9	4.3	10.2	2.0	10.2
Ebay	9.3	4.5	2.3	30.6	4.1	6.4	17.8	14.3	17.4	6.1	10.9	2.0	4.1	8.2	14.3	0.0	4.5	6.7	4.1	6.1	5.7		4.2	8.2	2.0	8.2
Gild	19.0	12.8	4.3	10.5	12.5	2.1	11.6	14.6	8.7	11.9	8.7	4.5	4.2	2.1	18.8	4.5	6.2	2.4	6.2	6.2	10.9	2.1		4.2	2.1	8.3
Amat	0.0	4.2	0.0	0.0	2.8	2.1	14.6	10.4	6.2	0.0	12.5	0.0	4.5	4.2	12.5	6.2	2.1	0.0	8.3	2.1	4.2	4.2	4.2		4.2	2.1
Ulta	2.4	0.0	0.0	2.4	2.4	2.4	9.8	4.9	7.3	2.4	4.9	9.8	0.0	4.9	19.5	9.8	0.0	0.0	5.1	0.0	9.8	2.4	4.9	7.3		4.9

Note. We report the proportion of extended trading sessions with a jump in the non-announcing firm (NAF, in columns) when an announcing firm (AF, in rows) report financial results. The column MKT reports the jump frequency of the equity market (as proxied by SPY), conditional on the various firms' announcement days.

Table 5: Logit estimates for the co-jump probability.

Variable	(1)	(2)	(3)	(4)	(5)
Panel A: Firm-level					
Intercept	−2.960	−3.020	−3.595	−2.900	−3.611
	(0.015)	(0.017)	(0.043)	(0.019)	(0.046)
IP		0.354			0.368
		(0.048)			(0.049)
V^{NAF}			0.132		0.148
			(0.009)		(0.009)
V^{AF}			0.063		0.046
			(0.010)		(0.010)
D^{EARLY}				0.060	0.117
				(0.036)	(0.036)
D^{LATE}				−0.372	−0.417
				(0.041)	(0.041)
Panel B: Market-index					
Intercept	−2.910	−3.063	−4.036		−3.941
	(0.137)	(0.153)	(0.363)		(0.364)
$D^{\#\mathrm{AF}}$		1.287			0.958
		(0.360)			(0.381)
CV^{AF}			0.359		0.293
			(0.098)		(0.103)
Panel C: Close-to-open					
Intercept	−3.128	−3.132		−3.130	−3.133
	(0.002)	(0.002)		(0.002)	(0.002)
IP		0.063			0.061
		(0.010)			(0.010)
D^{EARLY}				0.091	0.091
				(0.004)	(0.004)
D^{LATE}				−0.092	−0.092
				(0.004)	(0.004)

Note. In Panel A, we estimate the logit regression: $P\big(J_{jt}^{\mathrm{NAF}} = 1 \mid EA_{it} = 1\big) = F\big(a + b_1 IP_{ij} + b_2 \ln(V_{jt}^{\mathrm{NAF}}) + b_3 \ln(V_{it}^{\mathrm{AF}})\big)$, where F is the logistic distribution function. J_{jt}^{NAF} is equal to one if there is a jump in the price of the non-announcing firm (NAF) j on day t, zero otherwise. EA_{it} is equal to one if the announcing firm (AF) i releases its quarterly earnings report on day t, zero otherwise. IP_{ij} is an industry proximity score between 0 (no overlap) and 1 (perfect overlap) calculated from the SIC codes of company i and j following Wang and Zajac (2007). V^{NAF} and V^{AF} are the average number of transactions in the NAF and AF in the after-hours market in the month prior to t. D_{it}^{EARLY} and D_{it}^{LATE} are indicator variables of whether the AF discloses its fiscal statement early or late in the earnings cycle. In Panel B, we estimate the logit regression: $P(J_t^{\mathrm{SPY}} = 1 \mid \#\mathrm{AF}_t \geq 1) = F\left(a + b_1 D_t^{\#\mathrm{AF}} + b_2 \ln(CV_t^{\mathrm{AF}})\right)$. Here, J_t^{SPY} is equal to one if there is a jump in the market index (proxied by SPY) on day t, zero otherwise. Moreover, $D_t^{\#\mathrm{AF}}$ is equal to one if $\#\mathrm{AF}_t \geq 5$, zero otherwise, where $\#\mathrm{AF}_t = \sum_i EA_{it}$ is the number of AFs on day t. $CV_t^{\mathrm{AF}} = \sum_{i\,:\,EA_{it}=1} V_{it}^{\mathrm{AF}}$ is the cumulative average number of transactions in the AFs in the after-hours market in the month prior to t. The definition of the variables in Panel C are identical to Panel A, but the dependent variable is $J_{jt}^{oc,\mathrm{NAF}}$. The table reports parameter estimates of the full model in column (5) and of restricted versions in column (1)–(4). Standard errors are shown in parenthesis below the parameter estimate. The number of observations is 97,811 in Panel A, 1,084 in Panel B, and 10,273,595 in Panel C.

Table 6: Post-announcement return regression.

Variable	(1)	(2)	(3)	(4)
Intercept	0.145	−0.370	−0.760	−0.744
	(0.075)	(0.108)	(0.132)	(0.131)
z^{+}_{EPS}		0.345	0.283	0.269
		(0.037)	(0.038)	(0.037)
z^{-}_{EPS}		0.784	0.328	0.340
		(0.157)	(0.157)	(0.152)
$\sqrt{RV^{*}_{n}}$			0.140	0.129
			(0.063)	(0.064)
N_A			0.015	0.014
			(0.006)	(0.006)
OI				1.321
				(0.181)
$\bar{R}^2$		0.0682	0.0807	0.0962
P-value		0.0016	0.7701	0.6414

Note. We estimate the linear regression: $r^{\text{EA}}_{1m,it} = a + b_1 z^{+}_{\text{EPS},it} + b_2 z^{-}_{\text{EPS},it} + b_3\sqrt{RV^{*}_{n,it}}D_{it} + b_4 N_{A,it}D_{it} + b_5 OI_{it} + \epsilon_{it}$. $r^{\text{EA}}_{1m,it}$ is the one-minute post-announcement return, $z^{+}_{\text{EPS},it}$ ($z^{-}_{\text{EPS},it}$) is the standardized unexpected earnings for positive (negative) announcements, $\sqrt{RV^{*}_{n,it}}$ is the pre-averaged realized volatility calculated over the regular trading session on the announcement day, $N_{A,it}$ is the number of analyst earnings forecasts for the announcement, OI_{it} is the one-minute post-announcement cumulative net order imbalance, and $D_{it} = \text{sign}(z_{\text{EPS},it})$ is the sign function. The table reports parameter estimates of the full model in column (4) and of restricted versions in column (1)–(3). Standard errors are shown in parenthesis below the parameter estimate. The number of observations is 2,193. $\bar{R}^2$ is the adjusted coefficient of multiple determination. The P-value is for testing the hypothesis $H_0 : b_1 = b_2$ against $H_1 : b_1 \neq b_2$.

Table 7: Average return from trading strategy.

Panel A: Baseline termination rule

	Terminate at 6:30pm (EOD).		
	Full sample	2008–2015	2016–2020
Trade	1.80 (8.88)	2.30 (8.77)	1.11 (3.49)
Midquote	1.50 (7.67)	2.00 (7.87)	0.80 (2.65)
BBO	0.72 (3.68)	1.23 (4.84)	0.01 (0.03)
BBO+5s	0.41 (2.18)	0.93 (3.88)	-0.32 (-1.09)
BBO+10s	0.28 (1.51)	0.80 (3.32)	-0.44 (-1.48)

Panel B: Alternative termination rules

	Terminate after fixed number of minutes.			Terminate after fixed number of ticks.		
	Full sample	2008–2015	2016–2020	Full sample	2008–2015	2016–2020
	Panel B.1: Stop after 30 seconds			*Panel B.6: Stop after 50 ticks*		
Trade	0.74 (8.28)	0.82 (7.13)	0.62 (4.43)	1.14 (9.84)	1.34 (8.21)	0.86 (5.47)
Midquote	0.56 (6.31)	0.66 (5.35)	0.43 (3.39)	0.85 (8.04)	0.98 (6.93)	0.67 (4.23)
BBO	-0.47 (-4.75)	-0.35 (-2.60)	-0.64 (-4.42)	-0.11 (-1.03)	0.07 (0.47)	-0.37 (-2.17)
BBO+5s	-0.79 (-9.72)	-0.65 (-6.31)	-0.97 (-7.57)	-0.43 (-4.13)	-0.24 (-1.70)	-0.70 (-4.48)
BBO+10s	-0.91 (-12.11)	-0.78 (-8.00)	-1.09 (-9.34)	-0.56 (-5.45)	-0.37 (-2.70)	-0.82 (-5.35)
	Panel B.2: Stop after 1 minute			*Panel B.7: Stop after 100 ticks*		
Trade	1.05 (9.36)	1.26 (8.53)	0.76 (4.42)	1.20 (9.43)	1.44 (8.34)	0.88 (4.68)
Midquote	0.85 (7.97)	1.04 (7.09)	0.59 (3.86)	0.98 (7.61)	1.23 (7.06)	0.63 (3.35)
BBO	-0.17 (-1.43)	0.07 (0.46)	-0.50 (-2.96)	0.08 (0.61)	0.35 (1.99)	-0.29 (-1.51)
BBO+5s	-0.48 (-4.86)	-0.23 (-1.81)	-0.83 (-5.43)	-0.24 (-2.00)	0.04 (0.28)	-0.63 (-3.43)
BBO+10s	-0.61 (-6.29)	-0.36 (-2.86)	-0.95 (-6.48)	-0.36 (-3.18)	-0.09 (-0.59)	-0.74 (-4.29)
	Panel B.3: Stop after 2 minutes			*Panel B.8: Stop after 250 ticks*		
Trade	1.25 (9.97)	1.55 (9.73)	0.82 (4.14)	1.30 (9.07)	1.53 (8.14)	0.98 (4.44)
Midquote	0.98 (8.08)	1.25 (7.83)	0.59 (3.23)	1.07 (7.63)	1.33 (7.34)	0.69 (3.19)
BBO	0.02 (0.13)	0.32 (1.87)	-0.40 (-2.08)	0.19 (1.33)	0.47 (2.59)	-0.21 (-0.92)
BBO+5s	-0.30 (-2.64)	0.01 (0.09)	-0.74 (-4.18)	-0.13 (-0.99)	0.17 (1.03)	-0.54 (-2.58)
BBO+10s	-0.42 (-3.84)	-0.12 (-0.82)	-0.85 (-5.06)	-0.25 (-2.02)	0.03 (0.22)	-0.65 (-3.27)
	Panel B.4: Stop after 3 minutes			*Panel B.9: Stop after 500 ticks*		
Trade	1.34 (9.78)	1.64 (9.57)	0.92 (4.12)	1.42 (9.33)	1.74 (8.56)	0.96 (4.28)
Midquote	1.08 (8.13)	1.39 (8.04)	0.66 (3.16)	1.12 (7.56)	1.40 (7.29)	0.72 (3.14)
BBO	0.17 (1.24)	0.50 (2.82)	-0.29 (-1.31)	0.29 (1.94)	0.59 (3.03)	-0.12 (-0.53)
BBO+5s	-0.14 (-1.16)	0.19 (1.27)	-0.62 (-3.03)	-0.02 (-0.18)	0.28 (1.62)	-0.46 (-2.06)
BBO+10s	-0.27 (-2.20)	0.06 (0.42)	-0.74 (-3.73)	-0.15 (-1.11)	0.15 (0.87)	-0.57 (-2.69)
	Panel B.5: Stop after 5 minutes			*Panel B.10: Stop after 1,000 ticks*		
Trade	1.58 (10.82)	1.89 (10.39)	1.15 (4.80)	1.46 (8.90)	1.93 (9.03)	0.79 (3.17)
Midquote	1.27 (8.95)	1.60 (8.70)	0.81 (3.68)	1.24 (7.88)	1.56 (7.62)	0.78 (3.22)
BBO	0.41 (2.81)	0.78 (4.18)	-0.12 (-0.52)	0.44 (2.76)	0.78 (3.78)	-0.04 (-0.16)
BBO+5s	0.09 (0.69)	0.48 (2.84)	-0.45 (-2.11)	0.12 (0.84)	0.48 (2.55)	-0.37 (-1.57)
BBO+10s	-0.03 (-0.25)	0.35 (2.05)	-0.57 (-2.76)	-0.00 (-0.01)	0.35 (1.85)	-0.49 (-2.11)

Note. The table shows the average return in percent from a trading strategy that employs the standardized earnings surprise to predict the one-minute post-announcement return: $r^{\text{EA}}_{1m,it} = a + b_1 z^{+}_{\text{EPS},it} + b_2 z^{-}_{\text{EPS},it} + \epsilon_{it}$. A long (short) position in the stock is opened if the predicted excess return is greater (smaller) than 0.5% (-0.5%). In the baseline termination rule in Panel A, the position is held until 6:30pm (EOD). In Panel B, alternative termination rules are inspected. In Panels B.1–B.5, the position is closed after a fixed number of minutes, whereas in Panels B.6–B.10 the position is closed after a fixed number of tick updates. "Trade" employs the transaction price, "Midquote" the midquote, and "BBO" the best bid and offer. "+Xs" enforces a latency delay of X seconds before entrance. The test statistic for testing that the average return is zero, based on robust standard errors, is reported in parenthesis.

Table 8: Properties of monthly trading returns.

	Trade	Midquote	BBO	BBO+5s	BBO+10s
	Sample average return, Jensen's alpha, and Sharpe ratio				
Panel A: Full sample					
$\bar{r}_m$	10.349***	8.606***	4.152***	2.342**	1.624
	(1.315)	(1.305)	(1.233)	(1.148)	(1.139)
α	11.164***	9.231***	4.809***	3.178***	2.372**
	(1.306)	(1.307)	(1.198)	(1.103)	(1.074)
Sharpe ratio	2.264	1.897	0.969	0.587	0.410
Panel B: 2008 – 2015					
$\bar{r}_m$	12.751***	11.067***	6.836***	5.151***	4.426***
	(1.648)	(1.580)	(1.456)	(1.260)	(1.244)
α	13.155***	11.130***	7.076***	5.521***	4.688***
	(1.629)	(1.551)	(1.416)	(1.272)	(1.249)
Sharpe ratio	2.856	2.586	1.734	1.510	1.313
Panel C: 2016 – 2020					
$\bar{r}_m$	6.683***	4.851**	0.057	−1.945	−2.653
	(2.077)	(2.154)	(2.067)	(2.043)	(2.035)
α	7.746***	5.792***	0.723	−1.106	−1.946
	(1.992)	(2.124)	(1.978)	(1.884)	(1.834)
Sharpe ratio	1.463	1.024	0.012	-0.433	-0.593
	Full sample Fama-French regression				
β_{MKT}	−0.454	−0.267	−0.274	−0.390	−0.293
	(0.376)	(0.381)	(0.352)	(0.334)	(0.320)
β_{HML}	0.426	0.480	0.514	0.482	0.430
	(0.734)	(0.761)	(0.708)	(0.662)	(0.653)
β_{SMB}	−0.321	−0.271	−0.213	−0.276	−0.258
	(0.522)	(0.506)	(0.494)	(0.482)	(0.483)
β_{RMW}	−1.140	−1.152	−1.313	−1.520	−1.574*
	(0.848)	(0.901)	(0.915)	(0.946)	(0.931)
β_{CMA}	−0.607	−0.984	−1.090	−0.679	−0.466
	(0.945)	(1.048)	(0.994)	(0.934)	(0.919)
β_{MOM}	−0.185	−0.079	−0.078	−0.087	0.009
	(0.282)	(0.291)	(0.288)	(0.286)	(0.298)
R^2	0.028	0.023	0.032	0.043	0.040
P-value ($\beta_{\text{MKT}} = \ldots = \beta_{\text{MOM}} = 0$)	0.688	0.771	0.598	0.406	0.468

Note. We construct a monthly return series (in percent), $r_m = \sum_{t=1}^{\#\text{EA}_m} r_t^{\text{EA}} + (N_m - \#\text{EA}_m) r_{f,d}$, for $m = 1, \ldots, M$, where $\#\text{EA}_m$ is the number of announcement days with trading signals in month m, r_t^{EA} is the return generated from each trade, $r_{f,d}$ is the daily risk-free rate, N_m is the number of days in month m, and M is the number of months. In Panel A, $\bar{r}_m$ is the sample average monthly return. We subtract the monthly risk-free rate, $r_{f,m}$, from r_m to create an excess return. The Sharpe ratio is the average excess return divided by the sample standard deviation of the return series, which we convert to an annualized figure by multiplying with $\sqrt{12}$. We regress the excess return on an intercept, the five factors from the extended Fama and French (2015) asset pricing model, and the momentum factor of Carhart (1997): $r_m - r_{f,m} = \alpha + \beta_{\text{MKT}} r_m^{\text{MKT}} + \beta_{\text{HML}} r_m^{\text{HML}} + \beta_{\text{SMB}} r_m^{\text{SMB}} + \beta_{\text{RMW}} r_m^{\text{RMW}} + \beta_{\text{CMA}} r_m^{\text{CMA}} + \beta_{\text{MOM}} r_m^{\text{MOM}} + \epsilon_m$, where r_m^{MKT} is the monthly excess return on the market (MKT), r_m^{HML} is High Minus Low (HML), r_m^{SMB} is Small Minus Big (SML), r_m^{RMW} is Robust Minus Weak (RMW), r_m^{CMA} is Conservative Minus Aggressive (CMA), and r_m^{MOM} is Momentum (MOM). The table reports parameter estimates from the regression in Panel B. Standard errors are shown in parenthesis below the parameter estimate. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level. The number of observations is 146. R^2 is the coefficient of determination. The P-value is for testing the hypothesis $H_0 : \beta_{\text{MKT}} = \cdots = \beta_{\text{MOM}} = 0$.

Web appendices

A Proof of theoretical results

In this appendix, we start with a mathematical description of the dynamic of the log-price process under investigation, $p = (p_t)_{t\geq 0}$, which we suppose evolves over the unit time interval, $t \in [0, 1]$. As usual, randomness is described by a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P})$. The construction of this space in a noisy high-frequency setting is outlined in Jacod and Protter (2012). We decompose the cumulative intraday log-return at time t, or r_t, into a continuous part and a jump, or discontinuous, part: $r_t = r_t^c + r_t^d$.

Consistent with no-arbitrage, $r^c = (r_t^c)_{t\geq 0}$ comprises a drift and a diffusion term:

$$r_t^c = \underbrace{\int_0^t a_s \mathrm{d}s}_{\text{drift}} + \underbrace{\int_0^t \sigma_s \mathrm{d}W_s}_{\text{volatility}}, \tag{40}$$

where the drift $a = (a_t)_{t\geq 0}$ is a predictable and locally bounded process, the volatility $\sigma = (\sigma_t)_{t\geq 0}$ is an adapted and càdlàg process, and $W = (W_t)_{t\geq 0}$ is a standard Brownian motion.

