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Effectiveness of Trading Pauses: Evidence from the Tokyo Stock Exchange*

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Abstract

We estimate the causal effect of single-stock trading pauses on market quality using tick-by-tick order book data from the Tokyo Stock Exchange (TSE). Our instrumental variable exploits the TSE's fixed yen-denominated triggering thresholds, which generate plausibly exogenous variation in the percentage distance to a trading pause across stocks with different price levels. Trading pauses significantly reduce post-event volatility, narrow quoted bid–ask spreads, and facilitate price discovery. Order-level analysis reveals the mechanism: during pauses, liquidity providers submit opposite-direction limit orders at aggressively priced levels that push the matching price toward reversal, generating the observed improvements. These effects are strongest for less frequently traded stocks, where incremental liquidity has the largest impact. However, the benefits are attenuated for highly volatile stocks with recent negative returns, particularly during broad market downturns.

Keywords: Trading pauses, Circuit breakers, Volatility, Liquidity, Price discovery

JEL Classification: G12, G14, G18

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1 Introduction

Trading pauses—temporary suspensions of execution triggered by sharp price movements—are among the most widely adopted regulatory tools in modern financial markets. Despite their prevalence at both the market-wide and individual-stock levels, their effectiveness remains actively debated, as the theoretical literature yields ambiguous predictions and credible causal evidence is scarce (Harris, 1997). Because trading pauses are triggered precisely when volatility is elevated, naive comparisons between paused and non-paused episodes are confounded by selection.

We provide causal evidence on the effects of single-stock trading pauses using tick-by-tick order book data from the Tokyo Stock Exchange (TSE). Our instrumental variable (IV) exploits a distinctive feature of the TSE's implementation rules: trading pauses are triggered by fixed yen-denominated price thresholds, which generate plausibly exogenous variation in the percentage distance to the triggering boundary across stocks with different price levels. This institutional feature enables us to estimate the causal effect of an individual pause event on post-event market quality—a quantity that has been difficult to isolate in prior work.

Our empirical analysis yields the following findings:

1. Single-stock trading pauses significantly reduce post-event volatility.
2. They support liquidity provision, narrow quoted bid–ask spreads, and facilitate ongoing price discovery during the pause, with price efficiency converging by the time trading resumes.
3. They are particularly effective for less frequently traded stocks, as they attract liquidity providers and allow price reassessment, often leading to price reversals. However, their impact is limited for highly volatile stocks with recent negative returns, especially during broader market downturns.

These findings provide empirical support for the view that single-stock trading pauses improve market quality, offering a causal basis for the widespread adoption of such mechanisms across major exchanges.

These results differ markedly from the mixed findings of Hautsch and Horvath (2019), who exploit the introduction of the LULD rule on Nasdaq and report that, while trading pauses improve price discovery during the halt, they increase volatility and reduce liquidity afterward. A key difference is that their difference-in-differences design draws its counterfactual from the pre-regulation period, whereas our IV identifies effects within the existing regulatory regime. More broadly, any cross-period comparison faces the concern that changes in market structure, participant composition, or the prevalence of high-frequency trading between periods may confound the estimated effects—matching on observable characteristics such as return magnitudes does not guarantee balance on unobservable factors. In addition, our order-level data allow us to trace the underlying mechanism: during pauses, liquidity providers submit aggressively priced opposite-direction limit orders that reverse the initial price shock—a channel that is not institution-specific and should operate in any market where the order book remains active during a trading interruption. We elaborate on these distinctions in the Related Literature section below and in Section 6.

Related Literature. The theoretical literature on trading pauses yields ambiguous predictions. Proponents argue that periodic interruptions allow information aggregation, reduce panic, and protect liquidity providers (Greenwald and Stein, 1988, 1991; Kodres and O'Brien, 1994). Madhavan (1992) theoretically demonstrates that periodic batch auctions can aggregate information more efficiently and are more robust to problems of information asymmetry, enabling markets to operate reliably when continuous trading mechanisms break down. Critics counter that pauses delay price discovery and merely postpone volatility, since the underlying trading pressures remain unresolved during the interruption (Kyle, 1988; Fama, 1989). Furthermore, Subrahmanyam (1994) identifies the magnet effect, whereby the anticipation of a halt increases ex-ante volatility as traders rush to execute before the interruption. Empirical evidence of the magnet effect is provided by Cho et al. (2003) and, more recently, by Chen et al. (2024).

As Harris (1997) emphasizes, one of the main challenges in empirical research on circuit breakers lies in identifying appropriate counterfactual scenarios. For instance, Lee et al. (1994) observe higher trading volume and volatility following individual-stock trading halts at the NYSE. They compare actual halts to pseudo-halts—continuous trading periods for the same stock matched by time, duration, and net-of-market returns. Corwin and Lipson (2000) find that both market and limit order submissions, as well as cancellations, increase significantly during NYSE trading halts. However, they acknowledge the absence of a suitable counterfactual scenario, making their findings more descriptive than causal.

Most closely related to our work, Hautsch and Horvath (2019) exploit the introduction of the LULD rule on Nasdaq as a natural experiment. Using a difference-in-differences design, they compare post-event outcomes under the new regulation to matched episodes with similar price movements drawn from the pre-regulation period. Their findings reveal a trade-off: trading pauses improve price discovery during the halt but increase volatility and reduce liquidity afterward. Our approach differs in that we identify effects within an environment where trading pauses are already in place, using exogenous variation in the probability of pause triggering rather than cross-period comparisons. Section 6 discusses how this methodological distinction relates to the divergence in conclusions.

Other studies construct control samples from periods or markets without trading pauses (e.g., Jain et al., 2020). As noted above, such across-regime comparisons face the concern that unobservable confounders may evolve between periods. Moreover, market-participant behavior may itself differ depending on whether a pause mechanism is anticipated (Subrahmanyam, 1994). Our IV approach offers an alternative by exploiting variation in pause probability within a single regulatory environment, thereby avoiding cross-period or cross-market comparisons.

Major European trading venues also implement single-stock trading pauses, commonly referred to as volatility interruptions (Zimmermann, 2014). Using data from the Spanish Securities Exchange, Abad and Pascual (2010) show that market conditions remain unstable after pauses but normalize within about 90 minutes. However, they refrain from causal inference due to the absence of a suitable counterfactual.

The TSE's pricing mechanism has been the subject of extensive research. Hamao and Hasbrouck (1995) demonstrate that the TSE provides high immediacy through its public limit order system and document the frequency of Special Quotes. Kim and Rhee (1997) show that daily price limits cause volatility spillovers, while Deb et al. (2017) find that they curb transitory volatility. Our study extends this line of work by identifying the causal effects of short-term trading pauses.

The remainder of this paper is structured as follows: Section 2 describes the institutional background of trading pauses on the TSE and compares them to the U.S. LULD rule and similar mechanisms implemented in other countries. Section 3 outlines the data and presents preliminary analyses. Section 4 explains the empirical methodology and discusses the main results. Section 5 examines liquidity provision during trading pauses and analyzes heterogeneity in the effectiveness of trading pauses. Finally, Section 6 concludes.

2 Institutional Background

Abad and Pascual (2013) categorize price control mechanisms according to various criteria, such as whether their activation is rule-based or discretionary, and whether they apply market-wide or to individual securities. At the individual-stock level, the TSE employs a combination of trading pauses—officially known as Special Quotes (*tokubetsu-kehai*)—and daily price limits as its primary price control mechanisms. These are rule-based systems that specify objective conditions under which trading is temporarily paused or price movements are constrained, aiming to mitigate excessive volatility and maintain orderly market functioning during periods of stress.

On the TSE, trading pauses can be triggered at any time during the trading session, including during the opening call auctions at 9:00 AM and 12:30 PM[1]. However, as we discuss below, most pauses occur at the market open at 9:00 AM. Trading pauses alert market participants to the presence of orders outside the permissible price range, prompting them to submit counter-orders on the opposite side of the order book. If these counter-orders bring the matching price back within the allowable range, the pause is

[1] The TSE's trading day begins with a call auction at 9:00 AM, where pre-market orders are matched to set the opening prices. The morning session runs until 11:30 AM, followed by an afternoon session from 12:30 PM to 3:00 PM. The day ends with a closing auction, where orders are aggregated to determine the closing prices.

lifted. If not, the price limit is adjusted at three-minute intervals until the matching price falls within the updated range.

Figure 1 illustrates how trading pauses operate on the TSE, using Toyota Motor Corporation stock on March 13, 2020 as an example, when market volatility surged due to the COVID-19 pandemic. At 9:00 AM, the matching price was 5,850 JPY—well below the initial price limit indicated by the dashed line. As a result, the market opening was delayed, and trading eventually began at 9:09 AM at 5,926 JPY, when the price range had been relaxed for the third time. The order book remained active throughout the pause, and the matching price evolved continuously with the arrival of new orders. In this case, we observe that counter-orders raised the eventual opening price relative to the initial matching price at 9:00 AM.

[Insert Figure 1 here]

The update ranges for trading pauses vary depending on the reference price, typically ranging from 1.5% to 3.0%. The reference price is defined as the last execution price, which, at the market open, generally corresponds to the previous day's closing auction price, with minor exceptions. The TSE adjusts the reference price for stock splits and ex-dividend events based on the previous day's closing price. Table 1 summarizes the parameters used to determine the price limits. A distinctive feature of the TSE is that it sets fixed yen-denominated limits based on these reference prices. This institutional characteristic is discussed in detail in Section 4.1, as it serves as the basis for our key instrumental variable.

[Insert Table 1 here]

In the United States, following the Flash Crash in 2010, the SEC introduced a similar single-stock trading pause mechanism called the LULD rule. This rule establishes dynamic price bands around a stock's reference price, calculated based on the average transaction price over the prior five minutes. These bands adjust throughout the trading day, and if a stock's price moves outside them, trading is paused for a fixed duration of five minutes. The LULD rule applies to all listed stocks and is designed to prevent significant intraday price swings, similar in purpose to trading pauses on the TSE. Compared with the TSE, where the triggering threshold is generally tighter, the LULD bands are typically set at 5% from the reference price. Consequently, LULD pauses are relatively rare and tend to be concentrated in low-liquidity, small-cap stocks, unlike the broader and more liquid sample in our study.

Table 2 compares single-stock trading pause rules across major exchanges, highlighting key differences among the TSE, NYSE/Nasdaq, and the London Stock Exchange (LSE). Unlike the percentage-based triggers used in the U.S. and U.K., the TSE employs a fixed yen threshold to activate trading pauses, leading to varying sensitivities across stock prices. The TSE also allows for quicker market adjustments and permits the immediate resumption of trading if counter-orders bring the price back within the range. This contrasts with major European trading venues, which implement fixed-duration trading pauses followed by reopening auctions, commonly referred to as volatility interruptions (Zimmermann, 2014). Additionally, the TSE's trading pauses can occur during the opening auction, whereas the U.S. rule activates only after the market opens. Unlike complete trading halts, these mechanisms pause only executions while keeping order books active and enabling continuous price discovery.

[Insert Table 2 here]

3 Data and Preliminary Analysis

3.1 Data and Sample

We use proprietary order book data provided by the TSE. The TSE operates as a fully electronic, order-driven market, where trades are matched based on incoming buy and sell orders, rather than through market makers as in quote-driven markets. This market structure enables direct observation of each order's direction, price, and timing, which we exploit in Section 5 to decompose the order flow during trading pauses and identify the mechanism through which they affect market quality.

Our dataset captures the full lifecycle of orders, including submissions, executions, modifications (in price or quantity), and cancellations, across both pre-opening and continuous trading sessions. Each order record is time-stamped to the millisecond and contains detailed attributes such as order type, buy/sell indicator, order size, limit price, and flags indicating trading pauses. The data covers the period from January 14, 2014, to March 30, 2021.

To ensure economic significance, our analysis focuses on the 500 most valuable firms listed on the TSE, including both common stocks and J-REITs. We construct the sample based on market capitalization as of the last trading day of the previous calendar year. These firms, listed on the TSE's First Section or registered as J-REITs, represent the largest and most actively traded securities in the Japanese market, making them well suited for analyzing the effects of single-stock trading pauses. However, as demonstrated in the robustness checks below, our results are not sensitive to the specific threshold used to define the sample. The resulting panel comprises approximately 873,000 stock-day observations over 1,763 trading days, of which roughly 9% involve a trading pause at the morning open (Table 4).

3.2 Frequency, Determinants and Durations of Trading Pauses

We begin our empirical analysis with descriptive statistics. Table 3 reports when trading pauses occur within the trading day. Trading pauses are overwhelmingly concentrated at the morning open, with 77,528 newly occurring pauses, corresponding to 8.9% of all date–stock observations. By contrast, pauses are much less frequent during continuous trading: 0.6% in the morning session and 0.6% in the afternoon session, and only 0.3% at the afternoon open. Splitting by the sign of the overnight return shows that the morning-open frequency is nearly symmetric across negative and positive overnight moves (4.4% vs. 4.5%), with only modest differences during the continuous sessions. Given this concentration of pauses at the morning open, our analysis primarily focuses on those occurring at the start of the trading day.

