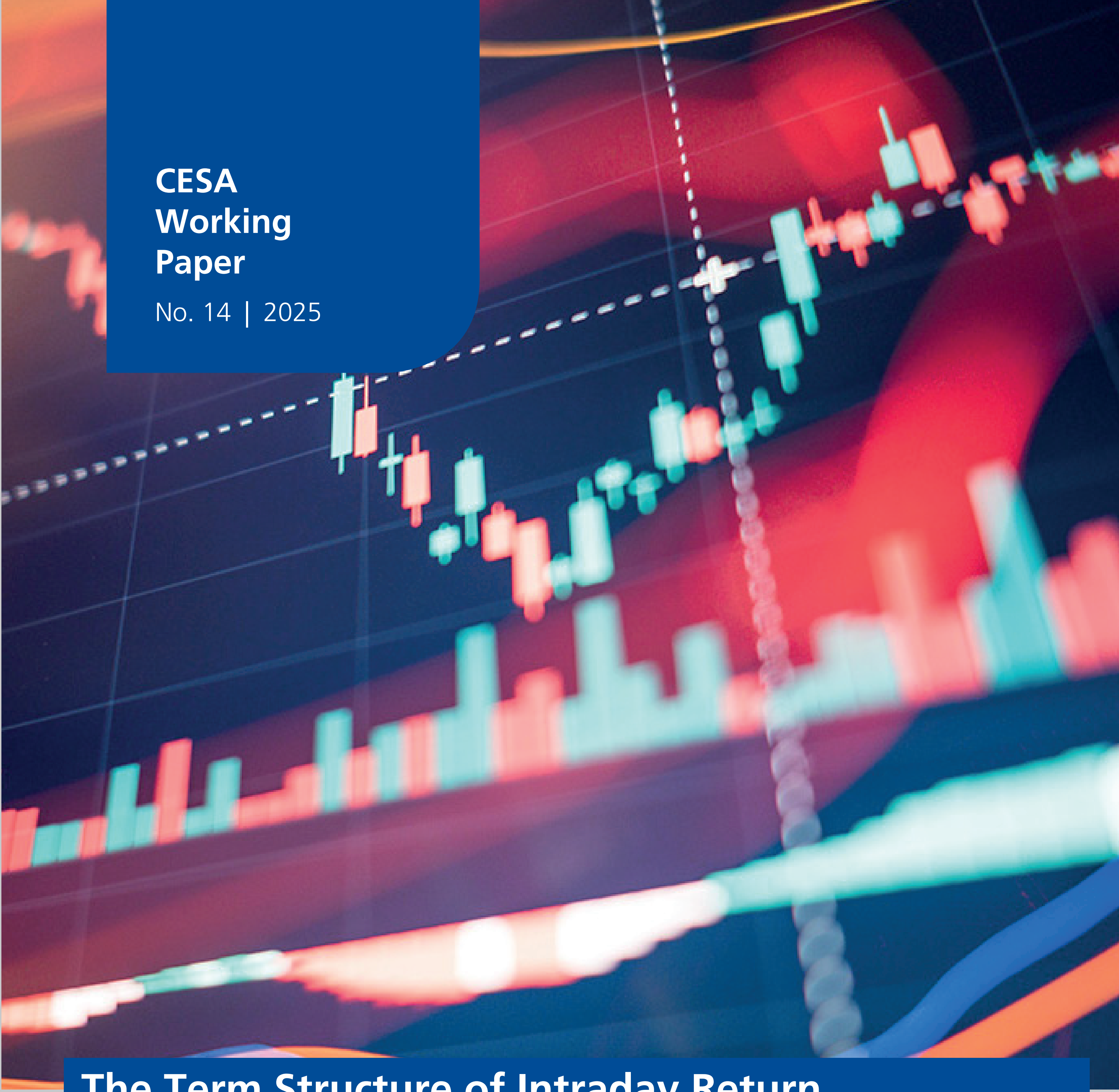

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# The Term Structure of Intraday Return Autocorrelations

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# The Term Structure of Intraday Return Autocorrelations

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**Abstract**

Using high-frequency data on the cross-section of U.S. stocks, we analyze intraday return autocorrelations across a fine grid of different horizons: the term structure of intraday return autocorrelations. While average return autocorrelations are mostly negative, the degree of autocorrelation depends on the return horizon. On 15-minute horizons, return reversals are most pronounced. On sub-minute horizons, return continuations occur in relatively larger stocks, during periods of market stress, and in the first half hour of trading. Drawing on the literature, we derive and test hypotheses that link intraday return autocorrelations to major sources of market frictions and trading needs that systematically depend on past returns. We find evidence that return autocorrelations depend on the ease with which intermediaries can mean-revert their inventories, the degree of informational asymmetry, and dynamic hedge adjustments of option market makers.

**JEL Classification:** D4, D53, D82, G14

**Keywords:** return autocorrelation, intraday, price pressure, option gamma

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## 1 Introduction

In frictionless and weak-form efficient markets, return autocorrelations should be zero (Fama, 1970). In real-world markets, however, return autocorrelations often deviate moderately from zero. This stylized fact is well documented for intraday returns (e.g., Conrad et al., 2015; Dong et al., 2017), as well as for returns over longer horizons (e.g., Jegadeesh and Titman, 1993; Avramov et al., 2006; Hendershott and Menkveld, 2014). The literature attributes these deviations to various sources of market frictions (Stoll, 2000; Duffie, 2010) and trading behavior that systematically depends on past returns (Sentana and Wadhwani, 1992; Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). Importantly, different reasons may generate opposing effects on return autocorrelation. For instance, liquidity-motivated trading of asynchronously arriving buyers and sellers with a risk-averse intermediary tends to induce negative return autocorrelation (e.g., Stoll, 1978; Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014), whereas informed trading in the presence of asymmetric information typically generates zero or positive return autocorrelation (e.g., Glosten and Milgrom, 1985; Sadka, 2006; Dong et al., 2017; Van Kervel and Menkveld, 2019). Given the presence of multiple and opposing forces, their relative importance could vary depending on the time horizon, in turn, altering return autocorrelations across frequencies.

Studies on stock-level intraday return autocorrelations typically analyze a single or a limited set of return horizons. As a consequence, little is known about how intraday return autocorrelations depend on the return horizon.[1] Our study addresses this gap by constructing and analyzing a term structure of intraday return autocorrelations. While computationally challenging, this approach allows us to examine two key questions: At which horizons are patterns of return continuations and reversals most pronounced, and how do specific market characteristics shape the term structure of return autocorrelations?

To answer these questions, we analyze high-frequency data on U.S. stocks. We start by computing return autocorrelations across a wide range of intraday frequencies, ranging from one second up to half a trading day. Additionally, we consider correlations between

[1] An exception is the finding that stock-level returns tend to mean-revert relative to contemporaneous market returns at high intraday frequencies (Heston et al., 2010).

overnight and daytime returns. Together, these correlations form the term structure of intraday return autocorrelations, which we document for the first time in the literature. We find that average intraday return autocorrelations are significantly negative across most intraday return horizons and also between overnight returns and subsequent daytime returns. Most interestingly, however, the term structure exhibits a distinct shape: return autocorrelations are close to zero for sub-minute returns, decline to a minimum for 15-minute returns, and then gradually revert toward zero for longer return horizons. This pattern indicates that reversals predominate in intraday returns. Moreover, we find that reversals are more pronounced and occur over longer horizons in smaller firms, which provides a first indication that market frictions affect the term structure. Lastly, on sub-minute horizons, we observe return continuations in relatively large stocks, during periods of market stress, and in the first half hour of trading – likely related to information-motivated trading. Overall, the results – robust to various modifications – confirm that the return horizon affects the strength of reversals and continuations in intraday returns.

We then draw on the literature on major market frictions and trading needs that depend systematically on past returns to develop three hypotheses that link intraday return autocorrelations to intermediaries' inventory-control procedures, asymmetric information, and dynamic hedging activities of option market makers. The first hypothesis is that the magnitude and the speed of price reversals depend on the ease with which intermediaries can mean-revert their inventories. When buyers and sellers arrive asynchronously, intermediaries absorb demand shocks in the absence of natural counterparties. As intermediaries are typically risk-averse or subject to position limits, they charge a bid-ask spread and respond to trades with transitory quote adjustments that reflect an inventory-control mechanism (Glosten and Harris, 1988; Grossman and Miller, 1988). That is, they revise their quotes to attract an offsetting order flow imbalance that allows them to mean-revert their non-optimal inventories to a desired level (Stoll, 2000). Once the offsetting order flow materializes, the transitory price impact is dropped and quotes rebound – given no change in the fundamental value estimate. This induces negative autocorrelation into mid-quote returns. Building on this framework, we expect that reversals are more pronounced and take longer to occur when it is more difficult for intermediaries to mean-revert their inventories. As intermediaries' inventories are not directly observable, we measure this difficulty based on trading volume, realized spreads, and internalized retail trading activity.

The second hypothesis is that return autocorrelations increase when the informational asymmetry is heightened because informed traders execute their orders more gradually in this environment. The rationale is as follows. When there is informational asymmetry, the direction of trades carries information, as some traders exploit their private information by submitting market orders (Glosten and Milgrom, 1985). To mitigate losses from such trades, liquidity providers charge an additional component in the bid-ask spread and permanently revise their fundamental value estimate and thus their mid-quote after a trade (Glosten and Harris, 1988). The impact of this price-setting policy on return autocorrelations depends on the persistence of order flow imbalances. Positive return autocorrelations can arise when information-motivated traders split their orders and execute them over time, a practice widely observed (Sadka, 2006; Murphy and Thirumalai, 2017; Van Kervel and Menkveld, 2019). We expect that information-motivated traders execute their orders relatively more gradual when informational asymmetry is heightened. This is because liquidity providers impose a larger permanent price impact in such environments, making rapid execution more expensive. To assess informational asymmetry, we measure the permanent price impact of trades.

The third hypothesis is that dynamic hedging activities of option market makers affect return autocorrelations. Option market makers dynamically adjust their hedges in the underlying stock to remain delta-neutral, and the direction of these adjustments depends on the option portfolio's sign of gamma. Prior evidence shows that such hedge adjustments systematically affect stock price dynamics at the end of the trading day (e.g., Baltussen et al., 2021; Barbon et al., 2021) and on daily horizons (e.g., Ni et al., 2021; Soebhag, 2023). Specifically, negative gamma requires hedgers to trade in the direction of past returns – inducing positive autocorrelation, while positive gamma requires them to trade in the opposite direction of past returns – inducing negative autocorrelation. We expect that hedge adjustments do not only affect end-of-day returns but return autocorrelations throughout the trading day. In this regard, our multi-period approach can shed light on the approximate return horizon where hedge adjustments start to affect price dynamics.

Following Baltussen et al. (2021), Soebhag (2023), and Huang et al. (2023), we estimate option market makers' gamma based on public data.

We test these hypotheses empirically using the above market characteristics. We find support for all three hypotheses. This means that when market conditions make it more difficult for intermediaries to mean-revert their inventories, return autocorrelations are more negative. In addition, when informational asymmetries are relatively high, return autocorrelations are more positive (less negative), particularly on short horizons. Finally, when option market makers' gamma exposure is positive (negative), return autocorrelations are significantly more negative (positive). This effect is most pronounced for return horizons of 30 minutes and longer, but limited to stocks of medium and large size. Overall, our results indicate that market characteristics related to inventory control and asymmetric information exert a relatively more pronounced effect on intraday return autocorrelations than hedge adjustments of option market makers.

We contribute to the literature in several ways. We extend the literature that documents price reversals and connects them to transitory price effects from intermediaries' inventory-control procedures (Hendershott and Menkveld, 2014; Boyarchenko et al., 2023; Krohn et al., 2024). Our findings provide insights into the specific intraday horizons at which these reversals occur and the factors that influence their magnitude. We also extend the empirical evidence that return autocorrelations increase when information-driven trading is more pronounced (Dong et al., 2017). In addition, we contribute to the growing body of evidence showing that hedge adjustments of option market makers systematically impact underlyings' price dynamics (Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). Our analysis indicates that hedge adjustments affect price dynamics not only at the end of the day, as previously shown, but also within the day. Finally, our paper relates to studies that use absolute return autocorrelations to assess price efficiency (e.g., Comerton-Forde and Putniņš, 2015). However, rather than focusing on non-directional deviations from zero, we investigate signed return autocorrelations.