We decompose $r^d = (r_t^d)_{t\geq 0}$ into small and big jumps:[61]

$$r_t^d = \underbrace{\int_0^t \int_{\mathbb{R}} \delta(s,x) 1_{\{|\delta(s,x)|\leq 1\}} (\mu - \nu)(\mathrm{d}s, \mathrm{d}x)}_{\text{“small” jumps}} + \underbrace{\int_0^t \int_{\mathbb{R}} \delta(s,x) 1_{\{|\delta(s,x)|>1\}} \mu(\mathrm{d}s, \mathrm{d}x)}_{\text{“big” jumps}}, \tag{41}$$

where μ is a Poisson random measure on $\mathbb{R}_+ \times \mathbb{R}$ with compensator $\nu(\mathrm{d}s, \mathrm{d}x) = \mathrm{d}s F(\mathrm{d}x)$. Here F is a σ-finite measure, δ is a predictable function, and $(\tau_k)_{k\geq 1}$ is a sequence of $\mathcal{F}_t$-stopping times increasing to ∞ such that $|\delta(\omega, s, x)| \wedge 1 \leq \psi_k(x)$ for all (ω, s, x) with $s \leq \tau_k(\omega)$ and $\int_{\mathbb{R}} \psi_k^\beta(x) F(\mathrm{d}x) < \infty$ for all $k \geq 1$ and $\beta \in [0, 2]$. β relates to the activity of the price jumps and can be interpreted as a generalized version of the Blumenthal and Getoor (1961) index for a Lévy process, see Aït-Sahalia and Jacod (2009a).[62]

Moreover, we need a condition on the volatility process and microstructure noise.

Assumption (V): σ is of the form:

$$\sigma_t = \sigma_0 + \int_0^t \tilde{a}_s \mathrm{d}s + \int_0^t \tilde{\sigma}_s \mathrm{d}W_s + \int_0^t \tilde{v}_s \mathrm{d}B_s, \tag{42}$$

where σ_0 is an $\mathcal{F}_0$-measurable random variable, while $\tilde{a} = (\tilde{a}_t)_{t\geq 0}$, $\tilde{\sigma} = (\tilde{\sigma}_t)_{t\geq 0}$ and $\tilde{v} = (\tilde{v}_t)_{t\geq 0}$ are adapted, càdlàg processes.

[61] The separation into “small” and “large” jumps is not crucial in the analysis.

[62] A higher value of β increases the frequency of the small jumps. Figure B.1 in Appendix B provides an illustration of this characteristic.

Assumption (N): The microstructure noise is of the form

$$\epsilon_{i\Delta_n} = \omega_{i\Delta_n}\pi_i, \tag{43}$$

where

(i) $\pi = (\pi_i)_{i=0}^n$ is a sequence of i.i.d. random variables with mean zero and unit variance and the distribution of π_0 is symmetric with moments of arbitrary order.

(ii) $\omega = (\omega_t)_{t\geq 0}$ is of the form:

$$\omega_t = \omega_0 + \int_0^t \bar{a}_s \mathrm{d}s + \int_0^t \bar{\sigma}_s \mathrm{d}W_s + \int_0^t \bar{v}_s \mathrm{d}B_s, \tag{44}$$

where ω_0 is an $\mathcal{F}_0$-measurable random variable, $\bar{a} = (\bar{a}_t)_{t\geq 0}$, $\bar{\sigma} = (\bar{\sigma}_t)_{t\geq 0}$, $\bar{v} = (\bar{v}_t)_{t\geq 0}$ are adapted, càdlàg processes, while $B = (B_t)_{t\geq 0}$ is a standard Brownian motion and $B \perp\!\!\!\perp W$.[63]

(iii) $\pi \perp\!\!\!\perp (p, \omega)$.

(iv) $\limsup_{|t|\to\infty} |\chi(t)| < 1$, where χ is the characteristic function of π_0.

Assumption (V) and Assumption (N,ii) allow us to establish the order of various approximating terms appearing in the proofs, once we freeze the volatility and noise processes locally on small blocks of high-frequency data.[64]

We assume without loss of generality that a, σ, $\tilde{a}$, $\tilde{\sigma}$, $\tilde{v}$, ω, $\bar{a}$, $\bar{\sigma}$, $\bar{v}$ and the jump components of p_t are bounded. That this is innocuous follows from the localization procedure described in Jacod and Protter (2012, Section 4.4.1).

We remark that the conditions on the noise process are weak and allow for complicated dynamics such as heteroscedasticity and nonlinear dependency. Specifically, Assumption (N) resembles Assumption 4 in Li, Todorov, and Tauchen (2017b) and Assumption (N) in Jacod, Li, and Zheng (2017). It generalizes previous work on pre-averaging based on i.i.d. and exogenous noise (Christensen, Oomen, and Podolskij, 2014; Jacod, Li, Mykland, Podolskij, and Vetter, 2009; Podolskij and Vetter, 2009a,b) to more realistic processes. Meanwhile, the i.i.d assumption on π implies the noise is *linearily* independent, i.e. uncorrelated. To further allow for serial correlation, we can follow Jacod, Li, and Zheng (2017) who assume π is a stationary process with suitable mixing conditions, but the distinction is not important here.

The theory also imposes weak regularity conditions on the weight function g, namely $g : [0, 1] \to \mathbb{R}$ is continuous and piecewise continuously differentiable with piecewise Lipshitz derivative g', $g(0) = g(1) = 0$, and $\int_0^1 g(s)^2 \mathrm{d}s > 0$.

Next, we prove our mathematical results. We employ a generic constant C to bound various terms. Its value may change from line to line without notice.

[63] The symbol $A \perp\!\!\!\perp B$ means A and B are stochastically independent.

[64] Assumption (V) can be extended to discontinuous volatility processes following Barndorff-Nielsen, Graversen, Jacod, Podolskij, and Shephard (2006).

A.1 An extended central limit theorem

We start by presenting an extended version of Theorem 1 for a generalized pre-averaged bipower variation estimator. With a slight abuse of the notation from the main text, we define here the estimator with an alternative normalization. We further omit the bias-correction part. This delivers an estimator that is more convenient to work with in the derivations:

$$BV_n(q,r) = \frac{1}{n}\sum_{i=0}^{n-2k_n+1} |n^{1/4}\bar{r}_i^*|^q |n^{1/4}\bar{r}_{i+k_n}^*|^r, \tag{45}$$

where $q, r \in \mathcal{S} \equiv \{0\} \cup [1,\infty)$.

We introduce the following notation:

$$\psi_1^n = k_n \sum_{j=0}^{k_n-1} (g_{j+1}^n - g_j^n)^2 \quad \text{and} \quad \psi_2^n = \frac{1}{k_n}\sum_{j=1}^{k_n} (g_j^n)^2.$$

Furthermore,

$$c_1^n = \frac{1}{k_n \psi_2^n} \quad \text{and} \quad c_2^n = \frac{\psi_1^n}{\psi_2^n \theta^2}.$$

After Podolskij and Vetter (2009a), we expect that under $\mathcal{H}_0$

$$BV_n(q,r) \xrightarrow{p} V(q,r) = \mu_q \mu_r \int_0^1 \left(\theta\psi_2 \sigma_s^2 + \frac{1}{\theta}\psi_1 \omega_s^2\right)^{\frac{q+r}{2}} \mathrm{d}s,$$

where $\mu_s = \mathbb{E}\big[|N(0,1)|^s\big]$,

$$\psi_1^n \to \psi_1 = \int_0^1 [g'(s)]^2 \mathrm{d}s \quad \text{and} \quad \psi_2^n \to \psi_2 = \int_0^1 g(s)^2 \mathrm{d}s.$$

Theorem 3. *Assume that r follows the process in (1) with $r_t^d \equiv 0$ (for all t), and that Assumptions (V) and (N) hold. As $n \to 0$, for $q_1, q_2, r_1, r_2 \in \mathcal{S}$,*

$$n^{1/4}\begin{pmatrix} BV_n(q_1,r_1) - V(q_1,r_1) \\ BV_n(q_2,r_2) - V(q_2,r_2) \end{pmatrix} \xrightarrow{\mathcal{D}_s} MN(0,\tilde{\Sigma}),$$

where $\tilde{\Sigma}$ is defined in (47) and $\xrightarrow{\mathcal{D}_s}$ denotes stable convergence in law.

To present an expression for the asymptotic covariance matrix in the above central limit theorem, we need to introduce some additional notation. In particular, for $i, j \in \{1,2\}$, we set

$$h_{ij}(x,y,z) = \mathrm{cov}(|H_1|^{q_i}|H_2|^{r_i}, |H_3|^{q_j}|H_4|^{r_j}), \tag{46}$$

where x, y are two-dimensional vectors, whereas z is a four-dimensional vector, and (H_1, H_2, H_3, H_4) are centered multivariate normal distributed random variables with covariance structure:

(i) $\mathbb{E}\big[|H_i|^2\big] = y_1 x_1^2 + y_2 x_2^2, \quad i \in \{1,2,3,4\}$,

(ii) $H_1 \perp H_2, \quad H_1 \perp H_4, \quad H_3 \perp H_4$,

(iii) $\mathrm{cov}(H_1, H_3) = \mathrm{cov}(H_2, H_4) = z_1 x_1^2 + z_2 x_2^2$,

(iv) $\mathrm{cov}(H_2, H_3) = z_3 x_1^2 + z_4 x_2^2$.

We also introduce the following functions:

$$f_1(s) = \frac{1}{\theta}\phi_1(s), \quad f_2(s) = \theta\phi_2(s), \quad f_3(s) = \frac{1}{\theta}\phi_3(s), \quad f_4(s) = \theta\phi_4(s),$$

for $s \in [0,2]$, where

$$\phi_1(s) = \int_0^{1-s} g'(u)g'(u+s)\mathrm{d}s, \quad \phi_2(s) = \int_0^{1-s} g(u)g(u+s)\mathrm{d}s,$$
$$\phi_3(2-s) = \int_0^{1-s} g'(u)g'(u+s-1)\mathrm{d}s, \quad \phi_4(s) = \int_0^{2-s} g(u)g(u+s-1)\mathrm{d}s.$$

We compactly write these in vectorized form as $f(s) = (f_1(s), \ldots, f_4(s))$. The (i,j)-th component of $\tilde{\Sigma}$ is then given by

$$\tilde{\Sigma}_{ij} = 2\theta \int_0^1 \int_0^2 h_{ij}\big((\omega_u, \sigma_u), (\psi_1/\theta, \theta\psi_2), f(s)\big)\mathrm{d}s\mathrm{d}u. \tag{47}$$

Compared to the estimators introduced in this appendix, the pre-averaged realized variance and bipower variation in (9) are merely rescaled and bias-corrected versions of (45) with $(q,r) = (2,0)$ and $(q,r) = (1,1)$, since (see also Lemma 11)

$$RV_n^* = c_1 BV_n(2,0) + o_p\big(n^{-1/4}\big) \quad \text{and} \quad BV_n^* = c_1 \frac{\pi}{2} BV_n(1,1) + o_p\big(n^{-1/4}\big),$$

where

$$c_1 = \frac{1}{\theta\psi_2}.$$

Hence, the relation between $\tilde{\Sigma}$ and Σ is as follows:

$$\Sigma_{ij} = c_i^2 \left(\frac{\pi}{2}\right)^{i+j-2} \tilde{\Sigma}_{ij}. \tag{48}$$

Proof of Theorem 3

For any $m \leq i$, we define

$$\bar{r}_{i,m}^* = \sum_{j=1}^{k_n} g(j/k_n)\big(\sigma_{m\Delta_n}(W_{(i+j)\Delta_n} - W_{(i+j-1)\Delta_n}) + \omega_{m\Delta_n}(\pi_{i+j} - \pi_{i+j-1})\big). \tag{49}$$

We note that $\bar{r}_{i,m}^*$ serves to approximate $\bar{r}_i^*$ by freezing the processes σ and ω locally at the time point $m\Delta_n$.

We also denote

$$\eta(q,r)_i^n = |n^{1/4}\bar{r}_i^*|^q |n^{1/4}\bar{r}_{i+k_n}^*|^r,$$
$$\eta(q,r)_{i,m}^n = |n^{1/4}\bar{r}_{i,m}^*|^q |n^{1/4}\bar{r}_{i+k_n,m}^*|^r.$$

Lemma 4. *Under the maintained assumptions of Theorem 3, for any $q, r \in \mathcal{S}$, and real number $v \geq 1$, it holds that*

$$\max\Big(\mathbb{E}\big[|n^{1/4}\bar{r}_i^*|^v \mid \mathcal{F}_{i\Delta_n}\big], \mathbb{E}\big[|n^{1/4}\bar{r}_{i,m}^*|^v \mid \mathcal{F}_{m\Delta_n}\big]\Big) \leq C,$$

and

$$\max\Big(\mathbb{E}\big[|\eta(q,r)_i^n|^v \mid \mathcal{F}_{i\Delta_n}\big], \mathbb{E}\big[|\eta(q,r)_{i,m}^n|^v \mid \mathcal{F}_{m\Delta_n}\big]\Big) \leq C,$$

uniformly in i and m.

Proof. The first bound is a standard result for the pre-averaged returns, which follows from the boundedness of g, σ and ω. Then, the second bound is due to the Cauchy-Schwarz inequality. ■

Lemma 5. *Under the maintained assumptions of Theorem 3, for any $q, r \in \mathcal{S}$, it holds that*

$$\mathbb{E}\big[\eta(q,r)_{i,m}^n \mid \mathcal{F}_{m\Delta_n}\big] = \mu_q\mu_r\Big(\theta\psi_2\sigma_{m\Delta_n}^2 + \frac{1}{\theta}\psi_1\omega_{m\Delta_n}^2\Big)^{\frac{q+r}{2}} + o_p(n^{-1/4}),$$

uniformly in i and m.

Proof. This follows from the proof of Lemma 4 in Podolskij and Vetter (2009a). ■

The next preliminary result concerns the error of $\alpha_{i,m}^n \equiv n^{1/4}(\bar{r}_i^* - \bar{r}_{i,m}^*)$.

Lemma 6. *Under the maintained assumptions of Theorem 3, for any real number $v \geq 2$, it holds that*

$$\mathbb{E}\big[|\alpha_{i,m}^n|^v \mid \mathcal{F}_{m\Delta_n}\big] \leq C\Big(n^{-v/4} + \big(\mathbb{E}\big[\Gamma(\sigma,m,i)^n + \Gamma(\omega,m,i)^n \mid \mathcal{F}_{m\Delta_n}\big]\big)^v\Big),$$
$$\mathbb{E}[|\eta(q,r)_i^n - \eta(q,r)_{i,m}^n|^v|\mathcal{F}_{m\Delta_n}] \leq C\Big(n^{-v/4} + \big(\mathbb{E}\big[\Gamma(\sigma,m,i)^n + \Gamma(\omega,m,i)^n \mid \mathcal{F}_{m\Delta_n}\big]\big)^v\Big),$$

where for any process γ we set

$$\Gamma(\gamma,m,i)^n = \sup_{m\Delta_n \leq s \leq (i+2k_n)\Delta_n} |\gamma_s - \gamma_{m\Delta_n}|.$$

Proof. By construction

$$\begin{aligned}\alpha_{i,m}^n = {} & n^{1/4}\int_{i\Delta_n}^{(i+k_n)\Delta_n} g_n(s - i\Delta_n)\big[a_s\mathrm{d}s + (\sigma_s - \sigma_{m\Delta_n})\mathrm{d}W_s\big] \\ & + n^{1/4}\sum_{j=0}^{k_n-1}\big[g(j/k_n) - g(j+1/k_n)\big](\omega_{(i+j)\Delta_n} - \omega_{m\Delta_n})\pi_{i+j},\end{aligned}$$

where $g_n(s) = \sum_{j=1}^{k_n} g(j/k_n)1_{\{(j-1)\Delta_n, j\Delta_n\}}(s)$. Note that g, a and σ are bounded and $|g(j/k_n) - g(j+1/k_n)| \leq C/k_n$. Furthermore, ω is bounded and independent of π.

The first result then follows from the Burkholder-Davis-Gundy inequality and Γ being bounded. The second applies Hölder's inequality and the inequalities $||y|^q - |x|^q| \leq C|x-y|\max(|x|^{q-1}, |y|^{q-1})$ and $|y_1y_2 - x_1x_2| \leq |y_1 - x_1||y_2| + |x_1||y_2 - x_2|$. ■

We proceed by applying the "big blocks–small blocks" technique of Jacod, Li, Mykland, Podolskij, and Vetter (2009). To this end, we fix an integer $p \geq 2$, which in the later stages of the proof tends to infinity, and introduce the notation

$$a_j(p) = 2j(p+1)k_n, \quad b_j(p) = 2j(p+1)k_n + 2pk_n,$$
$$A_j(p) = \mathbb{Z} \cap [a_j(p), b_j(p)), \quad B_j(p) = \mathbb{Z} \cap [b_j(p), a_{j+1}(p)).$$

$A_j(p)$ is the big block, which has size $2pk_n$, while the small block $B_j(p)$ only has a size of $2k_n$. The small blocks are going to separate the big blocks. This means that some important terms (defined later) are conditionally independent, since the summands in the pre-averaged bipower estimator employ $2k_n$ underlying high-frequency returns. We let $j_n(p) \equiv \lfloor n/2(p+1)k_n \rfloor$ be the number of such big block–small block pairs. We utilize these pairwise blocks until observation $i_n(p) \equiv j_n(p)2(p+1)k_n$, while leaving some residual unused data at the end.

Now, we define

$$\zeta(p,q,r,1)_j^n = \sum_{u=a_j(p)}^{b_j(p)-1} \tilde{Y}_u^n(q,r) \qquad \text{and} \qquad \zeta(p,q,r,2)_j^n = \sum_{u=b_j(p)}^{a_{j+1}(p)-1} \tilde{Y}_u^n(q,r).$$

with

$$\tilde{Y}_u^n(q,r) = \begin{cases} n^{-1/2}\left(\eta(q,r)_{u,a_j(p)}^n - \mathbb{E}\big[\eta(q,r)_{u,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\big]\right), & u \in A_j(p), \\ n^{-1/2}\left(\eta(q,r)_{u,b_j(p)}^n - \mathbb{E}\big[\eta(q,r)_{u,b_j(p)}^n \mid \mathcal{F}_{b_j(p)\Delta_n}\big]\right), & u \in B_j(p), \\ n^{-1/2}\left(\eta(q,r)_{u,i_n(p)}^n - \mathbb{E}\big[\eta(q,r)_{u,i_n(p)}^n \mid \mathcal{F}_{i_n(p)\Delta_n}\big]\right), & u \in i_n(p), \end{cases}$$

and denote

$$M(p,q,r)^n = n^{-1/2} \sum_{j=0}^{j_n(p)-1} \zeta(p,q,r,1)_j^n,$$
$$N(p,q,r)^n = n^{-1/2} \sum_{j=0}^{j_n(p)-1} \zeta(p,q,r,2)_j^n,$$
$$C(p,q,r)^n = n^{-1/2} \sum_{u=i_n(p)}^{n} \tilde{Y}_u^n(q,r).$$

Next, we introduce the decomposition

$$n^{1/4}(BV_n(q,r) - V(q,r)) = n^{1/4}\left[M(p,q,r)^n + N(p,q,r)^n + C(p,q,r)^n\right] + F(p,q,r)^n, \tag{50}$$

which implicitly defines $F(p,q,r)^n$ as a remainder term. In a series of lemmas, we will show that $M(p,q,r)^n$ is the leading term, while the remaining parts are asymptotically negligible.

