

From CAPE 15 to CAPE 35: Overnight Returns and Intraday Trading Patterns

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Abstract

Between 2008 and 2023, the Campbell-Shiller price-to-earnings ratio (CAPE) roughly doubled. During this time, a specific subset of S&P 500 stocks generated almost all of their total return overnight, with minimal intraday contribution. This suggests that the overnight break played an important role in adjusting to higher valuation levels. The stocks in this group are heavily traded near both the open and close and can be classified as high-attention stocks. The remaining S&P 500 stocks are mainly traded near the close. These stocks achieved most of their gains during the day. Despite the differences in return timing, the total returns for both groups were almost identical.

Keywords: Stock market valuation, CAPE, Overnight return, Intraday return, Intraday trading, Return decomposition

JEL: G12, G14, G41

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1. Introduction

In October 2008, following the bankruptcy of Lehman Brothers, the Campbell-Shiller price-to-earnings ratio (CAPE) stood at 16.4. It declined further to a low of 13.3 in March 2009 before rising steadily over the subsequent years, reaching 38.6 in November 2021. CAPE is commonly interpreted as an indicator of expected long-run stock market returns. Under this interpretation, expected returns declined substantially during the post-crisis period.

Although long-term interest rates also fell in the aftermath of the financial crisis, this factor can account for only a small proportion of the increase in CAPE. Moreover, the rise in valuations does not appear to have been primarily driven by higher analysts' earnings forecasts or improved growth prospects. Instead, the increase in market valuations is consistent with investors being willing to pay progressively higher earnings multiples for stocks, reflecting a decline in required risk compensation and therefore expected returns.

Importantly, this adjustment did not occur through a sudden repricing. When CAPE was close to 15, a valuation level twice as high would likely have been viewed as implausibly expensive. Such valuations became acceptable only gradually as investors adapted to persistently rising market valuations.

An important question is how such gradual increases occur. In this paper, we examine whether the valuation adjustments primarily took place overnight or during regular trading hours. We find that a subset of S&P 500 stocks generated nearly all of their total return overnight, with minimal intraday contribution. These stocks are heavily traded near both the open and close, resulting in a U-shaped intraday trading pattern. Based on their excess trading volume, they can be classified as high-attention stocks. Examples of stocks in this group are Micron Technology, Amazon, Apple, Nvidia, and AMD. Their high overnight returns do not reflect overshooting of

the opening price followed by a subsequent reversal. Rather, the higher opening prices were largely sustained throughout the trading day. The fact that this group’s total valuation increase occurred overnight suggests that the overnight break played an important role in adjusting to higher valuation levels.

For most other stocks, trading activity was concentrated near the close, leading to an L-shaped intraday trading pattern. While the share price appreciation of these stocks occurred primarily during regular trading hours, the total returns of both groups of stocks were remarkably similar.

Our main contribution is linking intraday trading patterns to how individual stocks appreciated when aggregate market valuations roughly doubled. Our results for high-attention stocks suggest that the overnight break was important for gradually adjusting to higher valuation levels.

The remainder of the paper is structured as follows. Section 2 reviews previous related literature. Section 3 describes the data and introduces our measures of intraday trading patterns. Section 4 presents evidence that intraday trading patterns predict overnight returns. Section 5 examines the characteristics of stocks with a U-shaped intraday trading pattern. Section 6 concludes with a discussion of the implications of our findings.

2. Literature Review

Our study relates to two strands of literature: research on overnight return patterns and research on the emergence of large valuation increases and, in the extreme, stock market bubbles.

The first strand documents several anomalous features of overnight returns. First, overnight returns in the U.S. equity market are consistently positive on average and exceed subsequent intraday returns (Berkman et al., 2012; Branch and Ma, 2006, 2012; Boyarchenko et al., 2023; Chan et al., 1996; Cooper et al., 2008; Kelly and Clark, 2011; Lachance, 2021, 2023). As a consequence, a substantial fraction of the equity premium of the S&P 500 has historically been

earned during non-trading hours (Cooper et al., 2008; Lou et al., 2019; Haghani et al., 2022; Bondarenko and Muravyev, 2023). Second, cross-sectional differences in overnight returns are persistent and give rise to momentum effects in both overnight and intraday returns. Stocks with high past overnight returns tend to continue earning high overnight returns in the future (Aboody et al., 2018). Similarly, stocks whose intraday returns have historically exceeded their overnight returns tend to maintain this return pattern over time (Lou et al., 2019).

The overnight return anomaly is difficult to reconcile with standard risk-based explanations. An additional overnight risk is that traders can hardly liquidate their positions when the market is closed (Hong and Wang, 2000). Consistent with this view, margin requirements and lending fees tend to be higher overnight (Bogousslavsky, 2021). Hendershott et al. (2020) find a positive relationship between beta and average return only during the overnight period, suggesting that systematic risk is relevant when trading is not possible. However, the overnight risks appear insufficient to explain the magnitude and persistence of the anomaly. Information released outside trading hours undoubtedly influences overnight returns (Barardehi et al., 2021; Huang et al., 2021; Bahcivan et al., 2023), but it does not explain why overnight returns are predominantly positive. Consequently, much of the literature has focused on behavioral explanations.

Kumar and Lee (2006) show that retail investors tend to trade the same stocks in the same direction. Building on this observation, Berkman et al. (2012) find that retail investors concentrate their purchases of high-attention stocks near the market open, generating temporary buying pressure and elevated opening prices that subsequently revert. Using data from 1993 to 2013, Lou et al. (2019) characterize this process as a “tug of war” between institutional and retail investors.¹ The two groups tend to trade at different times of the day. As Lou et al. (2019) argue, institutions

¹More generally, the opposing clienteles can be viewed as noise traders and arbitrageurs (Akbas et al., 2022).

are more likely to trade throughout the day and particularly near the close, whereas retail investors are more likely to initiate trades near the open. This imbalance can generate overnight returns that are subsequently reversed during the trading day (see, for example, the evidence on meme stocks in Lou et al., 2022; Haghani et al., 2022; Costola et al., 2021; Ricci and Sautter, 2021).

Our paper differs from this literature by focusing not on short-term overnight returns that reverse intraday, but on the decomposition of long-run cumulative total returns into overnight and intraday components during a prolonged period of rising stock market valuations.