Our results have important implications. While we document distinct patterns in the autocorrelations of intraday returns that are consistent with expected patterns in the presence of market frictions and systematic trading needs, we also find that their magnitude is modest on average. This suggests that deviations from weak-form market efficiency are relatively minor after all.

The remainder of the paper is organized as follows: Section 2 reviews the literature on intraday return autocorrelations and derives our hypotheses in more detail. Section 3 describes the data and the variables. Section 4 studies the shape of the term structure of intraday return autocorrelations and tests our hypotheses. Section 5 concludes.

## 2 Literature Review and Hypotheses Development

### 2.1 Return Autocorrelations

There are two strands of literature that explore intraday stock-level return autocorrelations.[2] Studies in the first strand measure stock returns relative to the contemporaneous market return (Heston et al., 2010, 2011; Murphy and Thirumalai, 2017). These studies find that first-order excess-return autocorrelations are significantly negative for short horizons, ranging from 1 minute to 30 minutes. However, the significance tends to deteriorate at longer horizons. This indicates reversals in short-term stock returns relative to the market return. The second strand of literature examines stock returns without adjusting for market-wide returns (Chordia et al., 2005, 2008; Conrad et al., 2015; Dong et al., 2017). These studies focus on a single or a limited set of return horizons and provide mixed evidence. For large stocks and high-frequency returns of about 1 minute, autocorrelations are typically close to zero or positive (Conrad et al., 2015). However, as the return frequency decreases or stock size shrinks, autocorrelations tend to become more negative. Specifically, small stocks exhibit negative autocorrelations even at high frequencies (Conrad et al., 2015), and stocks across all sizes tend to show negative autocorrelations at 5-minute (Chordia et al., 2005, 2008) and 10-minute (Dong et al., 2017) return horizons. Furthermore, daytime returns have a tendency to revert previous overnight returns (Akbas

[2]On short, non-intraday horizons, stock-level return autocorrelations are generally negative. This pattern has been documented for daily returns (e.g., Stoll, 2000; Hendershott and Menkveld, 2014) and weekly returns (e.g., Avramov et al., 2006). However, over longer horizons, return autocorrelations tend to turn positive, reflecting momentum effects (e.g., Jegadeesh and Titman, 1993).

et al., 2022; Ham et al., 2023; Hajiyev et al., 2024). However, the reverse effect – whether overnight returns revert prior daytime returns – has not yet been explored. Although these studies cover different time periods and subsets of the cross-section, they collectively provide a first indication that intraday return autocorrelations depend on the return horizon and firm-level market characteristics. Our study extends this second strand of literature by analyzing return autocorrelations across a wide range of intraday frequencies and the entire cross-section of stocks.

### 2.2 Hypotheses

An important source of market friction arises from the asynchronous arrival of buyers and sellers (Glosten and Harris, 1988). If there is no natural counterparty available, intermediaries absorb demand shocks and temporarily hold positions until a natural counterparty arrives. However, as intermediaries are typically risk-averse or subject to position limits, they require compensation for holding non-optimal inventories (e.g., Stoll, 1978; Amihud and Mendelson, 1980; Ho and Stoll, 1981; Grossman and Miller, 1988; Hendershott and Menkveld, 2014). To this end, they charge a transitory price impact as part of the bid-ask spread and revise their mid quote after a trade. This transitory change in the mid quote, also known as price pressure, reflects an inventory-control mechanism that allows an intermediary to mean-revert his inventory to a desired level (Stoll, 2000). The intuition is as follows: When sales to an intermediary raise his inventory above a desired level, he lowers both the bid and the ask to discourage further sales and to encourage purchases. Once the offsetting order flow imbalance materializes and his inventory has mean-reverted, the transitory price impact is dropped and quotes rebound to their former level – given no change in the fundamental value estimate. This process induces negative autocorrelation into mid-quote returns, as price pressure from inventory-control dynamics is transitory. Previous empirical evidence shows that not only traditional market makers, but also high-frequency traders acting as voluntary liquidity providers use price pressure (Menkveld, 2013). This suggests the existence of price pressure effects on various intraday horizons. Moreover, price pressure is economically sizable, and more pronounced and longer-lasting for smaller stocks (Hendershott and Menkveld, 2014). We therefore hypothesize that the magnitude and the speed of price reversals from intermediaries' usage of price pressure depends on the difficulty with which they can mean-revert their inventories.

**Hypothesis 1.** *Intraday return autocorrelations decrease when the difficulty with which intermediaries can mean-revert their inventories increases.*

To gauge difficulties in inventory control, we use three closely related variables: trading volume, realized spread, and retail trading activity – as intermediaries' inventories are not directly observable.

Another major source of market friction is informational asymmetry (Glosten and Harris, 1988). When there is informational asymmetry, some traders submit market orders to exploit their informational advantage. As a consequence, the direction of orders carries information. To protect against losses to information-motivated trades, liquidity providers add a permanent price impact component to the bid-ask spread and revise their mid quote after a trade (e.g., Glosten and Milgrom, 1985). Specifically, liquidity providers permanently revise their fundamental value estimate and thus their mid quote upward after executing buy trades and downward after executing sell trades. The impact of this price-setting policy on return autocorrelations depends on the autocorrelation in the order flow. Positive return autocorrelation can arise when information-motivated traders split their orders into smaller pieces and execute them over time, a practice widely observed in financial markets (e.g., Sadka, 2006; Murphy and Thirumalai, 2017; Van Kervel and Menkveld, 2019). Importantly, this illustrates a fundamental difference between the effects of liquidity-motivated and information-motivated trading on return autocorrelations (cf. Hypothesis 1). While the former causes temporary price deviations that tend to revert, the latter contributes to permanent price changes. We hypothesize that return autocorrelations depend on the degree of informational asymmetry. The rationale is as follows. When the proportion of information-motivated traders is high, liquidity providers will charge a relatively larger permanent price impact. In this environment it could be particularly attractive for information-motivated traders to spread their trades over time to reduce their impact on the price, contributing to positive (less negative) return autocorrelation. To quantify the degree of informational asymmetry, we estimate the permanent price impact of trades.

**Hypothesis 2.** *Intraday return autocorrelations increase when the informational asymmetry increases.*

Traders who systematically trade in the direction (opposite direction) of past returns can generate positive (negative) return autocorrelation (Sentana and Wadhwani, 1992). Among these traders are option market makers who dynamically adjust their hedges. To immunize the value of an option portfolio against changes in the price of the option's underlying, market makers engage in delta-hedging (e.g., Hull, 2021, ch. 19). The delta of an option at time $t$, defined as $\Delta_t = \frac{\delta V_t}{\delta P_t}$, represents the sensitivity of the option's price $V_t$ to changes in the underlying stock price $P_t$. Delta-hedging an option portfolio against small changes in $P_t$ thus requires to buy or sell an amount of shares of the underlying equal to $-\Delta_t$. This delta-hedge has to be adjusted to remain effective, as $\Delta_t$ fluctuates with changes in $P_t$. The rate at which $\Delta_t$ changes when $P_t$ changes is defined as gamma, $\Gamma_t = \frac{\delta^2 V_t}{\delta P_t^2}$. The sign of gamma thus determines whether hedgers have to buy or sell in response to positive or negative returns in the underlying. In other words, the sign of gamma determines whether the price impact of hedge adjustments has the potential to amplify ($\Gamma_t < 0$) or reverse ($\Gamma_t > 0$) recent returns and thus affects the degree of return autocorrelation.

A growing literature provides empirical evidence that hedge adjustments of option market makers exert systematic and economically sizable price pressure on the option's underlying, consistent with the above rationale.[3] On the daily horizon, the net gamma exposure of delta-hedgers is negatively related to the volatility of the underlying stock (Ni et al., 2021; Soebhag, 2023). This is plausible, as negative (positive) return autocorrelation suppresses (amplifies) volatility. On the intraday horizon, the price pressure from delta-hedge adjustments induces a negative ($\Gamma_t > 0$) or positive ($\Gamma_t < 0$) correlation between the last half-hour return and the return in previous part of the day for stocks, indices, and various futures (Baltussen et al., 2021; Barbon et al., 2021; Huang et al., 2023). This effect is statistically and economically significant. However, the broader impact of delta-

[3] Similar systematic price pressure results from the rebalancing of the exposure of leveraged exchange traded funds at the end of the day (Brøgger, 2021; Todorov, 2024). In addition, there are theoretical, model-driven investigations on the effect of delta-hedging on market quality in the underlying (Frey and Stremme, 1997; Sornette et al., 2022; Buis et al., 2022; Egebjerg and Kokholm, 2024).

hedging or anticipatory front-running on return autocorrelations across different parts of the day and return intervals is yet unexplored. While trading costs likely prevent hedge adjustments at very high frequencies, it is reasonable to expect adjustments at medium frequencies throughout the day, e.g. due to risk limits. Identifying the return horizons at which hedge adjustments begin to affect return autocorrelations is an empirical question that we aim to address. Therefore, we hypothesize that hedge adjustments of option market makers due to gamma exposure affect the term structure of intraday return autocorrelations.

**Hypothesis 3.** *Intraday return autocorrelations decrease when the gamma exposure of option market makers increases.*

# 3 Data and Variables

## 3.1 Data

We base our analysis on the cross-section of U.S. stocks from January 2017 through December 2021. We select sample stocks as follows: Among NYSE- and NASDAQ-listed common stocks, we require that the respective identifiers are not duplicated and do not change during the sample period, that the market capitalization is at least $100 Mio., and that the stock price is at least $1. The last two requirements are made to exclude thinly traded stocks and possible tick-size effects of penny stocks.

The sample includes both normal periods and the COVID-induced crash in February and March 2020. For the sample stocks, we retrieve tick-level national best bid and offer (NBBO) quotes and all trades reported to the consolidated tape, both from the Trade and Quote (TAQ) database. Based on these data, we calculate intraday return autocorrelations and trade and quote related variables.

We apply a two-stage cleaning procedure for both quotes and trades to assure accuracy and consistency of the data, motivated by the literature (e.g., Bogousslavsky and Muravyev, 2023; Barbon et al., 2021). In the first stage, we clean the quote data: We retain only quotes with a correct timestamp and positive values for bid, ask, bid size, offer size, and bid-ask spread. Moreover, we retain only quotes with bid (ask) prices that are at most 0.5% below (above) the daily low (high) of the quoted bid (ask) according to the daily CRSP files. In the second stage, we clean the trade data: We retain only trades with a correct timestamp, trade correction indicators 00 (correctly recorded trades) and 01 (late corrected trades, that reflect the actual trade price at the time), a positive trade price, and a positive volume. Moreover, we require that trade prices are at most 0.5% below (above) the daily low (high) of the quoted bid (ask) according to the daily CRSP files. Finally, we use only stock-days where there are at least 390 NBBO updates. This corresponds to one price update per minute of continuous trading, on average. This ensures price variation as the basis for the calculation of autocorrelations.

In addition, we use daily stock-level option data from OptionMetrics, specifically the gamma and the open interest, to estimate the daily net gamma exposure of options market makers. We further use stock-level data from the Center for Research in Security Prices (CRSP), including opening prices, closing prices, market capitalization, and trading volume. All datasets are merged on the stock-day level.

### 3.2 Return Autocorrelations

Let $p_\tau$ be the log stock price at time $\tau$, measured in seconds at a given trading day.[4] The one-second log return at time $\tau$ (from time $\tau - 1$) is then $r_\tau = p_\tau - p_{\tau-1}$ and the $q$-seconds log return is $r_\tau(q) = \sum_{k=1}^{q} r_{\tau-k+1}$. With this, the standard estimator for the first-order autocorrelation of $q$-seconds log returns for a time period from $\tau$ to $\tau + mq$ is defined as

$$\widehat{\rho_{\tau,m}(q)} = \frac{\frac{1}{m-1}\sum_{j=1}^{m-1} r_{\tau+(j-1)q}(q) \cdot r_{\tau+jq}(q)}{\frac{1}{m}\sum_{j=0}^{m-1} r_{\tau+jq}(q)^2}. \tag{1}$$

We assume that expected returns on these high frequencies are zero, aligning with the literature (e.g., Aït-Sahalia et al., 2011).[5] The standard estimator is however subject to potential sampling effects caused by (arbitrary) starting times in $q$-second return cal-

[4] To improve readability, we suppress the indices $i$ for individual stocks and $t$ for days in the variables.

