End-of-Day Reversal

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Abstract

Individual stocks experience sharp intraday return reversals during the last 30 minutes of the trading day. This "*end-of-day reversal*" pattern is economically and statistically highly significant, unique to the period before market close, and independent of market intraday momentum or gamma hedging effects. The reversal primarily comes from intraday losers, and we find that end-of-the-day risk management by short-sellers is driving this effect. Our evidence highlights the important role of overnight risk in driving the end-of-day stock prices.

JEL Classification: G11, G12

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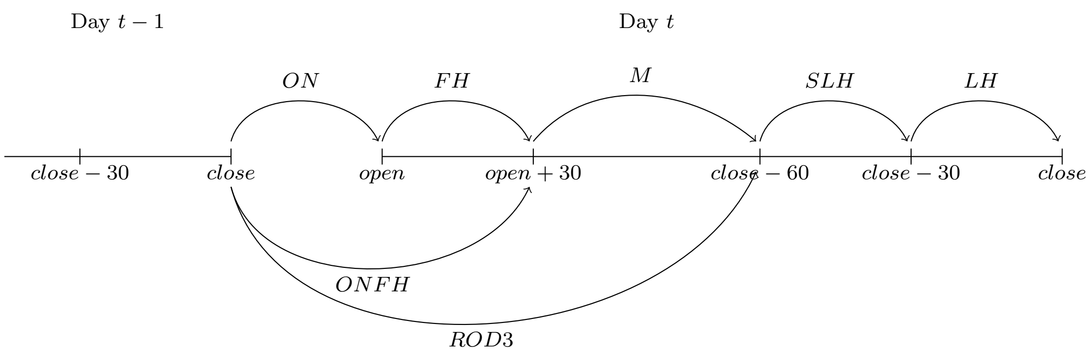
1 Introduction

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 stock market return during the early part of a day positively predicts its return in the last half an hour. They attribute such a market intraday momentum to infrequent trading and gamma hedging demand related to index products. In this paper, we first document a novel intraday return predictability: an individual stock return during the early part of a day *negatively* predicts its return in the last half an hour. We then identify novel mechanisms underlying such an end-of-day return reversal pattern for individual stocks.



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. The above timeline then partitions the trading day into five parts: Overnight (ON, from close to open); First Half-an-hour (FH, the first 30 minutes after the market open); Middle-of-the-day (M, from the end of FH to an hour before the market close); Second-to-last-half-an-hour (SLH, the second-to-last 30 minute interval); Last Half-an-hour (LH, the last 30 minutes before the market close). The combination of the first three partitions is labelled as "Rest-of-day-3" ($ROD3 = ON + FH + M$) and will be the focus of our paper. The combinations of the first two partitions is labelled as

$ONFH$ $(ON + FH)$.

While Heston et al. (2010) has already shown that stock's return over a given trading interval is negatively related to its returns over recent intervals, we find such an intraday reversal pattern to be strongest at the end of the day. Specifically, the $ROD3$ return strongly and negatively predicts the LH return in the cross-section. Note that the pattern is not a simple manifestation of the bid-ask bounce or other market microstructure noises, as we have deliberately skipped a 30-minute interval (SLH) between $ROD3$ and LH. A long-short daily trading strategy generates a highly significant return of between 3.45 and 4.45 bps per day (or 8.7% and 11.2% per year), depending on the weighting scheme and price filter.

The end-of-day reversal is extremely robust. It is present in almost every 3-year rolling window. It is significant in various subsamples (small vs. large stocks; liquid vs. illiquid stocks; high- vs. low-volatility stocks; over- vs. under-priced stocks). Both the $ONFH$ and the M components of $ROD3$ return negatively predict LH return. The predictability is not driven by using the closing price (Bogousslavsky and Muravyev (2023)), as skipping the last 5 minutes in the LH return calculation does not change the pattern. In panel regressions, $ROD3$ return remains significant in predicting LH return after controlling for stock (in addition to time) fixed effects and additional time-varying stock characteristics including lagged LH returns. Interestingly, consistent with the portfolio-sorting results, we find an asymmetry: the end-of-day reversal is driven by the subsample with negative $ROD3$ returns. Put differently, the reversal is much stronger following negative $ROD3$ returns than positive ones.

We then proceed to examining the economic mechanisms underlying the end-of-the-day reversal. A simple explanation 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 $ROD3$'s return predictability to disappear if we extend the future return horizon to include both LH today and $ONFH$ tomorrow, or both LH today and close-to-close tomorrow. In other words, the return during LH itself seems to contain a transitory price pressure that will be reverted next day.

What could be driving the end-of-day price pressure? We first examine the hedging demand from market makers as documented by Baltussen et al. (2021) and Barbon, Beckmeyer, Buraschi, and Moerke (2022). For instance, 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, then they have to trade in the opposite direction of the return in order 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 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.