Lemma 7. *Let $p \geq 2$ be fixed. Under the maintained assumptions of Theorem 3, it holds that*

$$\mathbb{E}\left[\left(n^{1/4}N(p,q,r)^n\right)^2\right] \leq C/p.$$

Proof. Write

$$L_k^n = n^{-1/2} \sum_{j=0}^{k} \zeta(p,q,r,2)_j^n.$$

We observe that the process $(L_k^n)_{k=0}^{j_n(p)-1}$ is a discrete-time martingale under the filtration $(\mathcal{F}_{b_j(p)\Delta_n})_{j=0}^{j_n(p)-1}$. Then, Doob's inequality yields that

$$\mathbb{E}\left[\left(n^{1/4}N(p,q,r)^n\right)^2\right] \leq Cn^{-1/2} \sum_{j=0}^{j_n(p)-1} \mathbb{E}\left[\left(\zeta(p,q,r,2)_j^n\right)^2\right]. \tag{51}$$

Lemma 4 implies that $\mathbb{E}\left[\left(\tilde{Y}_u^n(q,r)\right)^2\right] \leq C/n$ uniformly in j, p, q, and r. Consequently, we deduce that $\mathbb{E}\left[\left(\zeta(p,q,r,2)_j^n\right)^2\right] \leq C$. Then, using $j_n(p) \leq Cn^{1/2}/p$, ends the proof. ■

Lemma 8. *Let $p \geq 2$ be fixed. Under the maintained assumptions of Theorem 3, it holds that*

$$\mathbb{E}\left[\left|n^{1/4}C(p,q,r)^n\right|\right] \leq Cpn^{-1/4}.$$

Proof. Note that $n - i_n(p) \leq Cpn^{1/2}$ and $\mathbb{E}\left[\left|\tilde{Y}_u^n(q,r)\right|\right] \leq Cn^{-1/2}$. This immediately leads to the conclusion that $\mathbb{E}\left[\left|n^{1/4}C(p,q,r)^n\right|\right] \leq Cpn^{-1/4}$. ■

Lemma 9. *Under the maintained assumptions of Theorem 3, for any $\delta > 0$, it holds that*

$$\lim_{p\to\infty} \limsup_{n\to\infty} \mathbb{P}\left[|F(p,q,r)^n| > \delta\right] = 0.$$

Proof. Recalling the decomposition in (50), we write that

$$F(p,q,r)^n = A(p,q,r)^n + B(p,q,r)^n + D(p,q,r)^n - n^{1/4}C(p,q,r)^n, \tag{52}$$

where

$$A(p,q,r)^n = n^{1/4}BV_n(q,r) - n^{1/4}\frac{1}{n}\sum_{j=0}^{j_n(p)-1}\sum_{u=0}^{2(p+1)k_n-1} \eta(q,r)_{a_j(p)+u,a_j(p)}^n,$$

$$B(p,q,r)^n = n^{1/4}\frac{1}{n}\sum_{j=0}^{j_n(p)-1}\sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[\eta(q,r)_{a_j(p)+u,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right] - n^{1/4}V(q,r),$$

$$D(p,q,r)^n = n^{-3/4}\sum_{j=0}^{j_n(p)-1}\sum_{u=0}^{2k_n-1} \eta(q,r)_{b_j(p)+u,a_j(p)}^n - \mathbb{E}\left[\eta(q,r)_{b_j(p)+u,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right]$$

$$- n^{-3/4}\sum_{j=0}^{j_n(p)-1}\sum_{u=0}^{2k_n-1} \eta(q,r)_{b_j(p)+u,b_j(p)}^n - \mathbb{E}\left[\eta(q,r)_{b_j(p)+u,b_j(p)}^n \mid \mathcal{F}_{b_jp)\Delta_n}\right]$$

The $C(p,q,r)^n$ term was covered in Lemma 8, while the $D(p,q,r)^n$ term is dealt with following Lemma 7. We proceed to $A(p,q,r)^n$. Ignoring asymptotically negligible remainder terms, and

employing the shorthand notation $\tilde{\eta}(q,r)^n_{i,m} \equiv \eta(q,r)^n_i - \eta(q,r)^n_{i,m}$, it is enough to study

$$A_1^n = n^{-3/4} \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[\tilde{\eta}(q,r)^n_{a_j(p)+u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n}\right],$$

$$A_2^n = n^{-3/4} \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \tilde{\eta}(q,r)^n_{a_j(p)+u,a_j(p)} - \mathbb{E}\left[\tilde{\eta}(q,r)^n_{a_j(p)+u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n}\right].$$

Proceeding as in the proof of Lemma 7, applying Doob's inequality and Lemma 6 yields

$$\begin{aligned}
\mathbb{E}\left[\left(A_2^n\right)^2\right] &\leq Cn^{-3/2}pk_n \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[\left(\tilde{\eta}(q,r)^n_{a_j(p)+u,a_j(p)}\right)^2\right] \\
&\leq Cn^{-3/2}pk_n \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \left(n^{-1/2} + \mathbb{E}\left[\left(\Gamma(\sigma, a_j(p), a_j(p)+u)^n + \Gamma(\omega, a_j(p), a_j(p)+u)^n\right)^2\right]\right) \\
&\leq Cpn^{-1/2} + Cn^{-1/2}p^2 \sum_{j=0}^{j_n(p)-1} \mathbb{E}\left[\left(\Gamma(\sigma, a_j(p), a_{j+1}(p))^n + \Gamma(\omega, a_j(p), a_{j+1}(p))^n\right)^2\right],
\end{aligned}$$

which is negligible by Lemma 5.4 in Jacod, Li, Mykland, Podolskij, and Vetter (2009).

Moving to the A_1^n term we observe that, from the inequality $|y_1y_2 - x_1x_2| \leq |y_1 - x_1||y_2| + |x_1||y_2 - x_2|$ and Lemmas 4 and 6, it suffices to set $r = 0$ and look at the term

$$n^{-3/4} \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[\eta(q)^n_{a_j(p)+u} - \eta(q)^n_{a_j(p)+u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n}\right].$$

Now, take $f(x) = |x|^q$ and recall that $\alpha^n_{i,m} = n^{1/4}\left(\bar{r}^*_i - \bar{r}^*_{i,m}\right)$. By Taylor's theorem and Lemmas 4 and 6, we can reduce the problem to studying the term

$$n^{-3/4} \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[f'(\eta(q)_{a_j(p)+u,a_j(p)})\alpha^n_{a_j(p)+u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n}\right]. \tag{53}$$

At this stage, we need an extra decomposition:

$$\alpha^n_{i,m} = \alpha^n_{i,m}(1) + \alpha^n_{i,m}(2),$$

where

$$\begin{aligned}
\alpha^n_{i,m}(1) &= n^{1/4} \sum_{j=1}^{k_n-1} g(j/k_n) \left[\Delta_n a_{m\Delta_n} + \int_{(i+j-1)\Delta_n}^{(i+j)\Delta_n} \left[\tilde{\sigma}_{m\Delta_n}(W_s - W_{m\Delta_n}) + \tilde{v}_{m\Delta_n}(B_s - B_{m\Delta_n})\right] \mathrm{d}W_s\right] \\
&\quad + n^{1/4} \sum_{j=0}^{k_n-1} \left[g(j/k_n) - g(j+1/k_n)\right] \left[\bar{\sigma}_{m\Delta_n}(W_{(i+j)\Delta_n} - W_{m\Delta_n}) + \bar{v}_{m\Delta_n}(B_{(i+j)\Delta_n} - B_{m\Delta_n})\right] \pi_{i+j}, \\
\alpha^n_{i,m}(2) &= n^{1/4} \sum_{j=1}^{k_n-1} g(j/k_n) \left[\int_{(i+j-1)\Delta_n}^{(i+j)\Delta_n} (a_s - a_{m\Delta_n})\mathrm{d}s + \int_{(i+j-1)\Delta_n}^{(i+j)\Delta_n} \int_{m\Delta_n}^{s} \tilde{a}_u \mathrm{d}u \mathrm{d}W_s\right]
\end{aligned}$$

$$+ n^{1/4} \sum_{j=1}^{k_n-1} g(j/k_n) \left[\int_{(i+j-1)\Delta_n}^{(i+j)\Delta_n} \left[\int_{m\Delta_n}^{s} (\tilde{\sigma}_u - \tilde{\sigma}_{m\Delta_n}) \mathrm{d}W_u + \int_{m\Delta_n}^{s} (\tilde{v}_u - \tilde{v}_{m\Delta_n}) \mathrm{d}B_u \right] \mathrm{d}W_s \right]$$

$$+ n^{1/4} \sum_{j=0}^{k_n-1} \left[g(j/k_n) - g(j+1/k_n) \right] \left[\int_{m\Delta_n}^{(i+j)\Delta_n} \bar{a}_s \mathrm{d}s + (\bar{\sigma}_s - \bar{\sigma}_{m\Delta_n}) \mathrm{d}W_s + (\bar{v}_s - \bar{v}_{m\Delta_n}) \mathrm{d}B_s \right] \pi_{i+j}.$$

Returning to (53), we first note that

$$\mathbb{E}\left[f'(\eta(q)_{a_j(p)+u,a_j(p)}) \alpha^n_{a_j(p)+u,a_j(p)}(1) \mid \mathcal{F}_{a_j(p)\Delta_n} \right] = 0,$$

because $(W, B, \pi) \stackrel{d}{=} -(W, B, \pi)$, and since $f'(\eta(q)_{a_j(p)+u,a_j(p)})$ is odd and $\alpha^n_{a_j(p)+u,a_j(p)}(1)$ is even in (W, B, π). Furthermore,

$$\mathbb{E}\left[\left(\alpha^n_{a_j(p)+u,a_j(p)}(2) \right)^2 \right] \leq C(pk_n\Delta_n)^2 + Cpn^{-1/2} \mathbb{E}\left[(\gamma^n_j(p))^2 \right],$$

where

$$\gamma^n_j(p) = \sup_{a_j(p)\Delta_n \leq s \leq a_{j+1}(p)\Delta_n} \left[|a_s - a_{a_j(p)}| + |\tilde{\sigma}_s - \tilde{\sigma}_{a_j(p)}| + |\tilde{v}_s - \tilde{v}_{a_j(p)}| + |\bar{\sigma}_s - \bar{\sigma}_{a_j(p)}| + |\bar{v}_s - \bar{v}_{a_j(p)}| \right].$$

Then, for any fixed $p \geq 2$, it follows from the Cauchy-Schwarz inequality that

$$\mathbb{E}\big[|A^n_1|\big] \leq Cn^{-3/4} \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[\left(\alpha^n_{a_j(p)+u,a_j(p)}(2) \right)^2 \right]^{1/2}$$

$$\leq Cn^{-3/4} n(pk_n\Delta_n) + Cpn^{-1/2} \sum_{j=0}^{j_n(p)-1} \mathbb{E}\big[(\gamma^n_j(p))^2\big]^{1/2} \to 0,$$

as $n \to \infty$, which follows from Lemma 5.4 in Jacod, Li, Mykland, Podolskij, and Vetter (2009).

Now, we proceed to the last term, $B(p, q, r)^n$. This can be further divided into

$$B(p, q, r)^n = B(p, q, r)^n_1 + B(p, q, r)^n_2,$$

with

$$B(p, q, r)^n_1 = n^{1/4} \frac{1}{n} \sum_{j=0}^{j_n(p)-1} \sum_{u=0}^{2(p+1)k_n-1} \mathbb{E}\left[\eta(q, r)_{a_j(p)+u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n} \right] - n^{1/4} \mu_q \mu_r \sum_{j=0}^{j_n(p)-1} \int_{a_j(p)\Delta_n}^{a_{j+1}(p)\Delta_n} \upsilon_{a_j(p)} \mathrm{d}t,$$

$$B(p, q, r)^n_2 = n^{1/4} \mu_q \mu_r \sum_{j=0}^{j_n(p)-1} \int_{a_j(p)\Delta_n}^{a_{j+1}(p)\Delta_n} \big(\upsilon_{a_j(p)} - \upsilon_t \big) \mathrm{d}t - n^{1/4} \mu_q \mu_r \int_{i_n(p)\Delta_n}^{1} \upsilon_t \mathrm{d}t,$$

and where $\upsilon_t = \theta\psi_2\sigma^2_t + \frac{1}{\theta}\psi_1\omega^2_t$.

In view of Lemma 5,

$$\lim_{p\to\infty} \limsup_{n\to\infty} \mathbb{P}\big[|B(p, q, r)^n_1| > \delta|\big] = 0.$$

Concerning the term $B(p, q, r)^n_2$, we remark that υ_t is a continuous Itô process due to Assumptions (V) and (N). Hence, a known result on the error of Riemann integration (see, e.g., the proof of

Lemma A.1 (iv) in Christensen, Podolskij, Thamrongrat, and Veliyev (2017)) states that

$$\mathbb{E}\left[|B(p,q,r)_2^n|\right] \leq Cn^{1/4}(pk_n\Delta_n + pn^{-1/2}) \leq Cpn^{-1/4},$$

which completes the proof. ■

Lemma 10. *Let $p \geq 2$ be fixed. Under the maintained assumptions of Theorem 3, it holds that*

$$n^{1/4}(M(p,q_1,r_1)^n, M(p,q_2,r_2)^n) \xrightarrow{\mathcal{D}_s} MN(0,\Sigma(p)),$$

where the (i,j)-th component of the 2x2 covariance matrix $\Sigma(p)$ is defined as

$$\Sigma(p)_{ij} = \theta\frac{p}{p+1}\int_0^1\int_0^2\left(2-\frac{s}{p}\right)h_{ij}\big((\omega_u,\sigma_u),(\psi_1/\theta,\theta\psi_2),f(s)\big)\mathrm{d}s\mathrm{d}u.$$

Proof. We set $\zeta(p)_j^n = \big(\zeta(p,q_1,r_1,1)_j^n, \zeta(p,q_2,r_2,1)_j^n\big)^\top$ for notational convenience. In view of Theorem IX.7.28 in Jacod and Shiryaev (2003), it suffices to verify the following four conditions:

$$n^{-1/2}\sum_{j=0}^{j_n(p)-1}\mathbb{E}\left[\zeta(p)_j^n(\zeta(p)_j^n)^\top \mid \mathcal{F}_{a_j(p)}\right] \xrightarrow{p} \Sigma(p),$$

$$n^{-1/2}\sum_{j=0}^{j_n(p)-1}\mathbb{E}\left[\|\zeta(p)_j^n\|^4 \mid \mathcal{F}_{a_j(p)}\right] \xrightarrow{p} 0,$$

$$n^{-1/2}\sum_{j=0}^{j_n(p)-1}\mathbb{E}\left[\zeta(p)_j^n(W_{b_j(p)\Delta_n} - W_{a_j(p)\Delta_n}) \mid \mathcal{F}_{a_j(p)}\right] \xrightarrow{p} 0,$$

$$n^{-1/2}\sum_{j=0}^{j_n(p)-1}\mathbb{E}\left[\zeta(p)_j^n(N_{b_j(p)\Delta_n} - N_{a_j(p)\Delta_n}) \mid \mathcal{F}_{a_j(p)}\right] \xrightarrow{p} 0,$$

for any bounded martingale N that is orthogonal to W.

The last three convergences are omitted, since they can be proved exactly as in Podolskij and Vetter (2009a) and Jacod, Li, Mykland, Podolskij, and Vetter (2009). So we only prove the convergence in the first condition, which is done separately for each component of $\tilde{\Sigma}$. We only spell out the details for the first term.

To this end, for any $u, v \in A_j(p)$ and $u \leq v$, we note that

$$\mathbb{E}\left[\tilde{Y}_u^n\tilde{Y}_v^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right] = \frac{1}{n}\left(\mathbb{E}\big[\eta_{u,a_j(p)}^n\eta_{v,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\big] - \mathbb{E}\big[\eta_{u,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\big]\mathbb{E}\big[\eta_{v,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\big]\right).$$

We suppress the dependence on q and r for brevity. Let $\tilde{\eta}_{i,m}^n$ be a version of the variable $\eta_{i,m}^n$, where the noise variable π is replaced by a Gaussian distributed one. In view of Lemma 5,

$$\mathbb{E}\left[\eta_{u,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right] = \mathbb{E}\left[\tilde{\eta}_{u,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right] + o_p(n^{-1/4}).$$

This, together with Lemma 4 and the Cauchy-Schwarz inequality, implies that

$$\left|\mathbb{E}\left[\eta_{u,a_j(p)}^n\eta_{v,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right] - \mathbb{E}\left[\tilde{\eta}_{u,a_j(p)}^n\tilde{\eta}_{v,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right]\right| \leq \left|\mathbb{E}\left[(\eta_{u,a_j(p)}^n - \tilde{\eta}_{u,a_j(p)}^n)\eta_{v,a_j(p)}^n \mid \mathcal{F}_{a_j(p)\Delta_n}\right]\right|$$

$$+ \left| \mathbb{E}\left[(\eta^n_{v,a_j(p)} - \tilde{\eta}^n_{v,a_j(p)}) \tilde{\eta}^n_{u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n} \right] \right|$$
$$= o_p(n^{-1/8}).$$

Further, recalling the notation in (46), we have that

$$\mathbb{E}\left[\tilde{\eta}^n_{u,a_j(p)} \tilde{\eta}^n_{v,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n} \right] - \mathbb{E}\left[\tilde{\eta}^n_{u,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n} \right] \mathbb{E}\left[\tilde{\eta}^n_{v,a_j(p)} \mid \mathcal{F}_{a_j(p)\Delta_n} \right]$$
$$= h_{11}\big((\omega_{a_j(p)\Delta_n}, \sigma_{a_j(p)\Delta_n}), \psi^n, f^n((v-u)/k_n) \big),$$

where $\psi^n = (n^{1/2}\psi^n_1/k_n, k_n\psi^n_2/n^{1/2})$ and $f^n(s) = \big(f^n_1(s), \ldots, f^n_4(s)\big)$ with

$$f^n_1(s) = n^{1/2} \sum_{j=0}^{k_n(1-s)} \left(g\left(\frac{j}{k_n}\right) - g\left(\frac{j+1}{k_n}\right) \right) \left(g\left(\frac{j+sk_n}{k_n}\right) - g\left(\frac{j+1+sk_n}{k_n}\right) \right),$$

$$f^n_2(s) = n^{-1/2} \sum_{j=0}^{k_n(1-s)} g\left(\frac{j}{k_n}\right) g\left(\frac{j+sk_n}{k_n}\right),$$

$$f^n_3(s) = n^{1/2} \sum_{j=0}^{k_n(2-s)} \left(g\left(\frac{j}{k_n}\right) - g\left(\frac{j+1}{k_n}\right) \right) \left(g\left(\frac{j+sk_n-k_n}{k_n}\right) - g\left(\frac{j+1+sk_n-k_n}{k_n}\right) \right),$$

$$f^n_4(s) = n^{-1/2} \sum_{j=0}^{k_n(2-s)} g\left(\frac{j}{k_n}\right) g\left(\frac{j+sk_n-k_n}{k_n}\right).$$