[5] The measure equals the estimate of $\beta$ in the univariate return regression $r_\tau = \beta r_{\tau-1} + \epsilon_\tau$ (here for $q = 1$). Alternative measures are closely related, but do not show the term structure of return

culations. To reduce these effects, we average over multiple first-order autocorrelations calculated from overlapping $q$-second returns, leading to the estimator

$$\widehat{\rho(q)} = \frac{1}{|\mathcal{K}(q)|} \sum_{k \in \mathcal{K}(q)} \widehat{\rho_{q+k,m_k}}(q), \tag{2}$$

where $m_k = \lfloor (n-k)/q \rfloor$, $\mathcal{K}(q)$ is the set of time shifts $k \in \{0, 1, \ldots, q-1\}$ for which $m_k \geq 2$, and $|\mathcal{K}(q)|$ is the number of elements in $\mathcal{K}(q)$. The autocorrelation according to (2) is simple in interpretation: If there is positive (negative) return autocorrelation, i.e. returns trend (mean-revert), then its value is greater (smaller) than zero.

In addition, we augment the measure (1) to estimate the correlation between the overnight return $r_{Night^-}$ and the subsequent daytime return $r_{Day}$, as well as the correlation between the daytime return and the subsequent overnight return $r_{Night^+}$:

$$\widehat{\rho}^{\langle N^-,D \rangle} = \frac{r_{Night^-} \times r_{Day}}{\frac{1}{2}(r^2_{Night^-} + r^2_{Day})}, \tag{3}$$

$$\widehat{\rho}^{\langle D,N^+ \rangle} = \frac{r_{Day} \times r_{Night^+}}{\frac{1}{2}(r^2_{Day} + r^2_{Night^+})}. \tag{4}$$

Following Akbas et al. (2022), we compute overnight and daytime returns using opening and closing prices from CRSP. These prices are considered most representative, as they reflect auction prices that attract substantial trading volume (Bogousslavsky and Muravyev, 2023).

For each stock $i$ and day $t$, we use tick-level NBBO quotes to calculate mid-quote prices during regular trading hours, from 9:31 and 15:59.[6] We then span a grid of 1-secondly time stamps over the trading day and use the mid-quote prices at or immediately before

autocorrelations straight away. For example, the variance ratio defined as $VR(h) = \frac{Var[r_\tau(h)]}{h \times Var[r_\tau]}$, reveals the term structure of autocorrelations only via the relation $\rho(q) \approx \frac{VR(2q)}{VR(q)} - 1 \; \forall \; q > 1$.

[6] We rely on mid-quote prices to mitigate the bid-ask bounce effect that can exist in high-frequency trade prices. We exclude the first and last minutes of trading to avoid potential distortions from the opening and closing call auctions, as well as data errors. In a robustness check reported later, we repeat the analysis while additionally omitting the first and last 30 minutes of trading, coming to similar conclusions.

the knots. This results in a clock-time grid of 23,280 1-second observations per stock-day. Using Equation (2), we compute intraday return autocorrelations $\widehat{\rho_{i,t}(q)}$ for return horizons ranging from $q = 1$ (1-second log returns) to $q = 11{,}640$ (half-day log returns). This allows us to examine whether the relation between subsequent returns depends on the length of the return interval. Additionally, we employ Equations (3) and (4) to estimate correlations between day and night periods. Figure 1 summarizes all returns used in our calculations.

[Insert Figure 1 Here]

### 3.3 Market Characteristics

In the following, we define the variables used to measure the difficulty of inventory-control management, the degree of asymmetric information, and the net gamma exposure of option market makers.

**Volume.** Our first measure related to inventory control is trading volume, which captures overall market activity and therefore the ease of finding natural counterparties (Lou and Shu, 2017). Therefore, higher trading activity facilitates inventory management by allowing intermediaries to unwind positions more easily. We denote the logarithmic dollar trading volume from CRSP in stock $i$ on day $t$ as $Volume_{i,t}$.

**Realized Spread.** Our second measure related to inventory control is the realized spread, which reflects revenues earned by intermediaries that net out losses to better-informed traders (Conrad et al., 2015). The realized spread can be interpreted as the part of the effective spread that compensates intermediaries for the risk of temporarily holding inventory.[7] This compensation should be higher, when it is more difficult for an intermediary to unwind inventory. In these situations, return reversals from the usage of price pressure should be more pronounced. We estimate the realized half spread of trade $\psi$ in stock $i$ on

[7] More precisely, the realized spread compensates for all risks and costs faced by intermediaries, net of adverse selection costs, such as order processing costs. However, inventory risk likely constitutes a significant portion of this compensation.

day $t$ as the difference between the transaction price $T_{i,t,\psi}$ and the mid-quote 60 seconds later $M_{i,t,\psi}^{+60s}$, formally given by

$$Spread_{i,t,\psi} = \frac{(T_{i,t,\psi} - M_{i,t,\psi}^{+60s}) \times q_{i,t,\psi}}{M_{i,t,\psi}}, \tag{5}$$

where $M_{i,t,\psi}$ is the mid-quote immediately prevailing the trade, and $q_{i,t,\psi}$ is 1 ($-1$) if trade $\langle i,t,\psi \rangle$ is buyer (seller) initiated.[8] The horizon of 60 seconds is often chosen in the literature (e.g., Comerton-Forde et al., 2016). It should be long enough such that prices can adjust to the trade's permanent price impact, but not too long to introduce unrelated noise. We denote $Spread_{i,t}$ as the average of the realized half-spreads between 9:31 and 15:59 for each stock-day. To mitigate the influence of outliers, we winsorize the spreads at the 1st and 99th percentiles before averaging.

**Retail Trading Activity.** The third measure related to inventory control concerns retail trading activity. In the U.S. stock market, most retail orders are executed off-exchange by broker-dealers (Boehmer et al., 2021; Barber et al., 2024). Regulatory data reveal that at least 87% of all customer orders initiated through U.S. retail brokers are executed against the inventories of broker-dealers (SEC, 2024, p. 373). Compared to institutional order flow, retail order flow is more balanced (Hoffmann and Jank, 2024). In addition, imbalances in retail order flow are negatively correlated with imbalances in institutional order flow (Barardehi et al., 2025). These properties of retail order flow ease intermediaries' inventory-control because imbalances within the retail and overall order flow become less pronounced. As a consequence, we expect that a higher retail share in the order flow reduces price reversals caused by inventory-control mechanisms, thereby increasing return autocorrelations (i.e., making them less negative). We use the algorithm of Barber et al. (2024) to identify marketable non-directed retail orders that were executed by broker-dealers. The algorithm classifies off-exchange trades as retail trades when they have subpenny price-improvements and deviate from the prevailing mid-quote by at least 10% of the quoted spread.[9] The percentage proportion of retail trading activity for stock

[8] We use the Lee and Ready (1991) algorithm to sign trades.

[9] Although this algorithm measures retail trading activity with an error (Battalio et al., 2022), the identified order flow still exhibits properties consistent with Hypothesis 1 (Barardehi et al., 2025).

$i$ on day $t$ is then computed by summing up the trading volume over all retail trades and scaling it by the total trading volume:

$$Retail_{i,t} = \frac{Volume_{i,t}^{Retail}}{Volume_{i,t}^{Total}}, \tag{6}$$

where $Volume_{i,t}^{Retail}$ denotes the retail trading volume and $Volume_{i,t}^{Total}$ is the total trading volume.

**Permanent Price Impact.** Due to informational asymmetry, trades have a permanent impact on prices (Glosten and Milgrom, 1985). When informational asymmetry is more pronounced, the permanent price impact of trades is higher, raising the costs of trading.[10] We expect that these elevated trading costs incentivize informed traders to execute their orders more gradually over time to reduce price impact. This gradual execution leads to a more persistent order flow, thereby increasing return autocorrelations (i.e., making them less negative). We measure the permanent price impact as the change in the mid-quote prevailing the trade and the mid-quote 60 seconds later, formally given by

$$Impact_{i,t,\psi} = \frac{(M_{i,t,\psi}^{+60s} - M_{i,t,\psi}) \times q_{i,t,\psi}}{M_{i,t,\psi}}. \tag{7}$$

We then take the average of the price impact between 9:31 and 15:59 for each stock-day and denote this variable as $Impact_{i,t}$. Prior to averaging, we winsorize the price impacts at the 1st and 99th percentile.

**Option Gamma Exposure.** The literature provides evidence that option market makers tend to be net-long calls (Lakonishok et al., 2007; Cici and Palacios, 2015) and net-short puts (Bollen and Whaley, 2004; Gârleanu et al., 2009; Cici and Palacios, 2015).[11] Following Baltussen et al. (2021), Soebhag (2023), and Huang et al. (2023), we exploit this positioning pattern to estimate the net gamma exposure (NGE) of option market makers.

[10] Using absolute intraday returns to proxy for price discovery and informational asymmetry, we empirically verify on the stock level that permanent price impacts in the subsequent trading session increase significantly with the magnitude of the informational asymmetry.

[11] Studies using more granular trader-level data to estimate the option gamma exposure come to similar conclusions (Ni et al., 2021; Barbon et al., 2021).

To this end, we assume that market makers take long positions in calls and short positions in puts and engage in delta-hedging, while end customers do not. We compute the NGE for a call option on stock $i$, on day $t$, with strike $s$, and maturity $m$ as:

$$NGE^{Call}_{i,t,s,m} = \Gamma^{Call}_{i,t,s,m} \times OI^{Call}_{i,t,s,m} \times 100 \times P_{i,t}, \tag{8}$$

where $\Gamma^{Call}_{i,t,s,m}$ is the call option's gamma, $OI^{Call}_{i,t,s,m}$ is the call option's open interest, 100 denotes the adjustment from the option contracts to the number of shares of the underlying, and $P_{i,t}$ is the stock price. For a put option, the NGE is similarly defined as

$$NGE^{Put}_{i,t,s,m} = -1 \times \Gamma^{Put}_{i,t,s,m} \times OI^{Put}_{i,t,s,m} \times 100 \times P_{i,t}, \tag{9}$$

where the additional term $-1$ reflects the net-short positioning in puts. The total (scaled) NGE is obtained by summing over all option contracts:

$$NGE_{i,t} = \underbrace{\left( \sum_s \sum_m NGE^{Call}_{i,t,s,m} + \sum_s \sum_m NGE^{Put}_{i,t,s,m} \right)}_{\text{NGE in \$}} \times \underbrace{\frac{P_{i,t}}{100} \times \frac{1}{\overline{Volume_{i,t}}}}_{\text{Scaling Factors}}, \tag{10}$$

where the first term represents the NGE in dollar terms. This is the amount that market makers must trade for a change of one dollar in $P_{i,t}$. After applying the scaling factors, where $\overline{Volume_{i,t}}$ is the average dollar trading volume over the previous 21 trading days (1 month), $NGE_{i,t}$ can be interpreted as the percentage proportion of the average trading volume that market makers need to trade for a 1% change in the price of the underlying.

Table 1 provides descriptive statistics of the market characteristics. Panel A reports time-series averages of the cross-sectional mean, standard deviation, and quantiles of the variables. The results indicate substantial cross-sectional variation, suggesting a rich setting for investigating their impact on return autocorrelations. Notably, retail trading is sizable, accounting for an average of 7.43% of the daily volume. Moreover, NGE ranges from −3.70% (1% quantile) to 13.46% (99% quantile), consistent with values reported by Soebhag (2023). This highlights that hedging flows from option market makers are economically sizable and have the potential to both amplify and reverse recent returns.