Panel regressions show that while such hedging demands can contribute to the end-of-the-day reversal, they do not 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. More directly, even among the subset of stocks without option traded or among non-index stocks the end-of-day reversal is strongly present.

Second, 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) under-valued (over-valued) stocks during LH. If under-valued (over-valued) 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 these unwinding activities do not fully explain the reversal. We find under-valued $ROD3$ losers to also have higher LH returns than over-valued $ROD3$ winners. In addition, the end-of-the-day reversal is also present among stocks that are not mispriced.

Finally, we consider end-of-day trading by short-sellers. 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 when the $ROD3$ return is negative. Finally, supporting the important role of short sellers, we find the end-of-day reversal to be much stronger among stocks with low shorting costs.

Our paper contributes to the recent but emerging literature examining intraday return patterns. Lou, Polk, and Skouras (2019) document strong overnight and 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, Koch, Tuttle, and Zhang (2012) and Akbas, Boehmer, Jiang, and Koch (2022) show evidence of strong intraday versus overnight return return reversal in stocks. Related, Gao et al. (2018) and Baltussen et al. (2021) report intraday patterns at the market level in equities and other asset classes.[1] Further, Heston et al. (2010) find evidence of intraday return seasonality: returns continue during the same half-hour intervals as previous trading days. In this paper, we show the specialness of the last half-hour and document a sharp contrast between the market return and the individual stock return. While stock market displays strong intraday momentum at the end of the day, individual stock displays reversals. Investigation of the empirical mechanism reveals the important consideration of overnight risk in driving end-of-day trading.[2]

The rest of the paper is organized as follows. Section 2 describes our data and provides summary statistics. Section 3 presents the main stylized facts about the stock-level intraday reversal. Section 4 offers evidence supporting the gamma hedging demand channel. Section 5 concludes. The appendix contains additional descriptions of the data and various robustness results.

[1]Other intraday patterns have been document as well. For example, 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. Smirlock and Starks (1986) provide an early account of intraday efffects around weekends in DJIA stock returns. Muravyev and Ni (2020) document strong intraday and overnight differences in option returns.

[2]Further, several studies utilize intraday price data to examine intraday volatility (Chang, Jain, & Locke, 1995) or the efficiency of volatility estimators, see amongst others Bollerslev, Cai, and Song (2000), Martens and Van Dijk (2007), and Bollerslev, Hood, Huss, and Pedersen (2018).

2 Data

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 a share code of 10 or 11 that have intraday transactions covered by the Trade and Quote (TAQ) database. Stock market data are obtained from 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 occurred within the 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 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 of stock i on day t at second level to the frequencies outlined in the introduction, most importantly the return from market close at day $t-1$ till 3:00 p.m. at day t ($ROD3_{i,t}$) and the return from 3:30 p.m. till 4:00 p.m. at day t ($LH_{i,t}$):

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

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

In addition, we create other intraday return intervals. $ONFH$ is defined as return from market close at day $t-1$ till 10:00 a.m. at day t. We define MID as the return from 10:00 a.m till 15:00 p.m. at 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 using standard procedures[4], allowing us to employ firm-level characteristics and construct a set of control variables. Our empirical analysis employs a set of standard 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 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 Intraday reversal

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

We start our analyses by regressing returns on each stock during each 30-minute window during the trading day on the returns from 24-hours before the end of the window till an hour before the window.[5] For example, for the 15:30 - 16:00 window we regress its return for each stock 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

[4]We match TAQ to CRSP stocks using the CUSIP identifier, and CRSP to Compustat using PERMNOs.

[5]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).

market microstructure noises in traded prices, as argued by for example Heston et al. (2010). We follow this practice throughout the paper, but like to stress 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.[6] The sample runs from January 1993 to December 2019 and observations are weighted by their previous' day market capitalization.

Figure 1 shows the resulting slope coefficients and 95% confidence intervals. Most intervals display no significant predictability with slope coefficients close to zero. The three exceptions are (i) the first interval - the return during the previous day excluding overnight negatively predict 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 (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. 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 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 when skipping the 30-minute lag between the regressor and the dependent variable. Overall, end-of-day stock returns revert in the cross-section.

To examine the persistency of end-of-day reversal we next run rolling 3-years panel regressions of LH on ROD3 using the specifications as described above. Figure 2 shows the negative predictability of cross-sectional stock returns during the last half hour of trading are mostly persistent over time. Slope coefficients in 3-years rolling panel regressions are almost always negative (upper panel) and mostly significantly so (lower panel), also during the last years of our sample.

[6]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 like to stress our key results are also observed in Fama-MacBeth regressions.