As a consequence, for $u, v \in A_j(p)$ and $0 \leq v - u < 2k_n$, we obtain

$$\mathbb{E}\left[\tilde{Y}^n_u \tilde{Y}^n_v \mid \mathcal{F}_{a_j(p)\Delta_n} \right] = \frac{1}{n} h_{11}\big((\omega_{a_j(p)\Delta_n}, \sigma_{a_j(p)\Delta_n}), \psi^n, f^n((v-u)/k_n) \big) + o_p(n^{-1}),$$

while this term vanishes for $v - u \geq 2k_n$. In turn, this implies that

$$\mathbb{E}\left[(\zeta(p,1)^n_j)^2 \mid \mathcal{F}_{a_j(p)\Delta_n} \right] = R^n_1 + R^n_2,$$

where

$$R^n_1 = 2 \sum_{u=a_j(p)}^{b_j(p)-2k_n-1} \sum_{v=u}^{u+2k_n-1} \mathbb{E}\left[\tilde{Y}^n_u \tilde{Y}^n_v \mid \mathcal{F}_{a_j(p)\Delta_n} \right] - \sum_{u=a_j(p)}^{b_j(p)-2k_n-1} \mathbb{E}\left[(\tilde{Y}^n_u)^2 \mid \mathcal{F}_{a_j(p)\Delta_n} \right],$$

$$R^n_2 = 2 \sum_{u=b_j(p)-2k_n}^{b_j(p)-1} \sum_{v=u}^{b_j(p)-1} \mathbb{E}\left[\tilde{Y}^n_u \tilde{Y}^n_v \mid \mathcal{F}_{a_j(p)\Delta_n} \right] - \sum_{u=b_j(p)-2k_n}^{b_j(p)-1} \mathbb{E}\left[(\tilde{Y}^n_u)^2 \mid \mathcal{F}_{a_j(p)\Delta_n} \right].$$

Consider the first term,

$$n^{-1/2} \sum_{j=0}^{j_n(p)-1} R^n_1 = n^{-3/2} 2(2pk_n - 2k_n) \sum_{j=0}^{j_n(p)-1} \sum_{v=0}^{2k_n-1} h_{11}\big((\omega_{a_j(p)\Delta_n}, \sigma_{a_j(p)\Delta_n}), \psi^n, f^n(v/k_n) \big) + o_p(1)$$
$$\xrightarrow{p} 2\theta \frac{p-1}{p+1} \int_0^1 \int_0^2 h_{ij}\big((\omega_u, \sigma_u), (\psi_1/\theta, \theta\psi_2), f(s) \big) \mathrm{d}s\mathrm{d}u,$$

where the argument is as in Podolskij and Vetter (2009a) via continuity of the function h_{11} and

Lebesgue's theorem.

Furthermore, we deduce that

$$n^{-1/2}\sum_{j=0}^{j_n(p)-1} n^{-1/2}R_2^n = n^{-3/2}2\sum_{j=0}^{j_n(p)-1}\sum_{v=0}^{2k_n-1}(2k_n-v)h_{11}\big((\omega_{a_j(p)\Delta_n},\sigma_{a_j(p)\Delta_n}),\psi^n,f^n(v/k_n)\big)+o_p(1)$$
$$\xrightarrow{p}\frac{\theta}{p+1}\int_0^1\int_0^2(2-s)h_{ij}\big((\omega_u,\sigma_u),(\psi_1/\theta,\theta\psi_2),f(s)\big)\mathrm{d}s\mathrm{d}u.$$

The statement then follows by summing these two terms. ■

The proof of Theorem 3 now follows directly from (50) and Lemmas 7 – 10.

Proof of Theorem 1

The proof is mostly based on Theorem 3 above, after we take into account that the error in the noise variance estimator introduced in (10).

Lemma 11. *Assume that r follows the process in* (1) *and that Assumptions (V) and (N) hold. Then, as* $n\to\infty$,

$$\sqrt{n}\left(\hat{\omega}_n^2-\int_0^1\omega_s^2\mathrm{d}s\right)=O_p(1). \tag{54}$$

Proof. We can write

$$\hat{\omega}_n^2-\int_0^1\omega_s^2\mathrm{d}s=N_1^n+N_2^n+N_3^n, \tag{55}$$

where

$$N_1^n=-\int_0^1\omega_s^2\mathrm{d}s-\frac{1}{n-1}\sum_{i=2}^n(\epsilon_{i\Delta_n}-\epsilon_{(i-1)\Delta_n})(\epsilon_{(i-1)\Delta_n}-\epsilon_{(i-2)\Delta_n}),$$

$$N_2^n=-\frac{1}{n-1}\sum_{i=2}^n\left[(p_{i\Delta_n}-p_{(i-1)\Delta_n})(\epsilon_{(i-1)\Delta_n}-\epsilon_{(i-2)\Delta_n})+(\epsilon_{i\Delta_n}-\epsilon_{(i-1)\Delta_n})(p_{(i-1)\Delta_n}-p_{(i-2)\Delta_n})\right],$$

$$N_3^n=-\frac{1}{n-1}\sum_{i=2}^n(p_{i\Delta_n}-p_{(i-1)\Delta_n})(p_{(i-1)\Delta_n}-p_{(i-2)\Delta_n}).$$

In view of (2.1.44) in Jacod and Protter (2012), we find that $\sup_{1\le i\le n}\mathbb{E}\left[(p_{i\Delta_n}-p_{(i-1)\Delta_n})^2\right]\le C/n$. Combining this with the identity $\sup_{1\le i\le n}\mathbb{E}\left[(\epsilon_{i\Delta_n}-\epsilon_{(i-1)\Delta_n})^2\right]\le C$ leads to

$$\mathbb{E}\left[|N_n^2|+|N_n^3|\right]\le Cn^{-1/2}.$$

Concerning the main term, we apply a further decomposition $N_1^n=N_{11}^n+N_{12}^n+N_{13}^n$, where

$$N_{11}^n=-\int_0^1\omega_s^2\mathrm{d}s+\frac{1}{n-1}\sum_{i=2}^n\omega_{(i-1)\Delta_n}^2\pi_{i-1}^2,\qquad N_{12}^n=\frac{1}{n-1}\sum_{i=2}^n\omega_{(i-1)\Delta_n}^2(\pi_{i-1}^2-1),$$

$$N_{13}^n=-\frac{1}{n-1}\sum_{i=2}^n\left[\omega_{i\Delta_n}\pi_i\omega_{(i-1)\Delta_n}\pi_{i-1}-\omega_{i\Delta_n}\pi_i\omega_{(i-2)\Delta_n}\pi_{i-2}+\omega_{(i-1)\Delta_n}\pi_{i-1}\omega_{(i-2)\Delta_n}\pi_{i-2}\right].$$

Alluding to Assumption (N)(iii), a standard Riemann integration error argument yields $N_{11}^n = O_p(n^{-1/2})$. In the second term above, we note that

$$\mathbb{E}\left[\omega^2_{(i-1)\Delta_n}(\pi^2_{i-1}-1)\omega^2_{(j-1)\Delta_n}(\pi^2_{j-1}-1)\right]=0,$$

for $i \neq j$ by Assumption (N)(i) and (iv). It follows that $\mathbb{E}\left[(N_{12}^n)^2\right] \leq C/n$. In the third term, the summands are again uncorrelated, which leads to $\mathbb{E}\left[(N_{13}^n)^2\right] \leq C/n$. ■

We now turn to the proof of Theorem 1. For the convergence in probability part it follows from the above results that

$$BV_n(2,0) \xrightarrow{p} \int_0^1 \Big(\theta\psi_2\sigma_s^2 + \frac{1}{\theta}\psi_1\omega_s^2\Big)\mathrm{d}s + \theta\psi_2 \sum_{0\leq s\leq 1}(\Delta r_s)^2,$$

$$BV_n(1,1) \xrightarrow{p} \int_0^1 \Big(\theta\psi_2\sigma_s^2 + \frac{1}{\theta}\psi_1\omega_s^2\Big)\mathrm{d}s.$$

This can be shown by proceeding as in the proof of Theorem 2 in Podolskij and Vetter (2009a). Now, the consistency in Theorem 1 follows from Lemma 11. The central limit theorem is derived under the further assumption that p is continuous. Hence, it follows from Theorem 3 [choosing the exponents $(q_1, r_1) = (2, 0)$ and $(q_2, r_2) = (1, 1)$] and Lemma 11. ■

A.2 A jump- and noise-robust estimator of $\tilde{\Sigma}$

Here, we present an estimator of $\tilde{\Sigma}$, which appears in the extended central limit theorem in Theorem 3. Its connection with Σ is explained in (48).

We build on previous work of Christensen, Podolskij, Thamrongrat, and Veliyev (2017), who propose a subsampling estimator of $\tilde{\Sigma}$ (see also Politis, Romano, and Wolf, 1999; Kalnina, 2011; Mykland and Zhang, 2017). An appealing feature of their estimator is that it is positive semi-definite and has good small sample properties.[65] In that paper, the subsampling estimator is shown to be consistent if there is either price jumps or microstructure noise, but not in the presence of both. Microstructure noise is further restricted to be either heteroscedastic or dependent, but not both. Here, we extend their framework to account for all of these features at once.

We propose the following jump- and noise-robust covariance matrix estimator:

$$\tilde{\Sigma}_n = \frac{1}{L}\sum_{l=1}^{L}\left(\frac{n^{1/4}}{\sqrt{L}}\begin{bmatrix}\check{BV}_l(q_1,r_1) - \check{BV}_n(q_1,r_1)\\ \check{BV}_l(q_2,r_2) - \check{BV}_n(q_2,r_2)\end{bmatrix}\right)\left(\frac{n^{1/4}}{\sqrt{L}}\begin{bmatrix}\check{BV}_l(q_1,r_1) - \check{BV}_n(q_1,r_1)\\ \check{BV}_l(q_2,r_2) - \check{BV}_n(q_2,r_2)\end{bmatrix}\right)^\top,$$

[65] Podolskij and Vetter (2009a) develop an element-by-element estimator of $\tilde{\Sigma}$ in the i.i.d noise setting. However, this estimator is not positive semi-definite and is often ill-conditioned in practice. Moreover, it is not consistent for $\tilde{\Sigma}$ under the jump alternative.

with

$$\check{BV}_n(q,r) = \frac{1}{n}\sum_{i=0}^{n-2k_n+1} |n^{1/4}\check{r}_i^*|^q |n^{1/4}\check{r}_{i+k_n}^*|^r, \qquad \check{BV}_l(q,r) = \frac{Lpk_n}{n}\sum_{i=1}^{n/Lpk_n} v_{(i-1)L+l}(q,r)^n,$$

$$v_i(q,r)^n = \frac{1}{pk_n - 2k_n + 2}\sum_{j,j+2k_n-1\in B_i(p)} |n^{1/4}\check{r}_j^*|^q |n^{1/4}\check{r}_{j+k_n}^*|^r,$$

and

$$\check{r}_i^* = \bar{r}_i^* \mathbb{1}(|\bar{r}_i^*| \leq u_n), \tag{56}$$

where $\mathbb{1}(A)$ is an indicator function that equals one if A is true, zero otherwise, and $u_n = \alpha n^{-\bar{\omega}}$ with $\alpha > 0$ and $\bar{\omega} \in (0, 1/4)$.

In the main text, we present an estimator of Σ, Σ_n^*, for the particular setting with $(q_1, r_1) = (2, 0)$ and $(q_2, r_2) = (1, 1)$. Its connection with $\tilde{\Sigma}_n$ is given by:

$$\Sigma_{n,ij}^* = \left(\sqrt{n}c_1^n\right)^2 \left(\frac{\pi}{2}\right)^{i+j-2} \tilde{\Sigma}_{n,ij}.$$

To deal with microstructure noise, $\tilde{\Sigma}_n$ is based on the pre-averaged bipower variation. To further robustify it to jumps, we exploit the truncation device of Mancini (2009) in (56). This sets large negative or positive pre-averaged log-returns to zero, since they are most likely dominated by the jump component. The threshold, u_n, is adapted to an estimate of the square-root integrated variance by setting $\alpha = c\sqrt{BV_n(1,1)}$. With this configuration, we can interpret c as the number of local diffusive standard deviations a pre-averaged log-return must exceed to be labelled a jump. The rate parameter, $\bar{\omega}$, ensures that, asymptotically, continuous pre-averaged log-returns are unaffected by the truncation. In this way, $\tilde{\Sigma}_n$ is also made jump-robust.

Theorem 12. *Assume that r follows (1) with $\beta \leq 1$ and that Assumptions (V) and (N) hold. Moreover, for each $s \in \{q_1, q_2, r_1, r_2\} \cap [1, \infty)$, we require that*

$$\frac{q + \delta - 1/2}{4q - \beta} < \bar{\omega} < \frac{1}{4} - \delta$$

where $L \asymp n^{(1-\delta)/2}$. Then, as $n \to \infty$, $\to \infty$, $L/p \to \infty$, $\sqrt{n}/Lp^2 \to \infty$ and $\delta < 1/16$, it holds that

$$\tilde{\Sigma}_n \xrightarrow{p} \tilde{\Sigma}.$$

Proof of Theorem 12

By the polarization identity, it suffices to show the result $\tilde{\Sigma}_n - \tilde{\Sigma} \xrightarrow{p} 0$ in the univariate setting. To this end, we denote by $\bar{r}_i'$ the pre-averaged return based on the continuous part of p_t and ϵ_t. The corresponding subsampling estimator is denoted as

$$\Sigma_n' = \frac{1}{L}\sum_{l=1}^{L}\left(\frac{n^{1/4}}{\sqrt{L}}\Big(BV_l'(q,r) - BV_n'(q,r)\Big)\right)^2,$$

where

$$BV_n'(q,r) = \frac{1}{n}\sum_{i=0}^{n-2k_n+1} |n^{1/4}\bar{r}_i'|^q |n^{1/4}\bar{r}_{i+k_n}'|^r, \qquad BV_l'(q,r) = \frac{Lpk_n}{n}\sum_{i=1}^{n/Lpk_n} v'_{(i-1)L+l}(q,r)^n,$$

$$v_i'(q,r)^n = \frac{1}{pk_n - 2k_n + 2}\sum_{j,j+2k_n-1\in B_i(p)} |n^{1/4}\bar{r}_j'|^q |n^{1/4}\bar{r}_{j+k_n}'|^r.$$

Proceeding exactly as in the proof of Theorem 3.8 in Christensen, Podolskij, Thamrongrat, and Veliyev (2017), it immediately follows that $\Sigma_n' - \tilde{\Sigma} \xrightarrow{p} 0$. Hence, it suffices to show that

$$\tilde{\Sigma}_n - \Sigma_n' \xrightarrow{p} 0.$$

To establish this, we note that:

$$\tilde{\Sigma}_n - \Sigma_n' = \frac{1}{L}\sum_{l=1}^{L}\left(\frac{n^{1/4}}{\sqrt{L}}\Big(BV_l(q,r) - BV_l'(q,r) + BV_n'(q,r) - BV_n(q,r)\Big)\right)$$
$$\times\left(\frac{n^{1/4}}{\sqrt{L}}\Big(BV_l(q,r) - BV_n(q,r) + BV_l'(q,r) - BV_n'(q,r)\Big)\right),$$

which is an average of L terms. The main idea is to deduce that each of these L terms converges in probability to zero. In particular, we show uniform convergence in mean square:

$$\sup_{1\le l\le L}\mathbb{E}\left[\Big|\frac{n^{1/4}}{\sqrt{L}}\big(BV_l(q,r) - BV_l'(q,r)\big)\Big|^2\right] \to 0 \quad \text{and} \quad \sup_{1\le l\le L}\mathbb{E}\left[\Big|\frac{n^{1/4}}{\sqrt{L}}\big(BV_n(q,r) - BV_n'(q,r)\big)\Big|^2\right] \to 0. \tag{57}$$

Following the arguments in the proof of Lemma A.6 in Christensen, Podolskij, Thamrongrat, and Veliyev (2017) implies that

$$\sup_{1\le l\le L}\mathbb{E}\left[\Big|\frac{n^{1/4}}{\sqrt{L}}\big(BV_l'(q,r) - BV_n'(q,r)\big)\Big|^2\right] \le C. \tag{58}$$

Then, equation (57) – (58) lead to:

$$\sup_{1\le l\le L}\mathbb{E}\left[\Big|\frac{n^{1/4}}{\sqrt{L}}\big(BV_l(q,r) - BV_n(q,r)\big)\Big|^2\right] \le C.$$

The combination of the last three results and the Cauchy-Schwarz inequality implies:

$$\mathbb{E}\big[|\tilde{\Sigma}_n - \Sigma_n'|\big] \to 0,$$

so that $\tilde{\Sigma}_n - \Sigma_n' \xrightarrow{p} 0$. Thus, it is enough to show (57).