In addition, Panel B reports correlations between the variables. The volume exhibits a substantially negative correlation with both the realized spread (0.52) and the permanent price impact (0.61). This indicates that in stocks with a lot of trading activity – typically large firms – intermediaries can control their inventory more easily and traders possess less private information. Apart from these relationships, absolute correlations between all other variables are rather weak, ranging between 0.01 and 0.41 in absolute terms.

[Insert Table 1 Here]

# 4 Empirical Analysis

## 4.1 Term Structure

### 4.1.1 Baseline Analysis

We now examine the term structure of intraday return autocorrelations. To this end, we use the term structures from the stock-day level, consisting of the autocorrelations $\widehat{\rho_{i,t}(q)}$ for return horizons ranging from $q = 1$ (1-second log returns) to $q = 11{,}640$ (half-day log returns), as well as the correlations between day and night periods ($\widehat{\rho}^{\langle N^-,D\rangle}, \widehat{\rho}^{\langle D,N^+\rangle}$), and average them across all stock-days.

Figure 2 shows the average term structure of intraday return autocorrelations for the full cross-section (Pooled) and for three size groups (Small, Medium, Large) formed according to market capitalization. For selected points along the term structure, the corresponding values are also reported in Table 2. The pooled results indicate that average intraday return autocorrelations are negative, mostly significantly, across almost all return horizons during continuous trading. The term structure exhibits a distinct shape: autocorrelations start at $-0.66\%$ for 1-second returns, increase toward zero ($-0.03\%$) for 20-second returns, decline to a minimum of $-2.70\%$ for 15-minute returns, and then gradually revert toward zero for longer return horizons. This suggests that return reversals are most pronounced at approximately the 15-minute horizon, a finding consistent with transitory price pressures arising from inventory-control procedures. In addition, the convergence of autocorrelations toward zero at shorter return intervals aligns with the presence of positive autocorrelations in order flow imbalances, which could result from the piecewise execution of large parent orders (Chordia et al., 2005; Sadka, 2006). This practice partially offsets the negative return autocorrelation from inventory-control mechanisms. Finally, the sharper drop in autocorrelations at the shortest intervals may reflect price pressures exerted by liquidity-providing high-frequency traders (Menkveld, 2013).[12]

[Insert Figure 2 Here]

Turning to the correlations between returns during the night and the day, we find mixed evidence for return reversals. The correlation between the previous overnight return and the daytime return is significantly negative at $-1.89\%$. However, the correlation between the daytime return and the return in the following overnight interval is statistically insignificant. We interpret this asymmetric pattern as follows. Overnight, trading interest and price-relevant information accumulate and are incorporated into prices at the market opening, contributing to the overnight return. Intermediaries likely provide liquidity at the market opening while imposing a transitory price impact. When the accumulated trading interest is substantial, the transitory component of the overnight return can be pronounced. As natural counterparties arrive during the day, this transitory price impact dissipates, leading to a return reversal and explaining the observed negative correlation between the previous overnight return and the daytime return. But what accounts for the absence of a significant correlation between the daytime return and the subsequent overnight return? Intermediaries may use price pressure during the day to actively mean-revert their inventory toward desired levels by market close. As a result, end-of-day inventories are likely closer to intermediaries' desired levels than at the start of the day (Bogousslavsky, 2016). Consequently, end-of-day price pressures are less pronounced, reducing the absolute correlation between daytime returns and subsequent overnight returns.

The term structures calculated separately for the three size groups exhibit the same overall pattern as described above. However, both the strength of reversals and the return interval at which they are most pronounced tend to increase for smaller stocks. In the top tercile

[12] Reversals in high-frequency mid-quote returns are also consistent with the gradual replenishing of depth in an order book after a marketable order has removed liquidity. The speed of this process is referred to as resilience (Foucault et al., 2015).

(Large), the most negative return autocorrelation is −1.85% at approximately 8-minute intervals. In the middle tercile (Medium), the lowest return autocorrelation is −2.46% at around 14-minute intervals. In the bottom tercile (Small), return autocorrelations reach their lowest point at −3.98% on approximately 18-minute intervals. We observe a similar shift in the correlation between overnight returns and daytime returns, which becomes increasingly negative as firm size decreases. Interpreting market capitalization as a proxy for the presence of various market frictions, the results suggest that specific frictions which are associated with negative return autocorrelations (e.g., asynchronously arriving buyers and sellers) are relatively more present in smaller stocks. While prior studies document increasingly negative autocorrelations for smaller stocks at fixed intraday and daily frequencies (Conrad et al., 2015; Hendershott and Menkveld, 2014), our results extend this evidence by showing that firm size affects not only the magnitude but also the horizon over which return autocorrelations are most pronounced. Finally, it is noteworthy that average return autocorrelations remain relatively close to zero, implying that deviations from weak-form market efficiency, while systematic, are modest overall.

[Insert Table 2 Here]

In summary, we establish that average intraday return autocorrelations are significantly negative across most intraday return horizons. Similarly, correlations between overnight returns and subsequent daytime returns are also significantly negative. The term structure exhibits a distinct shape, with the most pronounced negative autocorrelations occurring at return intervals ranging from approximately 8 minutes for large stocks to 18 minutes for small stocks. These findings indicate the presence of short-term return reversals, which are more pronounced in smaller firms that are subject to greater market frictions.

#### 4.1.2 Further Analysis

To provide further insights and test the robustness of the distinct shape of the term structure, we re-estimate the return autocorrelations with some modifications. We start by investigating the sensitivity of intraday return autocorrelations to the time of day. To this end, we partition the continuous trading hours into three segments: the middle of the day (10:00 to 15:30), the first half hour (9:31 to 10:00), and the last half hour (15:30 to 15:59). Prior empirical evidence suggests that the composition of informed and uninformed traders varies throughout the trading day (e.g., Anand et al., 2005; Dong et al., 2017). While both trader types are similarly present during midday, the opening and closing periods are distinct. The morning period sees heightened activity from informed traders who incorporate private information into prices, whereas the end-of-day period is dominated by uninformed traders executing trades for non-informational reasons. As the informational component of a trade's price impact is permanent (e.g., Glosten and Milgrom, 1985), and private information is incorporated into prices gradually through multiple trades (e.g., Chordia et al., 2005; Comerton-Forde et al., 2016), return reversals are less likely when informed traders are relatively more active. As a consequence, we expect return autocorrelations to increase during periods when informed traders are particularly active.

Panel A of Table 3 reports the return autocorrelations separately for the three partitions of the continuous trading session. During the middle of the day, the term structure of intraday return autocorrelations closely resembles our baseline results, both for the pooled sample and across all three size groups. From that, we conclude that our baseline results are robust. In addition, we find that return autocorrelations in the first half hour tend to be higher than in the last half hour for return horizons up to 5 minutes. Notably, return autocorrelations are significantly positive for most intervals ranging from 1 second to 60 seconds in the first half hour. In contrast, all return intervals in the last half hour exhibit negative autocorrelations. These differences between the opening and closing periods align with variations in the informativeness of the traders operating during these times. Furthermore, this evidence supports and extends prior findings that intraday return autocorrelations tend to be higher in the first half of the trading day than in the second half (Dong et al., 2017).

We also investigate the sensitivity of the correlations between overnight and daytime returns to modifications in the definition of the time periods. Specifically, we consider two modifications: first, we adjust the daytime period to span from 9:45 to 15:45 (±15 Minutes), and second, we modify it to last from 10:00 to 15:30 (±30 Minutes). In turn, we extend the overnight periods to match these changes. Panel B of Table 3 reports the average correlations between returns in the modified daytime and overnight intervals. We observe that the average correlation between the return during the previous night and the return during the day becomes less negative in the pooled sample as well as in each size group, for both modifications. The correlation remains significantly negative only in the small-stock group. This suggests that night-to-day reversals materialize quickly around the opening time. Moreover, the average correlation between the daytime return and the subsequent overnight return is significantly negative only for the small-stock group. This confirms our earlier conclusion that there is few evidence of reversals between daytime returns and the subsequent night returns.

[Insert Table 3 Here]

Next, we explore whether the distinct shape of the term structure persists over time. For this purpose, we re-compute the term structure separately for each calendar year. In addition, we split the year 2020 into the period of the COVID crash (February to March 2020) and the remainder of the year, excluding the crash. Table 4 reports the results for each sub-period. Across all sub-periods, the term structure maintains a similar shape. Most importantly, the term structure consistently shows its distinct minimum between 10-minute and 30-minute return horizons. In addition, during periods of increased volatility – particularly during the 2020 crash and also in 2018 – return autocorrelations for short intervals become significantly positive. These findings have two important implications. First, the overall shape of the term structure is robust, even during periods of crisis. Second, there is some variability in the term structure that may be linked to specific market conditions, which we investigate further in the next section.

[Insert Table 4 Here]

Overall, we conclude that the term structure's shape is robust to various modifications. This suggests that reversals in intraday stock returns are a consistent feature across stocks of different sizes and across different time periods. Furthermore, we provide evidence that return autocorrelations at very high frequencies tend to become positive following periods of market closure and during times of high volatility. Given that substantial price discovery occurs during these periods, this may indicate that a relatively higher presence of informed traders contributes to higher return autocorrelations.

## 4.2 Links to Market Characteristics

### 4.2.1 Baseline Analysis

We now test our hypotheses regarding the relationship between the term structure of return autocorrelations and market characteristics. To examine how these characteristics influence return autocorrelations across different interval lengths, we estimate the following panel regression separately for each return interval $q$:

$$\begin{aligned} \widehat{\rho(q)}_{i,t} =& \alpha + \beta_1 \widetilde{Volume}_{i,t} + \beta_2 \widetilde{Spread}_{i,t} + \beta_3 \widetilde{Retail}_{i,t} \\ & + \beta_4 \widetilde{Impact}_{i,t-1} + \beta_5 \widetilde{NGE}_{i,t} + FE_t + \epsilon_{i,t}, \end{aligned} \tag{11}$$

where $\alpha$ is a constant, $FE_t$ denotes a time fixed effect, and the tildes indicate that the variables have been standardized. For each day, we standardize the independent variables by subtracting their cross-sectional means and scaling their standard deviations to one. This standardization allows us to immediately compare the effect sizes across different variables. The beta coefficients then represent the deviation from the average return autocorrelation due to a one-standard-deviation increase in the respective variable above its mean.[13] The intercepts represent the average return autocorrelations, as reported in the previous section.

[Insert Figure 3 Here]

[Insert Table 5 Here]

Figure 3 illustrates the regression results based on Equation (11). For selected points along the term structure, the corresponding results are also reported in Table 5. We find that

[13]We have also estimated the panel regressions without standardization and with additional firm-fixed effects, coming to the same conclusions.

higher trading volume significantly increases return autocorrelations across most intraday return horizons. Similarly, the correlation between the overnight returns and subsequent daytime returns increases with higher volume. However, the correlation between daytime returns and subsequent overnight returns is not significantly altered and for return intervals of approximately 1 minute to 2 minutes the effect is significantly negative. Regarding the realized spread, we observe that lower spreads are associated with increased return autocorrelations across all return intervals, with the most pronounced effect observed for half-minute returns. Furthermore, a higher share of retail trading activity leads to significantly higher return autocorrelations across all return intervals. Taken together, these findings strongly support Hypothesis 1: when market conditions make it easier for intermediaries to mean-revert their inventories, transitory price pressures diminish, and return autocorrelations become less negative. Moreover, a comparison of the average effect sizes across all return horizons reveals that trading volume (1.07%) and realized spreads (−0.63%) have a relatively larger impact on return autocorrelations than retail trading activity (0.46%).

We also find that when informational asymmetries are more pronounced – indicated by higher permanent price impacts – return autocorrelations tend to increase significantly for most return intervals. There is a significantly positive effect for return intervals between 1 second and 3 minutes, as well as for most return intervals longer than 30 minutes. In between, the effect turns slightly negative.[14] In addition, we find that higher permanent price impacts significantly increase the correlation between overnight returns and subsequent daytime returns. Overall, the predominantly positive effect of the permanent price impact on return autocorrelations supports our rationale that higher trading costs, due to more pronounced informational asymmetry, incentivize informed traders to execute their orders more gradually over time. This, in turn, increases return autocorrelations, consistent with Hypothesis 2.