3.1.1 Univariate portfolio sort

To further examine the link between $ROD3$ returns and LH returns in the cross-section of stocks we next form quintile portfolios. The timing of our portfolio strategy is as follows. At 15:30 p.m of each trading day t, we sort stocks into five portfolios based on their return between closing price on day $t-1$ and the price at 15:00 p.m. on day t (i.e., the $ROD3$ return). We compute value-weighted as well as equal-weighted returns on each portfolio, with both a \$5 and \$1 dollar price filter. In addition, we construct a "low-minus-high" (L-H) portfolio that takes long positions in stocks with low $ROD3$ returns, and takes short positions in stocks with high $ROD3$ returns. We hold these portfolios during the last half hour (LH) of the trading day t.

Table 1 reports 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, irrespective of the price filter, we document a decreasing relation between $ROD3$ returns and LH returns.

The first column in Table 1, shows a significantly decreasing relation between $ROD3$ returns and LH returns, in line with the results in Figure 1. The value-weighted daily portfolio return decreases from 3.45 bps per day on quintile L (low ROD) to -0.40 bps per day on quintile H (high ROD). The low-minus-high portfolio yields a spread returns of 3.45 bps per day, with a highly significant t-statistic of 10.49. The subsequent two columns show 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 3.38 bps per day, and highly significant with a t-statistic of 10.39. Using a lower price filter yields very similar results.

The reversal pattern becomes even stronger when considering equal-weighted portfolios; the equal-weighted spread portfolio (with a \$5 price filter) yields a return spread of 4.45 bps per

[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.

day with a t-statistic of 16.00. 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 3.45 bps reversal per day, or about 8.7% a year, for the value-weighted L-S portfolio, and 4.45 bps per day, or 11.2% a year, for the equal-weighted L-S portfolio.[8] Given that trading on end-of-day reversal requires frequent rebalancing, the strategy as presented might not be exploitable to many investors after accounting for transaction costs. That said, this is not to say that end-of-day reversal is 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 optimal by a direct trade-off between the strategy signal and transaction costs per stock. Further, end-of-day reversal may also be exploited in other manners that limit turnover or additional trading cost, for example via the timing of already planned trades. An exact examination of the best way to execute we leave for future research.

3.1.2 Controlling for other stock characteristics

To ensure that differences in ROD3 is 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

[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.

returns, overnight volatility (the standard deviation 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 each portfolio 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% firms earns a six-factor alpha of 19.02 bps per day with a t-statistic of 20.18. The intraday reversal effect is also significantly present among the 20% largest firms, where the six-factor alpha equals a significant 3.40 bps per day (t-statistic = 8.71).

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. Furthermore, besides being stronger in smaller stocks, some other interesting conditional effects appear. The end-of-day reversal effect is stronger for less traded stocks, more illiquid stocks, or stocks that are more volatile overnight.

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) under-valued (over-valued) stocks during LH. If under-valued (over-valued) 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 under-valued $ROD3$ losers to also have higher LH returns than over-valued $ROD3$ winners. In addition, the end-of-day reversal is significantly present among all mispricing quintiles, including stocks that are not mispriced. Noteworthy is that end-of-day reversal is strongest among undervalued stocks, in addition to being especially present amongst intraday loser stocks.

3.1.3 Panel regressions

In addition to our portfolio sorts, we next 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 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. The panel regressions lend further support to the existence of 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. The 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.

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) shows that 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. Hence, MIS or other control variables do also not explain end-of-day reversal. 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 and 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.

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), we add ROD3×I[ROD3<0] in our 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). In other words, the end-of-the-day reversal is driven by the subsample with negative $ROD3$ returns.

3.2 Temporary price pressure

Having documented a sizable and robust end-of-day reversal pattern we next examine its potential economic mechanisms. A simple explanation 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. Related, if end-of-day reversal is driven by informational trading motivations, we would expect it to persist beyond the last half hour.

In table 4, 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 $ROD3$'s 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 is at odds with an explanation based on a permanent liquidity shock or informational trading motivations.

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 7.1, table A.1 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.

3.3 Hedging demand and intraday 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 a 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. Further, 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 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. (2022) 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 extent our panel regressions with the various measures of hedging demand used by Baltussen et al. (2021) and Barbon et al. (2022). Firstly, 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 7.2. Secondly, 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 7.3. Thirdly, 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 7.4. 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 5 contains the results. First, we focus on the subsample of stocks for which we have option data available at day t, see 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. (2022) 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 with a t-statistic of -4.80 after controlling for gamma hedging demand from individual stock options. Columns (3) to (5) show a similar pattern once 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.

In panel B of table 5 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 with a 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 an well-tracked index 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 6 contains 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 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.

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

4 What drives intraday reversal?

In this section, we consider a potential explanation based on end-of-day trading by short-sellers. 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. Short-sellers might close short positions held intraday causing a reversal in price pressure. To examine this potential explanation we consider intraday shorting volume data. Furthermore, intraday reversal can also be driven by retail investors, which we consider in the last sub-section.

