End-of-Day Reversal

Guido Baltussen[1,3], Zhi Da[2], and Amar Soebhag[1,4]

[1]Erasmus School of Economics, Erasmus University Rotterdam, Rotterdam 3000 DR, Netherlands.
[2]University of Notre Dame, IN 46556, United States.
[3]Northern Trust Asset Management - Quantitative Strategies.
[4]Robeco Quantitative Investing, Weena 850, 3014 DA Rotterdam.

November, 2024

Abstract

Individual stocks experience sharp intraday return reversals in the cross-section during the last 30 minutes of the trading day. This "*end-of-day reversal*" pattern is economically and statistically highly significant, is distinct from market intraday momentum, and primarily comes from positive price pressure on intraday losers. The effect cannot be explained by liquidity or gamma hedging effects. Instead, two novel channels related to the attention-induced retail purchases and risk management by short-sellers at the end of the day are driving the effect.

JEL Classification: G11, G12

Keywords: High-frequency, intraday returns, return predictability, asset pricing

1 Introduction

An emerging literature has uncovered robust stock return predictability at the intraday frequency. For example, Heston, Korajczyk, and Sadka (2010) document that a stock's return during a particular trading interval today positively predicts its returns during the same interval in subsequent days. Bogousslavsky (2016) attributes such intraday patterns to infrequent rebalancing by institutional investors. At the market level, both Gao, Han, Li, and Zhou (2018) and Baltussen, Da, Lammers, and Martens (2021) document that the intraday returns in equities and other asset classes during the early part of a day positively predicts return in the last half an hour. In this paper, we document a novel, economically strong, and robust intraday return predictability: an individual stock return during the early parts of a trading day *negatively* predicts its return in the cross-section during the last half an hour of a trading day. This *"end-of-day reversal"* pattern for individual stocks differs markedly from intraday momentum patterns documented at the market level, which we subsequently attribute to two novel underlying mechanisms.
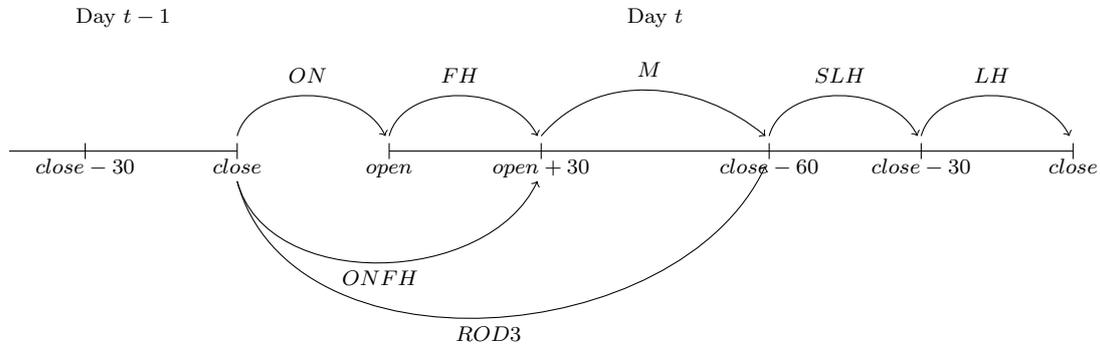
To facilitate the discussion of our analysis, we define a trading day as the 24-hour period from the market close on day $t-1$ to the market close on day t. Following Baltussen et al. (2021), we partition the trading day into five parts, as shown in the timeline above: (i) Overnight (ON, from close to open), (ii) First half-hour (FH, the first 30 minutes after the market open), (iii) Middle-of-the-day (M, from the end of FH to an hour before the market close), (iv) Second-to-last-half-hour (SLH, the second-to-last 30 minute interval), and (v) Last half-hour (LH, the last 30 minutes before the market close). The combination of the first two partitions is

labeled as $ONFH$ $(ON + FH)$, and the combination of the first three partitions is labeled as "Rest-Of-Day-3" $(ROD3 = ON + FH + M)$. $ROD3$ will be the key predictor for most of our paper.[1]

As our key empirical result, we show that the $ROD3$ return strongly and negatively predicts the LH return in the cross-section with t-statistics typically exceeding 5. Over our sample that starts in 1993, long-short intraday trading strategies generate highly significant average returns of between 3.49 and 4.74 bps per day (or 8.8% and 11.9% per year), depending on the weighting scheme and price filter. Importantly, the end-of-day reversal pattern is not a simple manifestation of the bid-ask bounce or other market micro-structure noise, as we have deliberately skipped a 30-minute interval (SLH) between $ROD3$ and LH. The end-of-day reversal result links to earlier findings of Heston et al. (2010), who have shown that a stock's intraday return over a given trading interval is negatively related to its returns over recent intervals. We show that such an intraday reversal pattern is mostly present and especially strong at the end of the trading day.

The end-of-day reversal is an extremely robust stylized fact. It is present in almost every 3-year rolling window. It is significant in various stock subsamples (small vs. large stocks; liquid vs. illiquid stocks; high- vs. low-volatility stocks; over- vs. under-priced stocks), including the largest, most traded, or most liquid stocks. Both the $ONFH$ and the M components of $ROD3$ return negatively predict LH return with similar importance, hence ruling out any explanation that relies solely on overnight or more recent returns. Moreover, the predictability is not driven by using the closing price (Bogousslavsky and Muravyev (2023)), as the pattern is robust to skipping the last 5 minutes in the LH return calculation. In (value-weighted) panel regressions, $ROD3$ returns remain significant in predicting LH return after controlling for stock (in addition to time) fixed effects and additional time-varying stock characteristics, including lagged LH (or seasonality) returns. Further, the effect is present in both traded prices and midpoint quote-based returns.

---

[1]Baltussen et al. (2021) also define $ROD = ON + FH + M + SLH$ and use this as main predictor for market intraday momentum. To mitigate concerns around reversals effects from bid-ask bounces and related micro-structure noise - effects which are typically more pronounced at the individual stock level - we skip SLH. However, the end-of-day reversal results presented in this paper are robust to including SLH in our analyses.

The end-of-day reversal in the cross section of stocks appears to be in contrast to the findings of Gao et al. (2018) and Baltussen et al. (2021), who show momentum in intraday returns at the market level. How does the end-of-day reversal related to this market intraday momentum? Through a return decomposition exercise employed by (Lewellen, 2002) and Baltussen, van Bekkum, and Da (2019), we find the positive cross-stock autocorrelations overweigh the positive autocorrelations for each individual stock, resulting in market intraday momentum. In other words, individual stock (and market) returns display momentum in the time-series but due to strong cross-stock autocorrelations display end-of-day reversal in the cross-section. Hence, the end-of-day reversal pattern for individual stocks differs markedly from intraday momentum patterns documented at the market level.

We then proceed to examine the economic mechanisms underlying the end-of-day reversal. An intuitive explanation relates to illiquidity. However, as stressed above the effect shows up while controlling for microstructure noise and amongst the most liquid, most traded, or large cap stocks. Another simple liquidity explanation that we also rule out is based on a persistent liquidity shock during $ROD3$: as the liquidity improves during LH, price reverts to its fundamental level. Under this explanation, the price correction during LH should be permanent and should not itself be reverted in the future. Empirically, we find that $ROD3$'s return predictability disappears if we extend the future return horizon to include both LH today and $ONFH$ tomorrow, or both LH today and the close-to-close return tomorrow. In other words, the return during LH itself seems to contain a transitory price pressure that reverts the next day.

What, then, could be driving the end-of-day price pressure? We next examine the impact of hedging demand from market makers. Baltussen et al. (2021) document that the gamma hedging demand related to index products drives market intraday momentum. Barbon, Beckmeyer, Buraschi, and Moerke (2021) show such gamma-hedging effects are also present at the stock-level driving intraday return predictability towards the close. Option market makers seldom maintain "naked" option positions and they systematically hedge their option inventory risk by trading the underlying asset. If their inventory has a positive gamma, they have to trade in the

opposite direction of the return to ensure delta-neutrality, giving rise to a price pressure during LH, in the opposite direction of $ROD3$ return. Such price pressure on an individual stock can originate directly from hedging options on that stock, or indirectly from hedging index options if the stock belongs to the index. Similarly, Leveraged ETFs (LETF) seek to deliver a multiple of their underlying index's daily returns. Market makers in LETFs need to rebalance daily, typically around the close, in the same direction as the underlying index's daily performance, again propagating price pressure to individual stocks that are in the index.

Panel regressions show that while such hedging demands impact intraday returns and can contribute to the end-of-day reversal when market makers have net long gamma exposure at the stock level, they fail to fully explain it. $ROD3$ return remains highly significant in predicting LH return, even after controlling for hedging demand from individual stock options, index options, and LETFs. To control for the possibility that the hedging demand is inaccurately measured, we also examine the subset of stocks without option trading or among non-index stocks. We find that the end-of-day reversal is strongly present there as well, suggesting it is not entirely driven by hedging demand.

Alternatively, the price pressure can arise from arbitrageurs' unwinding their positions at market close in order to avoid overnight risk and cost, as documented by Bogousslavsky (2021a). Specifically, arbitrageurs will sell (buy) undervalued (overvalued) stocks during LH. If undervalued (overvalued) stocks are also winners (losers) during $ROD3$, then such a position unwinding can explain the end-of-day reversal. Using the mispricing measures of Stambaugh, Yu, and Yuan (2012), we find that these unwinding activities do not explain the end-of-day reversal either, as undervalued $ROD3$ losers tend to have higher LH returns than overvalued $ROD3$ winners. Moreover, the end-of-day reversal is also strongly present among stocks that appear not mispriced.

We next show an important characteristic of the end-of-day reversal pattern. The reversal displays a very strong and persistent asymmetry, as it is much stronger after negative $ROD3$ returns than positive ones. In fact, we find that the end-of-day reversal is entirely driven by

the subsample with negative $ROD3$ returns, this effect holds across days of the week, and this asymmetry in intraday reversal especially emerges during the end of the trading day.

Building on the asymmetry in end-of-day reversal, we consider two more novel explanations; (i) the end-of-day 'buy-the-dip' trading by retail investors, and (ii) the end-of-day trading by short sellers. Large intraday returns could grab retail investors' attention (Barber, Huang, Odean, and Schwarz (2022)). Since retail investors rarely short, their attention results in purchases and, thus, positive price pressure on average (see Barber and Odean (2008) and Da, Engelberg, and Gao (2011) amongst others). To identify retail trades and retail buying we consider three methods. First, we use the small trade size classification from 1993 to 2000, the pre-decimalization era in our sample. Second, we apply the Boehmer, Jones, Zhang, and Zhang (2021) retail trade classification method from 2014 to 2019. Third, to address concerns about potential measurement errors in the Boehmer et al. (2021) method, as noted by Barber, Huang, Jorion, Odean, and Schwarz (2024) and Battalio, Jennings, Salgam, and Wu (2024), we also examine changes in Robinhood retail holdings from 2018 to 2019.

The three measures of retail order imbalance (and hence retail buying) paint a very similar picture. There is positive and significant retail buying during LH for stocks with extreme $ROD3$ returns (both winners and losers) that trigger their attention. We also find that the retail purchase is much stronger for $ROD3$ losers than winners, consistent with the notion of retail contrarian trading (see Kaniel, Liu, Saar, and Titman (2012) amongst others).

Considering the end-of-day trading by short-sellers, one could argue that overnight risk on individual stocks is particularly important for short-sellers, since the potential for loss can be unlimited and it is very hard to hedge. Using proprietary intraday data on the opening of short positions, we find a significant drop in new short positions during LH for stocks with extreme $ROD3$ returns (both winners and losers), consistent with the overnight risk management channel. In line with the asymmetry in the end-of-day reversal, the reduction in new short positions is more than three times stronger for $ROD3$ losers than winners, as a negative $ROD3$ return reduces potential shorting profit.

Overall, increased 'buy-the-dip' buying by retail investors, combined with reduced short selling, generates positive price pressure during LH. Since the positive price pressure is much stronger among $ROD3$ losers, we observe the end-of-day reversal.

Our findings relate to several studies that argue that retail investors are especially active before and around the open and their price pressures influences opening stock prices. Berkman, Koch, Tuttle, and Zhang (2012) show that retail-attention-induced price pressure pushes up the stock price at the open, thereby contributing to a high overnight return and a low intraday return on average. Jones, Pyun, and Wang (2024) show that retail investors are extrapolative in their trading at the beginning of the day. Next, we examine retail activity around the open, confirming the retail-attention-induced opening price pressure effect and showing that retail investors are extrapolative in their trading at the beginning of the day using $ROD3$ returns. This reveals an interesting contrast between retail trading at the end of the day and trading at the beginning; buy-the-dip trading around the close of trading versus extrapolative trading during the open of trading. Overall, we conclude that significant price pressures from retail investors happen during the open ('extrapolative') and close ('buy-the-dip') of the trading day, thereby causing predictible intraday rertun patterns.