Turning to the effect of option market makers' hedge adjustments, we observe significantly negative coefficients for all return intervals longer than 5 minutes. The effect size

[14]A possible explanation for the temporarily negative effect is that that the measure of the permanent price impact picks up some transitory effects, which are associated with negative return autocorrelation.

increases for longer return intervals until it stabilizes at around 30 minutes and beyond. This pattern suggests that hedge adjustments do indeed occur at medium frequencies but not at very high frequencies, likely due to transaction costs. In addition, the effect on the correlations between the overnight and subsequent daytime returns as well as between daytime and subsequent overnight returns is also significantly negative. Overall, our findings confirm that option market makers' hedge adjustments play a significant role in shaping return autocorrelations, consistent with Hypothesis 3. However, compared to other market characteristics, their effect size is relatively smaller, suggesting that while gamma hedging affects return dynamics, factors such as trading volume, spreads, and information asymmetry have a more dominant impact.

In regressions based on increasingly longer return horizons $q$, we observe a decline in the explained variance ($R^2$). This pattern arises because longer return horizons reduce the number of available observations at the stock-day level (see Equation 2). The smaller sample size increases the variance of the dependent variable, weakening the model fit. However, our primary focus is on the directional effects of market characteristics on average return autocorrelation. Since the estimated coefficients remain relatively stable, the decline in model fit does not impact our conclusions. For this reason, we show the results for the full term structure.

Next, we examine whether the observed patterns are driven by a specific size group, such as small stocks with larger frictions. For this purpose, we re-estimate the regressions according to Equation (11) separately for each of the three size groups. As before, we standardize the independent variables within each group. Table 6 reports the results for selected points along the term structure. We find that our previous results hold consistently across all size groups. The only notable exception is the effect of gamma exposure, which is mostly insignificant for small stocks. We attribute this finding to the generally lower levels of option gamma exposure in small stocks, with roughly 20% of them having zero gamma exposure on any given day.[15]

[Insert Table 6 Here]

[15] For comparison, fewer than 2% of stocks outside the small-size group have zero option gamma exposure per day.

In summary, we provide strong evidence for links between the term structure of intraday return autocorrelations and the analyzed market characteristics, supporting our Hypotheses 1, 2, and 3.

#### 4.2.2 Robustness

We now verify that our evidence on the links between return autocorrelations and market characteristics is robust. We start by modifying the daytime period to last from 10:00 to 15:30 and the overnight period to last from 15:30 to 10:00. Consequently, the shorter daytime period excludes trading activity that might be driven by the fact that exchanges open and close. Based on this modified framework, we re-calculate the return autocorrelations and then re-estimate the regressions according to Equation (11). The results are shown in Table 7. We detect the same patterns as before, indicating that the relationship between the variables is robust.

[Insert Table 7 Here]

In our main analysis, the time lag between return autocorrelations (the dependent variable) and gamma exposure (an independent variable) supports a causal interpretation of the effects. However, contemporaneous relationships can introduce potential reverse causality, complicating the interpretation. Although our hypotheses provide a strong basis that reverse causality is unlikely to drive our results for trading volume, spread, retail trading activity, and permanent price impact, it is worth closer examination. For this reason, we replace the contemporaneous independent variables with their 1-day lagged counterparts and re-estimate our main model (11). Table 8 shows the results. They closely resemble our main results in Table 5, although the statistical significance of some variables decreases, and the explained variance declines. Since the effects remain detectable even with lagged variables, we conclude that the impact of the contemporaneous variables on return autocorrelations is robust. This moreover shows that the variables have predictive power. Overall, we conclude that our main results are robust.

[Insert Table 8 Here]

## 5 Conclusion

Intraday return autocorrelations have not yet been studied widely across various return horizons. Given that multiple and opposing forces affect return autocorrelations, their relative importance could vary depending on the return horizon. As a consequence, we expect that the degree of autocorrelation depends on the return horizon. We address this gap by constructing and analyzing a term structure of intraday return autocorrelations.

Our results show that average return autocorrelations are mostly negative, and that the degree of autocorrelation depends indeed on the return horizon. On 15-minute horizons, return reversals are most pronounced. On sub-minute horizons, return continuations occur in relatively larger stocks, during periods of market stress, and in the first half hour of trading.

Furthermore, we draw on the literature and derive and test three hypotheses that link intraday return autocorrelations to specific sources of market friction and trading needs that depend systematically on past returns. We provide evidence that return autocorrelations depend on the ease with which intermediaries can mean-revert their inventories, the degree of informational asymmetry, and hedge adjustments of option market makers due to gamma exposure. Finally, despite these distinct and robust patterns in the term structure of return autocorrelations, it is noteworthy that return autocorrelations deviate only modestly from zero. This means deviations from weak-form efficiency are relatively minor after all.

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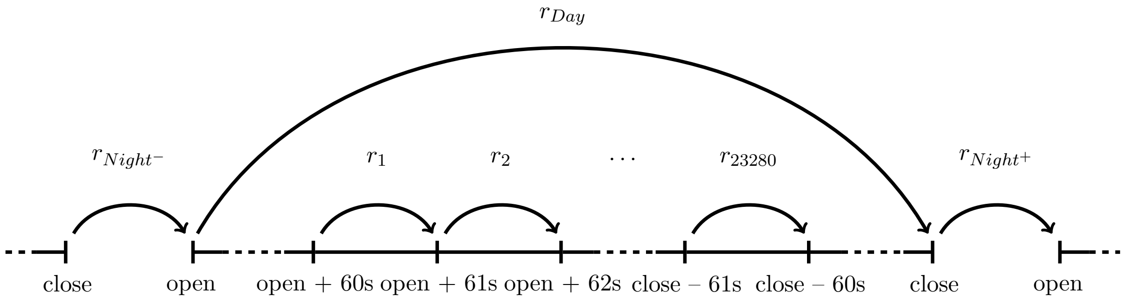


**Figure 1. Intraday Returns.** The Figure summarizes the partitioning of a trading day for the calculation of returns. We exclude both the first and the last minute (60 seconds) of trading in the calculation of 1-second intraday returns to avoid potential distortions from the opening and closing of continuous trading.

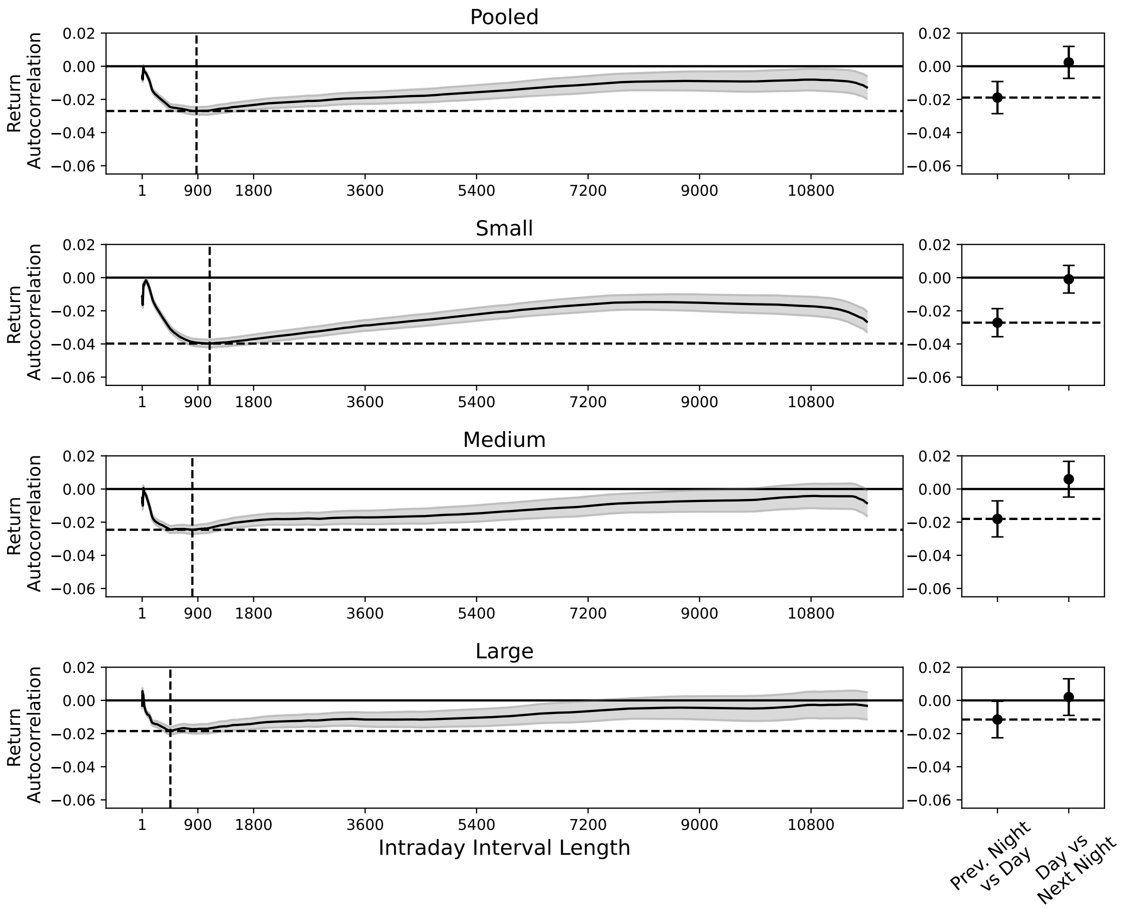


**Figure 2. Term Structure of Intraday Return Autocorrelations.** The figure shows the average autocorrelation of intraday returns for different lengths of return intervals. The intraday interval length is given in seconds. The term structure is computed as follows: First, the autocorrelation is calculated from Equation (2) for each stock-day and interval length $q$. Second, the autocorrelations are averaged for each interval length. Prior to averaging, the autocorrelations for each day and interval length are winsorized at the 1% and 99% quantiles. 95% confidence intervals are shown in gray and by whiskers. Inference is based on robust standard errors clustered by firm and day. Results are shown for the entire cross-section (Pooled), and for three size groups (Small, Medium, Large) formed according to terciles of 1-day lagged market capitalization. The dashed lines mark the lowest values. The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