The second strand of literature examines how large increases in stock market valuations and, in extreme cases, stock market bubbles arise. Standard asset-pricing decompositions attribute variation in valuation ratios to changes in expected cash flows and discount rates (Cochrane, 2011). Greenwood and Shleifer (2014) provide evidence of extrapolative expectations, whereby investors become more optimistic following periods of strong returns. This creates a mismatch between return expectations and model-based expected returns. Related research on investor sentiment argues that such effects are particularly pronounced for securities whose valuations are difficult to assess and therefore difficult to arbitrage (Baker and Wurgler, 2006). Disagreement models with short-sale constraints show how optimistic investors can sustain prices above fundamental values, especially when trading volume is high (Scheinkman and Xiong, 2003). A growing literature emphasizes the role of investor attention in information processing and asset valuation. Since investors face limited attention, they tend to focus on salient information that can easily be processed (Hirshleifer and Teoh, 2003). Attention-grabbing events can generate temporary buying pressure and increase trading activity, particularly among retail investors (Barber and Odean, 2008). More broadly, investor attention affects the speed with which information is incorporated into stock prices and contributes to return predictability (see, e.g., Da et al., 2011; Hirshleifer et al., 2011). Of particular interest is the model of Barberis et al. (2018), which predicts that stocks attracting

greater investor attention become focal points for extrapolative beliefs and bubble-like dynamics.

These studies focus primarily on why market valuations rise. In contrast, our paper examines how valuation increases are incorporated into stock prices over time. Specifically, we investigate whether the gradual increase in market valuation multiples during the post-crisis period was incorporated predominantly through overnight or intraday returns and how this process varied across stocks with different intraday trading patterns.

3. Data and Variables

3.1. Data Sources and Sample

Our sample consists of the constituents of the S&P 500 Index for the sample period from October 2008, the month following the Lehman bankruptcy, to December 2023. The index composition is updated daily to prevent survivorship and look-ahead bias.

For intraday stock prices and trading volumes, we use the Algoseek US Equity Trade Only Minute Bar data (algoseek, 2021b).² In the following, we use the shorthand “minute bar data” for this dataset. The Algoseek minute bar data is built from all trades executed on public exchanges (e.g. NASDAQ, NYSE, BATS, ARCA), excluding odd lot trades (less than 100 shares)³. Algoseek’s data source is the Securities Information Processor (SIP) data, also known as the “Consolidated Feed”. For each minute, Algoseek minute bars include the date, ticker symbol, first, high, low, and last trade prices, volume-weighted average price, total number of shares traded, and the total number of trades. We only consider minute bar data for the regular market hours of 9:30 am to 4:00 pm.

We obtain data on the opening and closing auctions of S&P 500 stocks from the Algoseek US

²We thank Algoseek for providing the data.

³Odd lots are not subject to the National Market System regulation (Regulation NMS), so best execution price is not guaranteed.

Equity Primary Exchange Daily OHLC dataset (algoseek, 2021a). In the following, we use the shorthand “auction data” for this dataset, which includes the official opening price on the stock’s primary exchange, the time (to the second) and number of shares of the opening auction, and the same information for the closing auction on the primary exchange.⁴ The opening and closing auctions are also included in the Algoseek minute bar data in the minute of the opening or closing auction. Using the OHLC dataset, we remove the opening and closing auction volumes from the Algoseek minute bar data so that the trading volume of auctions (in the auction data) is separated from the volume of continuous trading (in the minute bar data).

We match Algoseek tickers with LSEG Datastream identifiers.⁵ All prices are adjusted for corporate actions using Datastream adjustment factors. Dividends are incorporated in overnight returns on ex-dividend dates.⁶ We also obtain the market capitalization and book-to-market ratio from Datastream. Finally, we take the risk-free rate from Kenneth R. French’s Data Library.⁷

3.2. Metrics of Intraday Trading Patterns

The early literature has found that intraday trading volume follows a U-shaped pattern, characterized by increased activity at both the opening and closing of the trading day, with a relatively subdued period around midday (Admati and Pfleiderer, 1988; Hong and Wang, 2000; Wood et al., 1985). There is a tendency for trading to become more concentrated over time as liquidity traders prefer to execute trades when the market is “thick”, i.e. when trading activity is less likely to have a significant impact on prices (Admati and Pfleiderer, 1988). This tendency creates incentives for

⁴For details on how Algoseek identifies the opening and closing trades when the official opening or closing trade on the primary exchange is not available, see algoseek (2021a).

⁵For each stock, we ensure the accuracy of the match by verifying that the share price history from both data sources matches. Ticker changes (e.g., FB to META) are consolidated so that each stock is represented by a unique identifier. The resulting list of matching Algoseek and Datastream identifiers is available from the authors on request.

⁶The dividend is implied by the difference between returns based on the total return index RI and returns based on adjusted share prices (adjusted for capital measures, but not dividends).

⁷https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

liquidity traders in a particular stock to coordinate their trading activity, which then becomes less dispersed throughout the day.

During the last two decades, trading activity has increasingly shifted towards the end of the trading day, driven in particular by the growing importance of exchange-traded funds (ETFs), which has increased the importance of closing auctions (Bogousslavsky and Muravyev, 2023). In today's equity markets, average liquidity depth tends to be low at the open and gradually increases towards the close, resulting in what is now referred to as an (inverted) L-shaped volume distribution (Hussain, 2011; Ammar et al., 2020; Bogousslavsky and Muravyev, 2023).

However, the remaining variation in trading patterns remains significant. While most existing studies have focused on average patterns, for our study, the cross-sectional differences in intraday trading patterns are crucial. In particular, we are interested in the relative importance of trading at the beginning of the trading day. For each stock, we use the following four measures of intraday trading over the last 126 trading days:

First to Last Hour Ratio (M1): Sum of daily trading volume from 9:30 am to 10:30 am over the last 126 trading days / Sum of daily trading volume from 3:00 pm to 4:00 pm over the last 126 trading days. Auction volume is not included.

First to Last Half Hour Ratio (M2): Sum of daily trading volume from 9:30 am to 10:00 am over the last 126 trading days / Sum of daily trading volume from 3:30 pm to 4:00 pm over the last 126 trading days. Auction volume is not included.

Early to Late Volume Gravity (M3): $13 - (\sum_{i=1}^{13} i \cdot TV_i) / (\sum_{i=1}^{13} TV_i)$, where i is the number of ordered half-hour intervals (1 for 9:30-10:00 am, ..., 13 for 3:30-4:00 pm) and TV_i is the sum of daily trading volume in half-hour interval i over the last 126 trading days. Auction volume is not included.

Open to Close Ratio (M4): Sum of opening auction volume over the last 126 trading days / Sum of closing auction volume over the last 126 trading days.

Each timing metric increases with the concentration of trading at the start of the day relative to the end. For example, a high M1, M2 or M3 value indicates that a stock’s volume is heavily weighted toward the morning, whereas a low value indicates that most trading occurs late in the day. Concretely, M3 – which is constructed similarly to the duration of interest-rate instruments – attains its maximum of 12 if all volume occurs in the first half hour and its minimum of 0 if all volume occurs in the last half hour. A value of 6 corresponds to evenly distributed trading.