Our paper further contributes to the recent emerging literature examining intraday return patterns in stock returns. Heston et al. (2010) find evidence of intraday return seasonality: returns continue during the same half-hour intervals as previous trading days. Lou, Polk, and Skouras (2019) document strong overnight or intraday return continuation and an offsetting cross-period reversal at individual stock level and in equity return factors (see also Bogousslavsky (2021b) and Hendershott, Livdan, and Rösch (2020)). Berkman et al. (2012) and Akbas, Boehmer, Jiang, and Koch (2022) show evidence of strong intraday versus overnight return return reversal in stocks.[2] In this paper, we document a novel and strong stylized fact in the form of

---

[2]Related, several studies document intraday patterns at the market-level or in derivatives. Boyarchenko, Larsen, and Whelan (2023) and Bondarenko and Muravyev (2023) show that U.S equity market returns are large and positive around the opening of European markets. Baltussen, Terstegge, and Whelan (2023) document strong overnight and intraday reversals at the market level around option expiries. Smirlock and Starks (1986) provide an early account of intraday effects around weekends in DJIA stock returns. Muravyev and Ni (2020) document strong intraday and overnight differences in option returns. We show that while stock markets display strong market intraday momentum at the end of the day, individual stocks display reversals.

end-of-day reversal. Investigation of the empirical mechanism reveals the important consideration of overnight risk and retail trading in driving end-of-day prices.

The remainder of the paper is organized as follows. Section 2 describes our data and sample. Section 3 presents the main stylized facts about the stock-level end-of-day reversal. Section 4 compares the stock-level to market-level results. Section 5 examines the economic drivers of end-of-day stock prices. Section 6 offers concluding remarks. The appendix contains various robustness results and additional descriptions of the data.

2 Data

In this section, we provide detailed descriptions of our data sources, as well as the construction of our sample and main variables.

2.1 Intraday stock returns: TAQ and CRSP

Our sample consists of stocks listed on the New York Stock Exchange (NYSE), National Association of Securities Dealers Automated Quotations (NASDAQ), and American Stock Exchange (AMEX). We include common stocks with share codes 10 or 11 that have intraday transactions covered by the Trade and Quote (TAQ) database. Stock market data are obtained from the Center for Research in Security Prices (CRSP), and accounting data are from Compustat. Our sample period runs from January 1993 to December 2019.

We collect intraday returns from TAQ according to the following protocol. First, we collect price data of each stock at the trade-level and apply the cleaning procedures as described in Bollerslev, Li, and Todorov (2016) by (i) removing all observations with non-positive prices and trade sizes, (ii) removing trades with correction indicator (CORR) other than 0, 1, or 2, (iii) removing trades with the sale condition having a letter code other than @, *, E, F, @E, @F, *E, or *F, (iv) removing trades outside the regular trading hours (9:30 a.m. - 4:00 p.m. EST), and (v) removing all non-business days or days in which the exchange closed earlier, such as Memorial Day. Next, for each second within the 9:30 a.m. - 4:00 p.m. time interval we collect the latest traded price, or when multiple trades occur within a second we compute the

volume-weighted average traded price over all trades within the second. To limit the influence of illiquid or microcap stocks and to mitigate the influence of micro-structure issues, we remove stocks with a market capitalization below the NYSE 10th percentile or stocks that are priced below \$5 as a base case, or \$1 if explicitly mentioned. Lastly, we require stocks to have at least 126 days of observations in the TAQ database to be included in our sample.[3]

To examine intraday return predictability, we aggregate the price of stock i on day t at the second level to the frequencies outlined in the introduction. The return from market close on day $t-1$ till 3:00 p.m. on day t ($ROD3_{i,t}$) and the return from 3:30 p.m. till 4:00 p.m. on day t ($LH_{i,t}$) is computed as:

$$ROD3_{i,t} = \frac{P_{i,t,close-60}}{P_{i,t-1,close}} - 1$$
$$LH_{i,t} = \frac{P_{i,t,close}}{P_{i,t,close-30}} - 1$$

We cross-sectionally trim these returns at the 1% to negate the effect of outliers in our analyses. In addition, we create other intraday return intervals. $ONFH$ is defined as the return from market close on day $t-1$ till 10:00 a.m. on day t. We define MID as the return from 10:00 a.m till 15:00 p.m. on day t, and SLH as the return on the second last half-hour of the trading day t.

We match the TAQ intraday returns to the CRSP and Compustat database, allowing us to incorporate firm-level characteristics and construct a set of control variables. Our empirical analysis employs the following firm characteristics: $Size$ computed as the product of the closing price and the number of shares outstanding updated daily from CRSP, β_{mkt} computed as the β obtained from the CAPM regression on a 252-day rolling window requiring at least 126 unique observations, MOM computed as the cumulative return from day $t-252$ to day $t-21$ on day t updated daily, $SREV$ computed as the cumulative return from day $t-21$ to day $t-1$ for a given day t updated daily, $RVOL$, the realized variance of stock i on day t, defined as the sum of the squared five-minute intraday returns within day t, ILQ, the Amihud (2002) measure of

---

[3]TAQ also provides quote-level data as alternative to trade-level data. TAQ quote-level data tends to be more noisy, but less subject to bid-ask bounces. We have verified that the end-of-day reversal is also present in quote-level data aggregated to the second-level according to the algorithm described above.

illiquidity, defined as the average daily ratio of the absolute stock return divided by the dollar trading volume of the past 21-day period preceding each day.

3   End-of-day reversal

In this section, we present the baseline results for the end-of-day reversal among individual stocks and examine its robustness across definitions, samples, subgroups of stocks, and methodologies.

3.1   Baseline result: the specialness of the last half-hour

We start our analyses by regressing stock returns within a 30-minute interval at day t on the returns from 24-hours before the end of the window till an hour before the window.[4] For example, for the 15:30 - 16:00 window we regress the stock return in this window on the return between 16:00 the preceding day till 15:00 the current day. We include a 30-minute lag between the regressor and the dependent variable to control for bid-ask bounces or other market microstructure noise, as argued by, for example, Heston et al. (2010). We follow this practice throughout the paper, but emphasize that all our results are robust to this choice, generally becoming stronger when discarding the 30-minute lag. We estimate a panel regression including date and firm fixed effects, and correct standard errors for clustering in both the date and firm dimension.[5] The sample runs from January 1993 to December 2019 and, importantly, we weigh observations by their previous' day market capitalization to not give excessive weight to smaller cap stocks that are exposed to higher microstructure or trading effects.

Figure 1 shows the resulting slope coefficients and 95% confidence intervals. Most intervals display no significant predictability, with slope coefficients being close to zero. The three exceptions are (i) the first interval - the return during the previous day excluding overnight negatively predicts FH returns, (ii) the one but last interval - the return from the last half hour of trading the previous day till 14:30 today negatively predicts the return between 15:00 and 15:30

---

[4]In our analysis we divide the trading day in 14 intervals; the overnight return between close of trading (16:00) and open (09:30), and each 30 minute intervals between 09:30 and 16:00. All times are expressed in Eastern Standard Time (EST).

[5]To optimize testing power and given the nature of our data we use panel regressions with date fixed effects throughout the paper instead of Fama-MacBeth regressions. That said, we have verified that our main results are robust to using Fama-MacBeth regressions.

(SLH), and (iii) the last interval - returns from previous day close to one hour before close (i.e., $ROD3$) negatively predict last half hour (LH) returns. The latter end-of-day reversal pattern is especially strong and significant, typically being more than double the reversal effects observed during other intervals. Overall, these results tend to be in line with Heston et al. (2010) who show that stock's return over a given trading interval is negatively related to its returns over recent intervals. Importantly, we find such an intraday reversal pattern to be by far the strongest at the end of the day, which will be the main focus of the remainder of this paper. Figure A.1 in the appendix shows results for the last 30 minutes are comparable to stronger when discarding the 30-minute lag between the regressor and the dependent variable (which we include to control for the effects of microstructure noise).[6] Overall, we document a strong cross-sectional reversal in the stock return at the end of the trading day.

Next, to examine the persistence of the end-of-day reversal, we run rolling 3-year panel regressions of LH on $ROD3$ using the specifications as described above. Figure 2 shows that the negative predictability of cross-sectional stock returns during the last half hour of trading is largely persistent over time. Slope coefficients in 3-year rolling panel regressions are almost always negative (upper panel) and are mostly significant (lower panel), even in the later years of our sample.

3.2 Univariate portfolio sort

To further examine the link between $ROD3$ returns and LH returns in the cross-section of stocks, we form quintile portfolios. We sort stocks into five portfolios based on their return between the closing price on day $t-1$ and the price at 15:00 p.m. on day t (i.e., the $ROD3$ return). We hold these portfolios during the last half hour (LH) of the trading day t. We compute value-weighted as well as equal-weighted returns on each portfolio, with both a \$5 and \$1 dollar price filter. Additionally, we construct a "low-minus-high" (L-H) portfolio that takes long positions in stocks with low $ROD3$ returns and short positions in stocks with high $ROD3$ returns.

---

[6]In unreported analyses we find that the return between 9:30 and 16:00 on day $t-1$ positively predicts the first half-hour return on day t, but negatively predicts overnight returns, which is consistent with prior literature (Akbas et al. (2022) and Berkman et al. (2012)).

Table 1 presents the resulting portfolio returns (R; expressed in basis points per day) and risk-adjusted returns relative to the Fama-French 3-factor and the Fama-French 5-factor models, both augmented with momentum (FF4 or FF6, respectively).[7] For both value-weighted and equal-weighted portfolios, regardless of the price filter, we document a negative relation between $ROD3$ returns and LH returns.

The first column in Table 1 shows a significantly negative relation between $ROD3$ returns and LH returns, in line with the results in Figure 1. The value-weighted daily portfolio return decreases from 3.19 bps per day on quintile L (low ROD) to -0.31 bps per day on quintile H (high ROD). The low-minus-high portfolio yields a return spread of 3.49 bps per day (t-statistic of 10.33). The subsequent two columns show that exposures towards well-known factors as market, size, value, investments, profitability, and momentum are not able to explain the difference in returns between stocks with high ROD and low ROD. The 6-factor Fama-French alpha of the spread portfolio remains 3.43 bps per day, and highly significant with a t-statistic of 10.34. Using a lower price filter yields very similar results.

The reversal pattern becomes even stronger when considering equal-weighted portfolios, with the spread return being 4.56 bps per day (t-statistic of 16.12). These results indicate a stronger reversal for smaller stocks. Interestingly, most of the increase for equal-weighted portfolios comes quintile L, or the intraday loser stocks that gain in the last half hour of trading before the close. Again, results are robust for the price filter applied. Overall, the sorting results imply that high $ROD3$ stocks underperform low $ROD3$ stocks by a sizable and highly significant margin towards the end of the day, revealing an end-of-day reversal.

How should we look at the size of end-of-day reversal and transaction costs? The effect is very sizable in gross terms with a 3.49 bps reversal per day, or about 8.8% a year, for the value-weighted L-S portfolio, and 4.56 bps per day, or 11.5% a year, for the equal-weighted L-S

---

[7]We compute all factor returns during LH to align with the timing of the portfolio returns. We have verified that results are comparable when computing factor returns over the full day, as commonly done in asset pricing tests using daily data.

portfolio.[8] Given that trading on end-of-day reversal requires frequent rebalancing, the strategy as presented might not be exploitable by many investors after accounting for transaction costs. That said, this does not imply that the end-of-day reversal is entirely unexploitable for investors. For example, several investors are known to trade at very limited cost (e.g., market makers or proprietary trading desks and firms), the effect is stronger for stocks with even more extreme intraday returns (as evident from for example decile portfolios), and exploiting the effect can be done more optimally by a direct trade-off between the strategy signal and transaction costs per stock. Furthermore, end-of-day reversal may also be exploited in other ways that limit turnover, for example via the timing of already planned trades. A detailed examination of the most efficient execution strategies aimed to exploit the intraday reversal is left for future research.

3.3 Controlling for stock characteristics

To ensure that differences in $ROD3$ are driving the last-half-hour return rather than omitted stock-characteristics, we present conditional 5×5 portfolio sorts. We first form quintile portfolios based on a given stock characteristic, and subsequently, form quintile portfolios based on $ROD3$ returns within each stock characteristic sorted quintile. The conditioning characteristics that we consider are: size (market capitalization at day $t-1$), trading volume at day $t-1$, the illiquidity measure of Amihud (2002), realized volatility at day $t-1$ computed using 5-minute returns, overnight volatility (the standard deviation of overnight returns over the past 90 trading days), and the composite mispricing score of Stambaugh and Yuan (2017).

We present the bivariate portfolio sort results in table 2, where we report the six-factor alpha and its significance for the intraday loser (L), intraday winner (H), and long-short (L-H) portfolio. Panel A shows the bivariate sort based on market capitalization and ROD. We find that the intraday reversal pattern persists after controlling for size and is present across size groups. Intraday reversal is especially strong among small firms, as shown in column (S) and in line with the equal-weighted results reported in table 1. A long-short strategy within the smallest 20%

---

[8]Although the portfolios have positions during only 30 minutes a day, we annualize returns by multiplying with 252 given that the strategy trades once a day.

firms earns a six-factor alpha of 8.93 bps per day (t-statistic = 24.99). The intraday reversal effect is also present among the 20% largest firms, where the six-factor alpha equals 3.39 bps per day (t-statistic = 11.09).