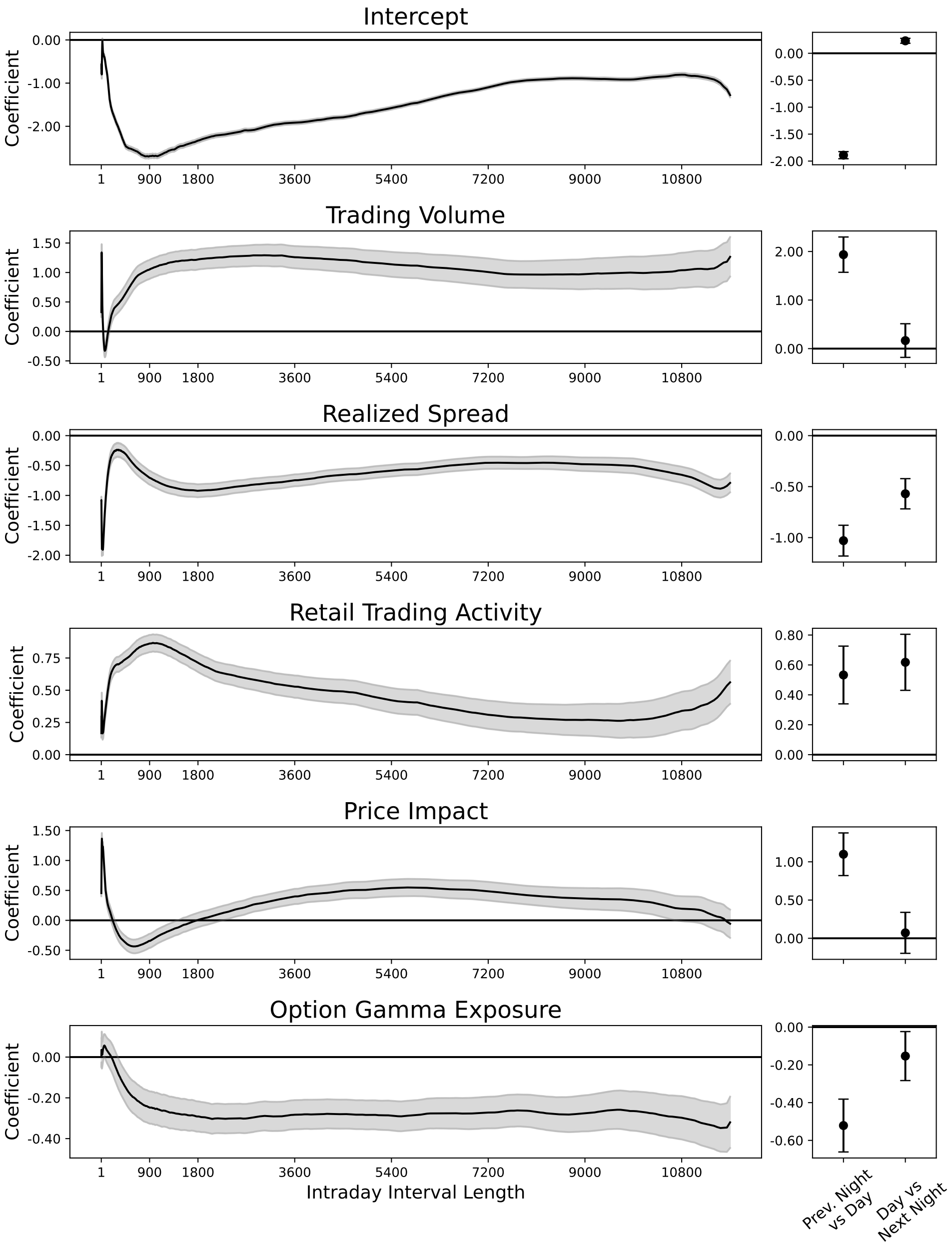


**Figure 3. Links to Market Characteristics.** The figure shows the estimated coefficients for the regressions according to Equation (11). A separate regression is estimated for each interval $q$. The coefficients from the respective regressions are shown in separate graphs for each independent variable. All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor $10^2$. 95% confidence intervals are shown in gray and by whiskers. Inference is based on robust standard errors clustered by firm and day. The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

**Table 1. Descriptive Statistics.** The table provides descriptive statistics of the independent variables. Panel A reports the mean, the standard deviation and quantiles of the variables. Panel B reports correlations between the variables. The statistics are calculated for each day and subsequently averaged over all days. All variables are winsorized at the 1% and 99% quantiles for each day. *Volume* represents the logarithmic dollar trading volume, *Spread* is the average realized spread per trade, *Retail* is the percentage proportion of retail trading volume over the total trading volume, *Impact* is the average permanent price impact per trade, and *NGE* is the net gamma exposure of option market makers. The variables *Spread* and *Impact* are reported in basis points, the variables *Retail* and *NGE* are reported in percentage points. The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

Panel A: Cross-Sectional Summary Statistics

| | *Volume* | *Spread* | *Retail* | *Impact* | *NGE* |
|---|---|---|---|---|---|
| Mean | 16.72 | 2.43 | 7.43 | 4.72 | 0.94 |
| Std. | 1.79 | 4.83 | 4.81 | 3.96 | 2.35 |
| 0.01 | 12.98 | −2.27 | 1.13 | 0.53 | −3.70 |
| 0.10 | 14.35 | −0.29 | 2.89 | 1.24 | −0.43 |
| 0.25 | 15.40 | 0.11 | 4.22 | 2.06 | −0.01 |
| 0.50 | 16.69 | 0.78 | 6.14 | 3.55 | 0.31 |
| 0.75 | 18.01 | 2.62 | 9.18 | 6.00 | 1.19 |
| 0.90 | 19.11 | 6.97 | 13.82 | 9.65 | 2.97 |
| 0.99 | 20.84 | 27.48 | 25.68 | 21.74 | 13.46 |

Panel B: Cross-Sectional Correlations

| | *Volume* | *Spread* | *Retail* | *Impact* | *NGE* |
|---|---|---|---|---|---|
| *Volume* | 1.00 | – | – | – | – |
| *Spread* | −0.52 | 1.00 | – | – | – |
| *Retail* | −0.01 | 0.12 | 1.00 | – | – |
| *Impact* | −0.61 | 0.41 | 0.27 | 1.00 | – |
| *NGE* | 0.22 | −0.09 | 0.06 | −0.13 | 1.00 |

**Table 2. Term Structure of Intraday Return Autocorrelations.** The table reports return autocorrelations for various intervals $q$ (seconds) and size groups formed according to terciles of 1-day lagged market capitalization (Pooled, Small, Medium, Large). All variables are winsorized at the 1% and 99% quantiles for each day. All coefficients are multiplied by the factor $10^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

| | $\widehat{\rho(q)}$ | | | |
|---|---|---|---|---|
| $q$ | Pooled | Small | Medium | Large |
| 1 | −0.66*** | −1.12*** | −0.53*** | −0.32*** |
| 20 | −0.03 | −0.44*** | +0.06 | +0.28*** |
| 40 | −0.33*** | −0.32*** | −0.23** | −0.43*** |
| 60 | −0.40*** | −0.16* | −0.36*** | −0.68*** |
| 300 | −1.98*** | −2.23*** | −2.15*** | −1.56*** |
| 600 | −2.55*** | −3.55*** | −2.41*** | −1.71*** |
| 900 | −2.69*** | −3.93*** | −2.42*** | −1.72*** |
| 1800 | −2.33*** | −3.70*** | −1.90*** | −1.39*** |
| 3600 | −1.92*** | −2.88*** | −1.71*** | −1.16*** |
| 5400 | −1.56*** | −2.19*** | −1.46*** | −1.04*** |
| 7200 | −1.08*** | −1.60*** | −1.00*** | −0.64* |
| 9000 | −0.90** | −1.52*** | −0.72* | −0.45 |
| 10800 | −0.81* | −1.74*** | −0.42 | −0.27 |
| 11640 | −1.28*** | −2.66*** | −0.85* | −0.33 |
| $\langle N^-, D\rangle$ | −1.89*** | −2.72*** | −1.80** | −1.15* |
| $\langle D, N^+\rangle$ | +0.23 | −0.10 | +0.59 | +0.20 |

**Table 3. Term Structure of Intraday Return Autocorrelations with Modified Specifications.** The table reports return autocorrelations for various intervals $q$ (seconds) and size groups. Panel A shows results separately for returns during the middle of the day (10:00 to 15:30), the first half hour (9:31 to 10:00), and the last half hour (15:30 to 15:59). Panel B reports results for modified day and night periods, where the day (night) period is shorted (extended) by shifting the start of the day period 15 (30) minutes after the open and the end 15 (30) minutes before the close. All variables are winsorized at the 1% and 99% quantiles for each day. All coefficients are multiplied by the factor $10^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

$\widehat{\rho(q)}$

Panel A: Separating Middle of the Day, First Half Hour and Last Half Hour Periods

| | 10:00 to 15:30 | | | | 9:31 to 10:00 | | | | 15:30 to 15:59 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $q$ | Pooled | Small | Medium | Large | Pooled | Small | Medium | Large | Pooled | Small | Medium | Large |
| 1 | −0.85$^{***}$ | −1.14$^{***}$ | −0.76$^{***}$ | −0.64$^{***}$ | 0.35$^{***}$ | −0.12$^{*}$ | 0.55$^{***}$ | 0.63$^{***}$ | −0.71$^{***}$ | −1.16$^{***}$ | −0.82$^{***}$ | −0.15$^{*}$ |
| 20 | −0.15$^{**}$ | −0.57$^{***}$ | −0.06 | 0.18$^{*}$ | 1.56$^{***}$ | 1.77$^{***}$ | 1.60$^{***}$ | 1.31$^{***}$ | −0.98$^{***}$ | −1.31$^{***}$ | −0.99$^{***}$ | −0.65$^{***}$ |
| 40 | −0.40$^{***}$ | −0.39$^{***}$ | −0.31$^{***}$ | −0.52$^{***}$ | 1.41$^{***}$ | 2.11$^{***}$ | 1.55$^{***}$ | 0.57$^{***}$ | −1.36$^{***}$ | −1.73$^{***}$ | −1.59$^{***}$ | −0.76$^{***}$ |
| 60 | −0.46$^{***}$ | −0.15$^{*}$ | −0.43$^{***}$ | −0.79$^{***}$ | 1.33$^{***}$ | 2.21$^{***}$ | 1.47$^{***}$ | 0.32$^{**}$ | −1.44$^{***}$ | −1.97$^{***}$ | −1.68$^{***}$ | −0.66$^{***}$ |
| 300 | −1.98$^{***}$ | −2.20$^{***}$ | −2.10$^{***}$ | −1.64$^{***}$ | −0.47$^{**}$ | 0.19 | −0.96$^{***}$ | −0.65$^{***}$ | −1.50$^{***}$ | −2.39$^{***}$ | −1.15$^{***}$ | −0.95$^{**}$ |
| 600 | −2.54$^{***}$ | −3.42$^{***}$ | −2.35$^{***}$ | −1.85$^{***}$ | −1.25$^{***}$ | −1.92$^{***}$ | −1.42$^{***}$ | −0.40 | −0.82$^{**}$ | −1.93$^{***}$ | −0.53 | −0.01 |
| 900 | −2.69$^{***}$ | −3.85$^{***}$ | −2.35$^{***}$ | −1.88$^{***}$ | | | | | | | | |
| 1800 | −2.33$^{***}$ | −3.70$^{***}$ | −1.89$^{***}$ | −1.40$^{***}$ | | | | | | | | |
| 3600 | −1.75$^{***}$ | −2.69$^{***}$ | −1.54$^{***}$ | −1.03$^{***}$ | | | | | | | | |
| 5400 | −1.34$^{***}$ | −1.84$^{***}$ | −1.28$^{***}$ | −0.89$^{**}$ | | | | | | | | |
| 7200 | −0.99$^{***}$ | −1.39$^{***}$ | −0.93$^{**}$ | −0.64 | | | | | | | | |
| 9000 | −0.77$^{*}$ | −1.28$^{***}$ | −0.65 | −0.40 | | | | | | | | |

Panel B: Shifting Day and Night Periods

| | ±15 Minutes | | | | ±30 Minutes | | | |
|---|---|---|---|---|---|---|---|---|
| $q$ | Pooled | Small | Medium | Large | Pooled | Small | Medium | Large |
| $\langle N^-, D\rangle$ | −0.81 | −1.18$^{**}$ | −0.77 | −0.48 | −0.63 | −1.05$^{**}$ | −0.66 | −0.19 |
| $\langle D, N^+\rangle$ | −0.42 | −1.57$^{***}$ | −0.12 | 0.44 | −0.09 | −1.12$^{**}$ | 0.27 | 0.57 |