4.1 Intraday short volume

We collect intraday short volume for stocks traded on major U.S. trading venues: NYSE, NASDAQ, CBOE (formerly known as BATS), and FINRA. 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 dollar trading volume in the last half hour and scale this by the total short volume.

We regress the short volume during the last half-hour on ROD3 and present the results in table 7. 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.

4.2 Short-selling costs

In this section, we provide additional evidence that support our short-selling channel. Short-selling is costly and can be limited by supply, both potentially leading to limits-to-arbitrage. We argue that end-of-day reversal is stronger among stocks that are cheap and easy to borrow. We proxy this by using data on active utilization and indicative fee from Markit. Active utilization represents the percentage of stocks currently lent by custodians relative to the realistic amount of stock held by them in their lendable inventory pool. High active utilization typically indicates that a stock is hard to borrow. Likewise, a stock with a higher lending fee is more costly to borrow. Hence, we expect end-of-day reversal to be weaker when active utilization and lending fee is high.

To test this hypothesis, we regress LH returns on $ROD3$ returns, and an interaction with $ROD3$ returns and active utilization or lending fee. We show the results in table 9. In panel A, we consider the results using active utilization. In column (1), we document a negative coefficient of $ROD3$, in line with what we have seen before. In column (2) we add active utilization in the regression specification. We do not find that active utilization has a direct impact on LH returns. In column (3), we add an interaction between $ROD3$ and active utilization. This interaction effect positively predicts LH returns. This implies that end-of-day reversal becomes weaker for stocks with high active utilization, i.e. stocks that are harder to borrow. We also split for negative $ROD3$ observations, and find no significant additional effect on last half-hour returns, nor an interaction effect between negative $ROD3$ and active utilization. The results are robust to the inclusion of control variables in column (5). Our evidence suggests that intraday reversal is weaker for stocks that are harder to borrow.

In panel B of table 9, we show the results when we consider lending fees. In column (1), we document our end-of-day reversal effect. In column (2), we add lending fees, and find that higher lending fees are weakly associated with higher LH returns. In column (3), we add an interaction effect of $ROD3$ and lending fees. We find a positive coefficient on this interaction effect, indicating that last half-hour returns increase in $ROD3$ when lending fees are higher. As such, end-of-day reversal is weaker when lending fees are higher. This effect is not different for negative $ROD3$ observations versus positive observations. In sum, we find that end-of-day reversal is stronger for stocks with low lending fees, supporting the important role of short sellers. Overall, the evidence in this section reveals that risk management by short-sellers contributes to the end-of-day reversal effect.

4.3 Retail investors

Alternatively, intraday reversal during the last half hour of the trading day can be driven by retail investors.

To identify retail trades, we use data from TAQ between 2010 to 2019 and use an adapted version (see (Barber, Huang, Jorion, Odean, & Schwarz, 2023)) of the algorithm developed by Boehmer, Jones, Zhang, and Zhang (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., 2023) modifies the algorithm by signing trades using the quoted spread midpoints. We use this algorithm to compute retail order imbalance in the last half hour of the trading session for each stock. The retail order imbalance is defined as:

$$ROI_{i,t,LH} = (Buy_{i,t,LH} - Sell_{i,t,LH})/(Buy_{i,t,LH} + Sell_{i,t,LH}) \tag{2}$$

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 retail buys according to this classification algorithm. $Sell_{i,t,LH}$ denotes the dollar trading volume from transactions classified as retail sales.

In table 10 we show the results of regressing the LH retail order imbalance (ROI) on $ROD3$ and LH returns. 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 the remaining columns, 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. Notwithstanding the measurement error associated with the BJZZ algorithm, our evidence supports the notion of buying-the-dip by some retail investors at the end of the day.

Lastly, we provide additional pieces of evidence from retail investors in table 11 and 12. In the former table, we consider holdings from retail traders on Robinhood. We compute changes in the last half-hour holdings of retail traders and regress this on ROD3. We find that retail traders are contrarian and trade against ROD3 as shown in column (1). Furthermore, they are in particularly increasing their holdings after negative ROD3 (column 2). The results are robust when we control for other variables. Lastly, the latter table considers retail trade identification via small orders in the pre-decimalization era. We follow the approach in (Lee & Radhakrishna, 2000) and compute retail order imbalance in the last half-hour. Consistent with our previous findings, we find increased buying pressure after a decrease in ROD3.

5 Conclusion

We find that individual stock return display a strong intraday reversal 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 and the major subsamples of stocks, not driven by using the closing price, nor by persistent liquidity shocks or stock- or market-level gamma hedging effects. We find the reversal to reflect a transitory price pressure and primarily come from intraday losers. Investigation of underlying economic mechanism reveals that risk management by short-sellers contributes to the effect.

6 Tables & Figures

Figure 1:
Predicting 30 minute returns.
The top figure shows the estimated univariate coefficients obtained from fixed effects panel regression, where we predict the 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) and on the x-axis the dependent variable is stated. Around the coefficients, 95% confidence intervals are shown. Standard errors are adjusted for clustering in both 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 all specifications.