Overall, the end-of-the-day reversal is extremely robust as we find qualitatively similar results in the other panels. In general, within each quintile of the conditioning variable, we observe a significant cross-sectional intraday reversal. The end-of-day reversal effect also occurs among the most liquid, most traded, and least volatile stocks.

Finally, we consider stocks that are underpriced or overpriced according to the mispricing score of Stambaugh and Yuan (2017). End-of-day price pressure can arise from arbitrageurs unwinding their positions at market close in order to avoid overnight risk and cost, as documented by Bogousslavsky (2021a). Specifically, arbitrageurs will sell (buy) undervalued (overvalued) stocks during LH. If undervalued (overvalued) stocks are also winners (losers) during $ROD3$, then such a position unwinding can yield end-of-day reversal. The bottom right part of table 2 show that these unwinding activities do not fully explain the reversal. We find undervalued $ROD3$ losers to have substantially higher LH returns than overvalued $ROD3$ winners. In addition, the end-of-day reversal is significantly present among all mispricing quintiles, including stocks that are not mispriced.

3.4   Panel regression results

In addition to our portfolio sorts, we employ panel regressions to assess the predictive power of $ROD3$ returns for subsequent LH returns and to examine robustness to the inclusion of several control variables. To this end, we estimate the following specification:

$$LH_{i,t} = \delta * ROD3_{i,t} + \sum_{j=1}^{K} \delta_j X_{k,i,t-1} + \epsilon_{i,t} \tag{1}$$

Where $LH_{i,t}$ is the stock return between 3:30pm and 4:00pm, and $ROD3_{i,t}$ is the stock return from the close on day $t-1$ until 3:00pm on day t. The control variables $X_{k,i,t-1}$ are measured on the close of day $t-1$. As before, we weight all observations by their previous' day market

13

capitalization and we included date - and firm fixed effects with standard errors adjusted for clustering in the date and firm dimension.

Table 3 reports the results of the panel regressions under multiple specifications, lending further support to the existence of the end-of-day reversal. Column (1) shows that ROD returns exhibit strong negative predictive power for the LH return with a t-statistic of -5.70, consistent with our sorting results. The subsequent columns show that results remain very similar after the inclusion of other predictors. In column (2), we decompose $ROD3$ into $ONFH$ and MID as Baltussen et al. (2021) show both components contain predictive power at the market-level. Our results indicate that both ONFH and MID negatively predict the last half-hour return with coefficients of similar size. Hence, both the overnight return and the intraday return tend to revert in the last half-hour. Consequently, any explanation for end-of-day reversal should account for both the overnight and the intraday return effect.

Heston et al. (2010) find evidence of intraday return seasonality: returns continue during the same half-hour intervals as during previous trading days. In column (3), we regress the LH return on $ROD3$ return and simultaneously control for intraday seasonality by including the LH returns in the past three trading days. We find that $ROD3$ remains a significant negative predictor of returns during the last half-hour of the trading day. In column (4), we add several commonly used control variables: one-year market beta (estimated using daily data), daily realized volatility (RV; computed using 5-minute returns), past month return (SREV), one-year momentum (MOM), the illiquidity measure of Amihud (2002) (ILQ), and the mispricing score of Stambaugh and Yuan (2017) (MIS). Bogousslavsky (2021a) show that a mispricing factor earns positive returns throughout the day but performs poorly during the last half-hour. We find that the coefficient on $ROD3$ remains of similar size and significance after including these controls. Hence, end-of-day reversal is not driven by stock characteristics or effects related to the mispricing factor.

End-of-day reversal may be driven by closing price effects caused by the closing price mechanism or the tremendous amount of orders executed at the market-on-close price (Bogousslavsky

& Muravyev, 2023). In column (5), we replace LH by the return from 3:30pm till 3:55pm on $ROD3$ returns - hence skipping the last 5 minutes of the trading day and avoiding effects present in the close price. We find that the coefficient on $ROD3$ becomes even more negative (-1.01) and significant (t-statistic = -9.28), and hence that the predictability is not driven by using the closing price. Our analyses so far has been based on returns computed from traded prices. Lastly, table A.1 in the appendix considers panel regression results using midpoint quote-based returns. Again, coefficients and significance levels are largely similar, confirming an end-of-day reversal effect is robust to using quote-based returns.

4   End-of-day reversal versus market intraday momentum

In this section, we reconcile the end-of-day reversal results at the individual stock-level to market-level results documented by Gao et al. (2018) and Baltussen et al. (2021). Both studies document intraday momentum during the last half hour at the market-level, whereas we document a robust cross-sectional reversal at the stock-level. To understand the link and sources of both patterns, we employ the return decomposition exercise inspired by Lo and MacKinlay (1990). We consider a value-weighted cross-sectional (XS) strategy with the following portfolio weights:

$$\omega_{i,t}^{XS} = \omega_{i,t-1}(ROD3_{i,t} - ROD3_{m,t}), \tag{2}$$

where $\omega_{i,t-1}$ is the market capitalization of firm i scaled by the total market capitalization of all firms on day $t-1$. $ROD3_{m,t}$ is the value-weighted average $ROD3$ return on day t. The portfolio return during the last half hour (LH) is as follows:

$$\pi_t = \sum_{i=1}^{N} \omega_{i,t}^{XS} LH_{i,t} = \sum_{i=1}^{N} \omega_{i,t-1}(ROD3_{i,t} - ROD3_{m,t})LH_{i,t} \tag{3}$$

We can decompose the expected XS strategy profit into three components:

$$E(\pi_t) = \omega \cdot diag(\Omega) - [\omega'\Omega\omega - \omega \cdot diag(\Omega)] + Cov(\mu_{ROD3}, \mu_{LH}), \tag{4}$$

where $\Omega = Cov(ROD3_t, LH_t)$ is the covariance matrix between $ROD3$ and LH returns, and $Cov(\mu_{ROD3}, \mu_{LH})$ is the cross-sectional covariance between average $ROD3$ and LH re-

turns. Eq. 4 shows three possible sources of the intraday reversal strategy. The first term, $\omega \cdot diag(\Omega)$, is the value-weighted average auto-covariance of individual stocks. The second term, $[\omega'\Omega\omega - \omega \cdot diag(\Omega)]$, is the negative of the average cross auto-covariance. The third term, $Cov(\mu_{ROD3}, \mu_{LH})$, is the cross-sectional covariance of average (value-weighted) $ROD3$ and LH returns, which captures dispersion in expected LH returns associated with $ROD3$ returns.

In addition, we also construct a time-series (TS) strategy with the following weights:

$$\omega_{i,t}^{TS} = \omega_{i,t-1} ROD3_{i,t}. \tag{5}$$

The expected returns of the time-series strategy can be decomposed as:

$$E(\pi_t) = \omega \cdot diag(\Omega) + \mu'_{ROD}\mu_{LH}. \tag{6}$$

The time-series strategy can be decomposed into the value-weighted auto-covariance term $(\omega \cdot diag(\Omega))$, which is also a component in the XS strategy, plus the product of the (value-weighted) average $ROD3$ and LH returns. Hence, these equations can provide a link between time-series and cross-sectional strategy profitability. It has been shown by Baltussen et al. (2021) that $ROD3$ (or ROD) positively predicts LH returns at the market-level. Hence, we expect that our estimated auto-covariance terms will be positive. In that case, the cross-sectional intraday reversal can only originate from the last two terms from equation 4.

One limitation of the decomposition using individual stocks is that it requires complete observations of stocks over the decomposition period. To address this, we randomly generate sub-samples of 6 months with replacement, and require complete observations within each sub-sample. We decompose the profits for each subsample and report the average in table 4.

The total return to the XS strategy is -2.76 basis points per day, which is significantly negative and in line with our previous results. We find that the auto-covariance component is positive and significant (1.09 basis points per day) as expected based on the market intraday momentum pattern. Importantly, the negative profitability of the XS strategy comes *solely* from the cross-covariance which is -3.74 basis points per day. Stocks that went up or down less compared to

other stocks catch up on the movement, yielding the end-of-day reversal pattern. Mean return effects are close to zero, and although highly significant they contribute little to the XS strategy return. Further, we show the expected profit of the TS strategy, which is 1.01 basis points per day, in line with intraday momentum at the market-level.

Overall, these results help to understand the difference between the cross-sectional intraday reversal that we observe, and the time series intraday momentum in Baltussen et al. (2021). Individual stock (and market) returns display momentum in the time-series but due to strong cross-stock autocorrelations display end-of-day reversal in the cross-section. Hence, the end-of-day reversal pattern for individual stocks is clearly distinct from, and complementary to, intraday momentum patterns documented at the market level.

5   What drives intraday reversal?

In this section, we examine the likely drivers of the end-of-day reversal. We start by examining permanent liquidity shocks versus temporary price pressures or news arrival, followed by gamma hedging effects found by Baltussen et al. (2021), any asymmetry in end-of-day reversal, and two novel channels related to end-of-day retail trading and reduced short selling. Finally, we present additional results on retail trading and returns at the start of the next day.

5.1   Temporary price pressure

Having documented a sizable and robust end-of-day reversal pattern, we next examine its potential economic mechanisms. A first, intuitive explanation relates to illiquidity. However, as stressed above the effect shows up while controlling for microstructure noise and amongst the most liquid, most traded, or large cap stocks. A potential other, simple explanation is based on a persistent liquidity shock during $ROD3$. As the liquidity improves during LH, the price reverts to its fundamental level. Under this explanation, the price correction during LH should be permanent and should not itself be reverted in the future. Related, if the end-of-day reversal is driven by informational trading motivations, we would expect it to persist beyond the last

17

half hour.

In table 5, we study whether stock-level intraday reversal persists beyond the current last half-hour. To this end, we extend the last half-hour interval with the subsequent overnight and daytime interval at trading day $t + 1$. Starting at our standard specification of regressing the last half hour return (LH_t) on $ROD3$ (row 1), we progressively add the two intervals to LH_t (rows 2 and 3). The results show that $ROD3$ return predictability disappears if we extend the future return horizon to include both LH today and $ONFH$ tomorrow, or both LH today and close-to-close tomorrow. The coefficient on $ROD3$ reverts to -0.18 (t-statistic of -0.72) when adding the subsequent overnight interval to LH_t, and to 0.27 (t-statistic of 0.65) when we extent the interval to close at $t + 1$. In other words, the intraday reversal during LH reflects a transitory price pressure that reverts during the next day. Such a reversal contradicts explanations based on a permanent liquidity shock or motivations stemming from informational trading.

5.2 News

To further examine whether end-of-day reversal is a reflection of fundamental news releases or informed trading we consider the panel regression with interaction dummies for earnings news (i.e., earnings announcement dates) or firm-specific corporate news dates. In Appendix 7, table A.2 we show the regression results, revealing that the relationship between $ROD3$ and LH is not affected by the presence of earnings announcements or other firm-specific news. Hence, end-of-day reversal is robust to the arrival of fundamental news.

5.3 Hedging demand and end-of-day reversal

What could then be driving end-of-day reversal? Baltussen et al. (2021) show that last half-hour returns at the market-level display momentum, driven by hedging demand of option market makers and the rebalancing of leveraged ETFs. Option market makers tend to systematically hedge their option inventory risk by trading the underlying asset. If their inventory has a positive gamma, then they have to trade in the opposite direction of the past return in order

to ensure delta-neutrality, giving rise to price pressure during LH in the opposite direction of $ROD3$ return. Baltussen et al. (2021) argue that a natural moment to hedge is before market close as risk or capital requirements tend to increase overnight. Furthermore, such price pressure on individual stocks can originate directly from hedging options on those stocks, or indirectly from hedging index options if a stock belongs to an index. Similarly, Leveraged ETFs (LETF) seek to deliver a multiple of their underlying index's daily returns. Market makers in LETFs need to rebalance daily and around the close in the same direction as the underlying index's daily performance, again propagating price pressure to individual stocks that are in the index. Barbon et al. (2021) show evidence of price dynamics at the stock-level during the end of the day driven by the same two hedging demand factors.

To examine the role of gamma-related hedging demand on end-of-day reversal, we extend our panel regressions with the various measures of hedging demand used by Baltussen et al. (2021). We obtain data from OptionMetrics on individual stock options to construct the Net Gamma Exposure (NGE) measure for each stock i at day t. A detailed explanation of the variable construction is provided in Appendix 7. Second, we compute $ROD3$ and NGE for several indexes, and map this to their constituents using a stock's weight in each index. Details are provided in Appendix 7. Third, we compute the rebalancing demand of LETFs of various indices and again map this to their constituents using a stock's weight in each index. Details are provided in Appendix 7. Our option data sample start in 1996 (the start date of OptionMetrics data) and our LETF sample in 2006 (Leveraged ETFs were introduced in 2006).