3.3. Return Metrics

The overnight return of stock i on day t is defined as $r_{i,t,night} = \ln(OPEN_{i,t}/CLOSE_{i,t-1})$, and the intraday return as $r_{i,t,day} = \ln(CLOSE_{i,t}/OPEN_{i,t})$, where $OPEN$ and $CLOSE$ are the opening and closing prices from Algoseek’s auction data adjusted for corporate actions and dividends. The total return is $r_{i,t,tot} = r_{i,t,night} + r_{i,t,day}$, and a long position overnight combined with a short position during the day gives the return $r_{i,t,diff} = \ln(1 + OPEN_{i,t}/CLOSE_{i,t-1} - CLOSE_{i,t}/OPEN_{i,t})$.⁸

For each trading day, we calculate equally weighted portfolio returns from the portfolio components $i = 1, \dots, n$ by first transforming the log stock returns to discrete returns, $R_{i,t,night} = e^{r_{i,t,night}} - 1$, taking the mean, $R_{p,t,night} = 1/n \sum_{i=1}^n R_{i,t,night}$, and transforming back to log returns, $r_{p,t,night} = \ln(1 + R_{p,t,night})$, where t is the trading day. The same calculations apply to $r_{p,t,day}$, $r_{p,t,tot}$, and $r_{p,t,diff}$. Finally, the cumulative portfolio return is the sum of the daily log returns. We denote excess returns with a superscript e , as in $r_{diff}^e = r_{diff} - r_f$, with r_f as the risk-free rate.

⁸Since the short position during the day requires no investment, there is no natural way to calculate a relative return. In our return calculation we assume that the short amount is the same as the overnight investment, and that the dollar returns on both positions are related to the overnight investment. It follows from our definition that $r_{i,t,diff}$ is generally not equal to $r_{i,t,night} - r_{i,t,day}$.

3.4. Descriptive Statistics

Figure 1 shows two examples of U-shaped and L-shaped intraday trading patterns. The bars represent the average trading volume per minute over all trading days from November 1, 2022 to April 30, 2023. The opening and closing auctions are not included. In the U-shaped case, trading activity starts high at market opening and then declines until 14:00. Volumes remain low for most of the afternoon, before increasing significantly in the last half hour. In the L-shaped case, volumes are low throughout the day and only pick up just before the market closes.

– Insert Figure 1 here –

The descriptive statistics in Table 1 show that, on average, trading volume is half as high in the first hour as in the last hour, and the opening auction represents only one fifth of the trading volume of the closing auction. The Early to Late Volume Gravity (M3) is, on average, 2.41 hours (4.82 half-hours) before market close. Trading is more active towards the end of the trading day not only on average, but also for most individual stocks. At the 95 percentile, late trading is still more important than early trading. In other words, while many stocks have heavy trading only in the last hour, those with heavy trading in the first hour also have substantial trading in the last hour, forming the U-pattern typical for these stocks.

– Insert Table 1 here –

As documented in the literature, the weight of trading volume has shifted towards the end of the trading day. This corresponds to a negative trend in our intraday trading measures, as shown in Figure 2 for five portfolios sorted on the First to Last Hour Ratio (M1). The figure also shows that the average portfolio values decrease in parallel so that the differences remain roughly

constant.

– Insert Figure 2 here –

Table 2 shows that our four measures of intraday trading are highly correlated, in particular measures M1, M2 and M3 (rank correlations of 0.98 or higher). The Pearson correlations of M3 with M1 and M2 (0.93; 0.90) are smaller than the rank correlations because the relationships are non-linear, as shown in Figure 3 for M3 and M1. This scatterplot also shows that there is considerable cross-sectional variation in the measures, although the weight of late trading is strong for most stocks. As M1, M2 and M3 are so similar, we will only present the empirical results for one of them (M1) in detail, and mention the other two in the robustness checks. The auction-based measure M4 differs significantly from the continuous-trading measures M1, M2 and M3, but the association is still strong, with rank correlations of around 0.7.

– Insert Table 2 and Figure 3 here –

The migration matrix in Table 3 shows that M1 is relatively stable over successive six-month periods (Panel A). When stocks are sorted semianually into five portfolios in ascending order, most of the stocks (70%) assigned to the portfolio with the lowest M1 values (Portfolio 1) remain in this portfolio at the next formation date six months later. Similarly, 73% of the stocks with the highest M1 values (Portfolio 5) still belong to this portfolio six months later. The results are similar for M2 and M3 (not tabulated), while the portfolio assignments according to M4 are slightly less stable (Panel B).

– Insert Table 3 here –

4. Intraday Trading Patterns and the Decomposition of Total Returns into Overnight and Intraday Returns

4.1. Portfolio Analysis

Figure 4 shows the cumulative returns for five portfolios from 2009 to 2023 when stocks are sorted into portfolios based on the First to Last Hour Ratio (M1) over the last six months (126 days). Portfolio 1 contains the stocks with the lowest M1 values (L-shape) and Portfolio 5 contains the stocks with the highest M1 values (U-shape). The portfolios are re-adjusted after a holding period of 126 days (non-overlapping holding periods).

Portfolio 5 achieves the highest overnight return (upper left panel). The overnight returns of Portfolios 1 to 4 are clearly positive and increase in the ordering of the portfolios, but remain significantly below the overnight return of Portfolio 5.

The intraday returns are arranged inversely, with Portfolio 1 at the top and Portfolio 5 at the bottom (upper right panel). Again, Portfolio 5 stands out as clearly different from the other four portfolios. However, the low intraday returns of Portfolio 5 do not imply that its high overnight returns are reversed. Rather, its intraday returns remain slightly positive, so on average investors pay the same or higher prices than the opening prices when trading during the day.

From the patterns of day and overnight returns it follows that the portfolio returns of being long at night and short during the day are most attractive for Portfolio 5 (lower left panel). In contrast, the total returns of the five portfolios are practically indistinguishable (lower right panel). The evolution of the cumulative total returns over time is also very similar for the five portfolios. Taken together, Portfolio 5 accumulates almost all of its total return overnight, while for Portfolios 1 to 4, overnight and intraday return contribute similarly to total return.

Table 4 shows annualized average returns, volatilities and t -values for a finer sorting of 10

portfolios, again based on M1. The average overnight returns of all portfolios are positive. Portfolio 10 (with the highest M1 value) has significantly higher overnight returns (t -value 4.51) and significantly lower intraday returns (t -value -3.15) than Portfolio 1, while total returns are very similar (t -value -0.07). All portfolios, even Portfolio 10 with the highest overnight return, have a lower volatility (SD) of overnight returns than intraday returns.

– Insert Figure 4 and Table 4 here –

For sorting on the Open to Close Ratio (M4), the overnight return surplus of Portfolio 10 to Portfolios 5 and 1 is smaller but still significant, while the intraday return differences have the same sign as before, but are at most significant at the 10% level (Table 5). Only Portfolio 10 with the highest Open to Close Ratios stands out, while the returns of the other portfolios are all on the same level. This is also apparent in Figure 5, which shows overnight, intraday and total returns for five portfolios sorted on M4 (similar to Figure 5 for M1). Portfolio 5, which consists of stocks with a U-shaped trading pattern, achieves the main part of its cumulative return overnight.