For each j, we define

$$\lambda_j^n(q,r) = |n^{1/4}\bar{r}_j^*|^q |n^{1/4}\bar{r}_{j+k_n}^*|^r \mathbb{1}_{\{|\bar{r}_j^*|\le u_n \cap |\bar{r}_{j+k_n}^*|\le u_n\}} - |n^{1/4}\bar{r}_j'|^q |n^{1/4}\bar{r}_{j+k_n}'|^r.$$

Note that

$$BV_n(q,r) - BV_n'(q,r) = \frac{1}{n}\sum_{i=0}^{n-2k_n+1}\lambda_i^n(q,r),$$

and

$$BV_l(q,r) - BV_l'(q,r) = \frac{Lpk_n}{n}\frac{1}{pk_n - 2k_n + 2}\sum_{i=1}^{n/Lpk_n}\sum_{j,j+k_n-1\in B_{(i-1)L+l}(p)}\lambda_j^n(q,r).$$

As a result of Cauchy-Schwarz, showing (57) is reduced to proving:

$$\sup_{1\le j\le n-2k_n+2}\mathbb{E}\left[\left|\frac{n^{1/4}}{\sqrt{L}}\lambda_j^n(q,r)\right|^2\right]\to 0.$$

Furthermore, the identity

$$\lambda_j^n(q,r) = \lambda_j^n(q,0)|n^{1/4}\bar{r}'_{j+k_n}|^r + \lambda_j^n(0,r)|n^{1/4}\bar{r}'_j|^q + \lambda_j^n(q,0)\lambda_j^n(0,r),$$

and Lemma 4 combined with Cauchy-Schwarz inequality yields:

$$\mathbb{E}\big[|\lambda_j^n(q,r)|^2\big] \le C\Big(\mathbb{E}\big[|\lambda_j^n(q,0)|^4\big]^{1/2} + \mathbb{E}\big[|\lambda_j^n(0,r)|^4\big]^{1/2} + \mathbb{E}\big[|\lambda_j^n(q,0)|^4\big]^{1/2}\mathbb{E}\big[|\lambda_j^n(0,r)|^4\big]^{1/2}\Big).$$

Then, in view of the rate condition $n^{1/4}/\sqrt{L}\to\infty$, it is enough that

$$\sup_{1\le j\le n-2k_n+2}\mathbb{E}\left[\left|\frac{n^{1/4}}{\sqrt{L}}\lambda_j^n(q,0)\right|^4\right]\to 0 \quad\text{and}\quad \sup_{1\le j\le n-2k_n+2}\mathbb{E}\left[\left|\frac{n^{1/4}}{\sqrt{L}}\lambda_j^n(0,r)\right|^4\right]\to 0.$$

We only look at the term $\lambda_j^n(q,0)$ with $q>0$, for which

$$\lambda_j^n(q,0) = n^{q/4}|\bar{r}'_j + \bar{r}_j^d|^q\mathbb{1}_{\{|\bar{r}_j^*|\le u_n\}} - n^{q/4}|\bar{r}'_j|^q.$$

Now, for any $u>0$, $a\ge 0$ and $b\ge 0$, it holds that

$$\big||x+y|^q\mathbb{1}_{\{|x+y|\le u\}} - |x|^q\big| \le C\left(\frac{|x|^{q+a}}{u^a} + |x|^q\frac{|y|^b}{u^b} + (|y|\wedge u)^q + \mathbb{1}_{\{q>1\}}|x|^{q-1}(|y|\wedge u)\right),$$

which can be verified by looking at the cases:

$$(1)\ |x|\ge u/2, \qquad (2)\ |x|<u/2 \text{ and } |x+y|>u, \qquad (3)\ |x|<u/2 \text{ and } |x+y|\le u.$$

If we exploit this result with $x=\bar{r}'_j$, $y=\bar{r}_j^d$ and $u=u_n$ (a and b are selected below) in combination with a second inequality $|c-d|^4\le|c^4-d^4|$, we find that:

$$|\lambda_j^n(q,0)|^4 \le Cn^q\left(\frac{|\bar{r}'_j|^{4q+a}}{u_n^a} + |\bar{r}'_j|^{4q}\frac{|\bar{r}_j^d|^b}{u_n^b} + \big(|\bar{r}_j^d|\wedge u_n\big)^{4q} + |\bar{r}'_j|^{4q-1}\big(|\bar{r}_j^d|\wedge u_n\big)\right).$$

Note that we discard the indicator function, because it holds for any $q>1/4$. Now, arguing as in Jacod and Protter (2012, p. 529), we deduce that

$$\mathbb{E}\left[(|\bar{r}_j^d|\wedge u_n)^2\right] \le C\frac{\rho_n}{n^{1/2+(2-\beta)\bar{\omega}}}.$$

In view of the fact that $(|x|\wedge u)^q \le u^{q-2}(|x|\wedge u)^2$ for $q\ge 2$ and recalling that $u_n = \alpha n^{-\bar{\omega}}$:

$$\mathbb{E}\left[(|\bar{r}_j^d|\wedge u_n)^q\right] \le C\times\begin{cases}\dfrac{\rho_n^{q/2}}{n^{q/4+(2-\beta)\bar{\omega}q/2}} & \text{if } q\le 2,\\ \dfrac{u_n^{q-2}\rho_n}{n^{1/2+(2-\beta)\bar{\omega}}} \le \dfrac{\rho_n}{n^{1/2+(q-\beta)\bar{\omega}}} & \text{if } q>2.\end{cases}$$

Moreover, for any $q > 0$:

$$\mathbb{E}\big[|\bar{r}_j'|^q\big] \leq C\frac{1}{n^{q/4}} \quad \text{and} \quad \mathbb{E}\big[|\bar{r}_j^d|^2\big] \leq C\frac{1}{n^{1/2}}.$$

Combining these inequalities with $a = 4$, $b = 1$ and and recalling $L \asymp n^{(1-\delta)/2}$ leads to

$$\mathbb{E}\left[\left|\frac{n^{1/4}}{\sqrt{L}}\lambda_j^n(q,0)\right|^4\right] \leq C\left(\frac{1}{n^{1-\delta-4\bar{\omega}}} + \frac{1}{n^{1/4-\delta-\bar{\omega}}} + \frac{\rho_n}{n^{1/2-\delta-q+(4q-\beta)\bar{\omega}}} + \frac{\rho_n^{1/2}}{n^{-\delta+(1-\beta/2)\bar{\omega}}}\right)$$

The first and second error terms converge to 0 due to the condition $\bar{\omega} < 1/4 - \delta$. The third error term converges to 0 due to the assumption $\bar{\omega} > (q + \delta - 1/2)/(4q - \beta)$. This also implies $\bar{\omega} > 1/8$, which combined with $\beta \leq 1$ and $\delta < 1/16$ deals with the fourth term. ■

Proof of Theorem 2

The result follows directly from the proof of Theorem 12 by taking $(q_1, r_1) = (2, 0)$, $(q_2, r_2) = (1, 1)$ and adjusting by the constants c_1 and c_2. It is worth highlighting that the constraint $\bar{\omega} > (q + \delta - 1/2)/(4q - \beta)$ is more binding for $q = 2$ compared to $q = 1$. ■

A.3 Irrelevance of truncation

To show that the truncation does not influence the limiting distribution in Theorem 3 and, hence, does not affect Theorem 1, we note that

$$n^{1/4}\begin{pmatrix} BV_n(q_1,r_1) - V(q_1,r_1) \\ BV_n(q_2,r_2) - V(q_2,r_2) \end{pmatrix} = n^{1/4}\begin{pmatrix} BV_n(q_1,r_1) - V(q_1,r_1) \\ \check{BV}_n(q_2,r_2) - V(q_2,r_2) \end{pmatrix} + n^{1/4}\begin{pmatrix} 0 \\ BV_n(q_2,r_2) - \check{BV}_n(q_2,r_2) \end{pmatrix}.$$

It is thus enough to show that $n^{1/4}\big(BV_n(q_2,r_2) - \check{BV}_n(q_2,r_2)\big) = o_p(1)$. An application of Boole's and Markov's inequalities and Lemma 4 in the proof of Theorem 3 yields that

$$\mathbb{P}\big[BV_n(q_2,r_2) \neq \check{BV}_n(q_2,r_2)\big] \leq \sum_{i=1}^{n-k_n+2} \mathbb{P}\big[|\bar{r}_i^*| > u_n\big] \leq \frac{C}{n^{M(1/4-\bar{\omega})-1}},$$

where $M > 0$. As M can be chosen arbitrarily large, the result follows. ■

B Monte Carlo Simulations

The jump-testing theory in Section 2 is derived using an infill asymptotic setup, which assumes that $\Delta_n \to 0$. This is unattainable in practice. In this appendix, we therefore conduct a series of Monte Carlo simulations to examine the finite sample properties of the test statistic in a more realistic setting.

We simulate from the following model:

$$r_t^* = r_t + \epsilon_t, \tag{59}$$

where $r_t = r_t^c + r_t^d$, and

$$\mathrm{d}r_t^c = \sigma_t \mathrm{d}W_t, \tag{60}$$

with $r_0 \equiv 0$.

The drift term is omitted (i.e., $a_t \equiv 0$) so the continuous part of r_t evolves as a local martingale. The contribution of the drift is small over short horizons and the terms involving it—including cross products—are asymptotically negligible. It therefore tends to play a minor role in the high-frequency setting.[66] Similarly, adding a realistic expected rate of return does not affect the conclusions in any material way.

The instantaneous variance is assumed to be driven by a square-root process (e.g., Cox, Ingersoll, and Ross, 1985; Heston, 1993):

$$\mathrm{d}\sigma_t^2 = \kappa(\sigma^2 - \sigma_t^2)\mathrm{d}t + \xi\sigma_t \mathrm{d}B_t, \tag{61}$$

with $\sigma_0^2 \sim \text{Gamma}(2\kappa\sigma^2\xi^{-2}, 2\kappa\xi^{-2})$. Our choice of parameters is based on previous work such as Aït-Sahalia and Kimmel (2007). Specifically, we set $\kappa = 5$, $\sigma = 0.4$, $\xi = 0.5$, and $\rho = -\sqrt{0.5}$, where ρ is the leverage correlation between the standard Brownian motions $\mathbb{E}[\mathrm{d}W_t \mathrm{d}B_t] = \rho \mathrm{d}t$. This yields a stationary and strictly positive variance in continuous-time (i.e., the Feller condition $\xi^2 < 2\kappa\sigma^2$ holds) with an annualized mean volatility of 40%.

r_t^d is an infinite-activity tempered stable process with Lévy measure

$$\nu(\mathrm{d}x) = \tau \frac{e^{-\lambda x}}{x^{1+\beta}} \mathrm{d}x, \tag{62}$$

where $\tau > 0$ and $\lambda > 0$.

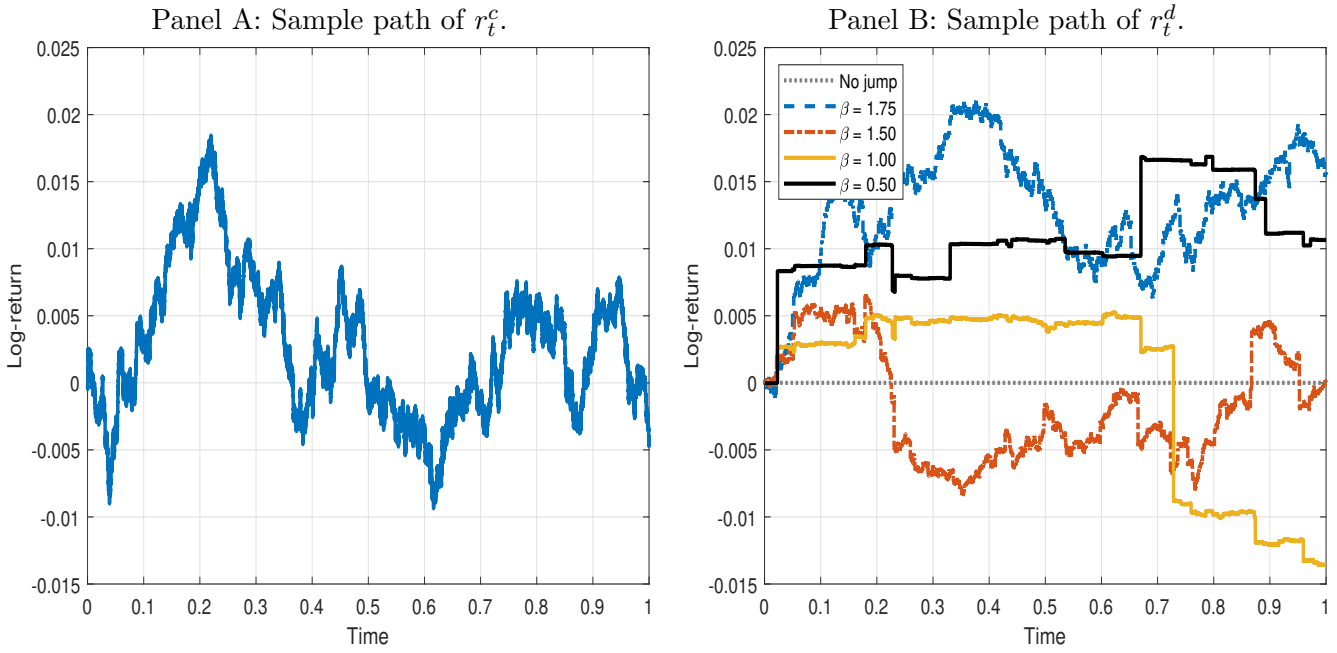
The activity of the jump process is controlled by β. As β increases, the density of the small jumps is enlarged, and the realizations of r_t^d become more vibrant and start to resemble those of a Brownian motion (see Figure B.1 for an illustration). As noted by Bollerslev and Todorov (2011), this renders the decomposition of diffusive and jump risk meaningless in practice and also makes it harder to separate the null from the jump alternative (Aït-Sahalia, Jacod, and Li (2012),). A priori, we therefore expect larger values of β to be detrimental to the rejection rate of the jump test statistic under the alternative. To gauge the impact of changing β, we follow Aït-Sahalia, Jacod,

[66] A notable exception is Christensen, Oomen, and Renò (2022).

and Li (2012) and examine $\beta = 0.50$, 1.00, 1.50 and 1.75. Moreover, we set $\lambda = 3$ and calibrate τ so that r_t^d induces 20% of the quadratic return variation, on average.

We simulate for $t \in [0, 1]$ with a time step of $\Delta_n = 1/23{,}400$. This can be interpreted as adding a new observation every second during a 6.5 hour trading session. A standard Euler discretization is employed for the continuous part.[67] As described in Todorov, Tauchen, and Grynkiv (2014), the jump component is computed as the difference between two spectrally positive tempered stable processes that are generated using the acceptance-rejection algorithm of Baeumer and Meerschaert (2010). The total number of Monte Carlo replications is $T = 10{,}000$. Figure B.1 illustrates a single sample path of r_t^c and r_t^d.

Figure B.1: A single simulation of the efficient log-return.



Note. We show a realization of the components of the efficient log-return r_t, which is a superposition of a continuous sample path Heston (1993)-type stochastic volatility model (r_t^c in Panel A) and a pure jump process of tempered stable-type (r_t^d in Panel B). The latter is plotted as a function of the activity index β using a common random seed.

We next explain how r_t is disrupted with microstructure noise, ϵ_t. In particular, we study four types of additive measurement error:

$$\epsilon_t = \begin{cases} \gamma\sqrt{\text{IV}\Delta_n}\epsilon_t^N, & \text{“Gaussian”}, \\ \gamma\sqrt{\text{IV}\Delta_n}\epsilon_t^T\sqrt{\dfrac{\eta-2}{\eta}}, & \text{“T-distributed”}, \\ \gamma\sqrt{\text{IV}\Delta_n}\dfrac{\epsilon_t^N + \phi\epsilon_{t-1}^N}{1+\phi^2}, & \text{“Autocorrelated”}, \\ \gamma\sigma_t\sqrt{\Delta_n}\epsilon_t^N, & \text{“Heteroscedastic”}. \end{cases} \tag{63}$$

[67] There is a small probability that the variance in (61) goes negative in finite samples. We therefore enforce a full truncation floor at zero to avoid this (e.g., Andersen, 2008).

where ϵ_t^N and ϵ_t^T are i.i.d. sequences of Gaussian and t-distributed (with η degrees of freedom) random variables.

While the Gaussian i.i.d. draws are standard, t-distributed noise is less common. The latter, however, can generate notable outliers if η is small. This leads to infrequent—but large—bouncebacks in the noisy log-price series which is a common trait of raw high-frequency data. We set $\eta = 2.5$ to be consistent with this observation.

We also examine cases with autocorrelated and heteroscedastic noise. The former scenario assumes ϵ_t is MA(1) with degree of memory determined by the parameter ϕ which is fixed at $\phi = -0.77$. Throughout, the variance of the noise (on a per increment basis) changes with the level of volatility, which is a well-documented feature in practice (e.g., Bandi and Russell, 2008; Kalnina and Linton, 2008). In scenario $1-3$, the noise scales with the square root of the integrated variance $\text{IV} = \int_0^1 \sigma_s^2 \text{d}s$, while in the last scenario it is a function of σ_t and thus time-varying within each simulation.

The γ parameter is the noise-to-volatility ratio of Oomen (2006) which determines the relative strength of the microstructure component. We assume $\gamma = 5$, which corresponds to heavy noise pertubation (e.g., Aït-Sahalia, Jacod, and Li, 2012; Christensen, Oomen, and Podolskij, 2014).

We follow standard practice in the pre-averaging literature by setting $g(x) = \min(x, 1-x)$ and $k_n = [\theta\sqrt{n}]$. We fix the tuning parameter at $\theta = [1, 2, 3]/3$, which is in line with prior work (e.g., Aït-Sahalia, Jacod, and Li, 2012; Christensen, Kinnebrock, and Podolskij, 2010; Christensen, Oomen, and Podolskij, 2014). The threshold for jump-truncation is implemented with $\bar{\omega} = 0.24$ and $c = 4, 5, 6$ as a robustness check.[68]

We compute Σ_n^* with $L = 10, 15, 20$ and $p = 10, 15, 20$ following the guidelines laid out in Christensen, Podolskij, Thamrongrat, and Veliyev (2017). However, the rejection rates of the jump test statistic are not sensitive to the concrete choice of tuning parameters. We therefore restrict attention to $L = 10$ and $p = 10$. The corresponding tables for other combinations of tuning parameters are available on request.

In Table B.1, we report the properties of the jump test statistic at the 5% significance level. Under the null $\mathcal{H}_0$ of no jumps, the rejection rates are close to the to the nominal level of significance. In Panel B, we observe a slight overrejection for t-distributed noise and minimal pre-averaging, which is insufficient to combat the large outliers generated by this distribution. However, increasing θ solves the problem.

Next, consider the results conducted under the alternative, $\mathcal{H}_a$. A near-perfect power close to 100% is recorded for the lowest jump activity indexes. As β increases, however, the rejection rate goes down. This reduction is consistent with Aït-Sahalia, Jacod, and Li (2012) and happens because

[68] The choice of minimal value for c follows Li, Todorov, and Tauchen (2017a). If this parameter is chosen too small, the threshold becomes rather narrow and the truncation device starts to eliminate continuous log-returns (drawn from states of high stochastic volatility), which instills a downward bias in the truncated pre-averaged bipower variation, as opposed to the non-truncated pre-averaged realized variance. This leads to a widening of their difference, a measure of the quadratic variation of the jump component, and hence an overrejection under the null.

the larger is β, the more the sample path of r_t^d resembles a Brownian motion (with smaller and more erratic increments, cf. Figure B.1). This makes it tough for the test to discriminate between $\mathcal{H}_0$ and $\mathcal{H}_a$ at least over discrete intervals of fixed length Δ_n. Moreover, we see that power is a decreasing function of c. The intuition is that as c increases, $B\check{V}_n^*$ and Σ_n^* are less jump resistant. This lack of robustness tends to reduce power, as also emphasized in the no-noise version of the test from Barndorff-Nielsen and Shephard (2006).

Finally, we observe that the rejection rates are negatively related to θ. The latter controls the pre-averaging horizon and too much smoothing reduces our ability to detect jumps on the trajectory of p. On the other hand, a larger pre-averaging window makes the estimator robust against more complicated noise structures than assumed here.

The right columns of Table B.1 compare our jump test to the noise-free version from Barndorff-Nielsen and Shephard (2006) implemented with a 5-minute realized variance and bipower variation. The latter are not robust to noise. As a consequence of this, the size and power of the standard jump test are distorted. In particular, the test is oversized under the null (rejects too often), while it lacks power under the alternative (rejects too little). This is true regardless of whether we allow the test statistic access to the latent efficient (no noise) log-price, p, or whether the statistic is computed from the observable noisy log-price, p^*. This finding is consistent with the empirical results in Table 2.