Table 6 presents the results. First, we focus on the subsample of stocks for which we have option data available on day t (panel A). In column (1), as before, we document that end-of-day reversal remains highly significant over this (shorter and smaller) subsample. Next, we regress the LH return on $ROD3$, the NGE of stock i and day t, and the interaction term between both (column (2)). We find that $ROD3$ interacts significantly with NGE, thus the more positive (negative) the NGE on a stock the more we observe intraday reversal (momentum). This aligns with the findings of Baltussen et al. (2021) at the market-level and Barbon et al. (2021) at the stock-level. When NGE is positive, option market makers need to rebalance against the initial

price movements, thereby creating a price reversal at the end of the day. Interestingly, the coefficient on $ROD3$ remains highly significant (t-statistic = -4.80) after controlling for gamma hedging demand from individual stock options. Columns (3) to (5) show a similar pattern after including the market-level gamma hedging measures; especially LETF demand contributes to stock-level intraday momentum, but the end-of-day reversal effect is robust to the controls for gamma hedging. These results indicate that while gamma hedging demands contribute to the end-of-day reversal, they do not fully explain it.

The above NGE measure relies on the assumption that market makers are short the entire put and long the entire call open interest at each point in time (see Baltussen et al. (2021)), which introduces measurement errors. Using a more precise measure that utilizes detailed positioning data to approximate option market makers positioning, Barbon et al. (2021) find gamma hedging effects that in line with our results presented in table 6. Next, to account for the possibility that the hedging demand is measured with errors, in panel B of table 6 we consider a more direct test by focusing on the sub-sample of stocks that have no option data available before day t.[9] If gamma-hedging from individual stock options would be fully driving the end-of-day price dynamics, we would expect to observe no end-of-day predictability for stocks without options trading on them. Column (1) in panel B shows that end-of-day reversal still occurs significantly in this sub-sample (t-statistic of -3.64). Subsequent columns shows the predictability remains once including the market-level gamma hedging measures.

Next, we rerun the above panel regressions for two additional sub-samples: stocks included in well-tracked indexes at day t ('Indexed) and all other stocks ('Non-Indexed'). Index inclusions covers the S&P 500, Nasdaq 100, Dow Jones 30, S&P 400 Midcap, or Russell 2000 indices. Table 7 presents the results. Stocks in an index will have gamma hedging effects from market-level options and LETF spilling over to its constituents. Panel A shows that also in this subset end-of-day reversal remains strong and highly significant, despite the presence of stock-level and market-level gamma hedging effects. Panel B considers all stocks outside major indices at day t, and hence without direct market-level gamma hedging demand effects. Also in this sub-sample

---

[9]More specifically, a stock is non-optionable until its first occurrence in the OptionMetrics database with valid Net Gamma Exposure data.

we observe a significant end-of-day reversal. Overall, stock- and market-level gamma hedging demand predicts momentum or reversal effects in returns towards the end-of-day, but they are at best a partial explanation of the end-of-day reversal effect.

5.4 Asymmetry in end-of-day reversal

Next, we consider whether there is an asymmetric effect of $ROD3$ on LH. The univariate sorting results have shown that the end-of-day reversal mainly originates from the long leg, or the relative loser stocks. In column (6) of the earlier table Table 3 we add ROD3×I[ROD3<0] to the panel regression specification. This measures the additional effect of $ROD3$ on LH given a negative $ROD3$ observation. We find that the coefficient on $ROD3$ becomes insignificant (t-statistic = -0.65), whereas ROD3×I[ROD3<0] significantly and negatively predicts LH returns (t-statistic = -6.28). Hence, end-of-day reversal especially originates from intraday loser stocks.

Next, we consider the asymmetry in intraday reversal across the various intraday intervals considered in Figure 1. Figure 3 shows the resulting slope coefficients and 95% confidence intervals for positive intraday returns (top panel) or negative intraday returns (bottom panel). Akin to Figure 1 most intervals display no significant predictability, with slope coefficients being close to zero. In general, positive intraday returns do not revert across intervals, including the LH interval (the exception being the FH interval). By contrast, negative intraday returns tend to revert, most notably during the beginning and end of the trading day. The results for the last interval clearly stand out, as the negative intraday returns tend to revert most strongly during SLH. Comparing the differences between both panels shows the intraday reversals are not much different across most intraday intervals except for LH, over which the slope coefficient changes from near zero for positive $ROD3$ returns to substantially negative for negative $ROD3$ returns. As robustness test, figure A.2 in the appendix, reports end-of-day reversal coefficients by the day of the week. We find that all coefficients do not differ significantly across different days of the week. Overall, our results show that the end-of-the-day reversal is driven by the subsample with negative $ROD3$ returns.

5.5 Retail trading

Intraday reversal during the last half hour of the trading day can be driven by retail investors. Relatively large intraday returns could grab retail investors' attention, and since retail investors rarely short, their attention results in purchases and, thus, positive price pressure on average. Barber and Odean (2008), Da et al. (2011), and Barber et al. (2022), amongst others, show that on average retail investors purchase the stocks that they pay attention to. Such an attention-induced retail purchase tend to result in positive price pressure contemporaneously and price reversal subsequently.

Existing literature provides evidence for such retail contrarian trading. Kaniel et al. (2012) examine retail trading of a large cross-section of NYSE stocks during 2000-2003 and show that retail investors, as a group, tend to trade in the opposite direction of earnings surprises. More recently, using account-level data from a large U.S. brokerage firm for the period of 2010-2014, Luo, Ravina, Sammon, and Viceira (2023) find that retail investors exhibit contrarian trading behavior in response to earnings surprises, particularly among attentive investors and in the case of negative announcements. Additional evidence of retail contrarian trades is documented by Grinblatt and Keloharju (2000, 2001), who find increased buying activity by Finnish households following negative returns. As such, retail contrarian trading should predict an even stronger retail purchase among $ROD3$ losers at the end of the day.

In this section, we next examine the effect of $ROD3$ on retail trading. We find that end-of-day trading by retailers are contrarian, and mainly engage in "buy-the-dip" after negative $ROD3$ realizations. To identify retail trading at the end of the trading day, we use three proxies: (i) retail order imbalances obtained from small trades during the pre-decimalization era, (ii) retail order imbalances via the retail classification algorithm, and (iii) changes in holdings of Robinhood traders.

First, we construct a firm-specific trade size proxy that is effective in separating the trading activities of individual and institutional investors during the pre-decimalization era, following Lee and Radhakrishna (2000): we compare the trading price to \$10.000 and determine the

largest number of round lot shares that is less than or equal to \$10.000. Trades transacted at this number of shares or less will be deemed as small (retail) trades. Furthermore, we use the Lee and Ready (1991) algorithm to classify trade into buy- or sell-initiated trades. Subsequently, we use the small trades in the last half-hour of stock i on day t, to compute the retail order imbalance (ROI):

$$ROI_{i,t,LH} = (Buy_{i,t,LH} - Sell_{i,t,LH})/(Buy_{i,t,LH} + Sell_{i,t,LH}) \qquad (7)$$

Where $ROI_{i,t,LH}$ denotes the retail order imbalance for stock i on day t during the last half hour. $Buy_{i,t,LH}$ denotes the dollar trading volume from transactions classified as small buys according to this classification algorithm. $Sell_{i,t,LH}$ denotes the dollar trading volume from transactions classified as small sales. Hvidkjaer (2008) notes that the likelihood that a small trade was a piece of a large institutional order became much higher after the shift to decimal pricing in 2001 and Reg NMS in 2005. Hence, we compute the retail order imbalance based on small trades over the sample period Jan. 1993 till Dec. 2000.

Second, we identify retail trades using the retail trade classification proposed by Barber et al. (2024), inspired by Boehmer et al. (2021). Most trades for US stocks initiated by retail investors are off-exchange, but rather placed by wholesalers or via broker internalization. Such trades are reported to FINRA's Trade Reporting Facility (TRF), and are classified in TAQ with exchange code "D". In addition, these trades are typically given a fraction of price improvement. The BJZZ algorithm identifies trades with prices that end with a fractional penny between (0,0.04) as a sell transaction, whereas trades with a fractional penny between (0.6,1) are classified as buy transactions. The adapted version of Barber et al. (2024) modifies the algorithm by signing trades using the quoted spread midpoints. We use the latter algorithm to compute retail order imbalance in the last half hour of the trading session for each stock over the sample period Jan. 2010 till Dec. 2019.

Lastly, we consider holding data obtained from the Robintrack dataset, created in 2018 by Casey Primozic. Robintrack is a website that ran an hourly script to gather the number of investors in all securities on the Robinhood platform over the period May 2018 - August 2020. We use

this data from May 2018 till Dec. 2019 and follow the cleaning procedures suggested by Ardia et al. (2023). The Robintrack dataset includes the number of Robinhood investors in a given security at an hourly frequency. For each stock, we compute the change in the $\log(1 + \text{retail holdings})$ at the end of the trading day.

In table 8 we regress each proxy of retail trading at the end of the day on $ROD3$ and a set of control variables. In panel A, the dependent variable is the retail order imbalance derived from small trades. In column (1), we show the estimates of the univariate regression of ROI on $ROD3$. We find a negative coefficient, implying that higher $ROD3$ is associated with more sell pressure from retail investors. In column (2), we split positive and negative $ROD3$ observations. We find that the predictive power from $ROD3$ stems from negative observations. In other words, when $ROD3$ is negative, ROI during the last half-hour tends to increase, indicating increased buying pressure. In column (3), we add several control variables. We find that the inclusion of control variables does not affect our findings. In line with our hypothesis, we indeed find increased buying pressure from retail investors when $ROD3$ is negative. In panel B, the dependent variable is the retail order imbalance derived from the retail classification algorithm of Barber et al. (2024). In panel C, the dependent variable is the change in retail holdings from Robinhood traders obtained from the Robintrack dataset. Consistent with panel A, the results also indicate increased buying pressure after a decrease in $ROD3$. Overall, we find evidence showing increased 'buy-the-dip' buying by retail investors during LH.

5.6   Reduced short-selling

Overnight risk on individual stocks is particularly important for short-sellers, since the potential for loss can be unlimited and it is very hard to hedge. For this reason, short-sellers might be reluctant to establish new positions at the end of the day or even close existing short positions. The reduced short selling, combined with attention-induced retail buying, could enhance the end-of-day reversal, especially among intraday losers.

We collect intraday short volume for stocks traded on all major U.S. trading venues. This data

virtually covers all short volume transactions where short positions have been opened on U.S. trading venues starting as of August 2010. We do not observe short covering. For each stock, we compute the short volume in the last half hour and scale this by the total daily short volume.

We regress the short volume during the last half-hour on $ROD3$ and present the results in table 9. In column (1), we show the univariate regression coefficient of LH short volume on $ROD3$. This coefficient is positive and statistically significant, indicating that $ROD3$ is positively associated with last half-hour short volume; higher $ROD3$ implies more short positions being opened. In column (2), we consider the marginal effect of negative $ROD3$ observations on top of $ROD3$. We find that the coefficient on $ROD3$ becomes significantly negative, whereas the coefficient on $ROD3 < 0$ is highly positive and significant. In combination the effect in negative $ROD3$ observations is more than double the effect of positive $ROD3$ observations. The coefficients indicate that last half-hour short volume decreases when $ROD3$ becomes more negative. In other words, when $ROD3$ is negative, we see less short sale positions being opened. As such, price pressure from short sellers decrease in the last half-hour when $ROD3$ is negative, likely resulting in a positive return during the last half-hour. Using proprietary intraday data on the opening of short positions, we find a significant drop in new short positions during LH when the $ROD3$ return is negative.

Overall, increased 'buy-the-dip' buying by retail investors, combined with reduced short selling, generates positive price pressure during LH. This price pressure weakens the latent end-of-day return reversal among $ROD3$ winners but enhances it among $ROD3$ losers. Since the positive price pressure is much stronger among $ROD3$ losers, we observe an end-of-day reversal pattern.

5.7 Retail trading: end-of-day versus open

Our results in the previous sections have shown that retail 'buy-the-dip' trading towards the close is an important driver of end-of-day stock price reversals. Several studies, however, argue that retail investors are especially active before and around the open and their price pressures

influences opening stock prices. Berkman et al. (2012) show that retail-attention-induced price pressure pushes up the stock price at the open, thereby contributing to a high overnight return and a low intraday return on average. Jones et al. (2024) show that retail investors are extrapolative in their trading at the beginning of the day. Next, we examine retail activity around the open and contrast it with our reversal results around the close, providing additional economic insights.

First, we confirm the result retail-attention-induced opening price pressure effect in column (1) of table 10, where we regress the overnight return (ON) on $ROD3$, the interaction between $ROD3$ and the negative $ROD3$ dummy, and additional stock characteristics. We find a positive and significant coefficient on $ROD3$ (1.28), suggesting higher ON returns for $ROD3$ winners. In addition, the sum of coefficients on $ROD3$ and $ROD3 \times I[ROD3 < 0]$ (1.28 − 2.10) is negative, suggesting higher ON returns for $ROD3$ losers as well. The higher ON returns for both $ROD3$ winners and losers are consistent with the notion that the opening price contains an attention-induced price pressure.

Second, columns (2) to (5) of table 10 confirm that retail investors are extrapolative in their trading at the beginning of the day using $ROD3$ returns. Using FH returns and the three measures of retail trading employed before (i.e., retail order imbalance based on small trades, BJZZ retail order imbalance, and Robinhood's retail holdings changes), we find evidence showing that retail investors buy (sell) $ROD3$ winners (losers) during the FH period the next day. As a result, the FH return tends to be higher (lower) for $ROD3$ winners (losers). Again, intraday analysis reveals this interesting contrast between retail trading at the end of the day and trading at the beginning.