– Insert Figure 5 and Table 5 here –

To test whether M1 has additional explanatory power independent of M4 and vice versa, we use a residualization approach. At each sorting date, we regress M1 on M4 and use the residuals (as the part of M1 not explained by M4) to sort stocks into 10 portfolios. The portfolio returns in Panel A of Table 6 are similar to the results for M1, suggesting that the intraday trading pattern M1 has additional explanatory power beyond the Open to Close Ratio M4. This is not the case in the opposite direction (Panel B).

– Insert Table 6 here –

A dramatic event in the sample period was the COVID-19 pandemic, which interrupted the upward trend in the market. Table 7 shows that our main results come from the period up to 2019 (t -value P10–P1 for r_{diff} of 6.44). Since the outbreak of the pandemic, the intraday trading patterns have lost their relationship with overnight returns (t -value P10–P1 for r_{diff} of -0.17). This is consistent with our interpretation that this relationship was closely linked to the gradual rise in CAPE.

– Insert Table 7 here –

All results presented in this section so far are robust when the First to Last Hour Ratio (M1) is replaced by the First to Last Half Hour Ratio (M2) or the Early to Late Volume Gravity (M3).

4.2. *Fama-MacBeth Regressions*

To complement our portfolio analysis, we conduct Fama and MacBeth (1973) regressions with additional control for size (ln market capitalization) and the book-to-market ratio of equity. The observations in the regressions are at the individual stock level. We follow the standard practice of running the cross-sectional regressions on a monthly basis. The dependent variable is the excess return in month t from being long overnight and short during the day (r_{diff}^e). The explanatory variables are calculated at the end of month $t - 1$. For the trade timing measures M1 to M4, we use an estimation window of 21 trading days (corresponding to the return frequency; see Panel A of Table 8) or 126 trading days (as before in the portfolio analysis; see Panel B of Table 8).

– Insert Table 8 here –

The regression results confirm the predictive power of the trade timing variables M1 to M3, with t -values ranging from 3.8 to 4.8. In contrast, M4 (the auction-based open-to-close ratio) has no significant coefficient. This is probably because the regression function assumes a linear relationship, whereas our portfolio analysis showed that returns did not change linearly from Portfolio 1 to Portfolio 10. In fact, the returns of Portfolios 1 to 9 were similar, whereas those of Portfolio 10 were significantly different. Fama-MacBeth regressions are unable to adequately capture such nonlinearities. This is why we placed greater emphasis on the portfolio analysis.

As a robustness check, we include the logarithm of total trading volume (over the last 21 or 126 trading days) as a control variable in the Fama and MacBeth (1973) regressions. The results remain unchanged, and the coefficients of total trading volume are insignificant. This suggests that our key measures capture timing per se, rather than just overall activity.

5. Characteristics of stocks with a U-shaped volume pattern

Previous literature has found that stocks with consistently high overnight returns are those that attract high investor interest. We hypothesize that these are also the stocks with a U-shaped volume pattern, which is reflected in a high value of the First to Last Hour Ratio (M1). To test this hypothesis, we run a logistic regression in which the dependent variable (Pf10) is the assignment to Portfolio 10 when sorting on M1. At a given portfolio formation date, the value of Pf10 is 1 for stocks included in Portfolio 10 and 0 otherwise.

The following stocks are most frequently included in portfolio 10 across the 30 formation dates, with the number of inclusions shown in parentheses:

Freeport-McMoRan (FCX, 30); Citigroup (C, 29); Bank of America (BAC, 28); Micron Technology (MU, 26); Apple (AAPL, 25); Amazon (AMZN, 25); Netflix (NFLX, 24); Wynn Resorts (WYNN, 23); Nvidia (NVDA, 22); Advanced Micro Devices (AMD, 21); Regions Financial (RF, 21); Meta Platforms/Facebook (FB, 18); KeyCorp (KEY, 18); Carnival (CCL, 17); and Newmont (NEM, 17).

Our measure of attention to a stock (VolExcess) is the total trading volume over the last 126 trading days (VolTot) in excess of what can be explained by the stock’s current market capitalization (MCap). Technically, VolExcess is the residual from a linear cross-sectional regression of $\ln(\text{VolTot})$ on $\ln(\text{MCap})$. We run this regression at each portfolio formation date (i.e. at six-month intervals). The idea behind this measure is that excess trading indicates high investor attention, but does not imply at what time the excess trading occurs. Since blue chips are expected to attract more investor attention than mid and small caps, we include $\ln(\text{MCap})$ as an explanatory variable. We also include the book-to-market value of equity (BTMV) to test if value or growth stocks are overrepresented in Portfolio 10.

Our logistic regression includes all observations from all portfolio formation dates in our sample period. The results in Table 9 confirm that VolExcess has a strong explanatory power for the assignment of stocks to the portfolio with the highest First to Last Hour Ratios. In a logistic regression, values for McFadden’s R^2 of 0.314 and 0.351 are considered to represent an excellent model fit. Thus, high investor interest seems to be associated with intense trading early in the trading day. Market capitalization and the book-to-market ratio are also associated with a higher likelihood of being in Portfolio 10, but the explanatory power of these variables is much smaller than that of VolExcess, our proxy for high investor attention.

– Insert Table 9 here –

6. Discussion

Most S&P 500 stocks exhibit an L-shaped intraday trading pattern, with trading activity concentrated near the market close and comparatively low volume during the morning and early afternoon. A smaller group of stocks displays a U-shaped pattern characterized by elevated trading volume both at the open and at the close. This group consists primarily of high-attention stocks. Both trading patterns are highly persistent and typically remain stable over periods of several months.

We compare the performance of U- and L-stocks between October 2008 and December 2023, a period during which stock market valuations increased substantially and the Campbell-Shiller CAPE roughly doubled. Despite their markedly different intraday trading patterns, the two groups achieved almost identical total returns and exhibited closely aligned return dynamics over time. Therefore, both groups appear to have been exposed to the same broad forces driving the rise in market valuations.

A different picture emerges when total returns are decomposed into overnight and intraday components. Stocks with U-shaped trading patterns earned almost all of their cumulative returns overnight. Importantly, their high overnight returns cannot be attributed to opening-price overshooting, as these gains were generally not reversed during the trading day. Intraday returns remained slightly positive or close to zero.

The U-stocks have excess trading volume and can be characterized as high-attention stocks. Our findings suggest that, for these stocks, the overnight break played a key role in the gradual adjustment of stock valuations from CAPE 15 to CAPE 35. This is consistent with the view that the overnight period is not merely a passive interruption of trading. Instead, it is a time during which investors process information, reassess valuations, and prepare orders for the next trading

session. If the post-crisis rise in CAPE reflects a gradual increase in investors' willingness to accept higher valuation multiples, then the overnight break may have provided an important setting for this reassessment.