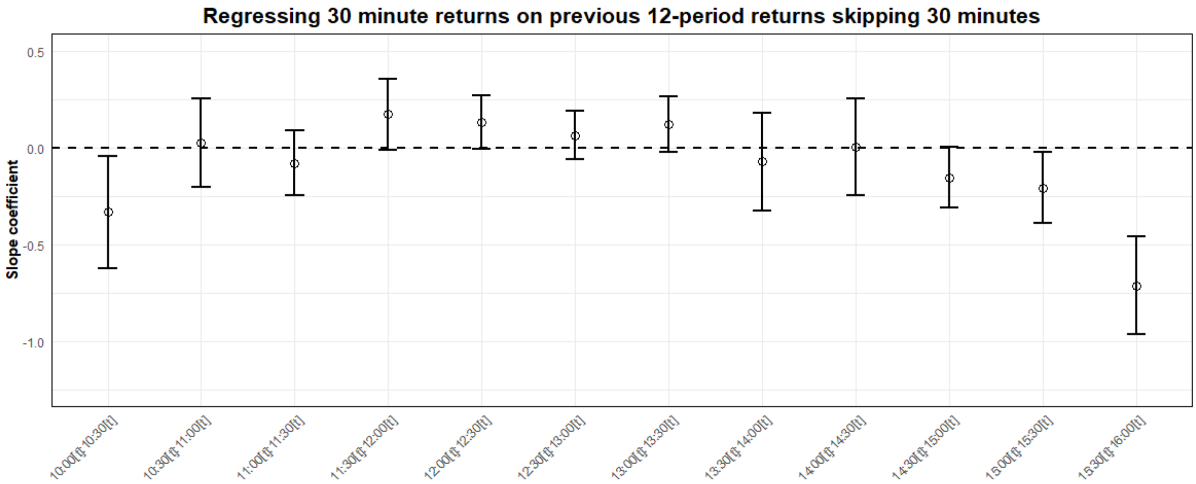


Figure 2:

Time-varying predictability of ROD3 on LH.

This figure shows the predictability of ROD3 on LH over time using rolling panel regressions on a three-year (black line) window. The upper figure shows the slope coefficient of ROD3 on LH. The bottom figure shows the t-statistic, which is adjusted for clustering in the time- and firm dimension. Both time - and firm fixed effects are included in the panel regressions. The full sample period runs from 04-01-1996 till 31-12-2019.

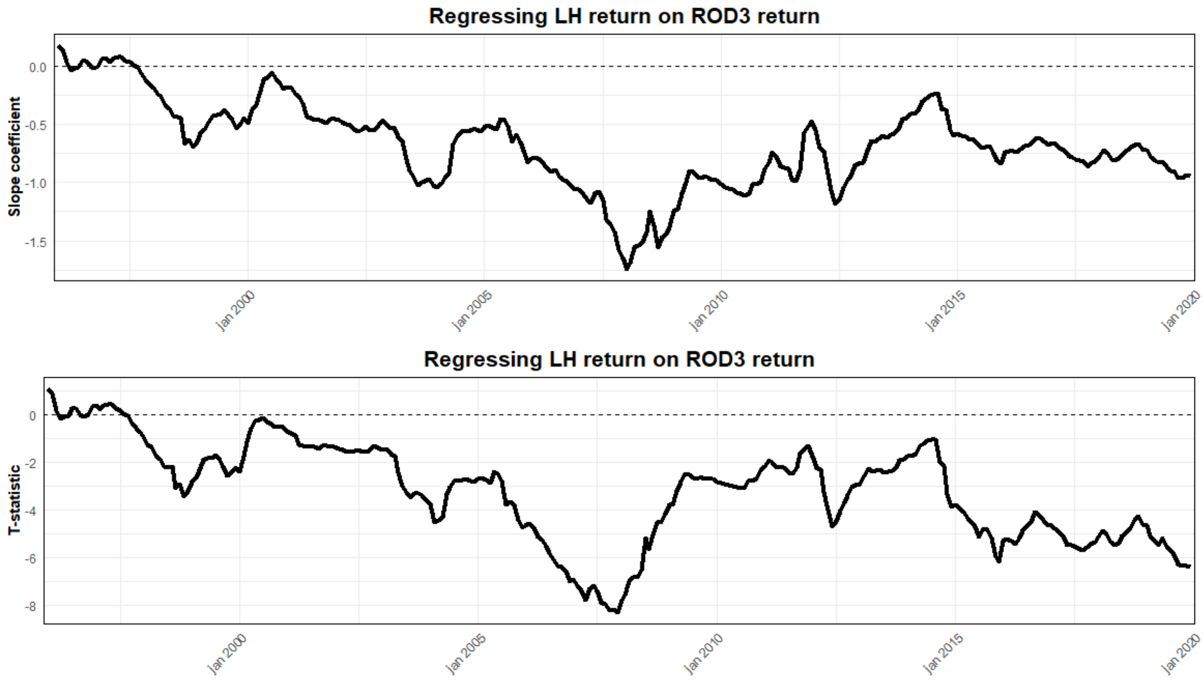


Table 1:

Performance of decile portfolios sorted on the ROD3 return.