Importantly, our novel finding of end-of-day reversal suggests that the attention-induced price pressure also happens earlier; during the last 30 minutes of the current trading day. The evidence is consistent with the recent finding in Barber et al. (2024). Using extreme daily return as a measure of positive retail investor attention shock on Robinhood, Barber et al. (2024) confirm that retail attention causes positive price pressure today and negative return reversal in the

26

future. Overall, we conclude that significant price pressures from retail investors happen during the open ('extrapolative') but also close ('buy-the-dip') of the trading day, thereby causing predictible intraday retun patterns.

6   Conclusion

We find that individual stock returns display a strong intraday reversal that is most pronounced at the end of the trading day. This "*end-of-day reversal*" pattern is economically and statistically highly significant, and stands in sharp contrast to intraday momentum documented for market returns. The end-of-the-day reversal is extremely robust, being present in almost every 3-year rolling window, across methodologies, and across various subsamples of stocks, including the largest, most traded, or most liquid stocks.

Importantly, the end-of-day reversal primarily comes from positive price pressure on intraday losers and reflects a transitory price pressure. We rule out explanations based on illiquidity, closing price effects, news, persistent liquidity shocks, and stock- or market-level gamma hedging effects. Instead, we argue two novel channels related to attention-induced retail trading during the end of the day and risk management by short-sellers contribute to the effect.

7 Tables & Figures

Figure 1:

Predicting intraday stock returns: an end-of-day reversal.

The figure shows the estimated coefficients obtained from regressing a stock's 30 minute return on its previous 12-period interval return - including a 30 minute skip period between the regressor and the dependent variable. On the y-axis we report the slope coefficient (multiplied by 100), while the x-axis shows the 30 minute interval of the dependent variable. The bars are the 95% confidence intervals based on standard errors that are adjusted for clustering in the firm and time dimension. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above $5. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in the panel regressions.
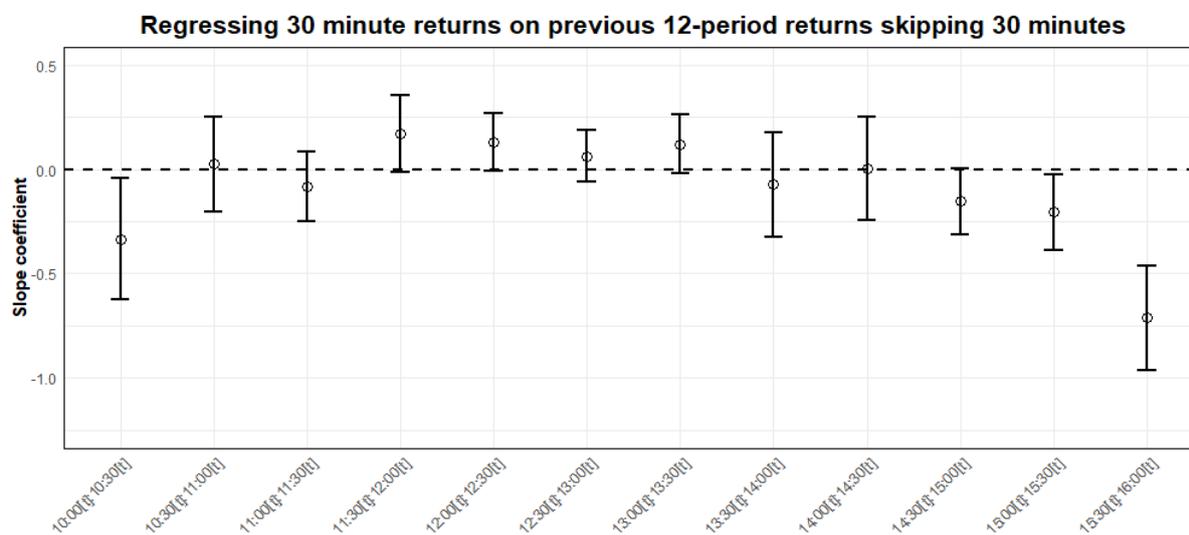
Figure 2:

End-of-day reversal: rolling coefficients.

This figure shows the results of regressing $ROD3$ on LH using rolling panel regressions over a three years window. The upper figure shows the slope coefficient, while the bottom figure shows its clustering-adjusted t-statistic (adjusted in the time- and firm dimension). The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in the panel regressions.
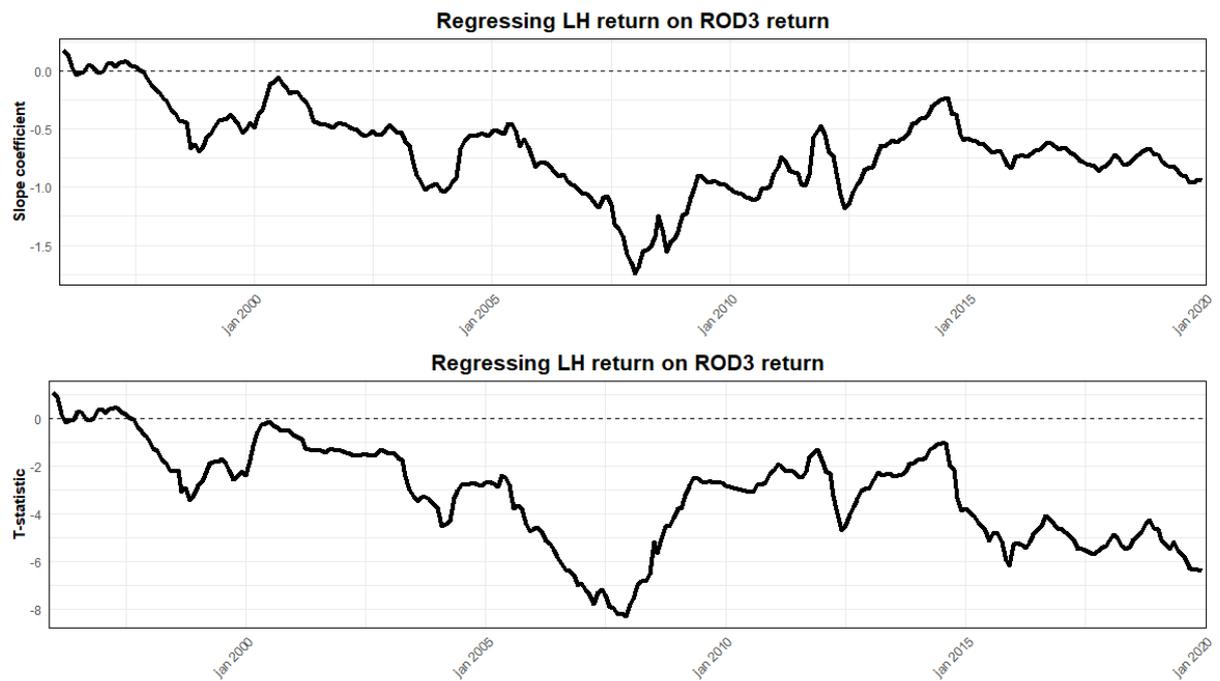
Figure 3:

Predicting intraday stock returns: an asymmetric effect.

The figure shows the estimated coefficients obtained from regressing a stock's 30 minute return on its previous 12-period interval return - including a 30 minute skip period between the regressor and the dependent variable. The top (bottom) figure uses positive (negative) values of the regressor. On the y-axis we report the slope coefficient (multiplied by 100), while the x-axis shows the 30 minute interval of the dependent variable. The bars are the 95% confidence intervals based on standard errors that are adjusted for clustering in the firm and time dimension. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in the panel regressions.
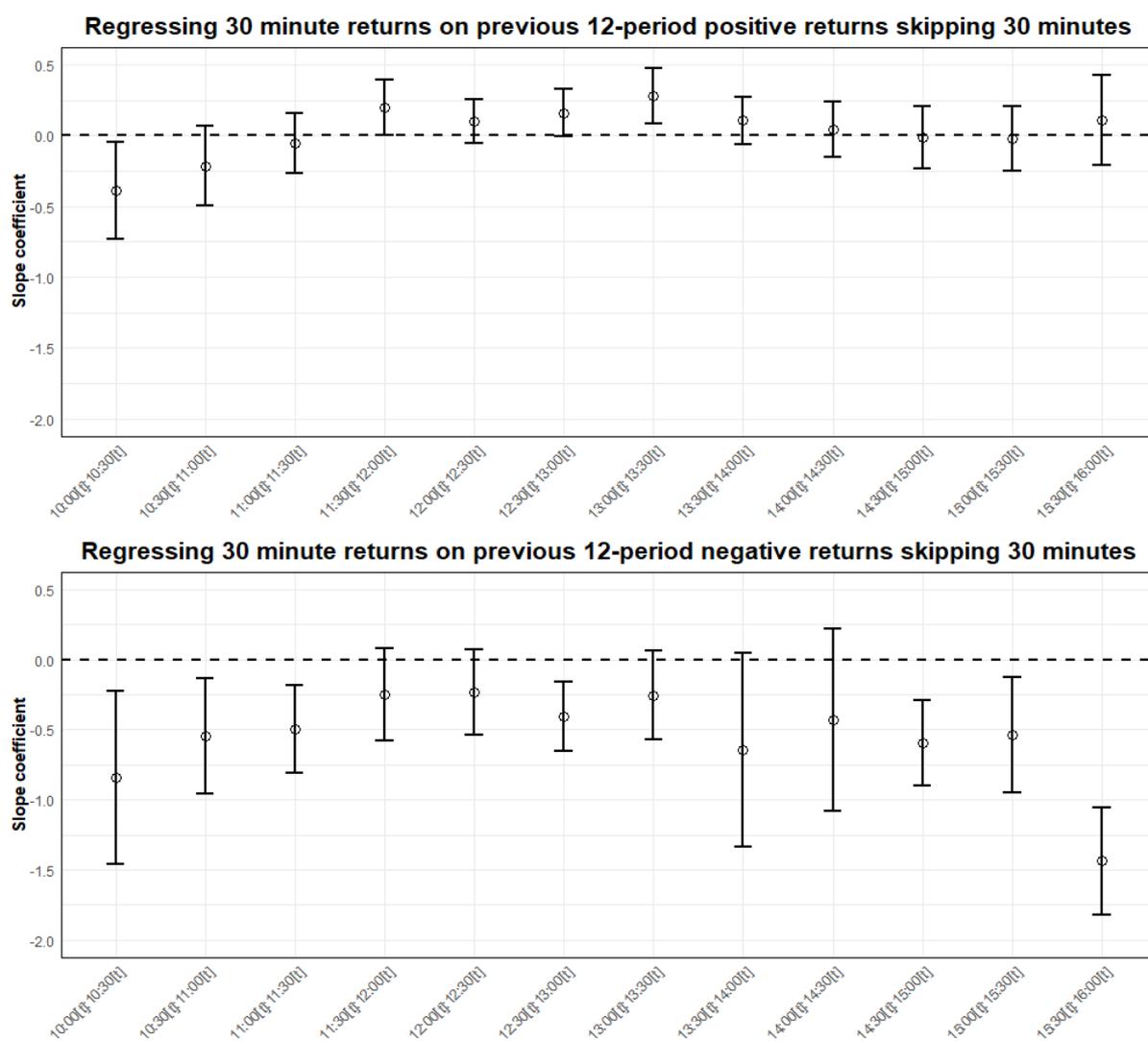
Table 1:

Performance of quintile portfolios sorted on $ROD3$ return.

This table reports the performance of quintile portfolios formed on the basis of the "rest-of-day" ($ROD3$) return, which is the return between market close at day $t-1$ till 3:00pm at day t. At 3:30pm of each day t we sort stocks into five portfolios based on their $ROD3$ return on day t, and hold this portfolio intraday from 3:30pm until 4:00pm (i.e., market close). We report the average 30-minute return ("R") in basis points, the Fama-French-Carhart four-factor alpha ("FF4 α"), and the Fama-French-Carhart six-factor alpha ("FF6 α") for each portfolio. The column labeled "L-H" is the self-financing low-minus-high portfolio. We show results for both value-weighted ('VW') and equal-weighted ('EW') portfolios, and imposing both a \$5 and \$1 price filter applied on our stock sample. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11. We remove stocks below the 10th NYSE size percentile. Newey-West adjusted t-statistics are shown between parentheses. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	VW+\$5 filter			VW+\$1 filter			EW+\$5 filter			EW+\$1 filter		
	R	FF4 α	FF6 α	R	FF4 α	FF6 α	R	FF4 α	FF6 α	R	FF4 α	FF6 α
L	3.19***	2.40***	2.18***	3.28***	2.47***	2.22***	6.09***	3.53***	3.31***	6.46***	3.78***	3.55***
	(7.71)	(12.48)	(11.69)	(7.85)	(12.67)	(11.73)	(13.11)	(19.83)	(19.13)	(13.26)	(19.83)	(19.23)
2	0.97***	0.43***	0.50***	0.98***	0.42***	0.49***	2.27***	0.18**	0.24***	2.39***	0.24***	0.30***
	(2.83)	(3.97)	(4.55)	(2.84)	(3.82)	(4.44)	(6.76)	(2.34)	(3.39)	(6.96)	(3.14)	(4.13)
3	-0.13	-0.58***	-0.44***	-0.12	-0.58***	-0.44***	1.50***	-0.52***	-0.39***	1.62***	-0.45***	-0.32***
	(-0.39)	(-5.84)	(-4.83)	(-0.36)	(-5.79)	(-4.80)	(4.71)	(-6.31)	(-5.26)	(4.97)	(-5.53)	(-4.45)
4	-0.69**	-1.19***	-1.01***	-0.66**	-1.17***	-0.99***	0.96***	-1.09***	-0.99***	1.07***	-1.03***	-0.93***
	(-2.09)	(-11.76)	(-10.61)	(-1.98)	(-11.54)	(-10.50)	(3.02)	(-11.16)	(-10.95)	(3.30)	(-10.57)	(-10.31)
H	-0.31	-1.15***	-1.25***	-0.27***	-1.13***	-1.24***	1.54***	-0.87***	-0.91***	1.72***	-0.76***	-0.81***
	(-0.77)	(-6.20)	(-6.83)	(-0.67)	(-6.07)	(-6.68)	(4.09)	(-7.19)	(-7.56)	(4.47)	(-6.10)	(-6.52)
L-H	3.49***	3.55***	3.43***	3.55***	3.60***	3.46***	4.56***	4.400***	4.23***	4.74***	4.55***	4.36***
	(10.33)	(10.41)	(10.22)	(10.34)	(10.46)	(10.20)	(16.12)	(16.43)	(16.06)	(16.16)	(16.52)	(16.13)

Table 2:

Performance of double-sorted portfolios sorted on $ROD3$ return.