L-stocks accounted for a significant proportion of their total returns intraday. This finding is consistent with various explanations. One possibility is that high-attention stocks led the increase in the stock market with their share price increases early in the morning, after which the other stocks rose during the day, following in their footsteps. Another possibility is that the share price increases of L-stocks mostly occurred at the close because that is when active trading took place. According to this interpretation, stocks with active trading at the open would immediately reflect such valuation adjustments, whereas stocks with less intensive early trading could adjust more gradually throughout the day.

One limitation of our study is that we are unable to distinguish between these explanations. We are also unable to identify the specific mechanisms through which the overnight break influenced valuation adjustments. More broadly, our aim is not to explain why the CAPE ratio increased from 15 to 35. Furthermore, we do not investigate whether similar patterns characterized other periods of rising market valuations, most notably during the dot-com boom of the late 1990s. Examining such time periods would be a useful way to test whether the results can be generalized.

An interesting question is whether the return patterns found in this study created exploitable arbitrage opportunities. During most of the sample period, simple buy-and-hold strategies already generated strong returns, limiting the attractiveness of relative-value strategies. One possible approach would have been to purchase L-stocks following strong overnight returns among stocks with heavy opening activity. However, implementing such a strategy would require trading in relatively thin morning markets, against the prevailing trend toward greater trading activity near the close. Moreover, any assessment of arbitrage opportunities must consider the risk of hindsight

bias. During a period of rising valuation multiples, it is inherently difficult to determine when the trend will end.

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Table 1: **Descriptive statistics of intraday trading variables**

This table presents descriptive statistics of the intraday trading variables defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on specific dates (formation dates) that are six months apart. At each formation date, we compute the intraday trading variables based on the formation period of the previous six months. The observations in this table consist of all S&P 500 stocks at all formation dates. SD is the standard deviation, and P05, P25, P75 and P95 are percentiles.

Variable	N	Mean	SD	Min	P05	P25	Median	P75	P95	Max
First to Last Hour Ratio (M1)	15,512	0.48	0.20	0.07	0.17	0.35	0.48	0.59	0.83	1.86
First to Last Half Hour Ratio (M2)	15,512	0.34	0.17	0.04	0.10	0.22	0.33	0.42	0.63	1.71
Early to Late Volume Gravity (M3)	15,512	4.82	0.80	1.84	3.13	4.47	5.00	5.32	5.86	7.16
Open to Close Ratio (M4)	15,512	0.20	0.12	0.01	0.07	0.10	0.17	0.28	0.42	1.44

Table 2: **Correlation matrix of intraday trading variables**

This table presents Pearson correlations (upper triangle) and Spearman correlations (lower triangle) between the intraday trading variables defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on specific dates (formation dates) that are six months apart. At each formation date, we compute the intraday trading variables based on the formation period of the previous six months. The observations in this table consist of all S&P 500 stocks at all formation dates.

	M1	M2	M3	M4
First to Last Hour Ratio (M1)	1	0.99	0.93	0.66
First to Last Half Hour Ratio (M2)	0.99	1	0.90	0.67
Early to Late Volume Gravity (M3)	0.99	0.98	1	0.62
Open to Close Ratio (M4)	0.72	0.72	0.70	1

Table 3: **Migration matrix**

This table shows the migration matrix of S&P 500 stocks between portfolios at successive portfolio formation dates during our sample period from October 2008 to December 2023. The formation dates are separated by six months. In Panel A, at each formation date, the stocks are sorted into five portfolios in ascending order based on the First to Last Hour Ratio (M1), and in Panel B, the sorting is based on the Open to Close Ratio (M4). These variables are defined in Section 3.2. The observations in this table consist of all S&P 500 stocks at all pairs of consecutive formation dates. The rows show the portfolio assignment at the earlier formation date and the columns show the portfolio assignment at the later formation date. The numbers in the table represent the number of transitions from the row portfolios to the column portfolios.

Panel A: Sorting on M1						
	P1	P2	P3	P4	P5	Sum
P1	1,636	501	144	36	4	2,321
P2	561	1,030	546	182	27	2,346
P3	137	615	954	553	103	2,362
P4	38	186	596	1,076	477	2,373
P5	11	31	118	489	1,715	2,364
Sum	2,383	2,363	2,358	2,336	2,326	11,766

Panel B: Sorting on M4						
	P1	P2	P3	P4	P5	Sum
P1	1,435	583	186	79	17	2,300
P2	593	903	556	252	54	2,358
P3	204	584	843	563	145	2,339
P4	76	214	624	1,004	462	2,380
P5	17	55	141	469	1,707	2,389
Sum	2,325	2,339	2,350	2,367	2,385	11,766

Table 4: **Portfolio returns for sorting on the First to Last Hour Ratio (M1)**

This table shows the annualized mean daily return and the annualized standard deviation (SD) of daily return for portfolios sorted on the First to Last Hour Ratio (M1) as defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 10 portfolios. Portfolio P1 (P10) contains the stocks with the lowest (highest) M1 value. Daily portfolio returns are recorded for the following six months, before the portfolios are rebalanced. The return statistics in this table are based on the holding period returns. “Night” refers to the returns of being long overnight; “Day” refers to the returns of being long during the day; “Difference” refers to the returns of being long overnight and short during the day; and “Total” refers to the returns of being long overnight and during the day (see Section 3.3 for exact definitions).

Portfolio	Mean	SD	t-value		Portfolio	Mean	SD	t-value	
Night					Day				
P1	0.07	0.11	2.60	**	P1	0.09	0.14	2.36	*
P2	0.06	0.11	2.13	*	P2	0.09	0.13	2.56	*
P3	0.07	0.11	2.42	*	P3	0.08	0.13	2.25	*
P4	0.06	0.12	2.08	*	P4	0.08	0.14	2.34	*
P5	0.07	0.12	2.41	*	P5	0.08	0.14	2.07	*
P6	0.08	0.12	2.39	*	P6	0.07	0.14	1.81	.
P7	0.09	0.13	2.67	**	P7	0.06	0.15	1.67	.
P8	0.08	0.13	2.47	*	P8	0.05	0.15	1.15	
P9	0.09	0.14	2.47	*	P9	0.05	0.16	1.22	
P10	0.17	0.17	3.89	***	P10	−0.01	0.19	−0.26	
P5−P1	0.003	0.03	0.34		P5−P1	−0.01	0.06	−0.60	
P10−P5	0.09	0.07	5.17	***	P10−P5	−0.09	0.10	−3.54	***
P10−P1	0.10	0.08	4.51	***	P10−P1	−0.10	0.12	−3.15	**
Difference					Total				
P1	−0.03	0.17	−0.74		P1	0.16	0.18	3.28	**
P2	−0.05	0.16	−1.10		P2	0.15	0.18	3.16	**
P3	−0.02	0.16	−0.58		P3	0.15	0.18	3.13	**
P4	−0.04	0.17	−0.80		P4	0.14	0.19	2.96	**
P5	−0.02	0.18	−0.45		P5	0.15	0.19	2.98	**
P6	−0.01	0.18	−0.23		P6	0.14	0.20	2.78	**
P7	0.004	0.19	0.08		P7	0.15	0.20	2.89	**
P8	0.02	0.19	0.35		P8	0.13	0.21	2.41	*
P9	0.01	0.21	0.25		P9	0.14	0.22	2.46	*
P10	0.14	0.25	2.20	*	P10	0.15	0.26	2.31	*
P5−P1	0.01	0.07	0.65		P5−P1	−0.01	0.07	−0.34	
P10−P5	0.16	0.12	5.07	***	P10−P5	0.003	0.11	0.12	
P10−P1	0.18	0.15	4.49	***	P10−P1	−0.002	0.14	−0.07	
<i>Note:</i>					. p<0.1; *p<0.05; **p<0.01; ***p<0.001				