This table reports the performance of decile 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 3:30 p.m. of each day t we sort stocks into ten portfolios on their rest-of-day return on day t, and hold this portfolio from 3:30 p.m. until 4:00 p.m. Panel A (B) presents results for value (equal)-weighted portfolios. We impose price filters at the start of the portfolio formation. We report the 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, which reports the difference in between portfolio L and portfolio H. 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, using 15 lags, adjusted t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 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
1	3.05***	2.29***	2.09***	3.09***	2.32***	2.09***	5.82***	3.29***	3.09***	6.16***	3.52***	3.30***
	(7.48)	(12.45)	(11.61)	(7.51)	(12.39)	(11.47)	(12.78)	(19.46)	(18.70)	(12.94)	(19.55)	(18.88)
2	0.94***	0.39***	0.46***	0.96***	0.41***	0.47***	2.24***	0.15**	0.22***	2.36***	0.21***	0.27***
	(2.74)	(3.62)	(4.19)	(2.81)	(3.65)	(4.24)	(6.69)	(1.97)	(3.05)	(6.87)	(2.71)	(3.72)
3	-0.13	-0.58***	-0.44***	-0.10	-0.56***	-0.42***	1.50***	-0.52***	-0.39***	1.62***	-0.45***	-0.33***
	(-0.40)	(-5.87)	(-4.83)	(-0.31)	(-5.67)	(-4.62)	(4.70)	(-6.31)	(-5.29)	(4.97)	(-5.54)	(-4.46)
4	-0.69**	-1.19***	-1.01***	-0.68**	-1.19***	-1.00***	0.97***	-1.08***	-0.98***	1.08***	-1.02***	-0.92***
	(-2.10)	(-11.80)	(-10.64)	(-2.04)	(-11.67)	(-10.57)	(3.03)	(-11.17)	(-10.91)	(3.31)	(-10.50)	(-10.20)
H	-0.40	-1.21***	-1.29***	-0.37	-1.19***	-1.28***	1.37***	-1.01***	-1.04***	1.54***	-0.92***	-0.95***
	(-1.02)	(-6.73)	(-7.29)	(-0.93)	(-6.64)	(-7.22)	(3.70)	(-8.36)	(-8.72)	(4.05)	(-7.41)	(-7.80)
L-H	3.45***	3.50***	3.38***	3.46***	3.51***	3.37***	4.45***	4.30***	4.13***	4.62***	4.44***	4.26***
	(10.49)	(10.58)	(10.39)	(10.37)	(10.52)	(10.30)	(16.00)	(16.37)	(16.02)	(16.07)	(16.51)	(16.12)

Table 2:
Performance of conditional bivariate portfolios sorted on the ROD3 return.
This table reports the performance of portfolios first formed on a conditioning characteristic and then on the basis of the 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 (Stambaugh & Yuan, 2017). Portfolio returns are value-weighted. 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, which reports the difference in between portfolio L and portfolio H. 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 dollar price filter. Newey-West (with 15 lags) t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	Size					**Volume**				
	S	2	3	4	B	L	2	3	4	H
L	16.99***	6.76***	2.52***	1.15***	1.96***	9.56***	4.95***	2.73***	1.86***	2.17***
	(22.57)	(17.81)	(11.91)	(5.60)	(8.70)	(22.85)	(17.03)	(12.27)	(8.26)	(7.85)
H	-2.03***	-1.88***	-0.74***	0.15	-1.44***	-4.79***	-1.82***	-0.24	0.70***	-1.29***
	(-4.93)	(-6.38)	(-3.66)	(0.86)	(-7.15)	(-12.80)	(-7.64)	(-1.29)	(3.98)	(-4.74)
L-H	19.02***	8.64***	3.26***	1.00***	3.40***	14.35***	6.77***	2.96***	1.16***	3.46***
	(20.18)	(14.90)	(9.46)	(3.40)	(8.71)	(19.96)	(14.69)	(9.04)	(3.69)	(7.17)
	Illiquidity					**Realized Volatility**				
	L	2	3	4	H	L	2	3	4	H
L	1.95***	0.85***	2.45***	6.81***	16.19***	2.95***	2.73***	2.71***	2.07***	5.92***
	(8.45)	(3.87)	(11.04)	(17.87)	(23.86)	(16.48)	(12.61)	(10.55)	(6.07)	(11.43)
H	-1.40***	0.53***	-0.15	-1.32***	-5.01***	-2.15***	-1.99***	-1.48***	-0.48	0.96**
	(-6.53)	(2.96)	(-0.73)	(-4.40)	(-9.54)	(-13.15)	(-10.08)	(-5.46)	(-1.38)	(2.16)
L-H	3.35***	0.32***	2.59***	8.12***	21.20***	5.10***	4.72***	4.19***	2.55***	4.96***
	(8.29)	(1.01)	(7.83)	(14.11)	(19.81)	(19.58)	(13.77)	(9.71)	(4.81)	(6.72)
	Overnight Volatility					**Mispricing**				
	L	2	3	4	H	L	2	3	4	H
L	2.98***	3.08***	2.41***	3.17***	6.14***	2.39***	2.49***	2.58***	2.79***	2.22***
	(15.08)	(12.66)	(9.10)	(9.06)	(8.62)	(10.19)	(10.83)	(10.23)	(9.40)	(6.04)
H	-1.94***	-1.47***	-0.57**	-1.01***	-1.68***	-2.09***	-1.65***	-0.82***	-0.43	0.37
	(-11.05)	(-7.60)	(-2.19)	(-3.03)	(-3.48)	(-9.94)	(-6.88)	(-3.09)	(-1.54)	(1.11)
L-H	4.92***	4.56***	2.97***	4.18***	7.82***	4.48***	4.14***	3.40***	3.23***	1.85***
	(16.63)	(12.70)	(7.28)	(8.11)	(7.75)	(12.45)	(10.92)	(8.31)	(6.66)	(3.28)