This table reports the performance of portfolios first formed on a conditioning characteristic and then on $ROD3$ return, which is the return between market close at day $t-1$ till 3:00pm at day t. The conditioning variables (all at day $t-1$) are size (market capitalization), volume (trading volume), illiquidity (Amihud, 2002), realized volatility computed using 5-minute returns, overnight volatility (standard deviation of overnight returns over the past 90 trading days), and the mispricing score of Stambaugh and Yuan (2017). We report the Fama-French-Carhart six-factor alpha of each portfolio. The row labeled "L-H" is the self-financing low-minus-high portfolio. Portfolio returns are value-weighted, and the sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11. We remove stocks below the 10th NYSE size percentile and impose a 5 price filter. Newey-West t-statistics are shown between parentheses. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	Size					Volume				
	S	2	3	4	B	L	2	3	4	H
L	10.29***	7.10***	4.55***	3.05***	2.46***	7.81***	5.57***	3.96***	3.05***	2.73***
	(20.21)	(15.07)	(10.93)	(8.32)	(5.95)	(18.37)	(13.39)	(10.42)	(8.25)	(6.18)
H	1.36***	1.56***	1.55***	1.62***	-0.93**	-0.27	0.79**	1.53***	1.56***	-0.63
	(3.28)	(3.80)	(4.12)	(4.92)	(-2.36)	(-0.71)	(2.19)	(4.50)	(4.71)	(-1.46)
L-H	8.93***	5.55***	3.00***	1.43***	3.39***	8.08***	4.79***	2.43***	1.49***	3.35***
	(24.99)	(18.22)	(12.08)	(6.38)	(11.09)	(23.81)	(16.80)	(9.88)	(5.87)	(9.20)

	Illiquidity					Realized Volatility				
	L	2	3	4	H	L	2	3	4	H
L	2.42***	2.81***	4.63***	7.29***	10.06***	2.96***	2.82***	3.44***	4.19***	5.09***
	(5.78)	(7.52)	(11.56)	(15.83)	(20.07)	(9.04)	(7.34)	(7.97)	(8.47)	(9.37)
H	-0.93**	1.90***	1.83***	1.47***	0.49	-1.95***	-1.79***	-0.66	1.53***	3.81***
	(-2.34)	(5.70)	(4.99)	(3.65)	(1.17)	(-6.61)	(-4.90)	(-1.54)	(3.21)	(6.64)
L-H	3.35***	0.91***	2.80***	5.82***	9.57***	4.92***	4.61***	4.11***	2.65***	1.28***
	(10.67)	(3.75)	(11.16)	(17.77)	(23.83)	(20.00)	(16.32)	(11.69)	(6.73)	(2.75)

	Overnight Volatility					Mispricing				
	L	2	3	4	H	L	2	3	4	H
L	2.86***	3.11***	3.18***	4.22***	4.69***	2.46***	2.91***	3.04***	3.87***	3.48***
	(8.34)	(7.75)	(7.38)	(8.50)	(8.43)	(5.94)	(7.12)	(7.22)	(8.36)	(7.08)
H	-1.89***	-1.53***	0.24	0.66	2.01***	-2.01***	-0.93**	-0.05	1.13***	2.44***
	(-5.88)	(-4.05)	(0.58)	(1.40)	(3.66)	(-5.20)	(-2.38)	(-0.12)	(2.66)	(5.07)
L-H	4.75***	4.64***	2.94***	3.56***	2.68***	4.47***	3.84***	3.08***	2.74***	1.05**
	(18.33)	(14.70)	(8.64)	(8.50)	(5.42)	(13.60)	(11.71)	(8.86)	(6.66)	(2.40)

Table 3:

End-of-day reversal: panel regression results.

This table reports the estimated coefficients from panel regressions in which the last half-hour (LH) return is regressed on the $ROD3$ return and a range of control variables. The LH return is the return from 3:30pm till 4:00pm at day t. The $ROD3$ return is the return from day $t-1$ market close up till day t 3:00pm. In column (5), the last half-hour return is computed from 3:30pm till 3:55pm. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	(1)	(2)	(3)	(4)	(5)	(6)
ROD3	-0.71***		-0.73***	-0.79***	-1.01***	-0.11
	(-5.70)		(-5.87)	(-6.18)	(-9.28)	(-0.65)
ROD3×I[ROD3<0]						-1.43***
						(-6.28)
ONFH		-0.71***				
		(-4.57)				
MID		-0.73***				
		(-4.82)				
LH_{t-1}			0.53	0.61	0.21	0.60
			(1.21)	(1.33)	(0.51)	(1.30)
LH_{t-2}			1.29***	1.37***	0.92***	1.37***
			(3.21)	(3.26)	(2.73)	(3.25)
LH_{t-3}			2.22***	2.27***	1.29***	2.26***
			(5.39)	(5.31)	(4.19)	(5.31)
β_{mkt}				-0.07	-0.48	-0.41
				(-0.14)	(-1.09)	(-0.88)
RV				0.00***	-0.00	0.00***
				(3.79)	(-0.40)	(4.01)
SREV				0.63	1.12*	0.89
				(0.88)	(1.73)	(1.25)
MOM				0.29	0.30*	0.28
				(1.58)	(1.83)	(1.57)
ILQ				0.77*	0.35	0.70*
				(1.93)	(1.50)	(1.90)
MIS				0.04***	0.02***	0.03***
				(4.52)	(3.00)	(4.06)
R^2	0.07%	0.07%	0.15%	0.18%	0.23%	0.22%
Obs.	14.04M	13.82M	13.35M	12.08M	12.07M	12.08M

Table 4:

End-of-day reversal versus market intraday momentum: decomposition results.

This table shows the results of decomposing cross-sectional end-of-day reversal and time-series intraday momentum strategy profits. We consider both a cross-sectional ('XS') and time-series ('TS') strategy, which we decompose into stock-level auto-covariance ('Auto'), cross-auto-covariance ('-Cross'), or the average stock return effect ('Mean') using formula 4, and 6, respectively. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above $5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We bootstrap the sample 500 times in blocks of 6 months, and report the average return (in basis points), and its corresponding bootstrapped t-statistics. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

Decomposition	ROD3	
	Ret (bps)	t-value
XS strategy	-2.76***	(-21.46)
Auto	1.09**	(2.51)
-Cross	-3.74***	(-8.14)
Mean	-0.11***	(-28.71)
TS strategy	1.01**	(2.30)
Auto	1.10**	(2.52)
Mean	-0.09***	(-14.97)

Table 5:

End-of-day reversal: temporary price pressure.

This table reports the slope estimates from regressing the cumulative return over LH (i.e., 3:30pm - 4:00pm), $LH + ON$ (i.e., 3:30pm - 9:30am), and LH + next day (i.e., 3:30pm - 4:00pm next day) on $ROD3$. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	ROD3	
	β	t-value
$3{:}30_t - 4{:}00_t$	-0.71***	(-5.70)
$3{:}30_t - 9{:}30_{t+1}$	-0.18	(-0.72)
$3{:}30_t - 4{:}00_{t+1}$	0.27	(0.65)

Table 6:

End-of-day reversal and hedging demand.

This table reports the estimated coefficients from panel regressions in which the LH return is regressed on $ROD3$, net gamma exposure (NGE or Γ) and leveraged ETF rebalancing ($LETF$). NGE is computed as described in section 7, market-level $ROD3$ ($ROD3_{mkt}$) and NGE (Γ_{mkt}) in section 7, and $LETF$ in section 7. In panel A, we include stocks that have gamma data available in OptionMetrics. In panel B, we include stocks without available gamma data until first occurrence. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1996 (the start date of OptionMetrics data) and December 2019 with share code 10 or 11, and prices above \$5 as of the portfolio formation. The sample period in columns (4) and (5) start when LETFs becomes available (June 2006). Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	Panel A: Options					Panel B: No options		
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)
ROD3	-0.74***	-0.67***	-0.83***	-0.88***	-0.88***	-0.44***	-0.67***	-0.49***
	(-5.61)	(-4.80)	(-5.35)	(-5.50)	(-5.51)	(-3.64)	(-6.15)	(-2.75)
ROD3×Γ		-6.58***	-6.97***	-7.15***	-7.16***			
		(-2.94)	(-2.77)	(-2.89)	(-2.87)			
Γ		9.04***	7.68***	6.00***	5.84***			
		(5.58)	(4.90)	(4.19)	(3.99)			
ROD3$_{mkt}$			27.28***	2.87	2.82		-79.50	204.17
			(2.90)	(0.39)	(0.38)		(-0.61)	(1.58)
Γ_{mkt}			4.73***	3.96***	4.12***		1.18	0.90
			(4.94)	(4.38)	(4.68)		(0.84)	(0.57)
ROD3$_{mkt}$×Γ_{mkt}			-298.21	104.00	98.59		-44.08	722.53***
			(-1.14)	(0.43)	(0.41)		(-0.30)	(3.55)
LETF				134.54***	135.17***			94.72***
				(4.04)	(4.02)			(4.54)
Controls	NO	NO	NO	NO	YES	NO	YES	YES
R^2	0.09%	0.11%	0.30%	0.34%	0.37%	0.02%	0.04%	0.65%
Obs.	9.33M	9.33M	6.88M	4.57M	4.54M	2.77M	0.94M	0.37M

Table 7:

End-of-day reversal and hedging demand (continued).

This table reports the estimated coefficients from panel regressions in which the LH return is regressed on $ROD3$, net gamma exposure (NGE or Γ) and leveraged ETF rebalancing ($LETF$). NGE is computed as described in section 7, market-level $ROD3$ ($ROD3_{mkt}$) and NGE (Γ_{mkt}) in section 7, and $LETF$ in section 7. In panel A, stocks on the S&P 500, Nasdaq 100, Dow Jones 30, S&P 400 Midcap, or Russell 2000 are included in the sample. Stocks that are not constituents of these indices are included in panel B. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, and prices above $5 as of the portfolio formation. The sample period starts in January 1996 whenever NGE is added to the regression specification. The sample period in columns (4) and (5) start when LETFs becomes available (June 2006). Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	Panel A: Indexed					Panel B: Non-Indexed	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)
ROD3	-0.77***	-0.73***	-0.83***	-0.88***	-0.88***	-0.27**	-0.32**
	(-5.73)	(-4.91)	(-5.34)	(-5.49)	(-5.50)	(-2.53)	(-2.13)
ROD3×Γ		-6.52***	-6.97***	-7.16***	-7.16***		-4.69*
		(-2.80)	(-2.77)	(-2.89)	(-2.87)		(-1.69)
Γ		9.01***	7.67***	5.99***	5.83***		7.79***
		(5.29)	(4.89)	(4.18)	(3.99)		(3.48)
ROD3$_{mkt}$			27.27***	2.87	2.82		
			(2.90)	(0.39)	(0.38)		
Γ_{mkt}			4.74***	3.97***	4.13***		
			(4.93)	(4.36)	(4.67)		
ROD3$_{mkt}$×Γ_{mkt}			-299.55	104.88	99.42		
			(-1.14)	(0.43)	(0.41)		
LETF				134.54***	135.17***		
				(4.04)	(4.02)		
Controls	NO	NO	NO	NO	YES	NO	YES
R^2	0.09%	0.12%	0.28%	0.34%	0.37%	0.01%	0.04%
Obs.	10.51M	8.06M	6.87M	4.56M	4.53M	3.66M	1.09M

Table 8:

Last half-hour retail trading.