[Insert Table 3 here]

To better understand the determinants of trading pauses at the morning open, Figure 2 reports average marginal effects from a probit model of pause incidence. The likelihood of a pause increases sharply on days with out-of-hours earnings announcements (or forecast revisions) and following large absolute overnight market moves, and it is also higher when previous-day intraday volatility is elevated. In contrast, *DistanceToSQ* has a negative marginal effect, indicating that trading pauses are more likely when the reference price is closer to the triggering threshold. Formally defined in Section 4.1, *DistanceToSQ* measures the percentage distance from the reference price to the price-limit threshold that triggers a pause. We report the underlying coefficient estimates in Table A.1.

[Insert Figure 2 here]

We next examine the duration of trading pauses once they are triggered at the morning open. Figure 3 plots the distribution of pause durations on a base-10 logarithmic scale. The distribution is highly right-skewed: many pauses resolve quickly within the first few minutes, while a non-trivial fraction persist for longer horizons. A salient feature is the pronounced clustering at three-minute multiples (e.g., 3, 6, and 9 minutes). This pattern reflects the institutional design: the price-limit range is widened at fixed three-minute intervals, mechanically generating spikes in the probability that a pause is lifted at those times. Unlike the U.S. LULD rule, trading pauses on the TSE can end at any time if counter-orders bring the matching price back within the permissible range. The median duration of trading pauses is 3 minutes, with longer pauses occurring only infrequently.

[Insert Figure 3 here]

To assess whether pause durations are predictable from information available at 9:00 AM, we next examine how duration varies with the magnitude of the opening order imbalance. Figure 4 plots the empirical cumulative distribution of trading-pause durations at the morning open, stratified by the severity of the opening order imbalance. We measure imbalance severity as the multiple of the price-limit update range implied by the hypothetical close-to-open return. For each group, the cumulative probability increases over time, with visible jumps at three-minute intervals that reflect the periodic widening of the price-limit range. The curves shift monotonically with imbalance: pauses are more likely to persist when the initial imbalance is larger, indicating that durations are, to some extent, predictable from information available at 9:00 AM.

This pattern is consistent with a market design that balances immediacy and liquidity provision. When imbalances are small, pauses tend to be short, prioritizing timely execution and a rapid market opening. When imbalances are large, the mechanism endogenously grants more time for liquidity providers to submit offsetting interest as the price-limit range widens, supporting price discovery under stressed conditions. In this sense, the TSE's opening procedure facilitates both prompt opening and orderly adjustment when the market faces substantial buy–sell pressure.

[Insert Figure 4 here]

Finally, Table 4 reports summary statistics for trading pauses at the morning open, along with key variables of interest used in our analysis. The first two rows provide descriptive statistics related specifically to trading pauses, while the remaining rows summarize the full sample. We define the daily frequency of trading pauses as the proportion of stocks experiencing a pause on a given day. This frequency varies substantially across trading days, indicating that market-wide shocks play a significant role in triggering these events. On March 13, 2020, when the COVID-19 pandemic caused a sharp market downturn, trading pauses were triggered for nearly all stocks at the morning open.

Our sample includes relatively large-cap stocks on the TSE, with an average market capitalization of 1,036 billion JPY, which corresponds to approximately 9.35 billion USD based on the exchange rate at the end of the sample period. When restricting the sample to stocks that experienced a trading pause, the average market capitalization slightly increases to 1,074 billion JPY, indicating that trading pauses are not concentrated among smaller firms.

[Insert Table 4 here]

3.3 Price Discovery during the Pre-opening Phase

Before turning to our instrumental-variable analysis, we examine price discovery during the pre-opening phase. Specifically, we ask how this process differs depending on whether a trading pause is triggered at the morning open and, if so, how long it lasts. To address this question, we employ the Unbiasedness Regression approach, following Biais et al. (1999), Barclay and Hendershott (2008), and Hautsch and Horvath (2019), and evaluate price efficiency by the slope coefficient β in the following regression:

$$v_{i,t} - E_0[v_{i,t}] = \alpha + \beta \left(P_{i,\tau} - E_0[v_{i,t}]\right) + \varepsilon_{i,t}, \quad \text{where} \quad \tau < t \tag{1}$$

where $v_{i,t}$ represents the fundamental value of stock i at time t, proxied by the log closing price of the current day, while $P_{i,\tau}$ denotes the log price at a specific time point during the trading session. $E_0[v_{i,t}]$ refers to the unconditional estimate of the fundamental value, which we approximate using the previous day's log closing price. A slope of $\beta = 1$ indicates that $P_{i,\tau}$ is fully efficient, while $\beta < 1$ and $\beta > 1$ indicate overshoot and momentum, respectively.

Figure 5 illustrates the progression of price discovery during the pre-opening phase by plotting the estimates of β from repeated regressions of Equation (1), using estimated matching prices derived from pre-opening order book data.[2] Three patterns stand out. First, price efficiency at 9:00 AM is lower when

[2] The standard errors of the β estimates are small; the subsample averages are 0.0016, 0.0042, and 0.0080, respectively. Ohta (2011) and Xiao and Yamamoto (2020) also examine price discovery during the pre-opening phase on the TSE, though they do not focus on the role of trading pauses.

trading pauses are triggered, and more so when pauses last longer, suggesting that market participants correctly anticipate a delayed market opening and withhold orders until closer to the expected resumption time. Second, price discovery continues during pauses and accelerates just before trading resumes, consistent with the findings of Bellia et al. (2020). Third, stocks that experience trading pauses exhibit higher price efficiency between 8:50 and 8:59, suggesting that information shocks triggering pauses draw earlier attention from market participants. We revisit these patterns with an instrumental-variable approach in Section 4.3.

[Insert Figure 5 here]

4 Empirical Results with Instrumental Variable

4.1 Instrumental Variables

The endogeneity of pause triggering confounds naive comparisons. Figure 6 illustrates this concern: stocks experiencing trading pauses exhibit higher post-open volatility, but this correlation reflects the underlying information shocks rather than a causal pause effect.

[Insert Figure 6 here]

To identify the causal effects of trading pauses, we instrument the trading-pause indicator with the relative distance from the reference price to the price-limit boundary that triggers a pause, which we denote by *DistanceToSQ*. Here, SQ stands for *Special Quotes*, the official term for trading pauses on the TSE. The reference price is the previous day's closing price, adjusted for dividend payments and stock splits. Let $P_{i,t}^{ref}$ denote the reference price and let $L(P_{i,t}^{ref})$ denote the absolute price-limit range (in JPY) determined by the TSE's price-limit schedule; then

$$DistanceToSQ_{i,t} \equiv \frac{L(P_{i,t}^{ref})}{P_{i,t}^{ref}} \times 100. \tag{2}$$

Figure 7 visualizes how *DistanceToSQ* varies with P^{ref} based on the price-limit parameters reported in Table 1. Because $L(\cdot)$ is specified in discrete JPY increments that depend on the reference-price level, *DistanceToSQ* changes discontinuously and non-monotonically as P^{ref} crosses the price-limit schedule thresholds, typically ranging between roughly 1.5% and 3%.

[Insert Figure 7 here]

We argue that *DistanceToSQ* plausibly satisfies the relevance and exogeneity conditions for a valid instrument. Relevance holds by construction: a smaller *DistanceToSQ* places the reference price closer to the triggering boundary, implying a higher likelihood of a trading pause. Consistent with this intuition, Figure 8 shows that observations with trading pauses are concentrated at smaller *DistanceToSQ* values than observations without pauses. Table A.2 reports the first-stage regression of the trading-pause indicator on *DistanceToSQ*. The estimates confirm a strong relationship, with an excluded F-statistic of approximately 600 across all specifications, well above conventional weak-instrument thresholds.

[Insert Figure 8 here]

For exogeneity, we require that *DistanceToSQ* affect outcomes only through the trading-pause indicator, conditional on covariates. Table A.3 reports reduced-form regressions of post-event volatility on *DistanceToSQ*, showing that larger *DistanceToSQ* is associated with higher post-event volatility. The positive sign is consistent with the first-stage relationship and trading pauses reducing post-event volatility: a larger *DistanceToSQ* lowers the probability of a pause, so the volatility-reducing effect is less likely to materialize. While alternative channels can never be ruled out completely, we argue that *DistanceToSQ* plausibly satisfies exogeneity for three reasons.

First, *DistanceToSQ* is a deterministic function of the predetermined reference price and the TSE's fixed price-limit schedule. As a result, it is set before trading begins and cannot be influenced by real-time order flow, investor sentiment, or contemporaneous market-wide volatility.

Second, it is difficult to motivate a direct effect of the absolute price level on the post-open outcomes we study. Our results are robust when restricting the sample to the largest-cap stocks on the TSE, thereby excluding penny stocks. Moreover, although other price-level-dependent microstructure features (most notably tick size) could in principle affect liquidity and volatility, we explicitly control for relative tick size, and the estimates remain stable. To the best of our knowledge, standard microstructure theories do not imply a systematic relationship between absolute price levels and the outcomes considered here once liquidity and volatility controls are included.

Third, *DistanceToSQ* varies non-monotonically and discontinuously with the reference price, generating substantial dispersion even among stocks with similar price levels. In our preferred specifications, we include both date and firm fixed effects, so identification comes from residual within-firm and within-date variation in *DistanceToSQ* beyond time- and firm-specific factors. In particular, the discontinuities in the price-limit schedule generate meaningful changes in *DistanceToSQ* when a stock's reference price crosses schedule thresholds, while leaving nearby prices otherwise similar.[3]

To further support the identification strategy, Figure A.1 plots the distributions and pairwise relationships among market capitalization, intraday realized volatility, share turnover, the reference price, and *DistanceToSQ*. The figure reveals no clear systematic association between *DistanceToSQ* and these fundamental characteristics, reinforcing its plausibility as an exogenous instrument.

4.2 Post-Event Volatility

Hereafter, we present and discuss our main empirical results using the instrumental variable approach. We specify the primary regression model as follows:

$$\xi_{i,t} = \alpha + \beta D_{i,t} + \mathbf{X}'_{i,t}\gamma + \varepsilon_{i,t}, \tag{3}$$

where $\xi_{i,t}$ denotes the outcome variable of interest, $D_{i,t}$ is an indicator variable for the occurrence of a trading pause, $\mathbf{X}_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. Among the covariates, we include the relative tick size, defined as the ratio of the minimum tick size to the reference price, to account for potential influences of price granularity. We also incorporate firm and date fixed effects to control for unobserved heterogeneity across firms and trading days.

The first part of our empirical analysis examines the impact of trading pauses on post-event volatility. Specifically, we assess whether volatility declines following the activation of a trading pause by analyzing the log of realized volatility, computed from minute-by-minute bid–ask midpoint prices over the 30-minute window after the market opens. We follow Abad and Pascual (2010) in selecting this window, though our results are robust to alternative specifications, as we will see below. We exclude observations if another trading pause occurs within the 30-minute window (excluding the opening trade), or if the window overlaps with the lunch break or the market close.

To address potential endogeneity, we estimate Equation (3) by two-stage least squares, instrumenting $D_{i,t}$ with $DistanceToSQ_{i,t}$ as described in Section 4.1. We report two-way clustered standard errors by firm and date to allow for arbitrary correlation within firms over time and common shocks across firms on a given date. Our inference is also robust to Driscoll–Kraay standard errors, which account for both autocorrelation and cross-sectional dependence.

Table 5 reports OLS and IV estimates with firm and date fixed effects. Across IV specifications, the coefficient on $D_{i,t}$ is significantly negative both with and without controls such as relative tick size

[3] In unreported analyses, we further confirm robustness using a fuzzy regression-discontinuity-style approach. Specifically, we compare observations in neighborhoods around jump points in *DistanceToSQ* with those outside such neighborhoods, adding jump-point fixed effects. The results are qualitatively and quantitatively similar across a wide range of neighborhood definitions.

and other covariates. We refer to Column (3) as our baseline specification; it includes the richest set of covariates. The corresponding estimate implies that a trading pause reduces post-event volatility by approximately 31% on average $\big(= 1 - \exp(-0.372)\big)$, confirming the effectiveness of trading pauses.

In contrast, the OLS coefficient is significantly positive, consistent with the endogenous triggering discussed above. The IV estimate thus captures the local average treatment effect for marginal observations whose pause status is shifted by $DistanceToSQ_{i,t}$.

[Insert Table 5 here]

As robustness checks, Table 6 examines alternative sample universes and alternative measures of volatility. Unless otherwise noted, we use the baseline specification (Column (3) of Table 5) as the set of right-hand-side variables. For sample selection, we consider (1) TOPIX 100 constituents and (2) stocks with a reference price of at least 500 JPY. The TOPIX 100 consists of the largest and most liquid firms on the TSE, and the estimated effects remain quantitatively and statistically similar within this subsample. We impose the 500 JPY cutoff to alleviate concerns that *DistanceToSQ* can take extreme values for low-priced stocks, which may introduce outlier-driven leverage in the IV estimates.