In Table B.2, we look at the rejection rates of the noise-robust jump test statistic from Aït-Sahalia, Jacod, and Li (2012). As our testing procedure, it is based on pre-averaging. However, the main building block is a ratio of power variation estimators, as opposed to the difference of multi-power variation estimators advocated here. This leads to small discrepancies in the implementation and, based on the table, their test statistic is a bit more sensitive to the structure of the noise. In particular, as with our test it rejects too often (even more so) with t-distributed noise, but it also does that with heteroscedastic noise. Here, increasing the pre-averaging horizon again removes the effect. Meanwhile, their test is rather conservative under $\mathcal{H}_0$ with autocorrelated noise (this setting was not inspected in Aït-Sahalia, Jacod, and Li (2012)). It prevails even with a larger pre-averaging window and leads to a sustained drop in the rejection rate under $\mathcal{H}_a$, yielding a lower power. Apart from that, the conclusion of their test is close to that of our test.

Our empirical application follows the parameter settings above with $\theta = 1/2$ for pre-averaging, $c = 5$ for jump truncation, and $L = p = 10$ for the subsampler.[69]

[69]In practice, fixing θ means k_n is time-varying since it changes with the actual number of high-frequency data available in each trading session, n. As a robustness check, we also experimented with fixed $k_n = 25$ and $k_n = 50$ without any noticeable change in the results.

Table B.1: Rejection rate of jump test statistic ($L = 10$ and $p = 10$).

		pre-averaging									5-minute sampling	
		$\theta = 1/3$			$\theta = 1/2$			$\theta = 1/1$				
		$c = 4$	$c = 5$	$c = 6$	$c = 4$	$c = 5$	$c = 6$	$c = 4$	$c = 5$	$c = 6$	p	p^*
Panel A: Gaussian												
No jump		0.050	0.049	0.049	0.050	0.048	0.048	0.053	0.051	0.051	0.092	0.087
$\beta =$	1.75	0.476	0.393	0.336	0.283	0.221	0.181	0.210	0.162	0.135	0.121	0.111
	1.50	0.832	0.754	0.687	0.610	0.507	0.422	0.454	0.354	0.283	0.169	0.153
	1.00	0.983	0.966	0.943	0.909	0.847	0.766	0.800	0.698	0.589	0.292	0.260
	0.50	0.997	0.994	0.990	0.976	0.955	0.914	0.928	0.872	0.785	0.398	0.342
Panel B: T-distributed												
No jump		0.119	0.097	0.087	0.059	0.055	0.054	0.053	0.051	0.051	0.092	0.089
$\beta =$	1.75	0.522	0.436	0.377	0.287	0.222	0.183	0.211	0.164	0.134	0.121	0.112
	1.50	0.848	0.780	0.713	0.614	0.509	0.427	0.455	0.354	0.283	0.169	0.153
	1.00	0.989	0.972	0.951	0.911	0.846	0.769	0.802	0.699	0.588	0.292	0.268
	0.50	0.998	0.995	0.991	0.976	0.954	0.914	0.926	0.871	0.786	0.398	0.349
Panel C: Autocorrelated												
No jump		0.047	0.046	0.046	0.052	0.051	0.051	0.054	0.052	0.052	0.092	0.085
$\beta =$	1.75	0.508	0.422	0.363	0.289	0.226	0.184	0.209	0.163	0.134	0.121	0.116
	1.50	0.855	0.785	0.721	0.618	0.513	0.431	0.455	0.356	0.286	0.169	0.147
	1.00	0.989	0.976	0.955	0.915	0.854	0.774	0.803	0.702	0.593	0.292	0.257
	0.50	0.998	0.996	0.993	0.977	0.958	0.919	0.928	0.875	0.789	0.398	0.330
Panel D: Heteroscedastic												
No jump		0.047	0.043	0.043	0.048	0.047	0.047	0.050	0.048	0.048	0.092	0.072
$\beta =$	1.75	0.434	0.354	0.299	0.277	0.215	0.176	0.205	0.159	0.131	0.121	0.089
	1.50	0.793	0.713	0.635	0.597	0.492	0.405	0.450	0.349	0.281	0.169	0.118
	1.00	0.980	0.961	0.927	0.904	0.838	0.747	0.798	0.695	0.580	0.292	0.189
	0.50	0.996	0.993	0.986	0.975	0.950	0.905	0.926	0.865	0.780	0.398	0.246

Note. In the left-hand side of the table, we report the rejection rates of the feasible noise-robust pre-averaging jump test statistic in (16), i.e. the fraction of times (out of 10,000) $\mathcal{J}_n$ exceeds $\Phi^{-1}(1-\alpha)$, where $\Phi(\cdot)$ is the standard normal distribution function and the nominal level of significance is $\alpha = 0.05$. θ controls the length of the pre-averaging window $k_n = [\theta\sqrt{n}]$. c is the number of local diffusive standard deviations a pre-averaged log-return must exceed to be classified as a jump and truncated to zero. L is the number of subsamples in Σ_n^*, whereas p is the block length (in multiples of k_n). "No jump" is the null hypothesis, while β governs the activity level of the jump process under the alternative (larger values of β imply jumps are smaller and resemble Brownian motion closer). Each separate panel describes the structure of the microstructure noise. In the right-hand side, we report the rejection rates of the Barndorff-Nielsen and Shephard (2006) jump test computed at a 5-minute sampling frequency (or $n = 78$). The latter is not resistant to noise, so as a comparison we implement it both on the inaccessible noise-free log-price (p) and the observable contaminated log-price (p^*). Further details are available in Appendix B.

Table B.2: Rejection rate of jump test statistic ($L = 10$ and $p = 10$).

		pre-averaging									5-minute sampling	
		$\theta = 1/3$			$\theta = 1/2$			$\theta = 1/1$				
		$c = 4$	$c = 5$	$c = 6$	$c = 4$	$c = 5$	$c = 6$	$c = 4$	$c = 5$	$c = 6$	p	p^*
Panel A: Gaussian												
No jump		0.054	0.052	0.052	0.055	0.055	0.055	0.063	0.063	0.063	0.092	0.087
$\beta =$	1.75	0.599	0.523	0.443	0.388	0.310	0.244	0.278	0.215	0.170	0.121	0.111
	1.50	0.905	0.851	0.769	0.727	0.617	0.480	0.571	0.437	0.316	0.169	0.153
	1.00	0.994	0.988	0.968	0.959	0.910	0.794	0.887	0.771	0.566	0.292	0.260
	0.50	0.998	0.998	0.996	0.993	0.983	0.940	0.975	0.924	0.773	0.398	0.342
Panel B: T-distributed												
No jump		0.196	0.190	0.188	0.049	0.048	0.047	0.060	0.059	0.059	0.092	0.089
$\beta =$	1.75	0.348	0.315	0.276	0.349	0.277	0.215	0.269	0.205	0.163	0.121	0.112
	1.50	0.624	0.580	0.521	0.679	0.572	0.446	0.560	0.427	0.306	0.169	0.153
	1.00	0.855	0.833	0.806	0.930	0.878	0.767	0.876	0.758	0.555	0.292	0.268
	0.50	0.925	0.916	0.907	0.979	0.965	0.923	0.969	0.918	0.770	0.398	0.349
Panel C: Autocorrelated												
No jump		0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.004	0.004	0.092	0.085
$\beta =$	1.75	0.242	0.222	0.191	0.220	0.161	0.104	0.190	0.129	0.089	0.121	0.116
	1.50	0.641	0.600	0.538	0.573	0.462	0.336	0.485	0.357	0.239	0.169	0.147
	1.00	0.960	0.948	0.919	0.918	0.857	0.738	0.854	0.730	0.523	0.292	0.257
	0.50	0.995	0.995	0.992	0.987	0.974	0.925	0.968	0.911	0.760	0.398	0.330
Panel D: Heteroscedastic												
No jump		0.142	0.131	0.131	0.050	0.050	0.050	0.055	0.055	0.055	0.092	0.072
$\beta =$	1.75	0.583	0.513	0.440	0.372	0.294	0.230	0.270	0.205	0.160	0.121	0.089
	1.50	0.875	0.821	0.741	0.703	0.589	0.458	0.561	0.430	0.308	0.169	0.118
	1.00	0.990	0.983	0.959	0.953	0.897	0.783	0.883	0.760	0.559	0.292	0.189
	0.50	0.998	0.997	0.994	0.991	0.981	0.935	0.974	0.920	0.768	0.398	0.246

Note. In the left-hand side of the table, we report the rejection rates of the noise-robust pre-averaging jump test statistic from Aït-Sahalia, Jacod, and Li (2012), i.e. the fraction of times (out of 10,000) $\mathcal{J}_n$ subceeds $\Phi^{-1}(\alpha)$, where $\Phi(\cdot)$ is the standard normal distribution function and the nominal level of significance is $\alpha = 0.05$. θ controls the length of the pre-averaging window $k_n = [\theta\sqrt{n}]$. c is the number of local diffusive standard deviations a pre-averaged log-return must exceed to be classified as a jump and truncated to zero. "No jump" is the null hypothesis, while β governs the activity level of the jump process under the alternative (larger values of β imply jumps are smaller and resemble Brownian motion closer). Each separate panel describes the structure of the microstructure noise. In the right-hand side, we report the rejection rates of the Barndorff-Nielsen and Shephard (2006) jump test computed at a 5-minute sampling frequency (or $n = 78$). The latter is not resistant to noise, so as a comparison we implement it both on the inaccessible noise-free log-price (p) and the observable contaminated log-price (p^*). Further details are available in Appendix B.

C Evolution of the after-hours market

In this appendix, we highlight key features of how the after-hours market has evolved over time. Our main finding is that trading volume has increased significantly from 2008 to 2020.

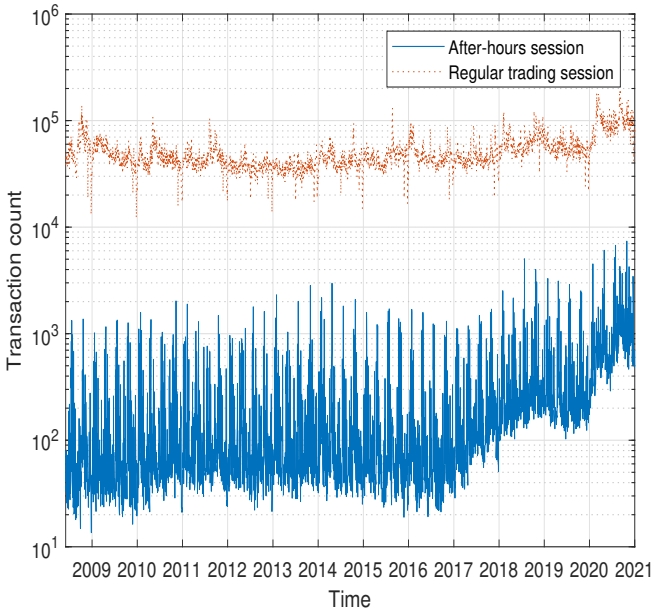
C.1 Trading Volume

The left panel in Figure C.1 shows how the daily transaction counts evolved during the regular trading session and the after-hours market over our sample which runs from 06/02/2008 to 12/31/2020, using a log-scale to improve readability. The right panel shows the median number of shares traded. In both cases, we report a single daily value computed as a cross-sectional average over the 50 companies included in our empirical analysis.

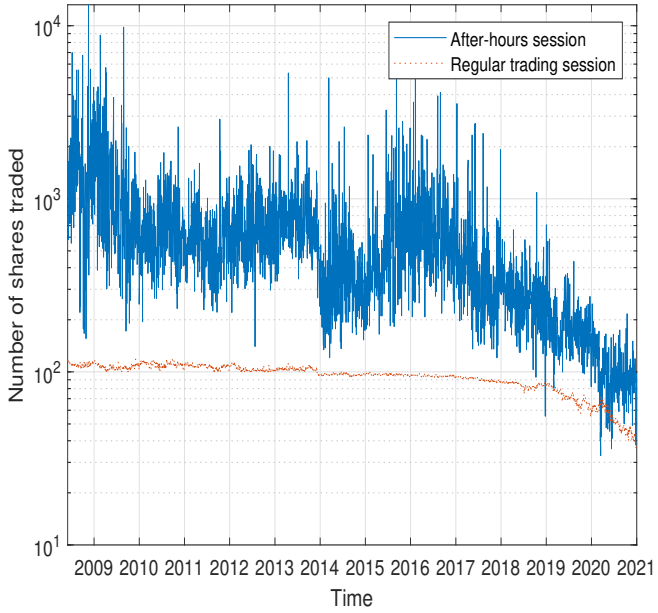
While after-hours transaction volume remains smaller than the regular trading session counterpart, it increases notably over time particularly after the structural changes in the after-hours market design were introduced in 2015. The opposite shift is evident in the number of shares traded, which has trended down systematically from 2016 onward.

Figure C.1: Transaction count and number of shares traded.

Panel A: Transaction count.



Panel B: Number of shares traded.

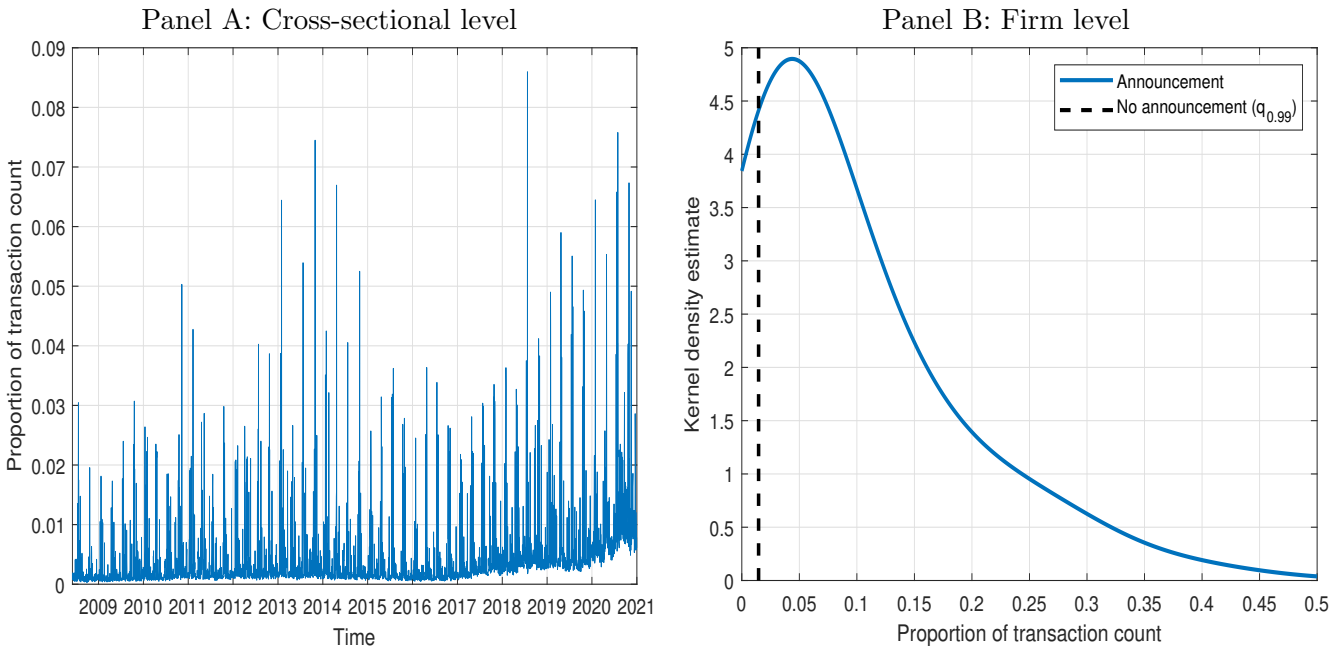


Note. The figure plots transaction counts in Panel A and the number of shares traded in Panel B during the regular trading session and after-hours session. The statistics are computed daily for each firm in our sample and then averaged over the cross-section.

The left panel in Figure C.2 shows the daily cross-sectional average transaction count in the after-hours market relative to the regular trading session. The relative trading volume increases from 0.17% in 2008Q3–2009Q2 to 0.62% in 2020. There are notable spikes in the series, which frequently exceeds 3% and goes as high as 9%. These surges occur mostly on days where large corporations publish their financial results. To corroborate this statement, the right panel in Figure

C.2 plots a kernel density estimate of the relative trading volume at the firm level on announcement days. To highlight the pronounced differences in trading activity, the figure includes the 99th percentile of the relative trading volume on no-announcement days ($q_{0.99}$), which falls far in the left tail of the distribution of relative trading volume on announcement days.

Figure C.2: Cross-sectional and firm level relative transaction count.



Note. In Panel A, we plot the daily transaction count in the after-hours session relative to the transaction count in the regular trading session, both aggregated over the cross-section of firms in our sample. In Panel B, we show the relative transaction count distribution at the firm level on announcement days. The dashed line marks the 99th percentile relative transaction count on no-announcement days.

C.2 Bid-Ask Spread

In Panel A of Figure C.3, we plot the daily cross-sectional average median quoted spread in basis points for the regular trading session and after-hours session, whereas Panel B reports the relative spread. The absolute spread (in basis points) is defined as

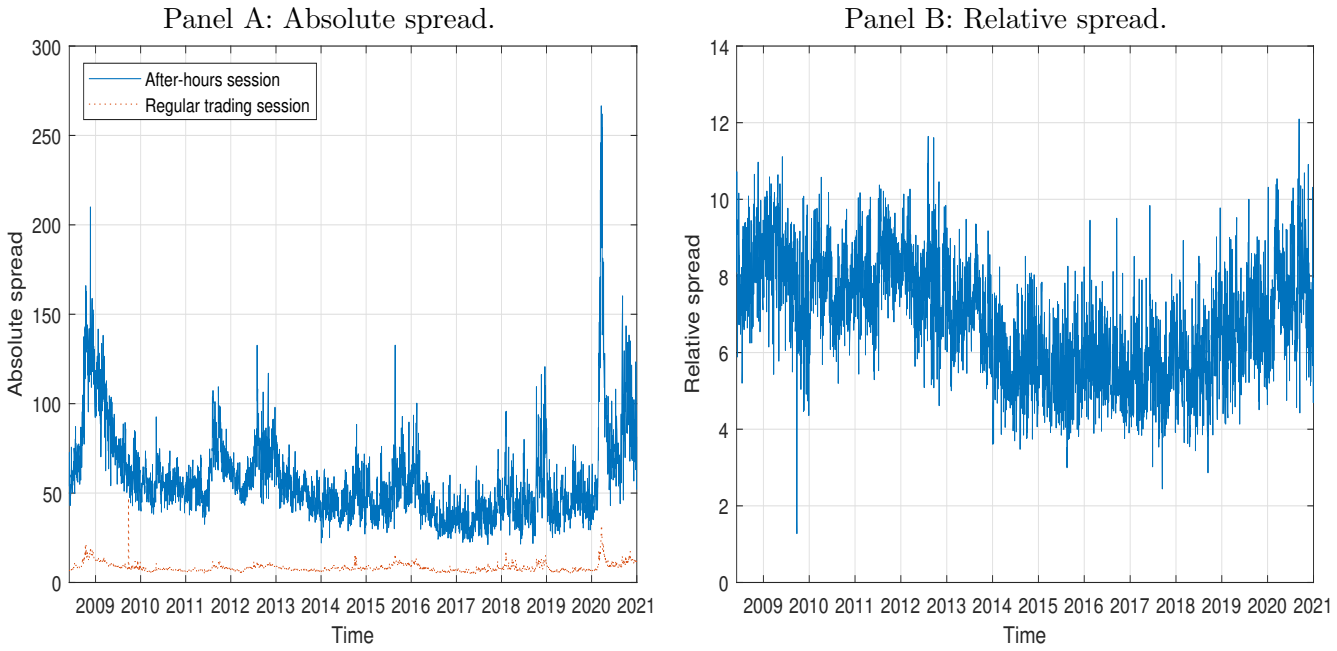
$$\text{Spread} = 10000 \times \frac{\text{ask} - \text{bid}}{\text{midquote}},$$

where midquote $= (\text{bid} + \text{ask})/2$.