This table reports the slope estimates from regressing proxies of last half-hour retail trading on *ROD3*. In panel A, the dependent variable is the retail order imbalance derived from small trades during the pre-decimalization period of our sample (Jan. 1993 till Dec. 2000), following Lee and Radhakrishna (2000). In panel B, the dependent variable is the retail order imbalance derived from an adapted version of the retail classification algorithm of Boehmer et al. (2021), suggested by Barber et al. (2024) for the sample period Jan. 2010 till Dec. 2019. In panel C, the dependent variable is the last half-hour change in Robinhood retail traders for the sample period Jun. 2018 till Dec. 2019. In all panels, the sample consists of stocks listed on NYSE/AMEX/NASDAQ with share code 10 or 11, and prices above \$5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	A: Small Trades			B: BJZZ			C: Robinhood		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ROD3	-0.26***	0.45***	-0.06	-0.37***	0.34**	0.14	-0.31***	-0.11**	-0.11*
	(-4.80)	(7.74)	(-1.01)	(-4.22)	(2.71)	(1.06)	(-8.29)	(-2.08)	(-1.91)
ROD3×I[ROD3<0]		-1.52***	-1.12***		-1.47***	-1.37***		-0.39***	-0.43***
		(-10.20)	(-8.49)		(-11.71)	(-10.43)		(-3.34)	(-3.49)
β_{mkt}			4.11***			0.56			-0.76***
			(2.66)			(0.98)			(-3.18)
RV			0.00			-0.00***			-0.04***
			(0.21)			(-15.57)			(-5.72)
SREV			-23.34***			-1.94**			0.81
			(-9.44)			(-2.50)			(1.32)
MOM			-1.45***			0.07			-0.05
			(-3.62)			(0.78)			(-0.33)
ILQ			9.18***			-0.07***			-14.68
			(7.70)			(-6.98)			(-0.89)
MIS			-0.19***			-0.06***			-0.02
			(-3.06)			(-4.39)			(-1.43)
OI			21.15***			37.82***			0.74
			(67.08)			(32.63)			(1.23)
Obs.	2.70M	2.70M	2.32M	4.88M	4.88M	4.52M	751K	751K	694K
R^2	0.02%	0.11%	6.68%	0.02%	0.05%	1.86%	0.00%	0.01%	0.01%

Table 9:

Last half-hour short volume.

This table reports the slope estimates from regressing the last half-hour short volume on $ROD3$. $ROD3$ is defined as the return between market close at day $t-1$ and 3:30pm on day t. Last half-hour short volume is the proportion shorted in the last half-hour relative to the full trading day. Intraday short volume data is collected from U.S. trading venues. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between August 2010 and December 2019 with share code 10 or 11, and prices above \$5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ROD3	0.08***	-0.15***	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***	-0.13***
	(8.06)	(-8.82)	(-7.56)	(-7.56)	(-7.56)	(-7.55)	(-7.55)	(-7.42)
ROD3×I[ROD3<0]		0.46***	0.43***	0.43***	0.43***	0.43***	0.43***	0.43***
		(14.34)	(12.65)	(12.65)	(12.65)	(12.63)	(12.63)	(12.43)
β_{mkt}			-1.10***	-1.10***	-1.10***	-1.09***	-1.09***	-1.06***
			(-6.94)	(-6.94)	(-6.94)	(-6.93)	(-6.93)	(-6.91)
RV				-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
				(-5.26)	(-5.26)	(-5.27)	(-5.27)	(-5.72)
SREV					-0.00	-0.00	-0.00	-0.26***
					(-1.27)	(-1.26)	(-1.26)	(-3.22)
MOM						-0.02	-0.02	-0.18***
						(-1.62)	(-1.62)	(-3.15)
ILQ							-0.07***	-0.07***
							(-4.46)	(-11.23)
MIS								-0.01***
								(-2.88)
Obs.	4.60M	4.60M	4.41M	4.41M	4.41M	4.41M	4.41M	4.26M
R^2	0.03%	0.16%	0.32%	0.33%	0.32%	0.33%	0.33%	0.38%

Table 10:

Overnight returns, first half-hour returns, and retail order imbalances.

This table reports the estimated coefficients from panel regressions, where dependent variable is regressed on $ROD3$ returns and a range of control variables. The $ROD3$ return is the return from day $t-1$ market close up till day t 3:00pm. The dependent variable in column 1 is the overnight return, from market close at day t through open at day $t+1$. The dependent variable in column 2 is the first half-hour return, from market open till 10:00am at day $t+1$. The sample period in (1) and (2) is from Jan. 1993 till Dec. 2019. The dependent variable in column (3) is the retail order imbalance during the first half-hour at day $t+1$ based on small trades (Lee & Radhakrishna, 2000). The sample period in (3) is from Jan. 1993 till Dec. 2000. The dependent variable in column (4) is the retail order imbalance during the first half-hour at day $t+1$ based on the classification algorithm of (Barber et al., 2024). The sample period in (4) is from Jan. 2010 till Dec. 2019. The dependent variable in column (5) is the retail holding change during the first half-hour at day $t+1$ based on Robinhood data. The sample period in (5) is from Jun. 2018 till Dec. 2019. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

|	ON_{t+1}	FH_{t+1}	FH_{t+1}^{small}	FH_{t+1}^{BJZZ}	FH_{t+1}^{Robin}
ROD3	1.28***	0.60***	0.88***	1.80***	0.02
	(4.69)	(2.79)	(11.08)	(23.41)	(0.44)
ROD3×I[ROD3<0]	-2.10***	1.62***	-0.32*	-0.74***	0.03
	(-5.18)	(4.83)	(-1.88)	(-6.51)	(0.51)
Dep_{t-1}	0.04	0.02	6.52***	4.84***	3.85
	(1.03)	(1.02)	(22.14)	(36.77)	(0.90)
Dep_{t-2}	0.02	0.02	5.13***	3.54***	-0.67
	(0.94)	(1.17)	(16.39)	(31.46)	(-1.03)
Dep_{t-3}	0.02	0.03	4.71***	3.00***	-4.42
	(1.44)	(1.16)	(15.71)	(26.71)	(-0.67)
β_{mkt}	4.26***	-1.57**	2.37**	2.39***	-0.00
	(3.94)	(-2.17)	(2.61)	(5.34)	(-0.49)
RV	-0.00**	-0.00***	-0.00	-0.00	0.00*
	(-2.39)	(-4.18)	(-1.15)	(-0.02)	(1.72)
SREV	-17.74***	2.64**	-8.72***	-2.87**	0.00
	(-3.72)	(2.03)	(-6.21)	(-2.48)	(0.17)
MOM	1.36***	-0.41	-0.24	-0.03	-0.00
	(3.25)	(-1.62)	(-1.15)	(-0.50)	(-1.11)
ILQ	-1.30**	0.33	-2.00***	0.04***	-0.48
	(-2.00)	(1.61)	(-3.01)	(4.60)	(-1.17)
MIS	-0.01	-0.04**	-0.13***	-0.01	-0.00
	(-0.49)	(-2.45)	(-3.52)	(-1.12)	(-0.85)
R^2	0.19%	0.10%	1.46%	0.72%	0.79%
Obs.	12.25M	12.25M	3.04M	4.52M	605K

Appendix

Additional tables and figures

Figure A.1:

Predicting intraday stock returns: end-of-day reversal without a 30-minute skip.

The figure shows the estimated coefficients obtained from regressing a stock's 30 minute return on its previous 13-period interval return. On the y-axis we report the slope coefficient (multiplied by 100), while the x-axis shows the 30 minute interval of the dependent variable. The bars are the 95% confidence intervals based on standard errors that are adjusted for clustering in the firm and time dimension. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in the panel regressions.
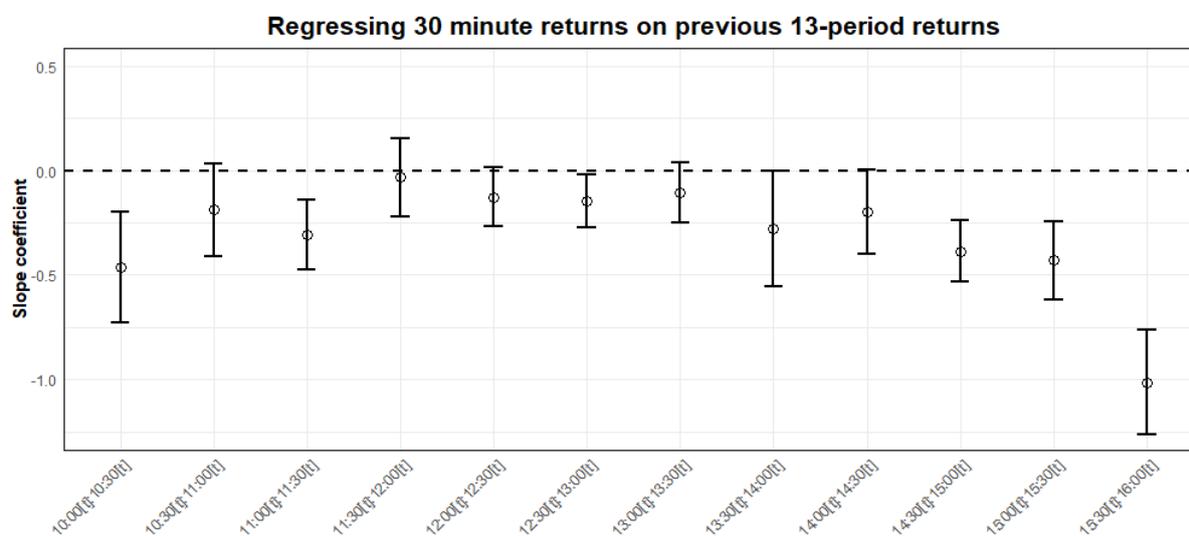
Figure A.2:

End-of-day reversal: predictability across days of the week.

We run the regression specification as in table 3 (column 6) sub-sampled by the day of the week. We plot the $ROD3$ coefficient in dark-grey, and the $ROD3 \times I[ROD3 < 0]$ in light-grey. The bars are the 95% confidence intervals based on standard errors that are adjusted for clustering in the firm and time dimension. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in the panel regressions.
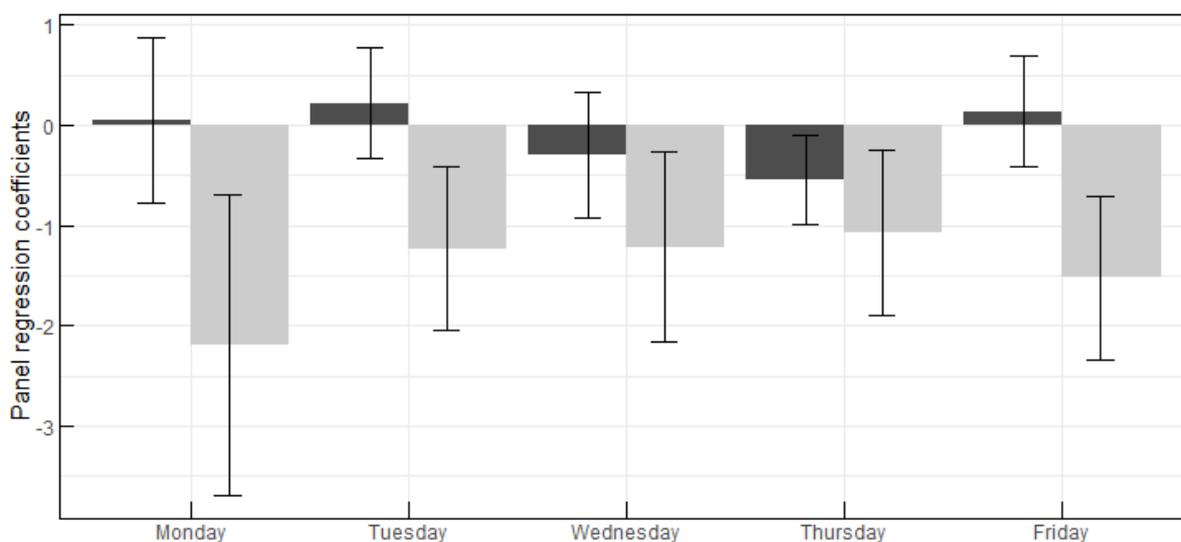
Table A.1:

Panel regression results using midpoint-quote returns.

We run the regression specification as in table 3 but with returns computed using the midpoint of quoted prices. We report the estimated coefficients from panel regressions in which the last half-hour (LH) return is regressed on the $ROD3$ return and a range of control variables. The LH return is the return from 3:30pm till 4:00pm at day t. The $ROD3$ return is the return from day $t-1$ market close up till day t 3:00pm. In column (5), the last half-hour return is computed from 3:30pm till 3:55pm. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	(1)	(2)	(3)	(4)	(5)
ROD3	-0.72***		-0.76***	-0.82***	-0.20
	(-6.44)		(-6.76)	(-7.26)	(-1.43)
ROD3×I[ROD3<0]					-1.30***
					(-6.03)
ONFH		-0.73***			
		(-5.66)			
MID		-0.77***			
		(-5.05)			
LH_{t-1}			0.52	0.57	0.56
			(1.19)	(1.29)	(1.26)
LH_{t-2}			1.54***	1.59***	1.59***
			(3.91)	(3.89)	(3.88)
LH_{t-3}			2.33***	2.38***	2.37***
			(5.60)	(5.52)	(5.52)
β_{mkt}				0.04	-0.27
				(0.09)	(-0.66)
RV				0.00	0.00
				(1.36)	(1.23)
SREV				0.90	1.15
				(1.34)	(1.71)
MOM				0.25	0.25
				(1.54)	(1.53)
ILQ				(0.19)	(0.19)
				(0.84)	(0.83)
MIS				0.03***	0.03***
				(3.89)	(3.44)
R^2	0.09%	0.09%	0.19%	0.22%	0.25%
Obs.	13.42M	12.50M	12.37M	11.35M	11.35M

Table A.2:

End-of-day reversal: the role of firm news.