We also assess the sensitivity of our findings to the definition of volatility. In addition to our baseline measure, we consider: (3) minute-by-minute volatility computed from mid-quote prices in levels (i.e., without log transformation), (4) the log of minute-by-minute volatility computed from transaction prices, (5) the log of absolute mid-quote returns relative to the opening price, and (6) the log of the high–low price ratio. To evaluate whether the effects persist beyond the immediate post-event window, we further consider same-day intraday volatility computed using 5-minute sampling from (7) mid-quote prices and (8) transaction prices. Across all specifications, the IV estimates consistently indicate that trading pauses reduce post-event volatility, with all but the most distant horizon yielding estimates significant at the 1% level.

[Insert Table 6 here]

Next, we examine the effects on post-pause volatility across different time horizons. Figure 9 plots the estimated coefficient on the trading-pause indicator from the baseline IV specification as we vary the start minute used to construct the post-event volatility measure. The point estimates are uniformly negative across all start minutes. The magnitude is largest when the window begins immediately after the event (around -0.37 at start minute 0) and attenuates gradually as the start minute increases (approaching -0.11 by 90 minutes). The shaded band denotes the corresponding confidence interval, which remains below zero throughout. The volatility-reducing effect of trading pauses is thus strongest in the immediate aftermath but persists even when the measurement window is shifted later in the trading session.

[Insert Figure 9 here]

4.3 Price Efficiency and Post-Event Liquidity

Next, we revisit the analysis of price efficiency previously examined without an instrumental-variable approach in Figure 5. To evaluate the causal effect of trading pauses on price efficiency, we extend the Unbiasedness Regression in Equation (1) by introducing a trading-pause indicator and its interaction term:

$$v_{i,t} - E_0[v_{i,t}] = \alpha + \beta^{SQ} D_{i,t} + (\beta + \gamma D_{i,t})\,(P_{i,\tau} - E_0[v_{i,t}]) + \varepsilon_{i,t}, \tag{4}$$

The variables $v_{i,t}$ and $E_0[v_{i,t}]$ are defined as in Equation (1). We estimate the model at two key points in time: the opening call auction and 9:00 AM. For 9:00 AM, we define $P_{i,\tau}$ as either the opening call price or the matching price, depending on whether a trading pause is triggered. Our primary parameter of interest is γ, which captures how trading pauses affect price efficiency.

Table 7 reports estimates of Equation (4) using both OLS and IV specifications. Following the existing literature on the Unbiasedness Regression, we do not include firm or date fixed effects, as the dependent variable is already expressed as a return relative to the previous day's close. The first-stage F-statistics remain well above conventional thresholds.[4] The estimated slope coefficient β is slightly below one in both specifications, indicating modest intraday reversal, consistent with Lou et al. (2019).

The OLS and IV estimates differ notably in the 9:00 AM specification (Column (1)). The OLS estimate of γ is -0.073, whereas the IV estimate is substantially larger in magnitude at -0.202. This gap is consistent with attenuation in OLS. Trading pauses are endogenously triggered by large information shocks that also move prices toward fundamentals, leading OLS to understate the loss of price efficiency at 9:00 AM.

In the opening-price specification (Column (2)), the OLS estimate of γ is positive and significant (0.020), suggesting slightly higher opening-price efficiency when pauses occur. However, the IV estimate reverses sign to -0.020 and becomes statistically insignificant, indicating that once the endogeneity of pause triggering is accounted for, there is no detectable effect of trading pauses on opening-price efficiency. Taken together, the IV results imply that trading pauses are associated with significantly lower price efficiency at 9:00 AM, while any difference at the market open is negligible.

A plausible mechanism is strategic order submission. Anticipating a delayed opening during trading pauses, some participants may withhold orders until shortly before trading begins, reducing informativeness in the early matching price. Consistent with this interpretation, Figure 5 shows that price discovery continues during pauses and that, once trading starts, price efficiency converges and becomes comparable regardless of whether a trading pause was triggered.

[Insert Table 7 here]

Next, we examine the effects of trading pauses on market liquidity, using the same empirical framework as in the post-event volatility analysis. Specifically, in Equation (3) we replace the dependent variable with the average quoted bid–ask spread, computed from minute-by-minute order book data from the start of trading through 30 minutes afterward (so that a lower value indicates higher liquidity).

Table 8 shows that both OLS and IV estimates imply a statistically significant decline in quoted spreads following trading pauses. The magnitudes, however, differ sharply: in the baseline specification (Column (3)), the OLS estimate is -0.331 bp, whereas the IV estimate is -7.606 bp—more than twenty times larger in absolute value. Unlike the sign reversal for volatility, OLS here attenuates toward zero: information shocks that trigger pauses independently widen spreads, partially offsetting the spread-narrowing effect of the pause and biasing OLS toward zero. The IV estimate mitigates this confounding and reveals a substantially larger causal effect. This spread compression is consistent with the observed decline in volatility and indicates that trading pauses improve market quality by tightening quoted prices.

Table A.4 in the Appendix further reports IV estimates for traded value and order book depth. While these measures increase significantly in specifications without additional controls, the effects become statistically insignificant once market capitalization, share turnover, and lagged volatility are included. Taken together, the results indicate that the liquidity improvement primarily manifests through tighter spreads rather than through mechanically higher trading activity or greater displayed depth, conditional on stock-level characteristics. We further investigate the mechanisms of liquidity provision in the following section using detailed order flow data.

[Insert Table 8 here]

[4] The TSE does not allow market participants to submit orders beyond the specified daily price limits. Consequently, matching prices cannot be observed outside these bounds. To mitigate potential bias from missing observations at the extremes, we exclude observations for which the close-to-9:00 AM return exceeds the minimum percentage distance to the daily price limits observed in the sample universe.

5 Mechanisms and Heterogeneous Effects

5.1 Liquidity Provision During Trading Pauses

The preceding sections establish that trading pauses reduce volatility, narrow spreads, and facilitate continued price discovery during the pause. A natural follow-up question is: through what mechanism? We argue that the primary channel is liquidity provision—trading pauses give market participants time to absorb information and submit counter-orders that offset the initial price shock. The remainder of this subsection presents evidence for this mechanism, progressing from aggregate price patterns to order-level decompositions.

We begin with the aggregate evidence. Panel A of Figure 10 plots the close-to-open return (using the actual opening price) against the close-to-9:00 AM return (using the matching price at 9:00 AM) for all trading-pause observations. If prices fully reverted during the pause, the slope would be zero; if no reversal occurred, the slope would be one. The estimated slope is 0.859, indicating that approximately 14% of the initial price movement is reversed by the time trading resumes. This pattern is consistent with the entry of liquidity providers during the pause.

Panels B and C of Figure 10 reveal an asymmetry: reversals are stronger following overnight price increases (slope = 0.844) than after decreases (slope = 0.877). This pattern suggests that liquidity providers are more willing to lean against positive shocks than negative ones, possibly reflecting greater uncertainty and risk aversion during market downturns. We return to this asymmetry in the heterogeneity analysis of Section 5.2. A related observation is the pronounced cluster of close-to-9:00 AM returns near -10%, consistent with participants anchoring their pre-opening orders to anticipated price-limit thresholds when large declines are expected.

[Insert Figure 10 here]

The aggregate price reversals documented above raise a natural question: what types of orders drive them? To answer this, we compare the total order volume submitted in the same direction as the pause ("Along" in Figure 11), which reinforces the initial price movement, with the volume submitted in the opposite direction ("Against"). Two distinct patterns emerge. Limit orders are predominantly placed in the opposite direction, consistent with liquidity provision that offsets the initial price shock. Market orders, by contrast, are more often submitted in the same direction, reflecting momentum-driven demand. Because opposite-direction limit order volume exceeds same-direction market order volume, the net effect is the price reversal observed in Figure 10.

[Insert Figure 11 here]

Having established that opposite-direction limit orders dominate, we next ask whether the reversal pressure comes from new order submissions or from the cancellation of existing orders. We decompose net order pressure into four components defined by order direction (Along vs. Against the pause) and event type (addition vs. cancellation), and plot their event-time averages scaled by each stock's average daily volume in Figure 12. Two components generate reversal pressure: opposite-direction additions (new liquidity provision) and same-direction cancellations (withdrawal of momentum orders). These two components dominate their counterparts—same-direction additions and opposite-direction cancellations—which would reinforce the initial price movement. The net order flow is thus shaped primarily by active liquidity provision rather than by the retreat of momentum traders, although both channels contribute.

[Insert Figure 12 here]

The finding that new opposite-direction orders are the primary source of reversal pressure raises a further question: are these orders placed aggressively at or beyond the matching price, or patiently away from it? We classify order additions as active (limit price more aggressive than the current matching price) or passive (less aggressive) and report the results in Figure 13. Opposite-direction orders are not only larger in total volume but also predominantly active—submitted at prices that improve upon the prevailing matching price, thereby directly pushing it toward reversal. Same-direction orders, by contrast, display a more balanced mix of active and passive submissions. This pattern indicates that liquidity providers do not merely queue passively behind the matching price; rather, they price their orders aggressively enough to shift the matching price in the reversal direction.

[Insert Figure 13 here]

Taken together, the order-level evidence traces a clear causal chain: trading pauses provide time for liquidity providers to submit aggressively priced opposite-direction limit orders that absorb the initial price shock and actively push the matching price toward reversal. This liquidity provision generates the price reversals observed at the aggregate level (Figure 10), consistent with a reduction in adverse selection faced by market makers, and ultimately accounts for the decline in volatility and the narrowing of bid–ask spreads documented in Section 4.

5.2 Heterogeneity in the Effectiveness of Trading Pauses

We next examine how the effectiveness of trading pauses varies across different dimensions, such as stock characteristics and the nature of overnight returns. Our main hypothesis on heterogeneous effects is:

Hypothesis: Trading pauses are less effective for stocks facing constraints on liquidity provision.

To this end, we introduce an interaction term between the trading-pause indicator $D_{i,t}$ and a binary variable $Z_{i,t}$ that captures each dimension of interest. The modified regression specification includes both $Z_{i,t}$ and the interaction term $Z_{i,t} \cdot D_{i,t}$ to estimate conditional treatment effects:

$$\xi_{i,t} = \alpha + (\beta + \delta Z_{i,t}) D_{i,t} + \zeta Z_{i,t} + \mathbf{X}'_{i,t}\gamma + \varepsilon_{i,t} \tag{5}$$

In Tables 9–11, we report IV estimates with post-event volatility as the dependent variable. We present the corresponding OLS estimates and IV estimates with quoted spreads in Tables A.5–A.10 in the Appendix.

Table 9 presents results from this specification using three indicator variables related to size and liquidity. The first is a TOPIX 100 indicator, which equals one if the stock is included in the TOPIX 100 index, comprising the largest and most liquid stocks on the TSE. As shown in Table 6, the baseline results are robust when the sample is restricted to the TOPIX 100 universe. Here, we investigate whether trading pauses are more or less effective within this group by interacting the trading-pause indicator with the TOPIX 100 indicator. The coefficient on the interaction term is statistically insignificant, suggesting that trading pauses are equally effective for TOPIX 100 stocks and the broader sample.

The Small Stock indicator equals one if the stock's previous-day market capitalization is below the daily median. Its interaction with the trading-pause indicator is negative but statistically insignificant, suggesting that firm size per se does not materially alter pause effectiveness. The Low Turnover indicator equals one if the stock's previous-day share turnover falls below the daily median. Its interaction term is significantly negative, indicating that trading pauses are particularly effective for less frequently traded stocks.[5]

Overall, the results in Table 9 show that trading pauses are generally effective across the board, including for large and liquid stocks, but are especially beneficial for less frequently traded stocks. This finding is consistent with the view that incremental liquidity provision has a more substantial impact where baseline turnover is limited.

[5]We use indicator variables instead of continuous measures because interacting *DistanceToSQ* with continuous variables introduces multicollinearity in the first-stage regressions. The results are qualitatively robust to alternative percentile thresholds used to define these indicators.

[Insert Table 9 here]

Next, we investigate whether the sign and context of overnight returns influence the effectiveness of trading pauses. Table 10 presents results that interact the trading-pause indicator with several indicator variables capturing overnight return characteristics. The coefficient on the interaction with the Negative Overnight Return indicator is significantly positive, indicating that trading pauses are less effective following price declines. This asymmetry remains robust even when we include an additional indicator variable capturing negative overnight market returns. Furthermore, interacting with a Large Market Return indicator reveals that trading pauses are less effective when the absolute overnight market return is large, suggesting that market-wide shocks limit the ability of liquidity providers to stabilize individual stocks. An interaction with an Earnings Announcement indicator indicates that trading pauses triggered by earnings-related events may also be less effective, although this result is less precisely estimated.

This regression result is consistent with the weaker price reversals following negative overnight returns documented in Figure 10. This asymmetry likely reflects differences in trader behavior: during market downturns, liquidity providers may be more hesitant to submit counter-orders due to increased uncertainty, heightened risk aversion, and concerns about "catching a falling knife."

[Insert Table 10 here]

Finally, Table 11 examines how lagged volatility and recent return characteristics affect the effectiveness of trading pauses. The High Lagged Volatility indicator equals one if a stock's previous-day intraday volatility exceeds the 90th percentile. Its interaction with the trading-pause indicator is significantly positive, indicating that trading pauses are less effective for stocks with high underlying volatility. This suggests that in more volatile environments, liquidity providers may be more hesitant to engage, thereby limiting the stabilizing effect of trading pauses.