Table 3:
Panel regression results.
This table reports the estimated coefficients obtained from panel regressions, where 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. 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 are used to indicate significance at a 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:
Temporary price pressure.
This table reports the slope estimates obtained from regressing the cumulative return over several holding periods 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. 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 are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	ROD3	
	β	t-stat
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 5:

Hedging demand and intraday reversal.

This table reports the estimated coefficients obtained from panel regressions whereby the LH return is regressed on ROD3, net gamma exposure (NGE) and leveraged ETF rebalancing (LETF). NGE is computed as described in section 7.2, market-level ROD and NGE in section 7.3 and LETF in section 7.4. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1996 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. The sample period in columns (4) and (5) start when LETF becomes available (June 2006). 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. Firm- and time fixed effects are included in all specifications. Observations are weighted by the firm's market capitalization on day $t-1$. Double-cluster (by firm and day) adjusted t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 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)
$\text{ROD3}_{mkt}\times\Gamma_{mkt}$			-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 6:

Hedging demand and intraday reversal (continued).

This table reports the estimated coefficients obtained from panel regressions whereby the LH return is regressed on ROD3, net gamma exposure (NGE) and leveraged ETF rebalancing (LETF). NGE is computed as described in section 7.2, market-level ROD and NGE in section 7.3 and LETF in section 7.4. 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. Stocks below the 10th NYSE size percentile are excluded from the sample. The sample period starts in January 1996 whenever net gamma exposure is added to the regression specification. The sample period in columns (4) and (5) start when LETF becomes available (June 2006). 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 indexes are included in panel B. Firm- and time fixed effects are included in all specifications. Observations are weighted by the firm's market capitalization on day $t-1$. Double-cluster (by firm and day) adjusted t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 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)		
$\text{ROD3}_{mkt} \times \Gamma_{mkt}$			-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 7:
Last half-hour short volume.
This table reports the slope estimates obtained 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 with a market capitalization below the 10th NYSE percentile are excluded. Observations are weighted by their previous' day market capitalization. All regression specifications include both time - and firm fixed effects. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks are used to indicate significance at a 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 8:

Short-sale costs and intraday reversal.

This table reports the slope estimates obtained from regressing the last half-hour return on ROD3, active utilization, and lending fees. ROD3 is defined as the return between 3:30pm on day $t-1$ till 3:00pm on day t. Active utilization, and lending fee data are obtained from IHS Markit. 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 with a market capitalization below the 10th NYSE percentile are excluded. Observations are weighted by their previous' day market capitalization. All regression specifications include both time - and firm fixed effects. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	Panel A: Active Utilization					**Panel B: Lending fee**				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
ROD3	-0.74***	-0.70***	-0.90***	-0.76***	-0.81***	-0.81***	-0.81***	-0.82***	-0.83***	-0.85***
	(-6.91)	(-6.84)	(-7.92)	(-4.58)	(-4.84)	(-8.02)	(-8.02)	(-8.06)	(-6.53)	(-6.39)
Borrow		0.00	0.00	-0.00	-0.01*		3.94*	4.14**	1.52	4.13
		(0.31)	(0.26)	(-0.40)	(-1.91)		(1.98)	(2.01)	(0.54)	(1.38)
ROD3×Borrow			0.02***	0.02***	0.03***			2.35***	3.91***	3.84***
			(7.14)	(5.31)	(5.13)			(2.47)	(3.94)	(2.65)
ROD3×I[ROD3<0]				-0.30	-0.23				0.02	0.00
				(-1.28)	(-1.00)				(0.10)	(0.02)
ROD3×I[ROD3<0]×Borrow				-0.00	-0.01				-2.80	-0.06
				(-0.67)	(-0.81)				(-1.16)	(-0.03)
Control	No	No	No	No	Yes	No	No	No	No	Yes
Obs	5.24M	5.17M	5.17M	5.17M	4.83M	3.41M	3.41M	3.41M	3.41M	3.17M
R^2	0.14%	0.12%	0.17%	0.17%	0.20%	0.18%	0.18%	0.18%	0.18%	0.21%