Table 5: **Portfolio returns for sorting on the Open to Close Ratio (M4)**

This table shows the annualized mean daily return and the annualized standard deviation (SD) of daily return for portfolios sorted on the Open to Close Ratio (M4) as defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 10 portfolios. Portfolio P1 (P10) contains the stocks with the lowest (highest) M4 value. Daily portfolio returns are recorded for the following six months, before the portfolios are rebalanced. The return statistics in this table are based on the holding period returns. “Night” refers to the returns of being long overnight; “Day” refers to the returns of being long during the day; “Difference” refers to the returns of being long overnight and short during the day; and “Total” refers to the returns of being long overnight and during the day (see Section 3.3 for exact definitions).

Portfolio	Mean	SD	t -value		Portfolio	Mean	SD	t -value	
Night					Day				
P1	0.08	0.12	2.43	*	P1	0.07	0.16	1.79	.
P2	0.09	0.12	2.82	**	P2	0.05	0.15	1.23	
P3	0.08	0.12	2.49	*	P3	0.06	0.14	1.62	
P4	0.07	0.12	2.12	*	P4	0.07	0.14	2.00	*
P5	0.07	0.12	2.25	*	P5	0.08	0.14	2.22	*
P6	0.08	0.12	2.64	**	P6	0.06	0.14	1.72	.
P7	0.08	0.13	2.54	*	P7	0.07	0.14	1.83	.
P8	0.08	0.12	2.61	**	P8	0.07	0.14	1.83	.
P9	0.09	0.13	2.63	**	P9	0.05	0.15	1.32	
P10	0.13	0.15	3.42	***	P10	0.04	0.18	0.82	
P5–P1	−0.01	0.04	−0.54		P5–P1	0.01	0.08	0.26	
P10–P5	0.06	0.06	3.94	***	P10–P5	−0.04	0.10	−1.66	.
P10–P1	0.06	0.06	3.63	***	P10–P1	−0.04	0.11	−1.30	
Difference					Total				
P1	−0.02	0.19	−0.45		P1	0.15	0.21	2.73	**
P2	0.02	0.18	0.43		P2	0.13	0.20	2.57	*
P3	−0.002	0.18	−0.03		P3	0.14	0.20	2.69	**
P4	−0.03	0.18	−0.56		P4	0.14	0.19	2.78	**
P5	−0.03	0.18	−0.60		P5	0.15	0.19	3.01	**
P6	0.001	0.18	0.03		P6	0.15	0.19	2.91	**
P7	−0.003	0.18	−0.07		P7	0.15	0.20	2.93	**
P8	−0.004	0.18	−0.09		P8	0.15	0.19	2.98	**
P9	0.02	0.19	0.32		P9	0.14	0.20	2.63	**
P10	0.06	0.23	1.04		P10	0.17	0.24	2.77	**
P5–P1	−0.01	0.09	−0.24		P5–P1	−0.001	0.09	−0.06	
P10–P5	0.09	0.12	2.97	**	P10–P5	0.02	0.11	0.84	
P10–P1	0.09	0.13	2.62	**	P10–P1	0.02	0.12	0.73	

Note:

. $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 6: **Additional explanatory power of the First to Last Hour Ratio (M1) and the Open to Close Ratio (M4)**

Panel A of this table shows the annualized mean daily return and the annualized standard deviation (SD) of daily return differences for portfolios sorted on the part of M1 not explained by M4 (i.e., the residuals of a regression of M1 on M4). Panel B shows the same information for portfolios sorted on the part of M4 not explained by M1 (i.e., the residuals of a regression of M4 on M1). The measures M1 and M4 are defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 10 portfolios. Daily portfolio returns are recorded for the following six months, before the portfolios are rebalanced. The return statistics in this table are based on the holding period returns. The table reports return differences between portfolios 5 and 1 (P5–P1), 10 and 5 (P10–P5), and 10 and 1 (P10–P1). “Night” refers to the returns of being long overnight; “Day” refers to the returns of being long during the day; “Difference” refers to the returns of being long overnight and short during the day; and “Total” refers to the returns of being long overnight and during the day (see Section 3.3 for exact definitions).

Panel A: Sorting on the part of M1 not explained by M4								
Portfolio	Mean	SD	t-value		Portfolio	Mean	SD	t-value
Night					Day			
P5–P1	0.01	0.04	0.77		P5–P1	0.01	0.06	0.51
P10–P5	0.09	0.06	5.48	***	P10–P5	−0.10	0.09	−4.04 ***
P10–P1	0.10	0.08	4.77	***	P10–P1	−0.09	0.11	−2.96 **
Difference (Night – Day)					Total			
P5–P1	−0.001	0.08	−0.06		P5–P1	0.02	0.08	0.86
P10–P5	0.17	0.11	5.81	***	P10–P5	−0.01	0.11	−0.30
P10–P1	0.17	0.14	4.64	***	P10–P1	0.01	0.14	0.24
Panel B: Sorting on the part of M4 not explained by M1								
Portfolio	Mean	SD	t-value		Portfolio	Mean	SD	t-value
Night					Day			
P5–P1	−0.01	0.04	−0.71		P5–P1	0.01	0.08	0.43
P10–P5	0.01	0.05	0.78		P10–P5	0.005	0.07	0.25
P10–P1	0.002	0.05	0.12		P10–P1	0.01	0.10	0.53
Difference					Total			
P5–P1	−0.01	0.09	−0.31		P5–P1	0.001	0.09	0.05
P10–P5	−0.001	0.09	−0.04		P10–P5	0.01	0.09	0.61
P10–P1	−0.01	0.11	−0.28		P10–P1	0.02	0.12	0.49
<i>Note:</i>					. p<0.1; *p<0.05; **p<0.01; ***p<0.001			

Table 7: **Subperiods before and since the COVID-19 pandemic**

This table shows the annualized mean daily return and the annualized standard deviation (SD) of daily return differences for portfolios sorted on the First to Last Hour Ratio (M1) as defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 10 portfolios. Daily portfolio returns are recorded for the following six months, before the portfolios are rebalanced. The return statistics in this table are based on the holding period returns from 2009 to 2019 (Panel A) and from 2020 to 2023 (Panel B). The table reports return differences between portfolios 5 and 1 (P5–P1), 10 and 5 (P10–P5), and 10 and 1 (P10–P1). “Night” refers to the returns of being long overnight; “Day” refers to the returns of being long during the day; “Difference” refers to the returns of being long overnight and short during the day; and “Total” refers to the returns of being long overnight and during the day.