We also examine whether past returns—excluding the overnight returns that triggered trading pauses—affect effectiveness. Specifically, we interact the trading-pause indicator with three indicator variables capturing negative return conditions: (i) a negative return on the previous trading day, (ii) a previous-day return below the 10th percentile, and (iii) a negative cumulative return over the previous three trading days. When these interactions are entered individually, both the Negative Lagged Return and Negative 3-Day Lagged Return interactions are significantly positive (Columns 2 and 4). When the Negative Lagged Return and Large Negative Lagged Return interactions are included together in Column (3), only the Large Negative Lagged Return interaction is significant, suggesting that the attenuating effect is concentrated in episodes of severe previous-day price declines. Overall, these results indicate that trading pauses are less effective following recent price declines. This may reflect greater reluctance among liquidity providers to intervene in falling markets, possibly due to heightened perceived risk or limited incentives to counter downward momentum.

[Insert Table 11 here]

In summary, this subsection highlights meaningful heterogeneity in the effectiveness of trading pauses across different stock characteristics and market conditions. While trading pauses are generally effective—even for large-cap, highly liquid stocks—they are particularly beneficial for those with low turnover and limited baseline liquidity. In contrast, they tend to be less effective for highly volatile stocks. Their impact is also diminished during market downturns, especially when overnight or recent returns are negative. These findings indicate that liquidity providers are more reluctant to engage under adverse market conditions or for riskier stocks, thereby reducing the stabilizing effect of trading pauses. In short, the effectiveness of trading pauses depends on how readily liquidity can be supplied during the pause.

6 Conclusion

Our analysis demonstrates that single-stock trading pauses effectively reduce post-event volatility and facilitate price discovery during periods of market stress. These mechanisms help narrow quoted bid–ask spreads, consistent with a reduction in the adverse selection problem faced by liquidity providers under extreme volatility, while also stabilizing the market by allowing participants time to reassess conditions. Specifically, during pauses, liquidity providers submit aggressively priced limit orders against the prevailing price trend, effectively absorbing the initial price shock and facilitating price reversals. This mechanism is particularly pronounced for less frequently traded stocks. However, the effectiveness of trading pauses is attenuated during market downturns and for stocks with elevated previous-day volatility, suggesting that the stabilizing effect depends on the willingness of liquidity providers to engage. For regulators, these findings provide empirical support for the continued use—and potential expansion—of single-stock trading pauses in other markets. Although our analysis focuses on individual stocks, the underlying mechanism may also inform the design of market-wide circuit breakers.

Our IV strategy exploits the TSE's fixed yen-denominated triggering thresholds to identify causal effects within an environment where trading pauses are already in place. This design avoids reliance on data from periods or markets in which pauses were not yet implemented—a setting in which market-participant behavior may differ systematically. Our conclusions diverge from those of Hautsch and Horvath (2019), who report increased post-pause volatility and reduced liquidity using a difference-in-differences design that draws its counterfactual from the pre-regulation period. The two studies differ both in identification strategy (within-regime IV versus cross-period difference-in-differences) and in institutional setting.

Disentangling the relative contributions of these two sources of divergence is beyond the scope of either study and remains an important open question. One dimension of this question concerns the role of pause design: the TSE mechanism is quote-based, adjusts limits gradually in response to order flow, and is typically triggered by small price movements (1.5–3%), whereas the LULD rule is trade-based and employs wider percentage bands. Because the LULD rule requires large price movements for activation, the treated sample in Hautsch and Horvath (2019) is concentrated among small, less liquid stocks. By contrast, the lower triggering thresholds on the TSE allow us to draw on a large sample of liquid, large-capitalization stocks. The local average treatment effects estimated in the two studies therefore apply to different segments of the market and to different shock magnitudes—a trade-off that should be considered when comparing results.

Whether the divergence reflects differences in identification strategy or in institutional design, the question of whether and how trading pauses improve market quality remains an important open policy question that warrants further investigation across markets and regulatory settings. Moreover, the economic mechanism we identify is not institution-specific: liquidity providers use the pause to submit aggressively priced opposite-direction orders that absorb the initial price shock. Any pause mechanism that maintains order book activity while suspending executions creates the same opportunity for liquidity provision. Consistent with this view, Hautsch and Horvath (2019) also document improved price discovery during halts, suggesting that a similar channel operates on Nasdaq.

Several directions for future research merit attention. First, because our sample consists primarily of opening-auction pauses triggered by relatively small price movements, extending the analysis to continuous-trading pauses and more extreme shocks would clarify the generalizability of our estimates. Relatedly, we do not find evidence of the magnet effect (Subrahmanyam, 1994) in our opening-auction setting, but whether this finding extends to continuous-trading sessions, where traders may have stronger incentives to accelerate order submissions, remains an open question. Second, granular server-level identifiers would offer the potential to isolate the role of high-frequency traders in liquidity provision during pauses (Chakrabarty et al., 2017).

Data availability

The data used in this study are proprietary and were provided by the Japan Exchange Group under a confidentiality agreement. Due to the terms of the agreement, the data cannot be shared publicly. The authors will assist with any inquiries about the data used in this study.

CRediT authorship contribution statement

Akitada Kasahara: Conceptualization, Investigation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Masahiro Yamada:** Conceptualization, Data curation, Investigation, Validation, Writing – review & editing.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT (OpenAI) and Claude (Anthropic) in order to improve language and readability, assist with code development for data analysis, and support manuscript formatting. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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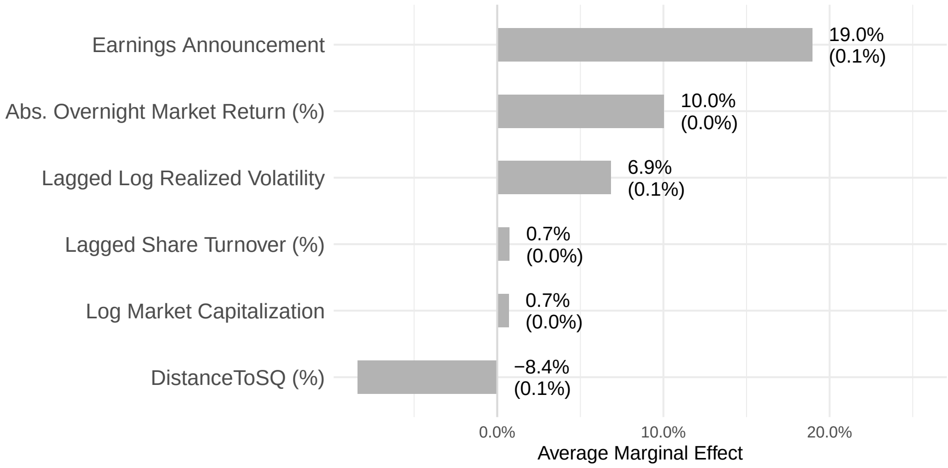
7 Figures and Tables

Figure 1: Trading Pauses at the TSE

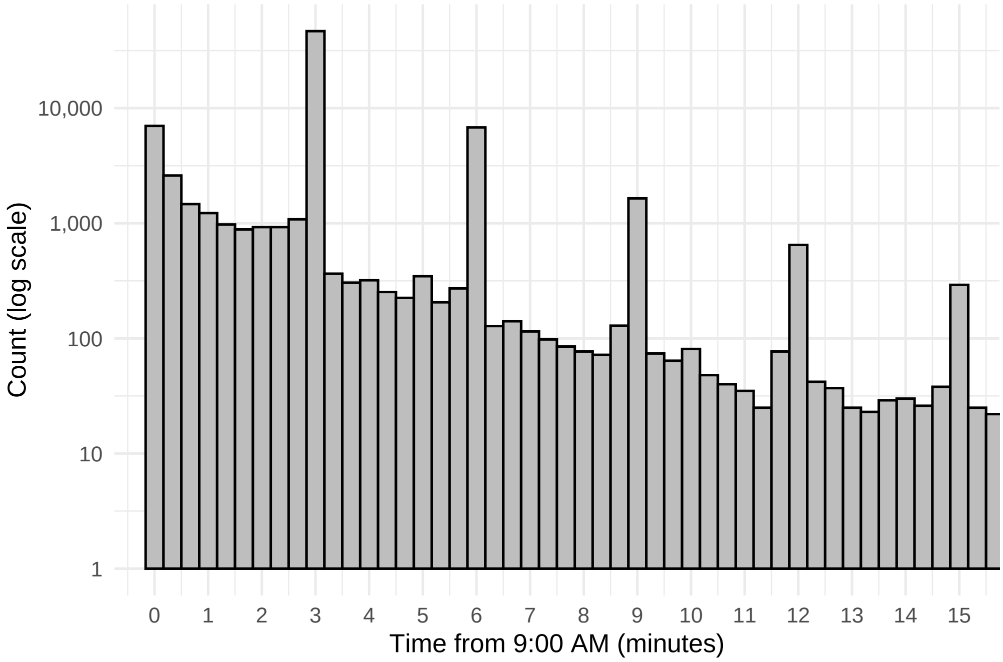
Note: This figure illustrates trading pauses on the Tokyo Stock Exchange (TSE), using Toyota Motor Corporation stock on March 13, 2020 as an example, when market volatility surged due to the COVID-19 pandemic. The black point at 9:00 AM represents the previous day's closing price of 6,309 JPY. The matching price at 9:00 AM was 5,850 JPY—well below the permitted price range—which triggered a trading pause. As a result, the market opening was delayed, and trading began at 9:09 AM at 5,926 JPY, when the price range was relaxed for the third time. The solid line indicates the matching price at one-second intervals, while the dashed lines represent the price limits, which were updated every three minutes. The gray bars at the bottom show the volume of new orders at five-second intervals.

Figure 2: Average Marginal Effects from Probit Model of Trading Pause Probability



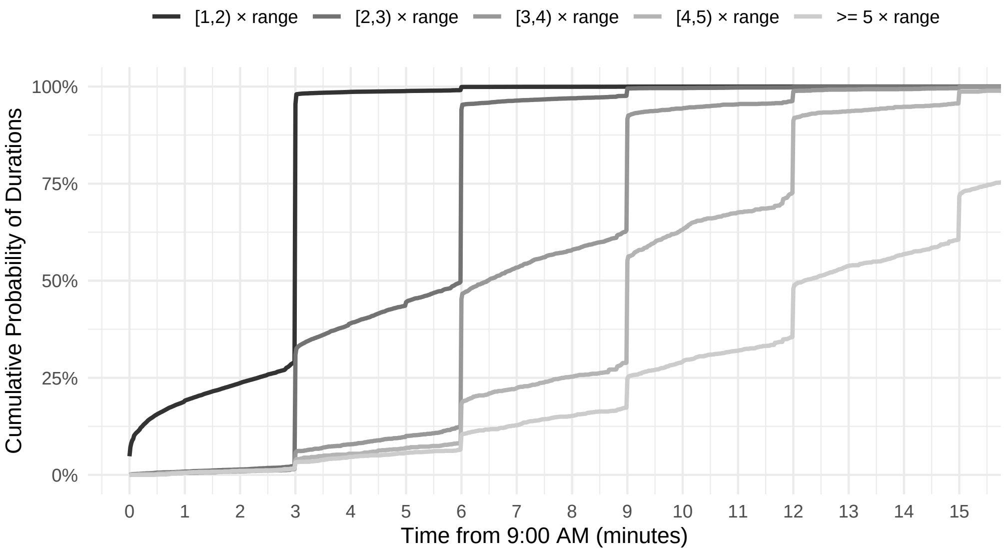
Note: This figure reports average marginal effects from a probit model of trading pause probability at the morning open. Earnings Announcement equals one if the firm released an earnings announcement or forecast revision outside trading hours. Abs. Overnight Market Return is the absolute value of the market return from the previous close to the current open. Lagged Log Realized Volatility is intraday volatility computed from five-minute sampling over the full trading day on the previous day, expressed in logarithmic form. Lagged Share Turnover is the ratio of trading volume to shares outstanding on the previous day. Log Market Capitalization is the log of market capitalization at the previous close. *DistanceToSQ* (short for Distance to Special Quote) is defined as the percentage distance from the reference price to the price limit that triggers a trading pause; see Section 4.1 for details. Percentages represent average marginal effects; standard errors are in parentheses.