**Table 4. Term Structure of Intraday Return Autocorrelations by Subperiod.** The table reports the return autocorrelations for various intervals $q$ (seconds) and calendar years. The year 2020 is split into the period of the COVID crash during February and March (2020b) and the remaining period excluding the crash (2020a). All variables are winsorized at the 1% and 99% quantiles for each day. All coefficients are multiplied by the factor $10^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

| | $\widehat{\rho(q)}$ | | | | | |
|---|---|---|---|---|---|---|
| $q$ | 2017 | 2018 | 2019 | 2020a | 2020b | 2021 |
| 1 | 0.02 | $1.08^{***}$ | 0.11 | $-1.58^{***}$ | $-1.36^{***}$ | $-2.27^{***}$ |
| 20 | 0.02 | $0.56^{***}$ | $-0.30^{**}$ | $-0.09$ | $1.39^{**}$ | $-0.45^{***}$ |
| 40 | $-0.50^{***}$ | $0.26^{**}$ | $-0.69^{***}$ | $-0.13$ | $2.20^{***}$ | $-0.83^{***}$ |
| 60 | $-0.79^{***}$ | 0.11 | $-0.79^{***}$ | $-0.21$ | $2.71^{***}$ | $-0.75^{***}$ |
| 300 | $-2.23^{***}$ | $-1.79^{***}$ | $-2.07^{***}$ | $-2.19^{***}$ | 0.35 | $-2.03^{***}$ |
| 600 | $-2.95^{***}$ | $-2.20^{***}$ | $-2.83^{***}$ | $-2.28^{***}$ | $-1.64$ | $-2.63^{***}$ |
| 900 | $-2.55^{***}$ | $-2.19^{***}$ | $-3.24^{***}$ | $-2.55^{***}$ | $-2.13^{*}$ | $-2.90^{***}$ |
| 1800 | $-2.78^{***}$ | $-1.63^{***}$ | $-2.70^{***}$ | $-2.13^{***}$ | $-2.80^{***}$ | $-2.31^{***}$ |
| 3600 | $-2.71^{***}$ | $-0.86$ | $-2.07^{***}$ | $-2.26^{***}$ | $-2.67^{*}$ | $-1.66^{***}$ |
| 5400 | $-2.73^{***}$ | $-0.14$ | $-1.45^{**}$ | $-1.68^{**}$ | $-2.24$ | $-1.70^{***}$ |
| 7200 | $-2.04^{***}$ | 0.72 | $-1.40^{**}$ | $-0.94$ | $-0.61$ | $-1.63^{**}$ |
| 9000 | $-1.43^{**}$ | 1.16 | $-1.39^{*}$ | $-0.87$ | 0.05 | $-1.79^{**}$ |
| 10800 | $-1.30^{*}$ | 0.88 | $-1.38^{*}$ | $-0.48$ | 1.33 | $-1.77^{**}$ |
| 11640 | $-1.55^{*}$ | 0.10 | $-1.57^{*}$ | $-0.83$ | $-0.05$ | $-2.35^{***}$ |
| $\langle N^-, D\rangle$ | $-2.85^{***}$ | $-3.03^{**}$ | $-0.50$ | $-2.58$ | $7.54^{*}$ | $-2.26^{*}$ |
| $\langle D, N^+\rangle$ | $-1.22$ | $-1.10$ | 0.14 | 2.11 | $-0.59$ | 1.12 |

**Table 5. Links to Market Characteristics.** The table shows the estimated coefficients for the regression according to Equation (11). A separate regression is estimated for selected intervals $q$ (seconds), including all sample stocks. All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor $10^2$. The last rows indicate time fixed effects, the number of observations, and the adjusted $R^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

| | $\widehat{\rho(q)}$ | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | 1 | 20 | 40 | 60 | 300 | 600 | 900 | 1800 | 3600 | 5400 | 7200 | 9000 | 10800 | 11640 | $\langle N^-, D\rangle$ | $\langle D, N^+\rangle$ |
| $\alpha$ | $-0.66^{***}$ | $-0.03$ | $-0.33^{***}$ | $-0.40^{***}$ | $-1.98^{***}$ | $-2.55^{***}$ | $-2.69^{***}$ | $-2.33^{***}$ | $-1.92^{***}$ | $-1.56^{***}$ | $-1.08^{***}$ | $-0.90^{***}$ | $-0.81^{***}$ | $-1.28^{***}$ | $-1.89^{***}$ | $0.23^{***}$ |
| | (−27.1) | (−0.89) | (−11.2) | (−14.7) | (−75.3) | (−98.0) | (−104.2) | (−96.8) | (−95.6) | (−83.3) | (−63.5) | (−48.9) | (−36.0) | (−47.3) | (−56.0) | (9.92) |
| $Volume_{i,t}$ | $0.33^{***}$ | $0.40^{***}$ | $-0.10$ | $-0.32^{***}$ | $0.45^{***}$ | $0.86^{***}$ | $1.06^{***}$ | $1.22^{***}$ | $1.26^{***}$ | $1.13^{***}$ | $1.00^{***}$ | $0.98^{***}$ | $1.04^{***}$ | $1.27^{***}$ | $1.94^{***}$ | $0.17$ |
| | (7.33) | (7.02) | (−1.78) | (−5.69) | (6.04) | (10.70) | (12.77) | (13.96) | (13.01) | (10.49) | (8.47) | (7.42) | (6.83) | (7.37) | (10.43) | (0.94) |
| $Spread_{i,t}$ | $-1.08^{***}$ | $-1.86^{***}$ | $-1.74^{***}$ | $-1.36^{***}$ | $-0.24^{***}$ | $-0.48^{***}$ | $-0.71^{***}$ | $-0.92^{***}$ | $-0.75^{***}$ | $-0.58^{***}$ | $-0.45^{***}$ | $-0.48^{***}$ | $-0.67^{***}$ | $-0.79^{***}$ | $-1.03^{***}$ | $-0.57^{***}$ |
| | (−38.0) | (−39.9) | (−37.9) | (−29.1) | (−4.01) | (−7.98) | (−11.9) | (−16.6) | (−14.6) | (−11.5) | (−8.67) | (−8.18) | (−9.54) | (−9.74) | (−13.4) | (−7.54) |
| $Retail_{i,t}$ | $0.17^{***}$ | $0.18^{***}$ | $0.19^{***}$ | $0.28^{***}$ | $0.70^{***}$ | $0.80^{***}$ | $0.86^{***}$ | $0.71^{***}$ | $0.53^{***}$ | $0.42^{***}$ | $0.31^{***}$ | $0.27^{***}$ | $0.34^{***}$ | $0.56^{***}$ | $0.53^{***}$ | $0.62^{***}$ |
| | (9.23) | (7.01) | (7.82) | (11.6) | (23.7) | (24.2) | (25.3) | (19.3) | (11.9) | (8.51) | (5.49) | (4.28) | (4.50) | (6.55) | (5.41) | (6.46) |
| $Impact_{i,t}$ | $0.45^{***}$ | $1.22^{***}$ | $1.09^{***}$ | $0.73^{***}$ | $-0.20^{***}$ | $-0.43^{***}$ | $-0.34^{***}$ | $0.01$ | $0.40^{***}$ | $0.54^{***}$ | $0.48^{***}$ | $0.36^{***}$ | $0.19$ | $-0.06$ | $1.10^{***}$ | $0.07$ |
| | (16.8) | (31.6) | (27.2) | (17.5) | (−3.82) | (−7.46) | (−5.66) | (0.15) | (6.16) | (7.43) | (6.01) | (3.99) | (1.78) | (−0.47) | (7.72) | (0.52) |
| $NGE_{i,t-1}$ | $0.00$ | $0.01$ | $0.05$ | $0.06$ | $-0.07$ | $-0.20^{***}$ | $-0.25^{***}$ | $-0.29^{***}$ | $-0.28^{***}$ | $-0.29^{***}$ | $-0.27^{***}$ | $-0.28^{***}$ | $-0.30^{***}$ | $-0.32^{***}$ | $-0.52^{***}$ | $-0.15^{*}$ |
| | (0.05) | (0.46) | (1.68) | (1.91) | (−1.86) | (−4.88) | (−6.13) | (−7.67) | (−7.73) | (−7.75) | (−6.84) | (−6.05) | (−5.52) | (−4.98) | (−7.30) | (−2.32) |
| $FE_t$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| #Obs. | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ |
| $R^2$ | 7.14% | 9.02% | 5.44% | 2.69% | 0.64% | 1.14% | 1.22% | 0.82% | 0.34% | 0.16% | 0.08% | 0.06% | 0.06% | 0.07% | 0.12% | 0.02% |

**Table 6. Links to Market Characteristics by Size.** The table shows the estimated coefficients for the regression according to Equation (11). A separate regression is estimated for selected intervals $q$ (seconds) and three size groups formed according to terciles of market capitalization (Small, Medium, Large). All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor $10^2$. The last rows indicate time fixed effects, the number of observations, and the adjusted $R^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

| | $\widehat{\rho(q)}$ | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Small | | | | | Medium | | | | | Large | | | | |
| Variable | 60 | 900 | 3600 | $\langle N^-, D\rangle$ | $\langle D, N^+\rangle$ | 60 | 900 | 3600 | $\langle N^-, D\rangle$ | $\langle D, N^+\rangle$ | 60 | 900 | 3600 | $\langle N^-, D\rangle$ | $\langle D, N^+\rangle$ |
| $\alpha$ | $-0.16^{***}$ | $-3.93^{***}$ | $-2.88^{***}$ | $-2.72^{***}$ | $-0.10^{*}$ | $-0.36^{***}$ | $-2.42^{***}$ | $-1.71^{***}$ | $-1.80^{***}$ | $0.59^{***}$ | $-0.68^{***}$ | $-1.72^{***}$ | $-1.16^{***}$ | $-1.15^{***}$ | $0.20^{***}$ |
| | (−4.05) | (−89.7) | (−78.9) | (−55.6) | (−2.55) | (−7.92) | (−71.7) | (−61.3) | (−31.4) | (24.7) | (−19.3) | (−54.7) | (−39.6) | (−19.4) | (4.69) |
| $Volume_{i,t}$ | $-0.49^{***}$ | $1.68^{***}$ | $1.59^{***}$ | $2.27^{***}$ | $0.62^{***}$ | $-0.19^{***}$ | $1.11^{***}$ | $1.17^{***}$ | $1.76^{***}$ | $0.49^{**}$ | $-0.13$ | $0.49^{***}$ | $0.70^{***}$ | $1.70^{***}$ | $-0.22$ |
| | (−11.8) | (29.2) | (21.8) | (15.4) | (4.51) | (−4.20) | (18.1) | (13.2) | (8.95) | (2.65) | (−1.71) | (3.33) | (6.03) | (9.29) | (−1.31) |
| $Spread_{i,t}$ | $-1.65^{***}$ | $-0.33^{***}$ | $-0.57^{***}$ | $-0.94^{***}$ | $-0.54^{***}$ | $-1.50^{***}$ | $-0.58^{***}$ | $-0.52^{***}$ | $-0.52^{***}$ | $-0.16$ | $-1.58^{***}$ | $-0.85^{***}$ | $-0.62^{***}$ | $-0.90^{***}$ | $-0.09$ |
| | (−32.53) | (−5.27) | (−9.35) | (−9.14) | (−5.50) | (−19.5) | (−7.75) | (−7.60) | (−4.51) | (−1.62) | (−15.5) | (−4.26) | (−4.76) | (−6.68) | (−0.96) |
| $Retail_{i,t}$ | $0.30^{***}$ | $1.22^{***}$ | $0.83^{***}$ | $0.59^{***}$ | $0.72^{***}$ | $0.31^{***}$ | $0.57^{***}$ | $0.35^{***}$ | $0.40^{***}$ | $0.42^{***}$ | $0.27^{***}$ | $0.36^{***}$ | $0.03$ | $0.03$ | $0.71^{***}$ |
| | (8.99) | (27.03) | (14.10) | (4.71) | (5.95) | (9.18) | (13.65) | (6.60) | (3.64) | (3.92) | (8.02) | (6.29) | (0.54) | (0.24) | (6.40) |
| $Impact_{i,t}$ | $0.77^{***}$ | $-0.53^{***}$ | $0.36^{***}$ | $0.84^{***}$ | $0.10$ | $0.58^{***}$ | $-0.26^{***}$ | $0.15^{*}$ | $0.60^{***}$ | $-0.11$ | $0.74^{***}$ | $0.01$ | $0.09$ | $0.70^{***}$ | $0.22$ |
| | (21.2) | (−11.3) | (6.37) | (6.75) | (0.82) | (14.07) | (−5.16) | (2.51) | (4.46) | (−0.88) | (9.56) | (0.07) | (0.86) | (4.76) | (1.53) |
| $NGE_{i,t-1}$ | $0.08^{**}$ | $0.07$ | $-0.03$ | $-0.03$ | $0.06$ | $0.05^{*}$ | $-0.16^{***}$ | $-0.17^{***}$ | $-0.43^{***}$ | $-0.04$ | $0.02$ | $-0.36^{***}$ | $-0.41^{***}$ | $-0.74^{***}$ | $-0.28^{**}$ |
| | (2.71) | (1.72) | (−0.68) | (−0.36) | (0.85) | (2.08) | (−4.62) | (−4.38) | (−4.50) | (−0.46) | (0.45) | (−5.70) | (−7.08) | (−6.67) | (−2.70) |
| $FE_t$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| #Obs. | 898$K$ | 898$K$ | 898$K$ | 898$K$ | 898$K$ | 900$K$ | 900$K$ | 900$K$ | 900$K$ | 900$K$ | 901$K$ | 901$K$ | 901$K$ | 901$K$ | 901$K$ |
| $R^2$ | 3.94% | 1.95% | 0.59% | 0.23% | 0.04% | 3.40% | 1.07% | 0.30% | 0.11% | 0.02% | 4.05% | 0.51% | 0.13% | 0.08% | 0.01% |