Portfolio	Mean	SD	<i>t</i> -value		Portfolio	Mean	SD	<i>t</i> -value	
Panel A: 2009-2019 (before COVID-19)									
Night					Day				
P5–P1	−0.002	0.03	−0.18		P5–P1	−0.01	0.05	−0.57	
P10–P5	0.12	0.06	6.39	***	P10–P5	−0.14	0.09	−5.08	***
P10–P1	0.12	0.06	5.85	***	P10–P1	−0.15	0.10	−4.80	***
Difference					Total				
P5–P1	0.01	0.06	0.39		P5–P1	−0.01	0.06	−0.55	
P10–P5	0.24	0.11	6.95	***	P10–P5	−0.02	0.10	−0.76	
P10–P1	0.25	0.13	6.44	***	P10–P1	−0.03	0.12	−0.95	
Panel B: 2020-2023 (since COVID-19)									
Night					Day				
P5–P1	0.01	0.04	0.68		P5–P1	−0.01	0.08	−0.26	
P10–P5	0.03	0.09	0.64		P10–P5	0.05	0.11	0.86	
P10–P1	0.04	0.12	0.75		P10–P1	0.04	0.16	0.48	
Difference					Total				
P5–P1	0.02	0.09	0.53		P5–P1	0.004	0.09	0.09	
P10–P5	−0.04	0.15	−0.54		P10–P5	0.08	0.14	1.14	
P10–P1	−0.02	0.20	−0.17		P10–P1	0.08	0.19	0.86	
<i>Note:</i>					. p<0.1; *p<0.05; **p<0.01; ***p<0.001				

Table 8: **Fama-MacBeth regressions**

This table shows the results of monthly cross-sectional Fama-MacBeth regressions of r_{diff}^e (excess return from being long overnight and short during the day) in month $t + 1$ on stock characteristics at the end of month t . The sample consists of S&P 500 stocks from October 2008 to December 2023. M1 is the First to Last Hour Ratio, M2 is the First to Last Half Hour Ratio, M3 is the Early to Late Volume Gravity, and M4 is the Open to Close Ratio as defined in Section 3.2. $\ln(\text{MCap})$ is the log of market capitalization and BTMV is the book-to-market value of equity. $Av.R^2$ is the average R^2 of the cross-sectional regressions. In Panel A, the variables M1-M4 are based on the last 21 trading days, while in Panel B they are based on 126 trading days. The top value is the average slope coefficient from the cross-sectional regressions and the bottom value is the t -statistic.

	(1)	(2)	(3)	(4)
Panel A: M1-M4 based on a 1-month estimation period				
M1	0.025*** (4.354)			
M2		0.028*** (4.242)		
M3			0.009*** (4.800)	
M4				0.017 (1.001)
$\ln(\text{MCap})$	0.000 (0.289)	0.000 (0.305)	0.000 (0.432)	0.001 (1.010)
BTMV	0.002 (1.265)	0.002 (1.329)	0.002 (1.383)	0.004* (2.459)
$Av.R^2$	0.041	0.041	0.038	0.039
Panel B: M1-M4 based on a 6-months estimation period				
M1	0.121*** (4.023)			
M2		0.130*** (3.795)		
M3			0.042*** (4.426)	
M4				0.012 (0.137)
$\ln(\text{MCap})$	-0.000 (-0.091)	-0.000 (-0.026)	0.000 (0.084)	0.004 (1.175)
BTMV	0.018 (1.418)	0.019 (1.484)	0.019 (1.550)	0.029* (2.210)
$Av.R^2$	0.045	0.045	0.040	0.039
Note: . p<0.1; *p<0.05; **p<0.01; ***p<0.001				

Table 9: **Logistic regressions**

This table shows the estimates from logistic regressions (with standard errors in parantheses). During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 10 portfolios based on the First to Last Hour Ratio (M1) as defined in Section 3.2. The dependent variable (Pf10) of the logistic regressions is equal to 1 if a stock belongs to Portfolio 10, and 0 otherwise. $\ln(\text{MCap})$ is the logarithm of a stock's market capitalization on the formation date and BTMV is the book-to-market value of equity. Let VolTot be the aggregate trading volume over 126 trading days prior to the formation date. VolExcess is then the residual from a linear cross-sectional regression of $\ln(\text{VolTot})$ on $\ln(\text{MCap})$. We run this regression at each portfolio formation date (i.e. at six-month intervals). The observations in this table consist of all S&P 500 stocks at all formation dates.

	Dependent variable: Pf10			
	(1)	(2)	(3)	(4)
VolExcess	3.687*** (0.093)			3.926*** (0.100)
$\ln(\text{MCap})$		0.333*** (0.025)		0.505*** (0.030)
BTMV			0.253*** (0.053)	0.242*** (0.042)
McFadden R^2	0.314	0.02	0.004	0.351
Observations	12,993	12,993	12,993	12,993
<i>Note:</i>	. p<0.1; *p<0.05; **p<0.01; ***p<0.001			

Figure 1: **Examples of U-shaped and L-shaped volume patterns**

This figure shows the aggregate trading volume of AMD (Advanced Micro Devices) and AME (Ametek) for the six-month period from 1 November 2022 to 30 April 2023, per minute of the trading day. The left graph shows a U-pattern and the right graph shows a (inverted) L-pattern.