Figure 3: Duration of Trading Pauses at Morning Open



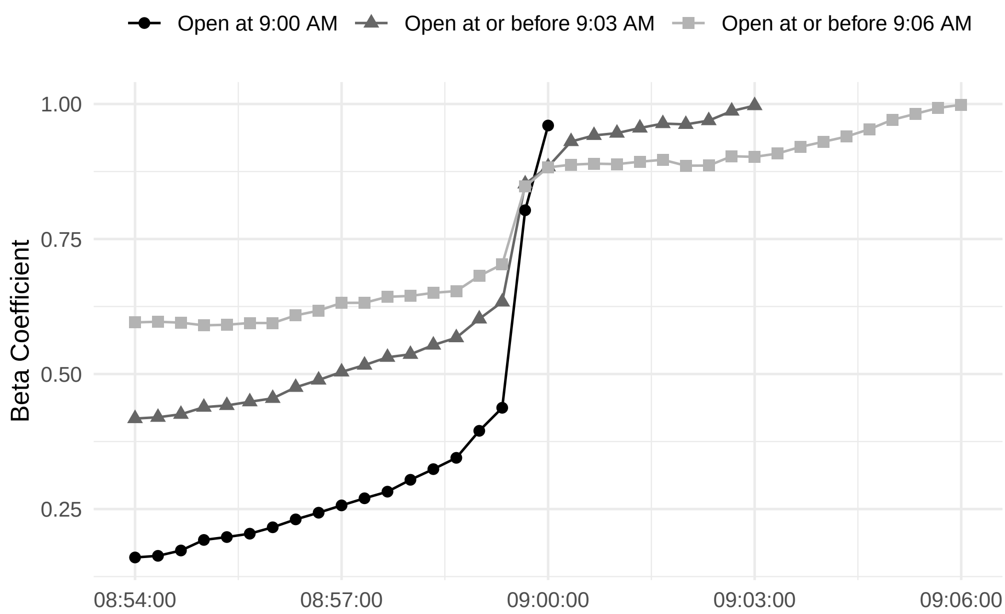
Note: This figure shows the distribution of trading pause durations at the morning open on a base-10 logarithmic scale. The clustering around three-minute intervals (e.g., 3, 6, 9 minutes) corresponds to the periodic widening of the price limit range.

Figure 4: Cumulative Probability of Durations for Different Levels of Order Imbalance



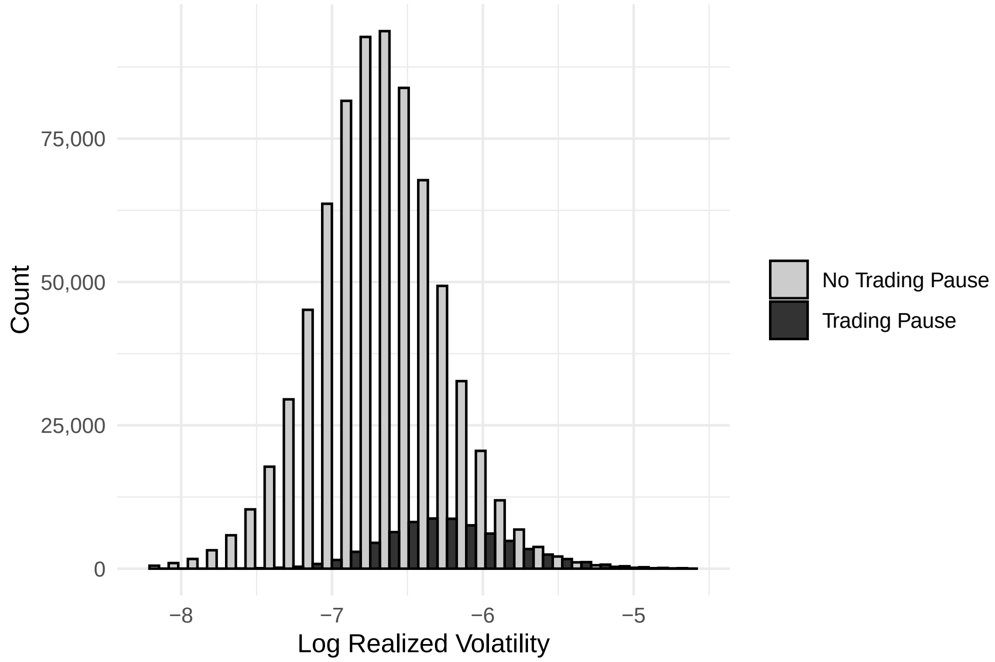
Note: This figure shows the cumulative probability of durations for trading pauses triggered at market open, stratified by order imbalance. We first calculate hypothetical returns from the previous day's close to 9:00 AM using matching prices. We then classify each trading pause by how many times the absolute hypothetical return exceeds the price-limit update range. The groups correspond to multiples of the update range: [1,2), [2,3), [3,4), [4,5), and ≥ 5. Lower multiples (e.g., [1,2) $\times$ range) indicate relatively low order imbalance, while higher multiples (e.g., $\geq 5 \times$ range) indicate high order imbalance.

Figure 5: Price Discovery Process During Pre-opening Phase with and without Trading Pauses



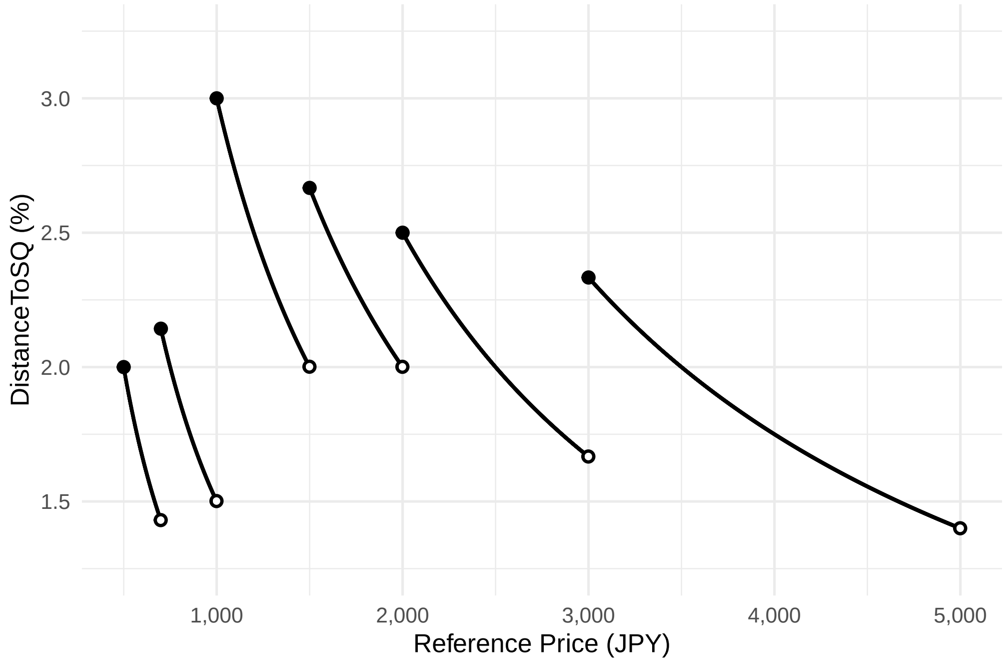
Note: This figure illustrates price discovery during the pre-opening phase across subsamples defined by trading pause occurrence and duration. The "Open at 9:00 AM" subsample includes stocks without trading pauses, while the "Open at or before 9:03 AM" and "Open at or before 9:06 AM" subsamples include stocks with trading pauses that end within the indicated times. For each subsample, we estimate Equation (1) every 20 seconds using matching prices derived from order book data.

Figure 6: Realized Volatility with and without Trading Pauses



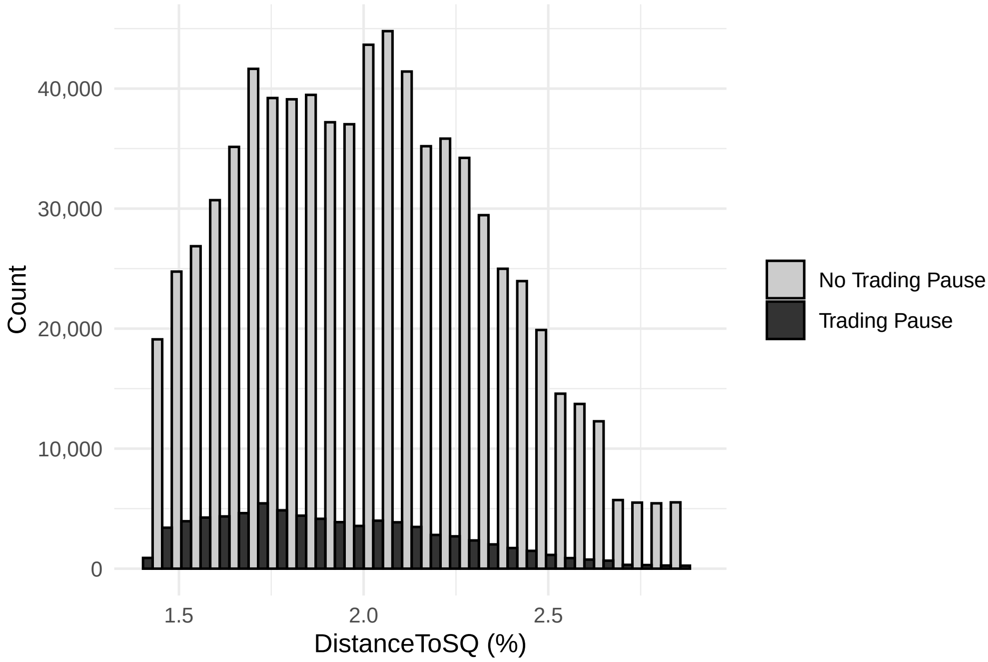
Note: This figure shows the distributions of log realized volatility, calculated using minute-by-minute bid–ask midpoint prices from the start of trading to 30 minutes afterward, conditional on the occurrence of trading pauses. Observations with zero realized volatility are excluded.

Figure 7: Definition of *DistanceToSQ* as a Function of the Reference Price



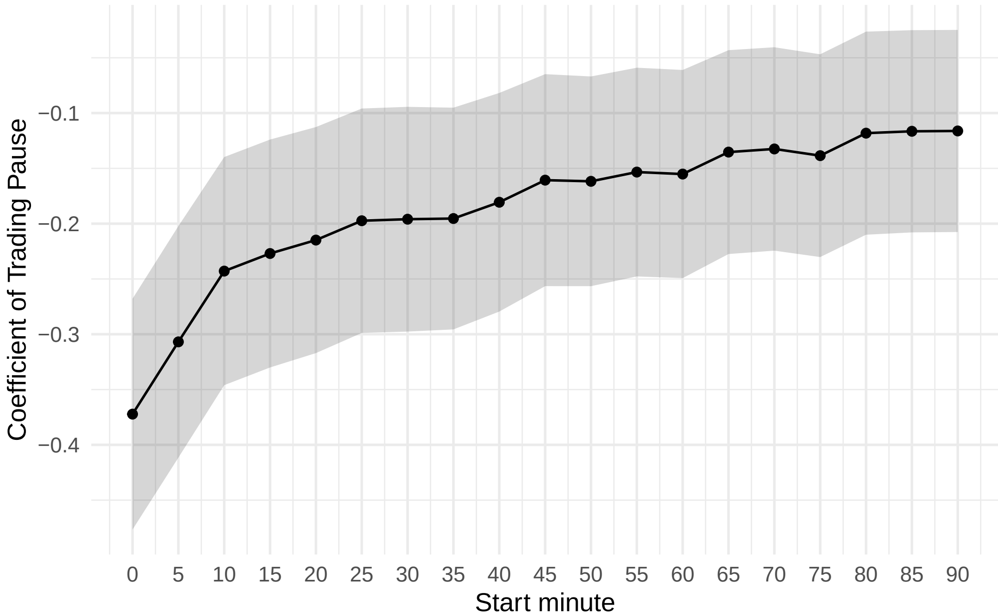
Note: This figure illustrates *DistanceToSQ* as a function of the reference price. The reference price is the previous day's closing price, adjusted for dividend payments and stock splits. *DistanceToSQ* is defined as the percentage distance from the reference price to the price limit that triggers a trading pause.