The relative spread is defined as $\text{Spread}^{\text{after-hours}}/\text{Spread}^{\text{regular trading}}$.

The behavior of the quoted spread is consistent with a positive correlation between price volatility and trading costs. Spreads peak during the financial crisis in 2008–09 before starting a secular downward trend lasting until 2020 which saw spreads increase significantly and reach all-time highs after the outbreak of Covid-19. Median spreads in after-hours markets are quite stable, mostly falling in a range of four to ten times the spreads in the regular session.

Figure C.3: Bid-ask spread.



Note. The figure plots the daily cross-sectional average median quoted bid-ask spread (in basis points) in the regular trading session and after-hours session in Panel A, while the relative spread is shown in Panel B.

C.3 Price Discovery

To show how lengthy the price adjustment process is after an earnings announcement, we employ a standard measure of price discovery, namely the weighted price contribution (WPC) of Barclay and Warner (1993). For company i this is defined over small intraday intervals t:

$$WPC_{it} = \sum_{a=1}^{\#EA_i} w_a \times \frac{r_{a,t}}{r_a}, \quad \text{for } t = 1, \ldots, T_A, \tag{64}$$

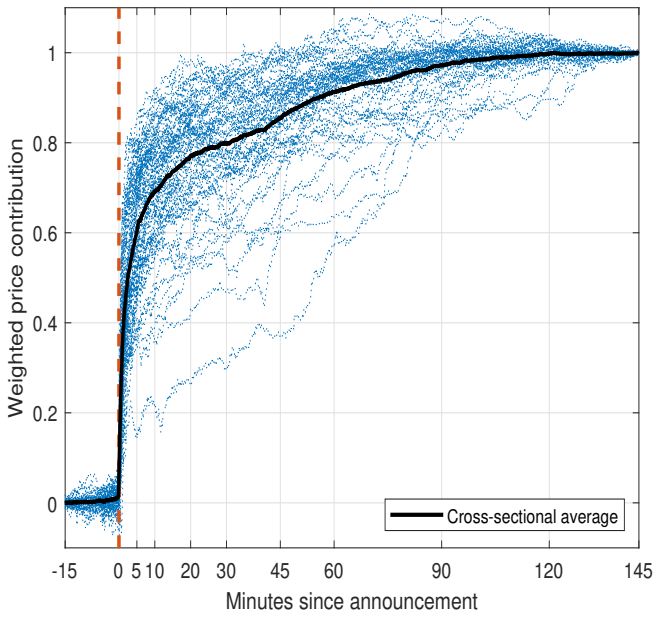
where $r_{a,t}$ is the log-return for announcement a over time interval t, T_A is the number of time intervals, $r_a = \sum_{t=1}^{T_A} r_{a,t}$ is the total announcement log-return, $w_a = |r_a| \times \left(\sum_{a=1}^{\#EA_i} |r_a|\right)^{-1}$ is announcement a's weight, and $\#EA_i$ is the number of earnings announcements for company i, as reported in Table 1. The WPC measure starts at zero and ends at one, so the price discovery process is assumed to be completed at T_A.[70]

In Figure C.4, we plot the cumulative WPC measure for each of the 50 stocks in our analysis along with their cross-sectional average. The return covers a period from 15 minutes before to 145 minutes after each announcement with the event window broken into 5-second subintervals.[71]

[70] We also calculated Hasbrouck (1995)'s information share (IS). Consistent with our results based on the WPC, the IS measure suggests that anywhere between 60–80% of the price discovery is accounted for in the first five minutes after the announcement.

[71] We also constructed the WPC measure over a longer window that begins 15 minutes prior to each announcement and extends through the overnight period and into next day's pre-market trading up to the opening of the stock exchange at 9:30am. The extended WPC curve is essentially flat after the end of the announcement day, suggesting

Figure C.4: Weighted price contribution.



Note. We plot the weighted price contribution (WPC) of Barclay and Warner (1993), which for company i is defined over small intraday intervals t: $WPC_{it} = \sum_{a=1}^{\#EA_i} w_a \times \frac{r_{a,t}}{r_a}$, for $t = 1, \ldots, T_A$, where $r_{a,t}$ is the log-return for announcement a over time interval t, T_A is the total number of time intervals, $r_a = \sum_{t=1}^{T_A} r_{a,t}$ is the cumulative announcement log-return, $w_a = |r_a| \times \left(\sum_{a=1}^{\#EA_i} |r_a|\right)^{-1}$ is the weight for announcement a, and $\#EA_i$ is the number of earnings announcements for company i, as reported in Table 1. The returns cover a time interval from 15 minutes before to 145 minutes after each announcement with the event window broken into 5-second subintervals. The WPC is shown for each company as a blue dotted line, while the full black line is the cross-sectional average.

Implicitly, the price at $t = -15$ is viewed as a proxy for the pre-announcement fundamental value, while the price at $t = 145$ is representative of the post-announcement fundamental value. Since the typical company announces earnings at 4:05pm, the pre-announcement fundamental value is typically determined at 3:50pm during the very active regular trading session, while the post-announcement fundamental value is measured around 6:30pm. The WPC curves in Figure C.4 suggest that price discovery is very fast with close to 70% of the post-announcement equilibrium price being discovered within five minutes of an announcement. This finding is consistent with Santosh (2019).

Next, to examine how the price discovery process has shifted over time, Table C.1 reports the daily weighted price contribution (WPC) divided into four time intervals that are motivated by our empirical application and closely follow those used in Barclay and Hendershott (2003) and Jiang, Likitapiwat, and McInish (2012), namely pre-market (6:00am–9:30am), regular trading (9:30am–4:00pm), after-hours (4:00pm–6:30pm), and the overnight period (6:30pm–6:00am). In Panel A, the WPC measure calculated over the full sample and across all days indicates that 7.49% of the price discovery process occurs in the pre-market, 73.19% in regular trading, 4.64% in the after-hours market, and 14.68% overnight. On earnings announcement days, however, these fractions shift markedly as the 4:00pm–6:30pm segment accounts for 80.07% of the WPC, with only 10.12%,

that very little additional price discovery takes place here.

6.87%, and 2.95% stemming from the remaining segments.

In Panels B and C of Table C.1, we split these results into subsamples, covering 2008–2015 and 2016–2020. Over time, the after-hours segment has gained in importance. On earnings announcement days, it accounts for 85.39% of the WPC in the 2016–2020 sample, nearly 10% higher than the proportion during 2008–2015 (76.37%). This increase has primarily come at the expense of the price discovery during the regular trading session and the overnight period, which on days with an earnings announcement has declined from 8.15% and 4.71% in the first sub-sample to 5.02% and 0.4%in the second sub-sample.

Table C.1: Weighted price contribution.

	Pre-market 6:00am–9:30am	Regular trading 9:30am–4:00pm	After-hours 4:00pm–6:30pm	Overnight 6:30pm–6:00am
Panel A: Full sample				
All	0.0749	0.7319	0.0464	0.1468
No announcement	0.0737	0.7638	0.0101	0.1524
Announcement	0.1012***	0.0687***	0.8007***	0.0295***
Panel B: 2008 – 2015				
All	0.0682	0.7571	0.0363	0.1383
No announcement	0.0664	0.7890	0.0020	0.1426
Announcement	0.1077***	0.0815***	0.7637***	0.0471***
Panel C: 2016 – 2020				
All	0.0850	0.6944	0.0618	0.1589
No announcement	0.0847	0.7264	0.0224	0.1666
Announcement	0.0918	0.0502***	0.8539***	0.0040***

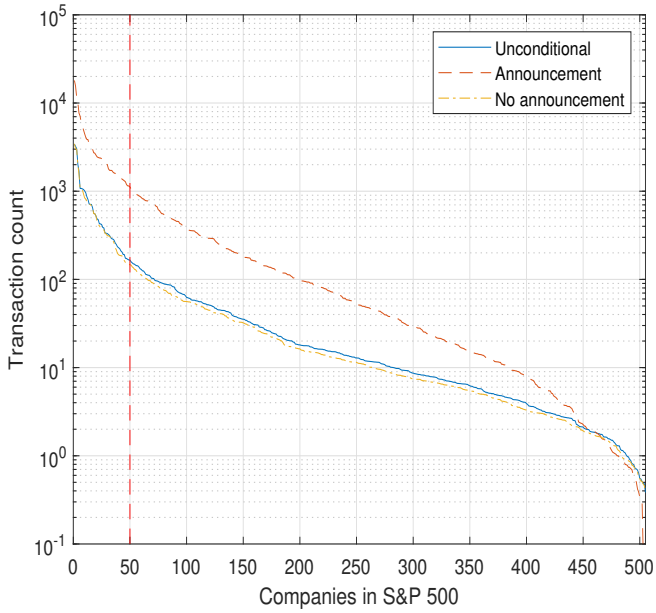
Note. We calculate the weighted price contribution (WPC) of of Barclay and Warner (1993) over the four time intervals pre-market (9:30am–4:00pm), regular trading (4:00pm–6:30pm), after-hours (6:30pm–6:00am), and overnight (6:00am–9:30am). The WPC measure is described in Section C.3. The table shows the unconditional WPC (All), and the conditional WPC for no-announcement and announcement days. Panel A reports the full sample estimates, whereas Panels B–C report estimates separately for the subsamples 2008–2015 and 2016–2020. *, **, and *** denote that the no-announcement WPC is statistically different from the announcement WPC at the 10%, 5%, and 1% level of significance, as inferred from a nonparametric permutation test with 10,000 shuffles.

D Trading activity in the pre- and after-hours market

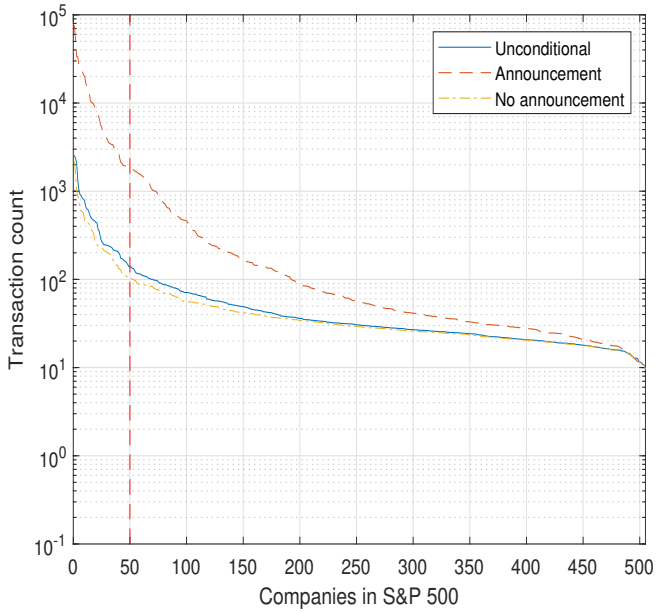
Our analysis of earnings announcements concentrates on the after-hours market and excludes announcements that occur in the pre-market. We make this choice because the trading volume of announcing firms tend to be much smaller in the pre-market than in the after-hours market as can be seen by comparing Panel A and B in Figure D.1, see also the contrast between Table 1 and Table D.1. In general, for the most liquid stocks trading volume on earnings announcement days is around 5–10 times larger during the after-hours session that during the pre-market session.

Figure D.1: S&P 500 extended trading session transaction count.

Panel A: Pre-market trading (6:00am–9:30am).



Panel B: After-hours market (4:00pm–6:30pm).



Note. We download NYSE Trade and Quote (TAQ) high-frequency data for the constituent members of the S&P 500 index as of 12/31/2020. We sort the companies by their average transaction counts for the sample period 06/02/2008–12/31/2020. Panel A shows the associated distribution for the pre-market session (6:00am–9:30am), whereas Panel B is for the after-hours session (4:00pm–6:30pm). Both are reported on a log-scale. We further split the unconditional transaction count distribution into days with and without earnings announcements. The vertical red dashed line indicates the transaction count for the fiftieth most liquid stock.

Table D.1: S&P 500 companies by pre-market (6:00am–9:30am) trading activity.

	conditional on no announcement							conditional on announcement							announcement information			
				quantile							quantile							
ticker	mean	fraction	std.	0.25	0.50	0.75	0.99	mean	fraction	std.	0.25	0.50	0.75	0.99	n_{EA}	time	r^{EA}_{30m}	z_{EPS}
GE	840	0.49	2,502	150	334	705	8,395	11,516	3.66	9,239	4,195	7,776	17,713	37,538	49	6:30am	0.752	1.209
																	(1.882)	(1.648)
BAC	2,990	1.25	6,085	656	1,412	3,157	25,089	18,007	4.86	14,185	6,815	11,798	23,330	52,800	50	7:00am	−0.530	0.934
																	(2.258)	(1.772)
WMT	147	0.18	544	12	32	87	1,908	4,954	2.99	7,725	1,237	2,377	4,912	46,543	50	7:00am	0.327	1.226
																	(2.220)	(1.648)
TGT	65	0.11	363	2	9	35	792	3,843	2.59	4,889	809	2,406	4,853	23,711	50	6:30am	−0.119	1.494
																	(1.836)	(2.354)
BBY	56	0.10	649	3	9	25	560	5,447	4.14	3,525	3,101	5,409	7,280	20,275	34	7:00am	−0.872	3.157
																	(3.572)	(2.473)
CAT	113	0.26	179	27	61	133	751	3,862	3.39	2,981	1,921	3,228	4,909	16,765	50	7:30am	−0.335	1.643
																	(2.381)	(2.768)
KR	33	0.05	359	0	3	14	348	2,050	1.41	2,593	248	796	3,392	9,053	51	8:45am	−0.742	1.213
																	(4.313)	(1.869)
GM	216	0.26	775	22	53	150	2,645	2,994	2.22	2,760	1,190	2,321	3,745	13,994	40	7:30am	0.155	1.541
																	(1.837)	(1.850)
JPM	387	0.26	920	82	170	373	3,074	5,993	2.75	4,624	3,069	4,374	7,394	22,071	50	6:59am	−0.092	1.596
																	(0.963)	(1.608)
HD	75	0.14	163	10	26	63	759	2,377	2.34	2,016	1,043	1,657	3,029	8,390	50	6:00am	0.046	2.012
																	(0.617)	(1.872)
BA	766	0.46	3,341	12	32	156	14,894	3,179	2.27	5,957	452	908	2,825	35,952	49	7:30am	0.204	1.271
																	(1.387)	(1.931)
BIIB	58	0.18	527	2	9	27	748	1,593	2.06	4,495	66	414	1,399	30,415	50	7:15am	0.551	1.769
																	(3.417)	(1.993)
C	1,566	0.74	4,860	132	367	1,218	18,126	10,189	3.31	14,867	2,714	5,757	11,118	87,389	50	7:59am	0.096	1.103
																	(1.605)	(1.858)
LOW	37	0.07	138	2	7	22	462	2,303	1.81	2,167	767	1,746	2,886	11,477	50	6:00am	−0.074	0.675
																	(0.955)	(2.109)
MCD	81	0.19	199	12	28	72	829	2,019	2.60	1,417	1,005	1,588	2,734	6,915	50	7:58am	0.184	1.190
																	(1.942)	(2.213)
CVS	64	0.09	374	1	6	30	637	2,007	1.18	4,258	127	390	1,917	21,491	49	7:00am	−0.017	1.856
																	(0.900)	(2.139)
VZ	150	0.15	741	20	45	105	1,477	1,649	1.34	1,363	777	1,256	2,244	6,216	49	7:30am	−0.132	0.598
																	(0.680)	(0.965)
WFC	363	0.18	1,907	36	86	221	3,786	4,484	1.74	4,485	1,738	3,165	4,726	21,858	50	8:00am	−0.645	0.316
																	(2.463)	(1.737)
PG	64	0.11	157	11	29	66	524	1,472	1.43	1,550	336	1,122	1,782	8,064	48	7:00am	0.110	1.642
																	(1.410)	(1.842)
F	756	0.62	1,566	97	263	745	6,792	7,702	3.16	10,035	747	2,526	10,591	45,122	49	7:00am	−0.035	1.098
																	(4.179)	(1.971)
GS	187	0.34	630	28	72	177	1,639	4,095	3.98	4,096	1,477	2,646	5,155	15,568	45	7:35am	−0.447	2.107
																	(1.443)	(2.145)
MS	185	0.15	1,034	15	45	132	1,448	3,340	2.11	2,721	1,446	2,449	4,361	13,841	47	7:15am	0.236	1.753
																	(2.410)	(2.258)
CCL	686	0.69	3,379	21	68	209	11,512	2,057	2.48	2,096	1,024	1,488	2,386	13,470	50	9:15am	0.162	2.626
																	(3.970)	(1.993)
DLTR	16	0.06	185	1	3	10	177	1,150	1.51	1,574	191	441	1,737	6,894	50	7:30am	0.143	1.364
																	(1.632)	(2.314)

Note. In the left-hand side, we show descriptive statistics of the most liquid companies from the S&P 500 index based on their pre-market (6:00am–9:30am) trading volume, which is separated into no announcement days (columns 2–8) and announcement days (columns 9–15). Ticker is the stock listing symbol. SIC is the standard industrial classification code. Mean and Std. are the transaction count sample average and standard deviation. Quantile are selected quantiles from the empirical transaction count distribution. Fraction is the number of transactions executed in the pre-market session divided by the total transaction count for the extended trading session from 6:00am–4:00pm. In the right-hand side, we report announcement information. #EA is the number of earnings announcements. Time is the modal announcement time (Eastern Standard Time). z_{EPS} and r^{EA}_{1m} are the sample average standardized unexpected earnings and one-minute post-announcement return (standard deviation across announcements reported below in parenthesis).

E Supplemental material

Table E.1: S&P 500 companies by after-hours (4:00pm–6:30pm) trading activity.