**Table 7. Links to Market Characteristics with Modified Specifications.** The table shows the estimated coefficients for the regression according to Equation (11). A separate regression is estimated for selected intervals $q$ (seconds), including all sample stocks. In contrast to Table 5, the specifications of the day and night periods are modified: The day (night) period is shorted (extended) by shifting the start of the day period 30 minutes after the open and the end 30 minutes before the close. All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor $10^2$. The last rows indicate time fixed effects, the number of observations, and the adjusted $R^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

| | $\widehat{\rho(q)}$ | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | 1 | 20 | 40 | 60 | 300 | 600 | 900 | 1800 | 3600 | 5400 | 7200 | 9000 | $\langle N^-, D\rangle$ | $\langle D, N^+\rangle$ |
| $\alpha$ | $-0.85^{***}$ | $-0.15^{**}$ | $-0.40^{***}$ | $-0.46^{***}$ | $-1.98^{***}$ | $-2.54^{***}$ | $-2.69^{***}$ | $-2.33^{***}$ | $-1.75^{***}$ | $-1.34^{***}$ | $-0.99^{***}$ | $-0.77^{*}$ | $-0.63^{***}$ | $-0.09^{***}$ |
| | (−19.1) | (−2.77) | (−7.38) | (−7.99) | (−22.9) | (−24.3) | (−21.6) | (−15.1) | (−8.66) | (−5.38) | (−3.37) | (−2.19) | (−20.3) | (−4.30) |
| $Volume_{i,t}$ | $0.27^{***}$ | $0.42^{***}$ | $-0.11^{*}$ | $-0.39^{***}$ | $0.17^{*}$ | $0.49^{***}$ | $0.74^{***}$ | $1.08^{***}$ | $1.13^{***}$ | $0.97^{***}$ | $0.88^{***}$ | $0.91^{***}$ | $2.00^{***}$ | 0.17 |
| | (5.80) | (7.10) | (−2.04) | (−6.97) | (2.33) | (6.02) | (8.77) | (12.1) | (11.1) | (8.47) | (6.84) | (5.88) | (10.4) | (0.90) |
| $Spread_{i,t}$ | $-1.01^{***}$ | $-1.74^{***}$ | $-1.59^{***}$ | $-1.23^{***}$ | $-0.18^{**}$ | $-0.42^{***}$ | $-0.62^{***}$ | $-0.78^{***}$ | $-0.63^{***}$ | $-0.46^{***}$ | $-0.38^{***}$ | $-0.38^{***}$ | $-0.30^{***}$ | $-0.86^{***}$ |
| | (−34.8) | (−36.7) | (−34.3) | (−26.2) | (−3.13) | (−7.09) | (−10.4) | (−13.9) | (−12.2) | (−8.74) | (−6.77) | (−5.56) | (−3.36) | (−10.2) |
| $Retail_{i,t}$ | $0.15^{***}$ | $0.14^{***}$ | $0.15^{***}$ | $0.23^{***}$ | $0.62^{***}$ | $0.72^{***}$ | $0.81^{***}$ | $0.65^{***}$ | $0.45^{***}$ | $0.33^{***}$ | $0.25^{***}$ | $0.17^{*}$ | $1.01^{***}$ | $0.22^{*}$ |
| | (7.96) | (5.13) | (6.10) | (9.51) | (21.5) | (22.4) | (23.4) | (16.6) | (9.66) | (6.19) | (4.07) | (2.29) | (10.3) | (2.32) |
| $Impact_{i,t}$ | $0.52^{***}$ | $1.19^{***}$ | $1.02^{***}$ | $0.70^{***}$ | $-0.39^{***}$ | $-0.65^{***}$ | $-0.53^{***}$ | $-0.13^{*}$ | $0.32^{***}$ | $0.50^{***}$ | $0.47^{***}$ | $0.41^{***}$ | $0.79^{***}$ | $-0.39^{**}$ |
| | (19.5) | (29.9) | (25.4) | (16.7) | (−7.39) | (−11.1) | (−8.57) | (−2.12) | (4.65) | (6.34) | (5.38) | (3.75) | (5.60) | (−2.83) |
| $NGE_{i,t-1}$ | 0.01 | 0.02 | 0.05 | 0.06 | −0.03 | $-0.16^{***}$ | $-0.21^{***}$ | $-0.25^{***}$ | $-0.26^{***}$ | $-0.25^{***}$ | $-0.25^{***}$ | $-0.27^{***}$ | $-0.50^{***}$ | $-0.15^{*}$ |
| | (0.42) | (0.63) | (1.56) | (1.92) | (−0.78) | (−3.96) | (−5.15) | (−6.50) | (−7.02) | (−6.42) | (−5.87) | (−5.09) | (−7.01) | (−2.29) |
| $FE_t$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| #Obs. | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ |
| $R^2$ | 6.19% | 8.00% | 4.64% | 2.32% | 0.42% | 0.77% | 0.83% | 0.58% | 0.22% | 0.09% | 0.05% | 0.03% | 0.09% | 0.03% |

**Table 8. Links to Non-Contemporaneous Market Characteristics.** The table shows the estimated coefficients for the regression according to Equation (11). A separate regression is estimated for selected return intervals $q$ (seconds), including all sample stocks. All variables are winsorized at the 1% and 99% quantiles for each day. Independent variables are subsequently normalized by subtracting their means and scaling their standard deviations to one for each day. All coefficients are multiplied by the factor $10^2$. The last rows indicate time fixed effects, the number of observations, and the adjusted $R^2$. Inference is based on standard errors clustered by time $t$ and firm $i$. T-statistics are reported in parenthesis. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). The sample consists of the cross-section of U.S. stocks between 2017 and 2021.

| | $\widehat{\rho(q)}$ | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | 1 | 20 | 40 | 60 | 300 | 600 | 900 | 1800 | 3600 | 5400 | 7200 | 9000 | 10800 | 11640 | $\langle N^-, D\rangle$ | $\langle D, N^+\rangle$ |
| $\alpha$ | $-0.66^{***}$ | $-0.03$ | $-0.33^{***}$ | $-0.40^{***}$ | $-1.98^{***}$ | $-2.55^{***}$ | $-2.69^{***}$ | $-2.33^{***}$ | $-1.92^{***}$ | $-1.56^{***}$ | $-1.08^{***}$ | $-0.90^{***}$ | $-0.81^{***}$ | $-1.28^{***}$ | $-1.89^{***}$ | $0.23^{***}$ |
| | $(-26.7)$ | $(-0.87)$ | $(-11.1)$ | $(-14.6)$ | $(-75.6)$ | $(-101)$ | $(-109)$ | $(-105)$ | $(-111)$ | $(-99.1)$ | $(-77.8)$ | $(-58.6)$ | $(-40.7)$ | $(-50.4)$ | $(-66.2)$ | $(9.96)$ |
| $Volume_{i,t-1}$ | $0.21^{***}$ | $0.09$ | $-0.41^{***}$ | $-0.59^{***}$ | $0.18^{*}$ | $0.56^{***}$ | $0.71^{***}$ | $0.67^{***}$ | $0.52^{***}$ | $0.37^{***}$ | $0.29^{*}$ | $0.31^{*}$ | $0.47^{**}$ | $0.81^{***}$ | $0.43^{*}$ | $-0.04$ |
| | $(4.68)$ | $(1.68)$ | $(-7.95)$ | $(-11.06)$ | $(2.57)$ | $(7.46)$ | $(9.27)$ | $(8.36)$ | $(5.78)$ | $(3.57)$ | $(2.52)$ | $(2.45)$ | $(3.21)$ | $(4.94)$ | $(2.40)$ | $(-0.23)$ |
| $Spread_{i,t-1}$ | $-0.84^{***}$ | $-1.24^{***}$ | $-1.07^{***}$ | $-0.88^{***}$ | $-0.32^{***}$ | $-0.55^{***}$ | $-0.72^{***}$ | $-0.82^{***}$ | $-0.60^{***}$ | $-0.43^{***}$ | $-0.32^{***}$ | $-0.35^{***}$ | $-0.54^{***}$ | $-0.69^{***}$ | $-0.77^{***}$ | $-0.56^{***}$ |
| | $(-30.0)$ | $(-26.4)$ | $(-23.3)$ | $(-18.9)$ | $(-5.89)$ | $(-10.0)$ | $(-13.3)$ | $(-15.9)$ | $(-12.5)$ | $(-8.97)$ | $(-6.40)$ | $(-6.15)$ | $(-7.97)$ | $(-8.93)$ | $(-10.2)$ | $(-7.42)$ |
| $Retail_{i,t-1}$ | $0.22^{***}$ | $0.31^{***}$ | $0.31^{***}$ | $0.33^{***}$ | $0.43^{***}$ | $0.42^{***}$ | $0.45^{***}$ | $0.29^{***}$ | $0.14^{***}$ | $0.10^{*}$ | $0.06$ | $0.00$ | $0.02$ | $0.17^{*}$ | $-0.02$ | $0.50^{***}$ |
| | $(12.0)$ | $(12.3)$ | $(13.2)$ | $(14.1)$ | $(15.8)$ | $(14.7)$ | $(14.8)$ | $(8.71)$ | $(3.36)$ | $(2.22)$ | $(1.08)$ | $(0.01)$ | $(0.21)$ | $(2.07)$ | $(-0.26)$ | $(5.23)$ |
| $Impact_{i,t-1}$ | $0.10^{***}$ | $0.27^{***}$ | $0.09^{*}$ | $-0.03$ | $-0.28^{***}$ | $-0.46^{***}$ | $-0.42^{***}$ | $-0.33^{***}$ | $-0.13^{*}$ | $-0.04$ | $-0.04$ | $-0.05$ | $-0.04$ | $-0.10$ | $-0.02$ | $-0.06$ |
| | $(3.87)$ | $(7.72)$ | $(2.39)$ | $(-0.77)$ | $(-5.69)$ | $(-8.73)$ | $(-7.62)$ | $(-5.94)$ | $(-2.23)$ | $(-0.59)$ | $(-0.50)$ | $(-0.59)$ | $(-0.41)$ | $(-0.87)$ | $(-0.17)$ | $(-0.49)$ |
| $NGE_{i,t-1}$ | $0.00$ | $0.01$ | $0.04$ | $0.06^{*}$ | $-0.01$ | $-0.12^{**}$ | $-0.16^{***}$ | $-0.18^{***}$ | $-0.16^{***}$ | $-0.17^{***}$ | $-0.16^{***}$ | $-0.16^{***}$ | $-0.18^{***}$ | $-0.19^{**}$ | $-0.28^{***}$ | $-0.12$ |
| | $(0.02)$ | $(0.27)$ | $(1.44)$ | $(1.99)$ | $(-0.35)$ | $(-3.06)$ | $(-4.12)$ | $(-5.13)$ | $(-4.63)$ | $(-4.72)$ | $(-4.10)$ | $(-3.53)$ | $(-3.30)$ | $(-3.05)$ | $(-4.11)$ | $(-1.78)$ |
| $FE_t$ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| #Obs. | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ | $2700K$ |
| $R^2$ | 4.78% | 3.83% | 1.78% | 1.04% | 0.35% | 0.76% | 0.81% | 0.49% | 0.14% | 0.04% | 0.02% | 0.02% | 0.03% | 0.04% | 0.03% | 0.01% |

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