Figure 8: Distribution of *DistanceToSQ* with and without Trading Pauses



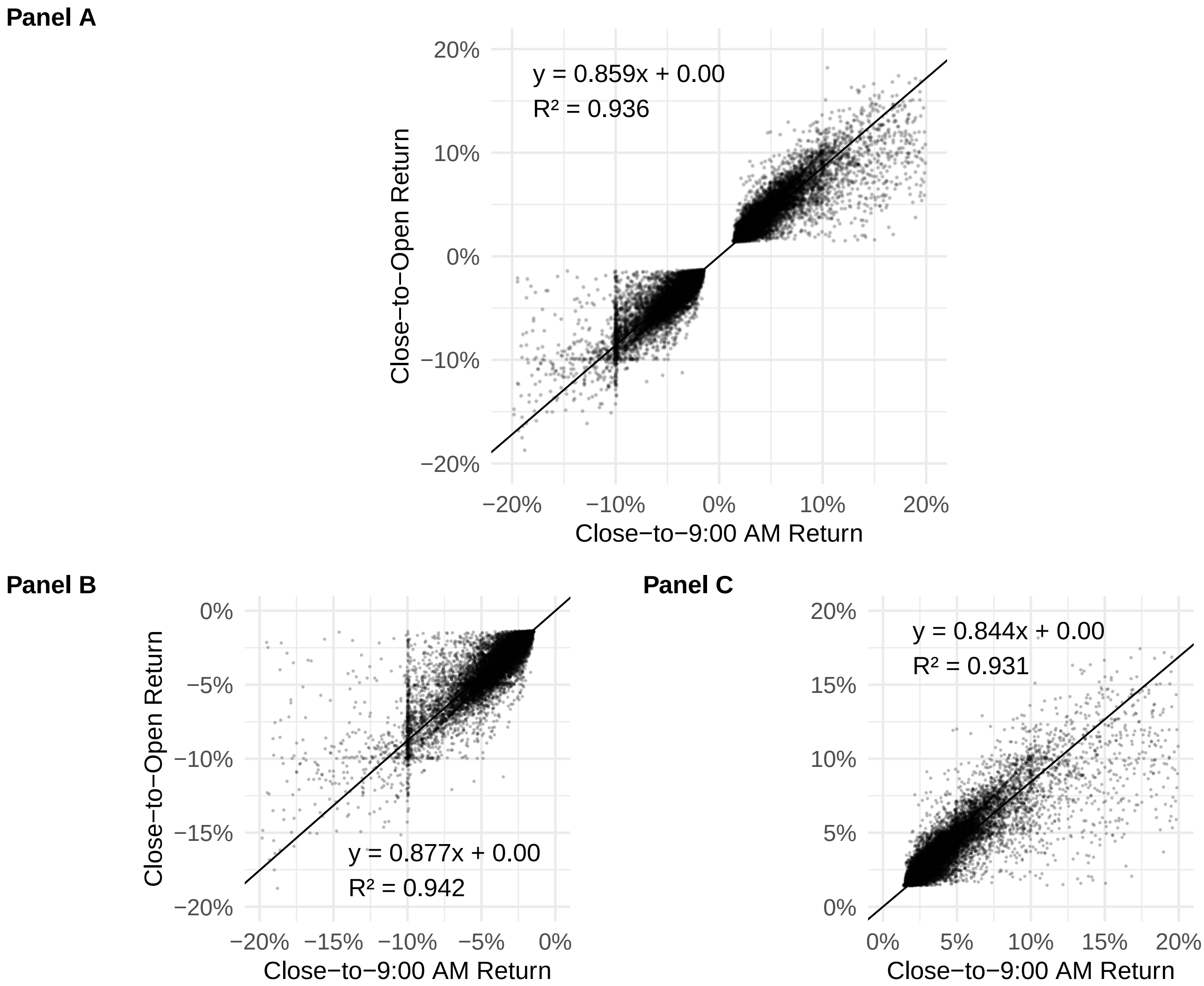
Note: This figure shows the distributions of *DistanceToSQ*, conditional on the presence or absence of trading pauses.

Figure 9: Post-pause Volatility across Different Time Horizons



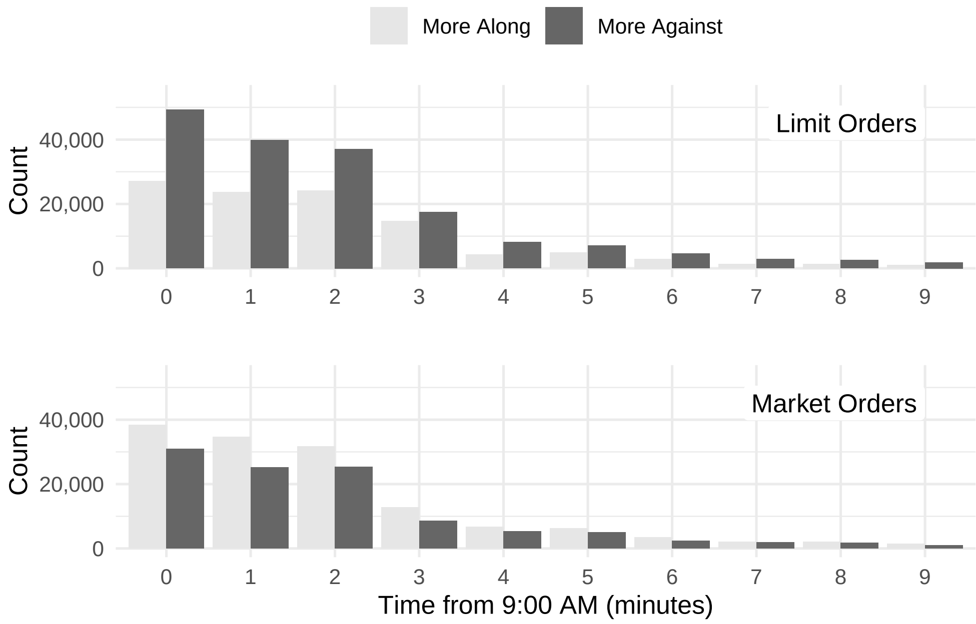
Note: This figure shows IV estimates of the trading pause coefficient on post-pause volatility across different time horizons. Each point represents the coefficient from an IV regression where the dependent variable is the log of minute-by-minute midpoint volatility computed over the $[x, x+30]$-minute window after trading begins. The horizontal axis indicates the window start minute x. The shaded area represents the 95% confidence interval. Control variables follow specification (3) in Table 5. All regressions include firm and date fixed effects. Standard errors are two-way clustered by firm and date.

Figure 10: Price Reversals during Trading Pauses



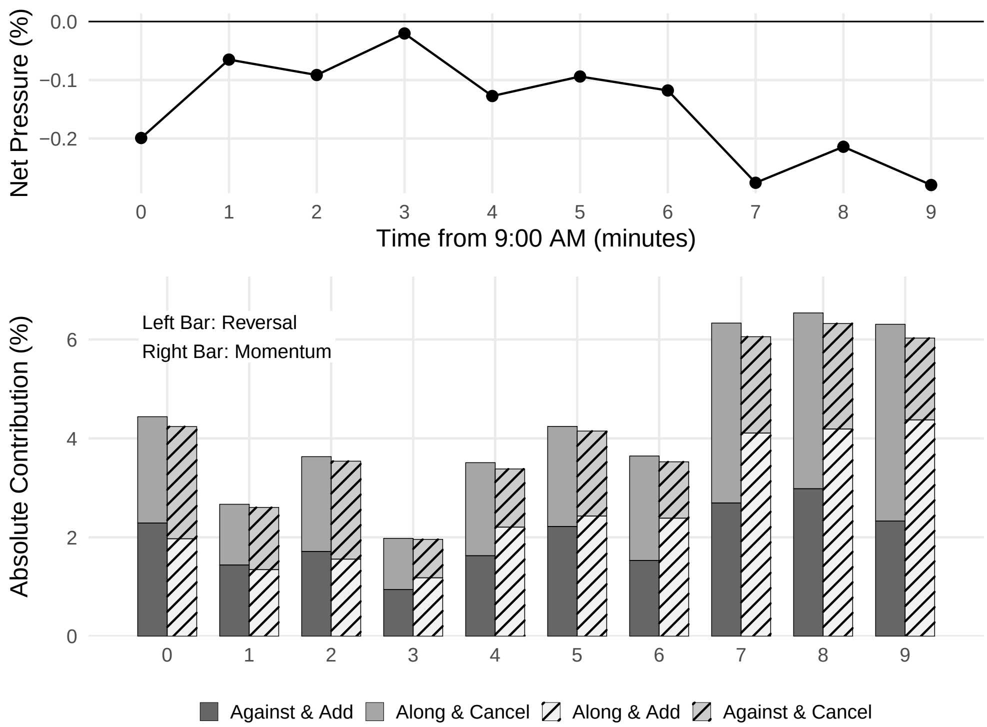
Note: This figure shows price reversals during trading pauses at the morning open. Panel A plots the close-to-open return against the close-to-9:00 AM return (calculated using matching prices) for all observations with trading pauses. The solid line is a regression line with the intercept constrained to zero. Panel B shows the subsample with negative overnight returns; Panel C shows the subsample with positive overnight returns.

Figure 11: Directional Dominance During Trading Pauses



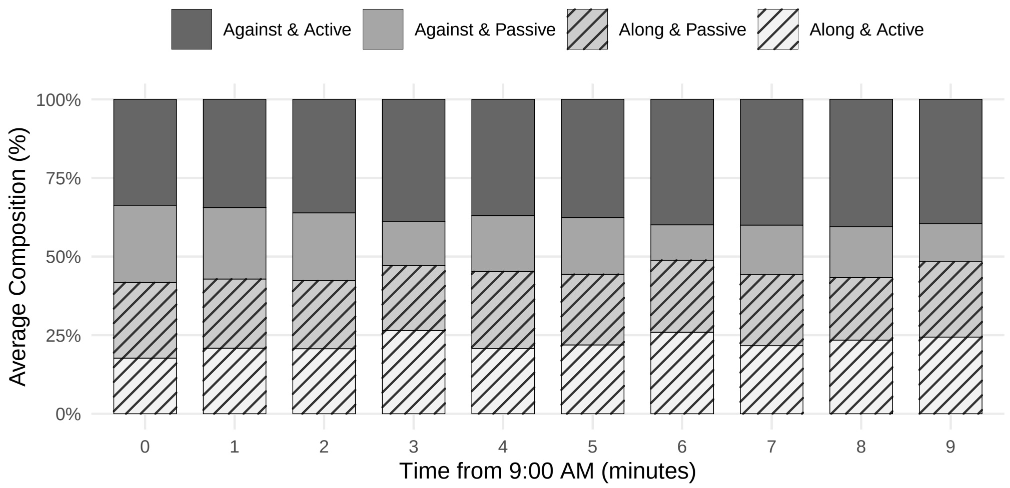
Note: This figure plots counts of stock–date–minute observations classified as More Along or More Against during trading pauses. The pause direction is defined by whether the pause is on the buy side or the sell side. For each stock–date and minute, we compare signed order volume along the pause direction with signed order volume against it. Order volumes are aggregated within a minute; cancellations enter with negative volume. Minutes with exactly equal signed volumes in the two directions are excluded. The upper panel uses limit orders and the lower panel uses market orders.

Figure 12: Net Order Pressure and Its Components During Trading Pauses



Note: This figure plots signed net order pressure during trading pauses, scaled by each stock's average daily trading volume. The top panel reports the event-time average across trading-pause events. We first assign an "upward-pressure" sign: bid-side new orders and ask-side cancellations are treated as upward pressure, whereas ask-side new orders and bid-side cancellations are treated as downward pressure. We then sign pressure so that positive values indicate pressure along the pause direction and negative values indicate pressure against it (along and against are defined as in Figure 11). The bottom panel decomposes the net measure into four components by order direction (Along vs. Against) and event type (Add vs. Cancel). For comparability, the panel plots absolute contributions: the left bar ("Reversal") stacks Against & Add and Along & Cancel, and the right bar ("Momentum") stacks Along & Add and Against & Cancel.

Figure 13: Order Submission Composition During Trading Pauses



Note: This figure reports the composition of order submissions during trading pauses, highlighting differences in submission aggressiveness through an active versus passive classification. The analysis focuses on order additions only (cancellations are excluded). For each trading-pause event and minute, we classify positive-volume order submissions into four categories based on (i) whether the order is along the pause direction or against it (defined as in Figure 11), and (ii) whether the submission is active or passive. An order is classified as active if it is a market order or, for limit orders, if its price is more aggressive than the matching price (buy: price above the matching price; sell: price below the matching price); otherwise it is classified as passive. Within each event–minute, we compute each category's share of total submitted volume and then average these shares across trading-pause events.

8 Tables

Table 1: Price Limits for Trading Pauses

Reference Price (JPY)	Price Limit (JPY)
$P < 200$	±5
$200 \leq P < 500$	8
$500 \leq P < 700$	10
$700 \leq P < 1{,}000$	15
$1{,}000 \leq P < 1{,}500$	30
$1{,}500 \leq P < 2{,}000$	40
$2{,}000 \leq P < 3{,}000$	50
$3{,}000 \leq P < 5{,}000$	70

Note: This table summarizes the parameters used to determine price limits for trading pauses, displaying only reference prices less than 5,000 JPY to save space. Reference prices are defined as the last execution price, with minor exceptions. These parameters apply to all trading sessions, except for closing auctions, during which the price limits are doubled.

Table 2: Comparison of Single-stock Trading Pause Rules Across Major Exchanges

Exchange and Mechanism	**Triggering Criteria**	**Duration and Extensions**	**Applicability at Market Open**
TSE (Japan); Special Quote	Fixed threshold based on the last transaction price	Can end at any time; price limits widen every three minutes	Applicable
NYSE, Nasdaq (U.S.); LULD Rule	Percentage threshold based on the average price over the last five minutes	Five minutes, extendable only once	Not applicable during the first 15 minutes
LSE (U.K.); Price Monitoring Extension	Percentage threshold based on the most recent auction prices and last transaction prices	Five minutes with a random period of up to 30 seconds, extendable	Applicable

Note: This table compares single-stock trading pause rules at the TSE (Japan), NYSE and Nasdaq (U.S.), and LSE (U.K.), focusing on triggering conditions, pause duration, and applicability at market open.