This table shows the estimated coefficients obtained from panel regressions, whereby the *LH* return is regressed on the *ROD*3 return, an earnings news date dummy, and the interaction between the earnings news dummy and the *ROD*3 return in panel A. In panel B, we replace the earnings news date dummy with a general news date dummy. The earnings date dummy takes value one if there is an earnings announcement on day t for stock i, else zero. Earnings announcement dates is obtained from the I/B/E/S database. The general firm news date dummy takes value one if there is a news item on day t for stock i, else zero. Firm-level news data is obtained from RavenPack. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1993 and December 2019 with share code 10 or 11, with prices above \$5 as of the portfolio formation. Stocks below the 10th NYSE size percentile are excluded from the sample. Observations are weighted by their previous' day market capitalization. We include time - and firm fixed effects in all specifications. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks indicate significance at the 10% (*), 5% (**) or 1% (***) level.

	Panel A: Earning Days				**Panel B: Firm News**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ROD3	-0.71***	-0.71***	-0.69***	-0.73***	-0.85***	-0.85***	-0.72***	-0.73***
	(-5.70)	(-5.70)	(-5.42)	(-5.63)	(-7.65)	(-7.65)	(-7.02)	(-7.06)
News		0.24	0.35	0.42		0.11	0.12	0.14
		(0.42)	(0.63)	(0.74)		(1.07)	(1.17)	(1.39)
ROD×News			-0.45	-0.47			-0.26	-0.25
			(-1.59)	(-1.65)			(-1.61)	(-1.56)
Controls	No	No	No	Yes	No	No	No	Yes
Obs.	14.04M	14.04M	14.04M	1.33M	8.61M	8.61M	8.61M	8.30M
R^2	0.07%	0.07%	0.08%	0.09%	0.15%	0.15%	0.15%	0.17%

Gamma Measures

Stock-level Net Gamma Exposure

We collect option data for individual U.S. stocks from Ivy DB US from OptionMetrics from January 1996 to December 2019. We obtain data on the implied volatility, trading volume, open interest and Greeks for each option contract, in particular the gamma. We remove observations for which there is no implied volatility available. We use the gamma data to construct a measure of the market maker's gamma exposure.

Let S_t be the value of the underlying asset at time t. The delta Δ_t of an option $C_t(S_t, K, T)$ is defined as the first derivative of the option price with respect to the underlying price: $\Delta_t = \frac{\delta C_t}{\delta S_t}$. Option market makers aim to neutralize their exposure to movements in S_t in their option portfolio by engaging in delta-hedging. At time t, delta-hedging of an option portfolio requires buying or selling an amount of the underlying equal to $-\Delta_t$. However, Δ_t is a function of S_t. Thus, changes in S_t also changes the value of Δ_t. Delta-hedging requires a dynamic adjustment of the position on the underlying. The extent in which Δ_t changes when S_t changes is the gamma, Γ_t, which is the second-order derivative of the option price w.r.t the price of the underlying, i.e. $\Gamma_t = \frac{\delta^2 C_t}{\delta S^2}$. A high absolute value of Γ_t implies that Δ_t is very sensitive to changes to S_t, and that the delta-hedger must trade more of the underlying to achieve delta-neutrality.

To estimate the Net Gamma Exposure (NGE) on a individual-stock level, we follow Baltussen et al. (2021) and Barbon et al. (2021). For a call option (C) on the underlying stock i on day t with strike price $s \in S_t^c$ and maturity $m \in M_t^c$, the NGE is computed as:

$$NGE_{i,s,m,t}^c = \Gamma_{i,s,m,t}^c \times OI_{i,s,m,t}^c \times 100 \times S_t$$

Where $\Gamma_{i,s,m,t}^C$ denotes the option's gamma, $OI_{i,s,m,t}^c$ is the option's open interest, 100 is the adjustment from option contracts to shares and S_t is the price of the underlying. For a put option (P) on the underlying stock i on day t with strike price $s \in S_t^p$ and maturity $m \in M_t^p$, the NGE is computed as:

$$NGE_{i,s,m,t}^p = \Gamma_{i,s,m,t}^p \times OI_{i,s,m,t}^p \times (-100) \times S_t$$

Here we multiply by (-100) as this represents short gamma for option market makers. To compute the aggregated net gamma exposure for stock i on day t, we sum over all NGE^c's and NGE^p's at every strike price and every maturity:

$$NGE_{i,t} = \left(\sum_{s \in S^c} \sum_{m \in M^c} NGE^c_{i,s,m,t} + \sum_{s \in S^p} \sum_{m \in M^p} NGE^p_{i,s,m,t} \right) \times \left(\frac{S_t}{100 \times VOL_{i,t-1}} \right) \quad (8)$$

The first term between brackets denotes the amount (in dollars) that option market makers need to trade for a one-dollar change in S_t. We facilitate cross-sectional comparison by multiplying this term by the second term: Multiplying by S_t and dividing by 100, and scale by the average dollar trading volume over the last 21 business days. This changes the interpretation to the amount that needs to be hedged for a 1% change in the underlying stock.

Market-level Net Gamma Exposure

We obtain historical tick-by-tick price data on the major futures contracts on various equity indices from Tick Data LLC.[10] We collect data for the following indices: S&P 500, Nasdaq 100, Dow Jones 30, S&P Midcap 400, and the Russell 2000, and compute the various intraday returns, most notably $ROD3$ for each. An indexed stock is a stock that is a constituent in any of the above mentioned indices. We map the market-level $ROD3$ to the constituent-level as follows:

$$ROD3_{i,t,mkt} = \sum_{j} w_{i,j,t-1} \times ROD3_{j,t,mkt}$$

$ROD3_{j,t,mkt}$ denotes the market-level $ROD3$ return for index j at day t. $w_{i,j,t}$ is the weight of stock i in index j at day $t-1$. $w_{i,j,t-1} \times ROD3_{j,t,mkt}$ measures the market $ROD3$ return that 'spills over' to stock i. Since a stock can be a constituent of multiple indices, we sum over indices j to compute $ROD3_{i,t,mkt}$.

Next, we also compute the Net Gamma Exposure (NGE_{mkt}) for each equity index as in equation 8. As before, we map this to the constituent-level by multiplying NGE_{mkt} to $w_{i,j,t-1}$, summed across indices j.

---

[10]www.tickdata.com

Leveraged ETFs 'Gamma' Exposure

The hedging behaviour of Leveraged ETFs causes price pressures near the end of the trading day. To measure this hedging behaviour, we obtain historical daily NAV data for leveraged ETFs from Bloomberg. We consider collect data for leveraged ETFS for the following indices: S&P 500, Nasdaq 100, Dow Jones Industrial Average, Russel 2000, and the S&P 400 Midcap Index. LETF data is available since 2006 onwards, as leveraged ETFs are introduced in 2006. We compute the rebalancing demand (RD) of index j on day t by following Cheng and Madhavan (2009):

$$RD_{j,t} = NAV_{j,t-1}(x^2 - x)r^{j,c,t}_{j,c,t-1}$$

Where NAV_t denotes the net asset values on day t for a leveraged ETF, and x is the leverage factor (e.g., -2,-1,2,3). The rebalancing demand on day t is at the index-level. We multiply RD by the constituents weight in the index, to proxy the amount that needs to be rebalanced on the stock-level. Note that a stock can be listed on multiple indices. In that case, we sum across indices j.

References

Akbas, F., Boehmer, E., Jiang, C., & Koch, P. D. (2022). Overnight returns, daytime reversals, and future stock returns. *Journal of Financial Economics*, *145*(3), 850–875.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), 31–56.

Ardia, D., Aymard, C., & Cenesizoglu, T. (2023). Fast and furious: A high-frequency analysis of robinhood users' trading behavior. *arXiv preprint arXiv:2307.11012*.

Baltussen, G., Da, Z., Lammers, S., & Martens, M. (2021). Hedging demand and market intraday momentum. *Journal of Financial Economics*.

Baltussen, G., Terstegge, J., & Whelan, P. (2023). The derivative payoff bias. *Available at SSRN 4562800*.

Baltussen, G., van Bekkum, S., & Da, Z. (2019). Indexing and stock market serial dependence around the world. *Journal of Financial Economics*, *132*(1), 26–48.

Barber, B., Huang, X., Jorion, P., Odean, T., & Schwarz, C. (2024). A (sub) penny for your thoughts: Tracking retail investor activity in taq. *Journal of Finance*.

Barber, B., Huang, X., Odean, T., & Schwarz, C. (2022). Attention-induced trading and returns: Evidence from robinhood users. *Journal of Finance*, *77*, 3141-3190.

Barber, B., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, *21*(2), 785–818.

Barbon, A., Beckmeyer, H., Buraschi, A., & Moerke, M. (2021). Liquidity provision to leveraged etfs and equity options rebalancing flows: Evidence from end-of-day stock prices. *Available at SSRN 3925725*.

Battalio, R., Jennings, R., Salgam, M., & Wu, J. (2024). Identifying market maker trades as "retail" from TAQ: No shortage of false negatives and false positives. (Working Paper)

Berkman, H., Koch, P. D., Tuttle, L., & Zhang, Y. J. (2012). Paying attention: overnight returns and the hidden cost of buying at the open. *Journal of Financial and Quantitative Analysis*, *47*(4), 715–741.

Boehmer, E., Jones, C. M., Zhang, X., & Zhang, X. (2021). Tracking retail investor activity.

The Journal of Finance, *76*(5), 2249–2305.

Bogousslavsky, V. (2016). Infrequent rebalancing, return autocorrelation, and seasonality. *The Journal of Finance*, *71*(6), 2967–3006.

Bogousslavsky, V. (2021a). The cross-section of intraday and overnight returns. *Journal of Financial Economics*, *141*(1), 172–194.

Bogousslavsky, V. (2021b). The cross-section of intraday and overnight returns. *Journal of Financial Economics*, *141*(1), 172–194.

Bogousslavsky, V., & Muravyev, D. (2023). Who trades at the close? implications for price discovery and liquidity. *Journal of Financial Markets*, *66*, 100852.

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

Bondarenko, O., & Muravyev, D. (2023). Market return around the clock: A puzzle. *Journal of Financial and Quantitative Analysis*, *58*(3), 939–967.

Boyarchenko, N., Larsen, L. C., & Whelan, P. (2023). The overnight drift. *The Review of Financial Studies*.

Cheng, M., & Madhavan, A. (2009). The dynamics of leveraged and inverse exchange-traded funds. *Journal of Investment Management*, *16*(4), 43.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461–1499.

Gao, L., Han, Y., Li, S. Z., & Zhou, G. (2018). Market intraday momentum. *Journal of Financial Economics*, *129*(2), 394–414.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of finland's unique data set. *Journal of Financial Economics*, *55*(1), 43–67.

Grinblatt, M., & Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, *56*(2), 589–616.

Hendershott, T., Livdan, D., & Rösch, D. (2020). Asset pricing: A tale of night and day. *Journal of Financial Economics*, *138*(3), 635-662.

Heston, S. L., Korajczyk, R. A., & Sadka, R. (2010). Intraday patterns in the cross-section of

stock returns. *The Journal of Finance*, *65*(4), 1369–1407.

Hvidkjaer, S. (2008). Small trades and the cross-section of stock returns. *The Review of Financial Studies*, *21*(3), 1123–1151.

Jones, C. S., Pyun, S., & Wang, T. (2024). Return extrapolation and day/night effects. *Night Effects (April 2024)*.

Kaniel, R., Liu, S., Saar, G., & Titman, S. (2012). Individual investor trading and return patterns around earnings announcements. *The Journal of Finance*, *67*(2), 639–680.

Lee, C. M., & Radhakrishna, B. (2000). Inferring investor behavior: Evidence from torq data. *Journal of Financial Markets*, *3*(2), 83–111.

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733–746.

Lewellen, J. (2002). Momentum and autocorrelation in stock returns. *The Review of Financial Studies*, *15*(2), 533–564.

Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction? *The Review of Financial Studies*, *3*(2), 175–205.

Lou, D., Polk, C., & Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, *134*(1), 192–213.

Luo, C. P., Ravina, E., Sammon, M., & Viceira, L. M. (2023). Retail investors' contrarian behavior around news, attention, and the momentum effect.

Muravyev, D., & Ni, X. C. (2020). Why do option returns change sign from day to night? *Journal of Financial Economics*, *136*(1), 219-238.

Smirlock, M., & Starks, L. (1986). Day-of-the-week and intraday effects in stock returns. *Journal of Financial Economics*, *17*(1), 197–210.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288–302.

Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies*, *30*(4), 1270–1315.