		Conditional on no announcement							Conditional on announcement							Announcement information			
					Quantile							Quantile							
Ticker	SIC	Mean	Fraction	Std.	0.25	0.50	0.75	0.99	Mean	Fraction	Std.	0.25	0.50	0.75	0.99	#EA	Time	z_{EPS}	r_{1m}^{EA}
ULTA	5990	33	0.37	52	8	17	41	201	3,368	11.32	4,549	427	2,576	4,311	22,330	41	4:03pm	3.569	0.773
																		(2.586)	(5.370)
EA	7372	57	0.19	95	22	38	71	264	3,113	5.63	3,677	1,014	1,951	4,140	19,349	44	4:01pm	2.396	−0.002
																		(2.422)	(3.016)
ATVI	7372	87	0.18	132	22	41	107	535	3,040	3.41	4,362	478	1,432	4,018	20,379	41	4:05pm	3.147	0.161
																		(2.358)	(2.680)
AVGO	3674	65	0.26	175	13	33	75	472	2,066	4.44	2,309	121	1,268	3,323	11,491	43	4:05pm	1.051	0.382
																		(1.192)	(1.924)
EXPE	4700	46	0.21	134	22	31	46	219	3,076	7.19	2,847	1,137	2,457	4,207	14,853	43	4:01pm	0.339	0.203
																		(1.591)	(3.779)
ETSY	7389	89	0.32	322	11	32	74	658	4,557	9.12	5,908	874	2,323	6,244	24,530	23	4:05pm	0.106	−0.259
																		(2.276)	(4.912)
TXN	3674	68	0.14	257	26	40	66	394	2,796	3.80	2,590	903	1,670	4,405	10,863	47	4:30pm	1.724	−0.435
																		(2.074)	(2.760)
V	7389	113	0.21	221	27	49	114	989	2,834	5.03	2,165	1,023	2,514	4,198	8,457	46	4:05pm	1.953	0.385
																		(1.501)	(1.074)
GPS	5651	52	0.14	189	15	23	38	565	1,884	2.96	3,531	300	575	1,874	20,942	50	4:00pm	1.184	0.136
																		(1.204)	(4.359)
ADSK	7372	36	0.19	31	20	28	44	143	1,754	4.80	2,006	446	1,108	2,228	8,943	47	4:01pm	2.333	−0.601
																		(1.984)	(4.168)
BKNG	4700	69	0.55	43	44	58	79	233	1,938	8.93	1,334	962	1,847	2,821	4,674	37	4:01pm	2.204	0.046
																		(1.830)	(3.487)
NTAP	3572	44	0.16	197	24	33	47	148	4,368	7.30	5,452	1,492	2,789	5,187	36,053	46	4:01pm	1.859	−0.486
																		(2.429)	(5.315)
ANET	3576	33	0.33	40	7	23	48	128	2,130	9.11	3,062	469	1,143	2,275	12,335	25	4:05pm	3.993	−0.561
																		(2.007)	(6.560)
WYNN	7011	71	0.30	145	24	37	60	683	1,779	5.70	1,638	735	1,449	2,389	8,046	44	4:05pm	0.274	−0.460
																		(1.854)	(2.710)
AKAM	7389	42	0.22	148	21	30	43	179	3,566	9.54	2,539	1,540	2,715	5,412	9,060	50	4:01pm	2.513	1.481
																		(2.636)	(4.115)
TTWO	7372	40	0.27	138	11	18	45	223	1,811	5.48	3,005	227	573	2,068	17,850	14	4:05pm	2.176	0.976
																		(2.283)	(2.110)
WDC	3572	57	0.18	112	18	31	62	411	1,678	3.25	2,573	283	770	2,108	14,628	46	4:15pm	1.814	0.303
																		(2.215)	(2.780)
LRCX	3559	51	0.23	65	20	29	59	320	1,072	2.80	1,797	73	140	1,599	7,800	48	4:05pm	3.439	0.412
																		(2.778)	(1.618)
ALGN	3842	27	0.32	33	9	15	39	140	1,314	5.59	2,245	94	432	1,406	10,699	46	4:00pm	3.628	−0.440
																		(3.432)	(5.337)
AXP	6199	65	0.16	118	24	38	62	453	1,701	2.95	1,832	278	1,224	1,849	7,815	43	4:05pm	0.624	0.057
																		(2.218)	(1.956)
ISRG	3842	36	0.54	89	14	22	44	145	1,780	13.10	1,334	888	1,287	2,194	7,118	49	4:05pm	2.019	1.427
																		(1.828)	(3.707)
HPQ	3570	84	0.13	559	29	45	71	476	5,664	5.39	5,608	1,195	3,892	9,440	22,986	45	4:05pm	1.541	0.335
																		(1.670)	(2.362)
SWKS	3674	54	0.23	74	21	35	59	352	1,571	4.01	1,255	761	1,353	1,939	5,865	49	4:30pm	2.445	0.753
																		(1.978)	(3.110)
NOW	7372	32	1.69	240	3	11	30	210	1,359	4.12	1,582	294	522	2,162	6,283	34	4:10pm	2.485	−0.500
																		(2.253)	(3.870)
CSX	4011	39	0.11	59	16	28	47	190	1,138	2.31	1,244	340	629	1,466	6,222	48	4:02pm	1.728	0.607
																		(1.819)	(1.535)

Note. In the left-hand side, we show descriptive statistics of the most liquid companies from the S&P 500 index based on their after-hours market (4:00pm–6:30pm) trading volume, which is separated into no announcement days (columns 2–8) and announcement days (columns 9–15). Ticker is the stock listing symbol. SIC is the standard industrial classification code. Mean and Std. are the transaction count sample average and standard deviation. Quantile are selected quantiles from the empirical transaction count distribution. Fraction is the number of transactions executed in the after-hours session divided by the total transaction count for the extended trading session from 9:30am–6:30pm. In the right-hand side, we report announcement information. #EA is the number of earnings announcements. Time is the modal announcement time (Eastern Standard Time). z_{EPS} and r_{1m}^{EA} are the sample average standardized unexpected earnings and one-minute post-announcement return (standard deviation across announcements reported below in parenthesis).

Table E.2: Sample average of realized variance, bipower variation, and jump proportion.

	Panel A: Regular trading session (9:30am–4:00pm)								Panel B: Extended trading session (9:30am–6:30pm)							
	no EA				EA				no EA				EA			
	RV	BV	JP	JF	RV	BV	JP	JF	RV	BV	JP	JF	RV	BV	JP	JF
ULTA	32.5	31.3	5.7	2.4	37.4	35.6	5.4	7.3	32.5	31.3	5.7	2.6	100.1	63.8	50.4	78.0
EA	28.7	27.7	6.7	3.4	34.4	33.0	7.3	11.4	28.8	27.8	6.8	3.7	94.7	57.1	60.3	100.0
ATVI	27.6	26.3	9.2	5.6	32.1	30.4	10.4	17.1	27.8	26.4	9.5	6.4	80.7	45.4	58.6	90.2
AVGO	26.9	25.9	5.9	3.1	30.7	29.9	5.6	2.3	27.0	26.0	6.2	3.8	57.2	39.3	42.4	72.1
EXPE	30.0	29.1	5.4	2.9	33.4	32.3	6.4	4.7	30.2	29.2	5.6	3.2	127.2	74.0	61.6	93.0
ETSY	46.6	45.5	4.9	1.0	60.0	58.6	3.9	0.0	46.8	45.5	5.1	1.1	162.2	108.9	50.9	91.3
TXN	22.3	21.7	5.3	2.8	24.7	23.9	6.1	2.1	22.5	21.8	5.7	3.6	59.2	36.0	56.3	91.5
V	20.7	20.2	4.1	3.0	22.5	21.6	6.0	4.3	20.8	20.3	4.3	3.7	51.3	33.3	55.2	100.0
GPS	31.0	30.0	6.7	3.3	38.5	37.5	6.5	2.0	31.7	30.1	7.4	4.2	86.4	53.0	49.7	74.0
ADSK	27.4	26.6	5.5	3.4	33.7	32.8	5.0	2.1	27.4	26.6	5.5	3.5	91.4	52.8	58.7	91.5
BKNG	25.0	24.6	2.3	1.6	29.7	29.1	3.8	0.0	25.2	24.7	2.7	2.6	94.6	58.7	57.9	100.0
NTAP	27.0	26.2	6.1	3.3	30.7	29.6	6.8	4.3	27.1	26.2	6.2	3.4	107.4	58.4	64.7	95.7
ANET	31.4	30.9	2.6	0.4	34.1	33.3	3.7	0.0	31.4	31.0	2.6	0.5	104.2	59.3	57.2	92.0
WYNN	37.3	36.8	2.3	1.5	41.6	40.7	3.5	0.0	37.6	36.9	2.7	2.3	92.0	61.6	51.4	97.7
AKAM	27.4	26.7	4.8	2.0	33.6	32.7	4.9	0.0	27.5	26.8	5.0	2.3	126.1	82.9	54.7	100.0
TTWO	32.2	30.9	7.4	3.0	35.4	34.7	4.3	0.0	32.7	31.1	7.7	3.6	76.1	42.3	54.2	71.4
WDC	32.8	32.1	4.2	2.3	39.7	39.4	2.0	0.0	33.0	32.1	4.6	3.2	82.5	56.0	43.4	76.1
LRCX	28.7	28.1	4.1	2.4	30.9	29.5	7.9	4.2	28.7	28.1	4.2	2.8	48.6	36.8	30.6	45.8
ALGN	32.4	31.2	6.6	3.0	39.3	36.7	9.3	4.3	32.5	31.3	6.6	3.0	104.6	56.6	51.3	65.2
AXP	23.2	22.7	4.0	1.9	26.2	25.4	4.4	0.0	23.3	22.8	4.2	2.2	49.1	35.1	46.6	81.4
ISRG	24.8	24.3	3.9	2.6	30.5	29.8	4.4	0.0	25.0	24.4	4.0	2.7	91.2	64.0	49.6	93.9
HPQ	24.2	23.1	8.8	4.7	26.8	24.9	14.0	17.8	24.4	23.2	9.1	5.4	69.9	43.9	56.0	93.3
SWKS	33.4	32.6	4.0	1.7	37.6	35.8	7.0	6.1	33.7	32.7	4.7	2.9	85.8	51.1	58.9	93.9
NOW	31.6	30.7	5.1	1.7	35.9	34.9	5.7	2.9	31.7	30.8	5.2	1.8	84.8	47.7	55.3	79.4
CSX	24.6	23.9	6.1	2.9	28.6	27.6	6.6	2.1	24.6	23.9	6.2	3.0	52.6	33.5	53.4	83.3
Average	29.2	28.4	5.3	2.6	33.9	32.8	6.0	3.8	29.4	28.4	5.5	3.1	87.2	54.1	53.2	86.0

Note. This table reports the pre-averaged realized variance (RV) and pre-averaged bipower variation (BV). We also construct the jump proportion (JP), which is defined as Jump Proportion = 1 - Bipower variation/Realized Variance. We further compute the jump frequency (JF), which is derived from the jump indicator in (24). The realized variance and bipower variation are converted to annualized standard deviation in percent for convenience. The full sample is split into days without (no EA) and with (EA) earnings announcements. The measures are then averaged across subsamples by company. In Panel A, we report the analysis for the regular trading session (9:30am–4:00pm), whereas Panel B displays the associated results for the extended trading session (9:30am–6:30am). The bottom row reports the grand mean ("Average") over all stock-days.

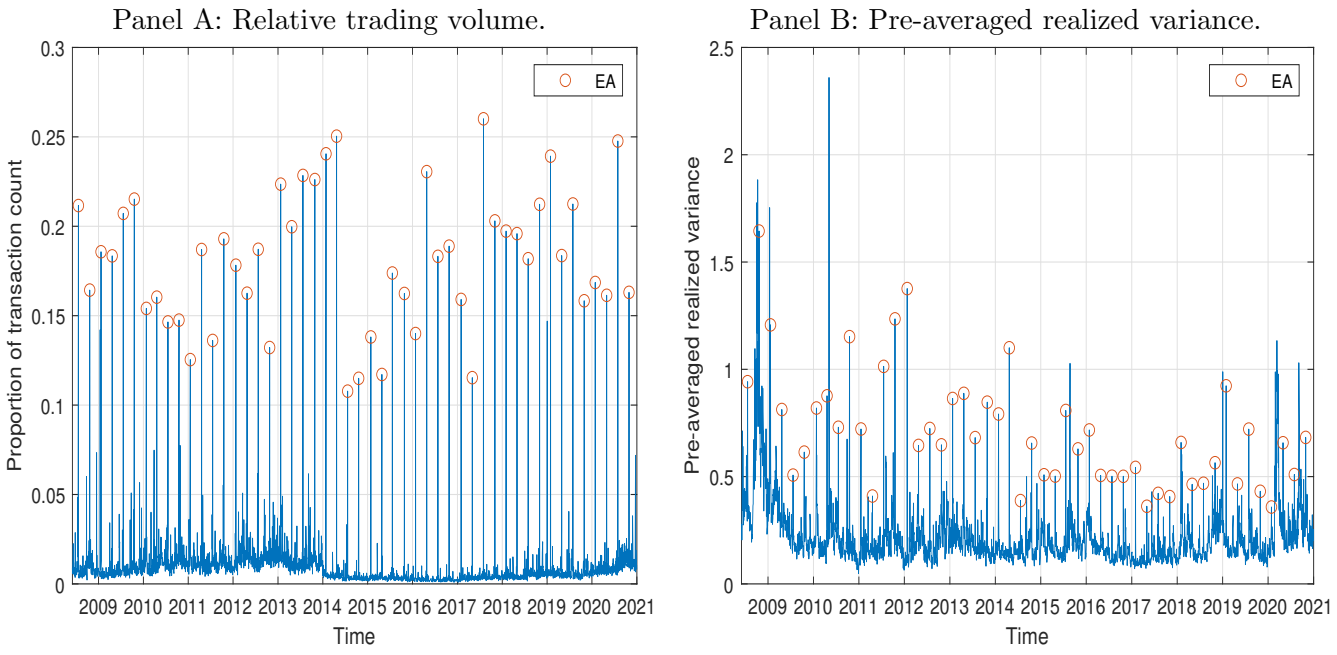
F Apple case study

This appendix illustrates our broader results using Apple as a case study. Apple is among the most important stocks throughout our entire sample and it has a broad coverage of analysts.

In Panel A of Figure F.1, we plot the proportion of the total volume (measured in transaction counts) traded during the after-hours session (4:00pm–6:30pm) relative to the extended trading session (9:30am–6:30pm). Liquidity in the after-hours market is typically small with an unconditional sample average value of 1.1% of the total volume. However, there are clear spikes on earnings announcements days where the after-hours market is highly active and the relative trading volume exceeds 18% on average on such days.

In Panel B of Figure F.1, we show the pre-averaged realized variance. The realized variance displays regularly occurring spikes that, consistent with the peaky trading volume in Panel A, almost always occur on days with earnings announcements.

Figure F.1: Relative trading volume and pre-averaged realized variance of Apple.



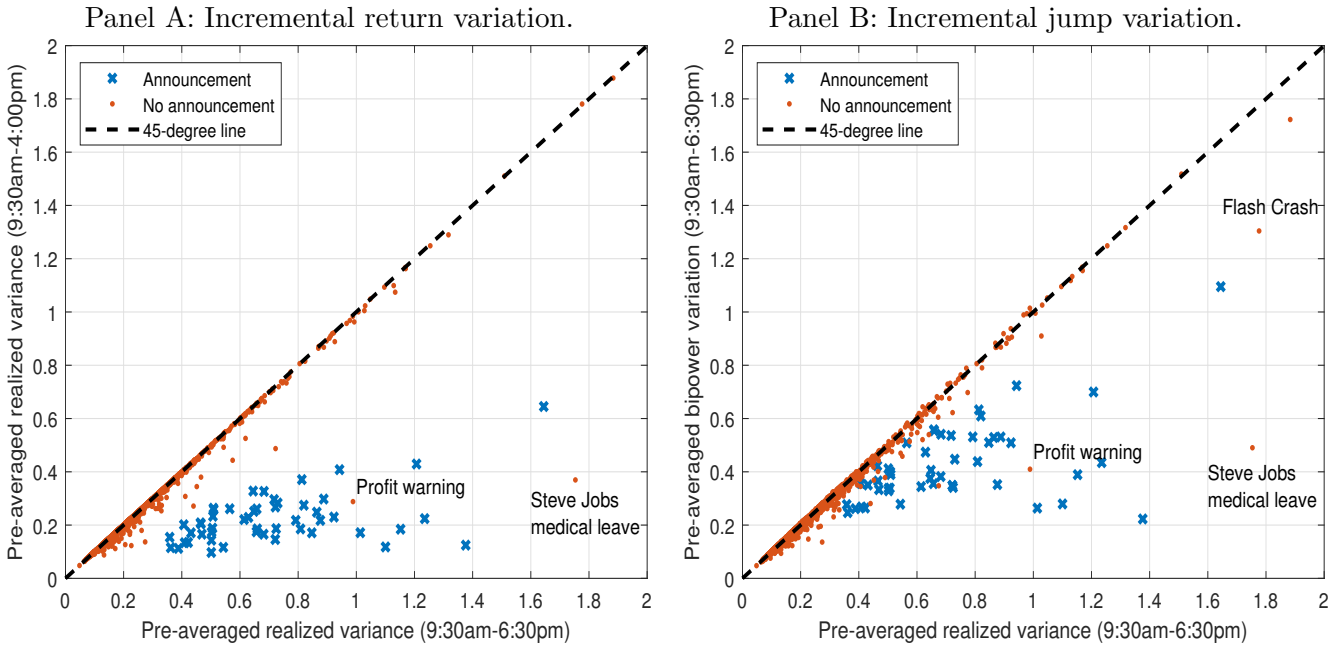
Note. In Panel A, we show the daily after-hours market (4:00pm–6:30pm) transaction count scaled by the total transaction count in the extended trading session (9:30am–6:30pm). In Panel B, we plot the daily pre-averaged realized variance, converted to an annualized standard deviation. In both panels, a red circle indicates a day on which Apple made an earnings announcement.

The left panel in Figure F.2 plots the pre-averaged realized variance computed over the regular trading session (9:30am–4:00pm) against its corresponding value computed over the extended trading session (9:30am–6:30pm). The figure also marks days on which Apple announced earnings. On days with no announcement, the estimates fall close to the 45-degree line. In contrast, on days with an announcement, the estimates are very different. The only notable exception in our sample is 01/17/2009, where Apple sent out an e-mail informing about Steve Jobs' medical leave, and 01/02/2019, where the company issued a profit warning. Both messages were released during the

after-hours session.

To examine whether the incremental variance in after-hours markets took the form of jumps, Panel B in Figure F.2 plots the pre-averaged bipower variation against the pre-averaged realized variance, both computed over the extended trading session. Because bipower variation does not increase in the presence of jumps whereas the realized variance does, points on the 45-degree line are indicative of days without jumps, whereas days with such jumps should appear to the right of the line. Almost all days with price jumps in the extended trading session coincide with earnings announcement days. The primary exceptions are the day of the Steve Jobs medical leave e-mail, the profit warning, and the S&P 500 Flash Crash on 05/06/2010.

Figure F.2: Pre-averaged realized variance and bipower variation of Apple.



Note. We show point estimates of the pre-averaged realized variance and pre-averaged bipower variation of Apple, converted to an annualized standard deviation. The axis label shows which estimator is plotted. In parenthesis, we further indicate for which part of the day high-frequency data are employed to calculate the estimate.