Table 3: Intraday Frequency of Trading Pauses

	Morning Open	Morning Session	Afternoon Open	Afternoon Session
Total	77,528	5,458	2,208	4,846
	(8.9%)	(0.6%)	(0.3%)	(0.6%)
Negative Return	38,523	1,700	1,525	1,462
	(4.4%)	(0.2%)	(0.2%)	(0.2%)
Positive Return	39,005	3,758	683	3,384
	(4.5%)	(0.4%)	(0.1%)	(0.4%)

Note: This table presents the intraday frequency of trading pauses. We count newly occurring trading pauses at the morning open, during the morning continuous session, at the afternoon open, and during the afternoon continuous session. Values in parentheses represent the frequency as a proportion of total date–stock pair observations in the sample. The first row reports the overall frequency, while subsequent rows break down the distribution by whether the overnight return was negative or positive.

Table 4: Summary Statistics of Trading Pauses at Morning Open and Key Variables of Interest

	Mean	Median	Std. Dev.	Min	Max	P5	P95	N
Daily Frequency (%)	8.9	3.8	14.5	0.0	98.2	0.8	36.9	1,763
Duration (Min)	3.5	3.0	8.2	0.0	360.0	0.0	8.7	77,528
DistanceToSQ (%)	2.0	2.0	0.4	1.4	6.3	1.5	2.7	872,773
Relative Tick Size (bp)	9.8	7.4	8.4	1.0	125.0	1.7	21.5	872,732
Realized Volatility (bp)	14.5	13.1	7.2	0.0	208.1	6.5	27.2	802,219
Close-to-Open Return (%)	0.0	0.0	1.3	-31.0	29.1	-1.8	1.9	872,732
Close-to-Close Return (%)	0.0	0.0	2.0	-27.6	30.0	-3.0	3.1	872,773
Quoted Spread (bp)	17.1	15.6	9.7	1.6	773.4	5.8	33.3	802,233
Traded Value (Million JPY)	559	204	1,616	0	132,261	31	1,954	802,182
Depth Value (Million JPY)	273	168	767	6	94,912	36	717	802,233
Market Capitalization (Billion JPY)	1,036	482	1,737	71	29,877	175	3,889	872,323

Note: This table reports summary statistics for trading pauses at the morning open and key variables of interest. The first two rows present statistics for trading pause characteristics, while the remaining rows cover the full sample. Daily Frequency is the proportion of stocks experiencing trading pauses each day. Duration is the time in minutes from 9:00 AM to the end of the trading pause. *DistanceToSQ* is defined in Section 4.1. Relative Tick Size is the minimum tick size relative to the opening price. Realized Volatility is calculated using minute-by-minute bid–ask midpoint prices from the start of trading to 30 minutes afterward. Quoted Spread is the average quoted bid–ask spread, Traded Value is total traded value, and Depth Value is the average depth at the best bid and ask—all computed over the same 30-minute window. Market capitalization is measured using the previous day's closing price.

Table 5: Regression Results for Post-pause Volatility

	OLS			IV		
	(1)	(2)	(3)	(1)	(2)	(3)
Trading Pause	0.201***	0.202***	0.161***	-0.546***	-0.415***	-0.372***
	(0.007)	(0.007)	(0.006)	(0.087)	(0.088)	(0.053)
Relative Tick Size (%)		0.332***	0.237***		0.263***	0.182***
		(0.048)	(0.034)		(0.056)	(0.037)
Log Reference Price			0.012**			0.018***
			(0.005)			(0.005)
Log Market Capitalization			0.017*			0.012
			(0.009)			(0.009)
Lagged Share Turnover (%)			0.039***			0.046***
			(0.006)			(0.007)
Lagged Log Realized Volatility			0.377***			0.409***
			(0.008)			(0.009)
Firm & Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.463	0.464	0.539			
First-stage F-statistic				633.2	624.6	685.7
Observations	800,017	800,016	799,047	800,017	800,016	799,047

Note: This table reports regression results for Equation (3) with post-pause volatility as the dependent variable. The dependent variable is the log of realized volatility, calculated using minute-by-minute bid–ask midpoint prices from the start of trading to 30 minutes afterward (observations with zero volatility are excluded). For comparison and robustness, we report both OLS and IV results under alternative specifications. Relative Tick Size is the minimum tick size relative to the opening price. Reference Price is the log of the previous day's closing price, adjusted for dividend payments and stock splits. Log Market Capitalization is the log of market capitalization at the previous close. Lagged Share Turnover is the ratio of trading volume to shares outstanding on the previous day. Lagged Log Realized Volatility is computed using five-minute midpoint returns from the previous trading day. All specifications include firm and date fixed effects. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Robustness Checks for IV Estimates of Post-pause Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trading Pause	-0.393***	-0.327***	-6.257***	-0.321***	-0.216***	-0.260***	-0.145***	-0.093*
	(0.107)	(0.051)	(0.876)	(0.052)	(0.062)	(0.058)	(0.050)	(0.054)
Relative Tick Size (%)	0.107	0.109**	2.195***	1.233***	-0.383***	-0.352***	0.202***	1.344***
	(0.218)	(0.043)	(0.784)	(0.040)	(0.050)	(0.037)	(0.033)	(0.044)
Log Reference Price	-0.010	0.016***	0.210**	0.018***	0.031***	0.025***	0.010**	-0.006
	(0.018)	(0.006)	(0.082)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Log Market Capitalization	0.022	0.019*	-0.029	0.004	-0.007	0.005	0.014*	0.016*
	(0.020)	(0.010)	(0.168)	(0.009)	(0.011)	(0.010)	(0.008)	(0.008)
Lagged Share Turnover (%)	0.114***	0.052***	1.295***	0.032***	0.049***	0.053***	0.042***	0.035***
	(0.028)	(0.007)	(0.189)	(0.005)	(0.009)	(0.009)	(0.006)	(0.005)
Lagged Log Realized Volatility	0.421***	0.409***	5.917***	0.337***	0.445***	0.446***	0.392***	0.320***
	(0.022)	(0.009)	(0.160)	(0.007)	(0.013)	(0.010)	(0.009)	(0.008)
Firm & Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	140.4	693.2	675.5	684.7	675.5	685.7	665.3	663.0
Observations	105,854	749,628	800,755	790,775	800,760	799,135	870,752	868,762

Note: This table presents robustness checks for the IV estimates of post-pause volatility using alternative samples and volatility measures. Column (1) restricts the sample to TOPIX 100 stocks; Column (2) restricts to observations with reference prices of 500 JPY or higher. Columns (3)–(6) employ alternative volatility measures computed over the first 30 minutes of trading: (3) minute-by-minute midpoint volatility in levels, (4) log transaction-price volatility, (5) log absolute mid-quote return from the opening price, and (6) log high–low price ratio. Coefficients in Column (3) are not directly comparable in magnitude due to the scale of the dependent variable. Columns (7) and (8) use intraday volatility computed from five-minute sampling over the full trading day: (7) log midpoint volatility and (8) log transaction-price volatility. Control variables follow specification (3) in Table 5. All specifications include firm and date fixed effects. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Regression Results for Price Efficiency

	(1)		(2)	
	OLS	IV	OLS	IV
Trading Pause	0.001***	-0.001	0.001***	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Close-to-9:00 AM Return	0.961***	1.044***		
	(0.002)	(0.022)		
Close-to-Open Return			0.961***	0.985***
			(0.002)	(0.020)
(Interaction Term)	-0.073***	-0.202***	0.020***	-0.020
	(0.004)	(0.033)	(0.004)	(0.032)
Firm & Date FE	No	No	No	No
Adjusted R^2	0.385		0.396	
Excluded-instrument F		76.9		66.3
Observations	872,029	872,029	872,029	872,029

Note: This table shows regression results of Equation (4) for price efficiency. Column (1) evaluates the efficiency of prices (or matching prices) at 9:00 AM; Column (2) evaluates opening prices. For comparison and robustness, we report both OLS and IV results. Standard errors in parentheses are heteroskedasticity-robust. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Regression Results for Post-pause Quoted Spreads

	OLS			IV		
	(1)	(2)	(3)	(1)	(2)	(3)
Trading Pause	-0.650***	-0.258***	-0.331***	-50.065***	-8.497***	-7.606***
	(0.124)	(0.039)	(0.036)	(11.051)	(1.664)	(1.547)
Relative Tick Size (%)		78.362***	78.417***		77.428***	77.676***
		(1.756)	(1.911)		(1.685)	(1.849)
Log Reference Price			0.339*			0.414**
			(0.174)			(0.171)
Log Market Capitalization			-1.109***			-1.182***
			(0.261)			(0.263)
Lagged Share Turnover (%)			-0.717***			-0.624***
			(0.139)			(0.133)
Lagged Log Realized Volatility			1.327***			1.752***
			(0.101)			(0.130)
Firm & Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.653	0.823	0.824			
First-stage F-statistic				615.4	609.3	675.5
Observations	802,233	802,232	800,765	802,233	802,232	800,765

Note: This table reports regression results for Equation (3) with post-pause quoted spreads as the dependent variable. The dependent variable is the average quoted bid–ask spread in basis points from the start of trading to 30 minutes afterward. For comparison and robustness, we report both OLS and IV results under alternative specifications as in Table 5. All specifications include firm and date fixed effects. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Heterogeneous Effects by Size and Liquidity Characteristics

	(1)	(2)	(3)
Trading Pause	-0.383***	-0.321***	-0.316***
	(0.060)	(0.073)	(0.061)
Trading Pause × TOPIX 100	0.036		
	(0.138)		
Trading Pause × Small Stock		-0.107	
		(0.111)	
Trading Pause × Low Turnover			-0.154**
			(0.074)
Controls	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes
First-stage F-statistic	632.8	532.5	670.6
Observations	799,047	799,047	799,047

Note: This table reports 2SLS results for Equation (5) examining heterogeneous effects on post-pause volatility by size and liquidity characteristics. The dependent variable is defined as in Table 5. We interact the Trading Pause indicator with three indicator variables: TOPIX 100 (equals one for TOPIX 100 constituents), Small Stock (equals one if previous-day market capitalization is below the daily median), and Low Turnover (equals one if previous-day share turnover is below the daily median). For brevity, we omit the coefficients on the standalone indicator variables. Other control variables follow specification (3) in Table 5, but their coefficients are also omitted. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Heterogeneous Effects by Overnight Return Characteristics

	(1)	(2)	(3)	(4)
Trading Pause	-0.461***	-0.448***	-0.489***	-0.377***
	(0.064)	(0.062)	(0.076)	(0.054)
Trading Pause × Negative Overnight Return	0.182***	0.340***		
	(0.039)	(0.118)		
Trading Pause × Negative Overnight Market Return		-0.186		
		(0.116)		
Trading Pause × Large Market Return			0.319***	
			(0.065)	
Trading Pause × Earnings Announcement				0.313*
				(0.172)
Controls	Yes	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes	Yes
First-stage F-statistic	473.0	382.9	506.7	656.1
Observations	799,047	799,047	799,047	799,047

Note: This table reports 2SLS results for Equation (5) examining heterogeneous effects on post-pause volatility by overnight return characteristics. The dependent variable is defined as in Table 5. We interact the Trading Pause indicator with four indicator variables: Negative Overnight Return (equals one if the firm's overnight return is negative), Negative Overnight Market Return (equals one if the market overnight return is negative), Large Overnight Market Return (equals one if the absolute market overnight return is above the 90th percentile), and Earnings Announcement (equals one if the firm released an earnings announcement or forecast revision outside trading hours). Negative Market Return and Large Market Return are collinear with date fixed effects; only their interactions with Trading Pause are identified. For brevity, we omit the coefficients on the standalone indicator variables. Other control variables follow specification (3) in Table 5, but their coefficients are also omitted. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