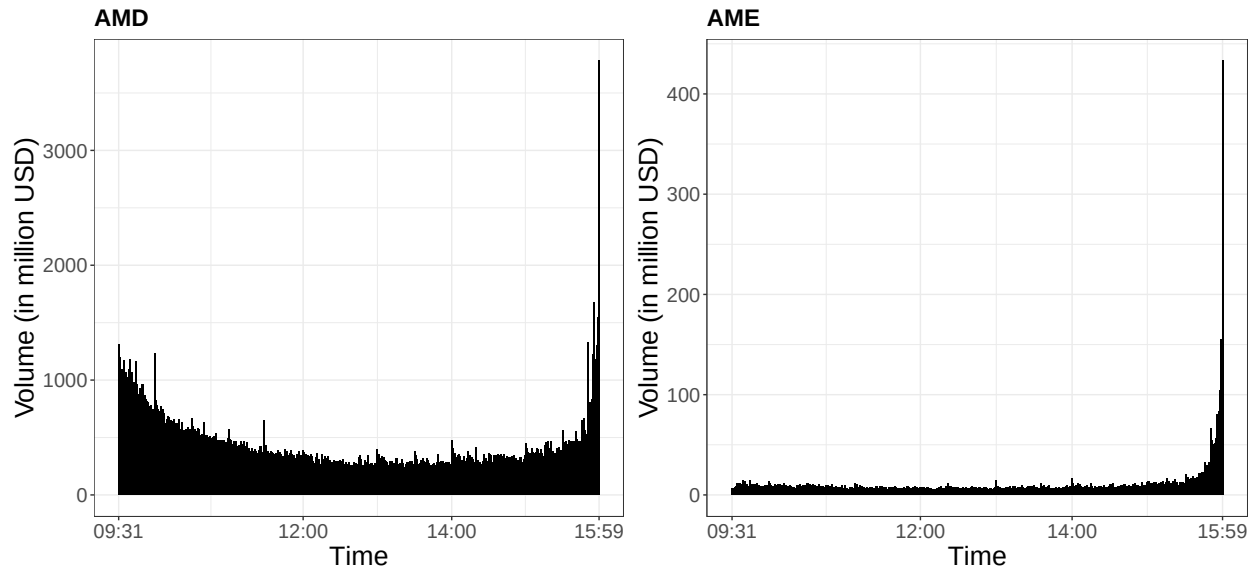


Figure 2: **First to Last Hour Ratio (M1) over time for portfolios sorted on M1**

This figure shows the average First to Last Hour Ratio (M1) (as defined in Section 3.2) for portfolios over time. During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 5 portfolios based on the First to Last Hour Ratio (M1). The lines represent the average M1 value of the stocks included in a portfolio.

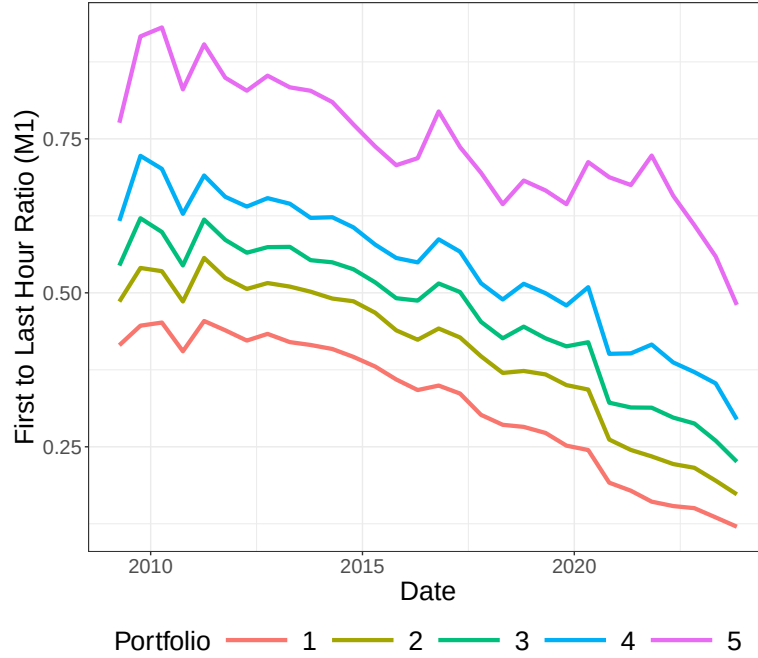


Figure 3: **Scatterplot of intraday trading variables**

This figure shows pairs of the First to Last Hour Ratio (M1) and the Early to Late Volume Gravity (M3) as defined in Section 3.2. During our sample period from October 2008 to December 2023, we construct portfolios on specific dates (formation dates) that are six months apart. At each formation date, we compute the intraday trading variables based on the formation period of the previous six months. The observations in this figure consist of all S&P 500 stocks at all formation dates.

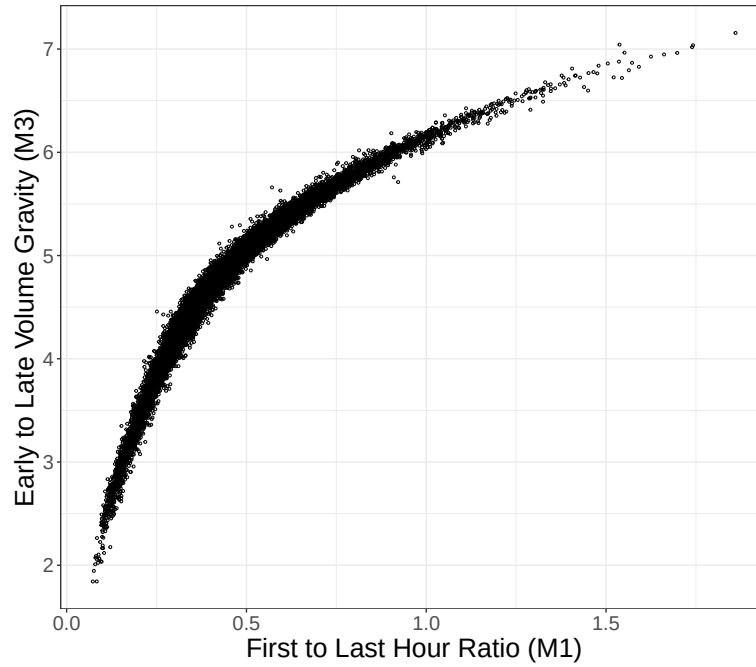


Figure 4: **Portfolio sorts on the First to Last Hour Ratio (M1)**

This figure shows cumulative daily returns for portfolios sorted on the First to Last Hour Ratio (M1). During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 5 portfolios. Daily portfolio returns are recorded for the following six months, before the portfolios are rebalanced. The lines in this figure represent the cumulative holding period returns. “Night” refers to the returns of being long overnight; “Day” refers to the returns of being long during the day; “Difference” refers to the returns of being long overnight and short during the day; and “Total” refers to the returns of being long overnight and during the day (see Section 3.3 for exact definitions).



Figure 5: **Portfolio sorts on the Open to Close Ratio (M4)**

This figure shows cumulative daily returns for portfolios sorted on the Open to Close Ratio (M4). During our sample period from October 2008 to December 2023, we construct portfolios on formation dates that are six months apart. On each formation date, we sort the S&P 500 stocks in ascending order into 5 portfolios. Daily portfolio returns are recorded for the following six months, before the portfolios are rebalanced. The lines in this figure represent the cumulative holding period returns. “Night” refers to the returns of being long overnight; “Day” refers to the returns of being long during the day; “Difference” refers to the returns of being long overnight and short during the day; and “Total” refers to the returns of being long overnight and during the day (see Section 3.3 for exact definitions).