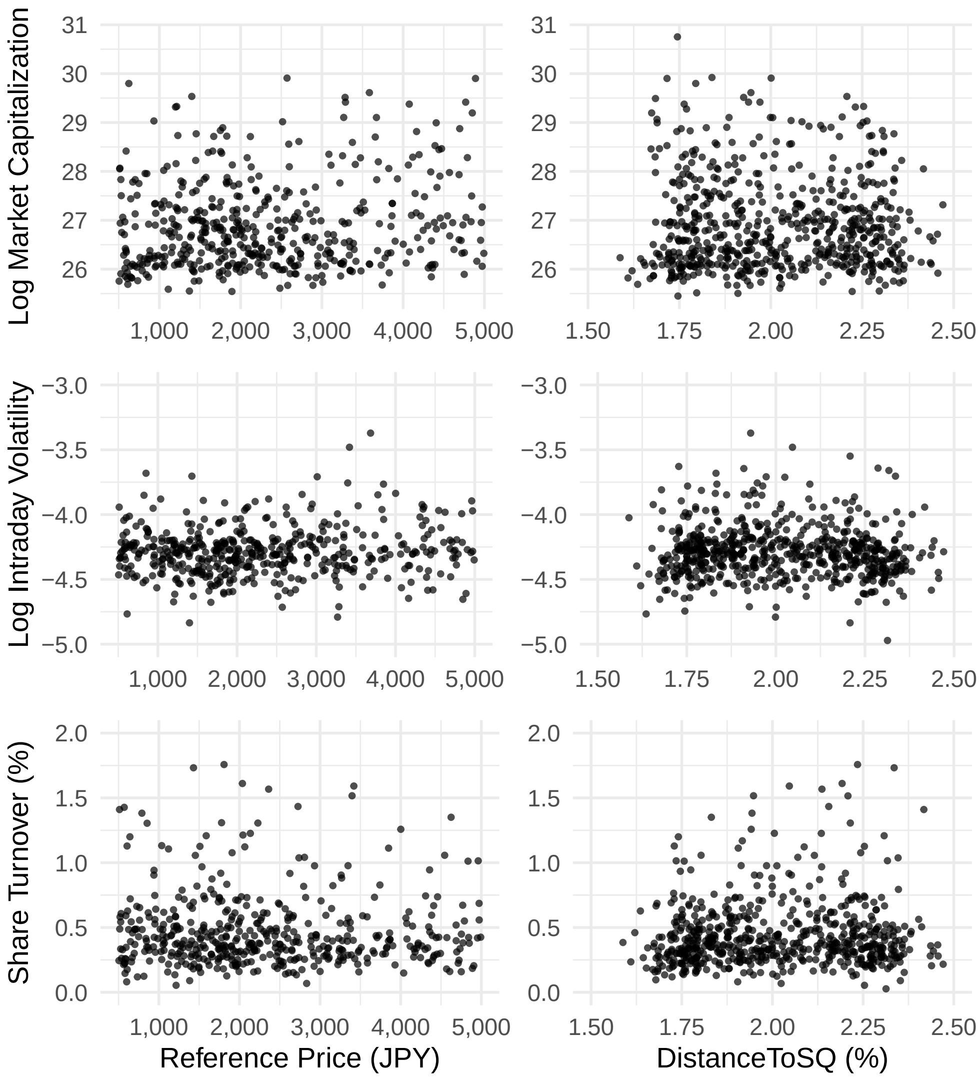
Table 11: Heterogeneous Effects by Lagged Volatility and Return Characteristics

	(1)	(2)	(3)	(4)
Trading Pause	-0.405***	-0.405***	-0.417***	-0.461***
	(0.060)	(0.057)	(0.058)	(0.068)
Trading Pause × High Lagged Volatility	0.144**			
	(0.071)			
Trading Pause × Negative Lagged Return		0.070**	-0.025	0.070**
		(0.035)	(0.052)	(0.035)
Trading Pause × Large Negative Lagged Return			0.240***	
			(0.074)	
Trading Pause × Negative 3-Day Lagged Return				0.103***
				(0.035)
Controls	Yes	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes	Yes
First-stage F-statistic	604.8	530.9	534.9	411.9
Observations	799,047	799,045	799,045	799,045

Note: This table reports 2SLS results for Equation (5) examining heterogeneous effects on post-pause volatility by lagged volatility and return characteristics. The dependent variable is defined as in Table 5. Column (1) interacts Trading Pause with High Lagged Volatility (equals one if previous-day realized volatility is above the 90th percentile). Column (2) interacts Trading Pause with Negative Lagged Return (equals one if previous-day close-to-close return is negative). Column (3) adds an interaction with Large Negative Lagged Return (equals one if the firm's previous-day close-to-close return is below the 10th percentile). Column (4) replaces the large-negative-return interaction with Negative 3-Day Lagged Return (equals one if cumulative return over the past three days is negative). For brevity, we omit the coefficients on the standalone indicator variables. Other control variables follow specification (3) in Table 5, but their coefficients are also omitted. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Figure A.1: Distributions of Market Capitalization, Intraday Realized Volatility, Share Turnover, Reference Price, and *DistanceToSQ*



Note: This figure illustrates the distributions and relationships among market capitalization, intraday realized volatility, share turnover, reference price, and *DistanceToSQ*. Data are averaged by stock code. Market capitalization and intraday realized volatility are shown in logarithmic scale. Intraday realized volatility is computed using five-minute bid–ask midpoint prices. Share turnover is the ratio of daily trading volume to shares outstanding.

Table A.1: Probit Estimates of Trading Pause Probability

	(1)	(2)	(3)
DistanceToSQ (%)	-0.493***	-0.724***	-0.780***
	(0.006)	(0.007)	(0.007)
Earnings Announcement		1.774***	1.755***
		(0.013)	(0.013)
Abs. Overnight Market Return (%)		1.001***	0.930***
		(0.003)	(0.003)
Lagged Log Realized Volatility			0.635***
			(0.006)
Lagged Share Turnover (%)			0.069***
			(0.003)
Log Market Capitalization			0.066***
			(0.002)
Firm & Date FE	No	No	No
Log Likelihood	-257318.9	-183902.2	-175451.6
Pseudo R^2 (McFadden)	0.017	0.297	0.329
Observations	872,773	872,773	871,276

Note: This table reports probit coefficient estimates for the probability of a trading pause, the model underlying Figure 2. See Figure 2 for variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.2: First-Stage Regression: Trading Pause Indicator on *DistanceToSQ*

	(1)	(2)	(3)
DistanceToSQ (%)	-0.081***	-0.081***	-0.083***
	(0.003)	(0.003)	(0.003)
Relative Tick Size (%)		0.003	-0.011
		(0.015)	(0.014)
Log Reference Price			0.003
			(0.002)
Log Market Capitalization			-0.014***
			(0.004)
Lagged Share Turnover (%)			0.012***
			(0.002)
Lagged Log Realized Volatility			0.061***
			(0.002)
Firm & Date FE	Yes	Yes	Yes
Adjusted R^2	0.282	0.282	0.288
Partial R^2	0.010	0.009	0.010
Excluded-instrument F	633.2	624.6	685.7
Observations	800,017	800,016	799,047

Note: This table reports first-stage regressions for the 2SLS estimation in Table 5. The dependent variable is the trading pause indicator. The instrument is *DistanceToSQ*. All specifications include firm and date fixed effects. Control variables follow specification (3) in Table 5. Partial R^2 measures the incremental explanatory power of *DistanceToSQ* relative to the restricted model without the instrument. Excluded-instrument F is the Wald F-statistic for the null that the coefficient on *DistanceToSQ* equals zero. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.3: Reduced Form Regression: Post-pause Volatility on *DistanceToSQ*

	(1)	(2)	(3)
DistanceToSQ (%)	0.044***	0.034***	0.031***
	(0.006)	(0.007)	(0.004)
Relative Tick Size (%)		0.261***	0.186***
		(0.053)	(0.035)
Log Reference Price			0.017***
			(0.005)
Log Market Capitalization			0.017*
			(0.009)
Lagged Share Turnover (%)			0.042***
			(0.006)
Lagged Log Realized Volatility			0.386***
			(0.008)
Firm & Date FE	Yes	Yes	Yes
Adjusted R^2	0.452	0.452	0.531
Observations	800,017	800,016	799,047

This table reports reduced-form regressions for the 2SLS estimation in Table 5. The dependent variable is the log of realized volatility, as defined in Table 5. The main explanatory variable is *DistanceToSQ*. All specifications include firm and date fixed effects. Control variables follow specification (3) in Table 5. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.4: Regression Results for Post-pause Traded Value and Market Depth

	Traded Value			Market Depth		
	(1)	(2)	(3)	(4)	(5)	(6)
Trading Pause	1.107***	0.867***	0.162	0.901***	0.814***	0.132
	(0.327)	(0.326)	(0.149)	(0.250)	(0.260)	(0.134)
Relative Tick Size (%)		-0.448**	-0.586***		-0.161	-0.090
		(0.224)	(0.121)		(0.178)	(0.134)
Log Reference Price			-0.059***			-0.022
			(0.015)			(0.016)
Log Market Capitalization			0.981***			0.719***
			(0.029)			(0.028)
Lagged Share Turnover (%)			0.340***			0.136***
			(0.057)			(0.021)
Lagged Log Realized Volatility			0.360***			-0.248***
			(0.027)			(0.023)
Firm & Date FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-statistic	615.4	609.4	675.5	615.4	609.3	675.5
Observations	802,182	802,181	800,720	802,232	802,232	800,765

Note: This table reports 2SLS results for Equation (3) with traded value (Traded Value) and depth value at the best bid and ask scaled by relative tick size (Market Depth) as the dependent variables. For comparison and robustness, we report results under alternative specifications as in Table 5. All specifications include firm and date fixed effects. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.5: Heterogeneous Effects by Size and Liquidity Characteristics: OLS Estimates

	(1)	(2)	(3)
Trading Pause	0.167***	0.148***	0.162***
	(0.007)	(0.007)	(0.007)
Trading Pause × TOPIX 100	-0.041***		
	(0.008)		
Trading Pause × Small Stock		0.025***	
		(0.006)	
Trading Pause × Low Turnover			-0.003
			(0.005)
Controls	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes
Adjusted R^2	0.539	0.539	0.540
Observations	799,047	799,047	799,047

Note: This table reports OLS counterparts to the IV estimates in Table 9. See Table 9 for variable definitions. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.6: Heterogeneous Effects by Size and Liquidity Characteristics

	(1)	(2)	(3)
Trading Pause	-8.982***	-4.129***	-7.431***
	(1.811)	(1.524)	(1.881)
Trading Pause × TOPIX 100	11.426***		
	(3.527)		
Trading Pause × Small Stock		-6.714**	
		(3.123)	
Trading Pause × Low Turnover			-0.310
			(2.739)
Controls	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes
First-stage F-statistic	622.1	527.1	663.0
Observations	800,765	800,765	800,765

Note: This table replaces the dependent variable in Table 9 with the average quoted bid–ask spread in basis points and reports 2SLS results. See Table 9 for variable definitions. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.7: Heterogeneous Effects by Overnight Return Characteristics: OLS Estimates

	(1)	(2)	(3)	(4)
Trading Pause	0.174***	0.177***	0.237***	0.110***
	(0.008)	(0.008)	(0.007)	(0.005)
Trading Pause × Negative Overnight Return	-0.029***	-0.018		
	(0.010)	(0.012)		
Trading Pause × Negative Overnight Market Return		-0.015		
		(0.013)		
Trading Pause × Large Market Return			-0.231***	
			(0.009)	
Trading Pause × Earnings Announcement				0.126***
				(0.013)
Controls	Yes	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.539	0.539	0.543	0.553
Observations	799,047	799,047	799,047	799,047

Note: This table reports OLS counterparts to the IV estimates in Table 10. See Table 10 for variable definitions. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.8: Heterogeneous Effects on Quoted Spreads by Overnight Return Characteristics

	(1)	(2)	(3)	(4)
Trading Pause	-9.115***	-8.698***	-10.607***	-7.642***
	(1.843)	(1.755)	(2.182)	(1.567)
Trading Pause × Negative Overnight Return	3.118***	8.169***		
	(0.848)	(2.395)		
Trading Pause × Negative Overnight Market Return		-5.972***		
		(2.104)		
Trading Pause × Large Market Return			8.209***	
			(1.810)	
Trading Pause × Earnings Announcement				2.208
				(1.764)
Controls	Yes	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes	Yes
First-stage F-statistic	467.4	379.8	501.2	645.7
Observations	800,765	800,765	800,765	800,765

Note: This table replaces the dependent variable in Table 10 with the average quoted bid–ask spread in basis points and reports 2SLS results. See Table 10 for variable definitions. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.9: Heterogeneous Effects by Lagged Volatility and Return Characteristics: OLS Estimates

	(1)	(2)	(3)	(4)
Trading Pause	0.179***	0.169***	0.172***	0.189***
	(0.007)	(0.007)	(0.007)	(0.008)
Trading Pause × High Lagged Volatility	-0.079***			
	(0.007)			
Trading Pause × Negative Lagged Return		-0.017*	-0.040***	-0.017*
		(0.009)	(0.008)	(0.009)
Trading Pause × Large Negative Lagged Return			-0.018**	
			(0.009)	
Trading Pause × Negative 3-Day Lagged Return				-0.037***
				(0.006)
Controls	Yes	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.539	0.539	0.542	0.539
Observations	799,047	799,045	799,045	799,045

Note: This table reports OLS counterparts to the IV estimates in Table 11. See Table 11 for variable definitions. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.10: Heterogeneous Effects on Quoted Spreads by Lagged Volatility and Return Characteristics

	(1)	(2)	(3)	(4)
Trading Pause	-7.870***	-7.466***	-7.503***	-8.724***
	(1.602)	(1.591)	(1.600)	(1.795)
Trading Pause × High Lagged Volatility	1.399			
	(2.268)			
Trading Pause × Negative Lagged Return		-0.280	-3.582***	-0.275
		(0.523)	(1.047)	(0.521)
Trading Pause × Large Negative Lagged Return			6.716***	
			(1.765)	
Trading Pause × Negative 3-Day Lagged Return				2.317***
				(0.625)
Controls	Yes	Yes	Yes	Yes
Firm & Date FE	Yes	Yes	Yes	Yes
First-stage F-statistic	595.0	523.4	527.7	409.7
Observations	800,765	800,763	800,763	800,763

Note: This table replaces the dependent variable in Table 11 with the average quoted bid–ask spread in basis points and reports 2SLS results. See Table 11 for variable definitions. Standard errors in parentheses are two-way clustered by firm and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.