Table 9:
Short covering.

Gross Covering	(1)	(2)	(3)	(4)	(5)
ROD3	-0.01	0.23	0.22	0.21	0.21
	(-1.04)	(8.95)	(8.76)	(8.52)	(8.73)
ROD3_neg		-0.50	-0.50	-0.46	-0.45
		(-10.97)	(-10.88)	(-10.78)	(-10.80)
LH			-0.21	0.47	0.44
			(-3.51)	(3.95)	(3.70)
LH_neg				-1.38	-1.32
				(-7.15)	(-7.01)
Control	No	No	No	No	Yes
Obs.	5.33M	5.33M	5.24M	5.24M	4.89M
R^2	0.0&	0.03%	0.03%	0.04%	0.13%
Net Covering	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
ROD3	-0.00	0.13	0.12	0.11	0.11
	-0.08	7.35	7.09	6.50	6.44
ROD3_neg		-0.27	-0.26	-0.24	-0.24
		-9.53	-9.44	-8.62	-8.38
LH			-0.39	0.05	0.03
			-6.60	0.76	0.51
LH_neg				-0.89	-0.89
				-6.41	-6.24
Control	No	No	No	No	Yes
Obs.	5.26M	5.26M	5.17M	5.17M	4.82M
R^2	0.0%	0.01%	0.01%	0.02%	0.05%

Table 10:

Last half-hour retail order imbalance.

This table reports the slope estimates obtained from regressing the last half-hour retail order imbalance on ROD3. ROD3 is defined as the return between market close at day $t-1$ and 3:30pm on day t. Retail trades are identified used the algorithm of Boehmer et al. (2021). We compute the retail order imbalance, during the last half hour, as the (buy-sell)/(buy+sell), where buy and sell are retail trading volumes. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 2014 till December 2019 with share code 10 or 11, and prices above \$5 as of the portfolio formation. Stocks with a market capitalization below the 10th NYSE percentile are excluded. Observations are weighted by their previous' day market capitalization. All regression specifications include both time - and firm fixed effects. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ROD3	-0.27***	0.44***	0.41***	0.41***	0.41***	0.41***	0.41***	0.41***
	(-2.97)	(3.20)	(2.90)	(2.89)	(2.88)	(2.89)	(2.89)	(2.81)
ROD3×I[ROD3<0]		-1.47***	-1.43***	-1.43***	-1.43***	-1.43***	-1.43***	-1.45***
		(-10.28)	(-9.80)	(-9.80)	(-9.78)	(-9.80)	(-9.80)	(-9.73)
β_{mkt}			0.85	0.85	0.85	0.84	0.84	0.91
			(1.25)	(1.25)	(1.25)	(1.25)	(1.25)	(1.33)
RV				-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
				(-10.55)	(-10.54)	(-10.53)	(-10.53)	(-15.47)
SREV					-0.25	-0.22	-0.22	-0.15
					(-1.55)	(-1.35)	(-1.35)	(-0.53)
MOM						0.12	0.12	0.33*
						(1.50)	(1.50)	(1.84)
ILQ							-0.06***	-0.06***
							(-10.04)	(-8.54)
MIS								-0.06***
								(-4.41)
Obs.	3.05M	3.05M	2.92M	2.92M	2.92M	2.92M	2.92M	2.81M
R^2	0.01%	0.04%	0.04%	0.04%	0.04%	0.04%	0.04%	0.06%

Table 11:
Changes in Robinhood retail holdings.
This table reports the slope estimates obtained from regressing the last hour change in retail holdings from Robinhood on ROD3. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between June 2018 till December 2019 with share code 10 or 11, and prices above $5 as of the portfolio formation.Stocks with a market capitalization below the 10th NYSE percentile are excluded. Observations are weighted by their previous' day market capitalization. All regression specifications include both time - and firm fixed effects. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	c1	c2	c3	c4	c5	c6	c7	c8
ROD3	-0.39	-0.16	-0.16	-0.16	-0.19	-0.18	-0.17	-0.18
	-6.18	-3.57	-3.62	-3.19	-2.82	-2.77	-3.02	-2.77
ROD3×I[ROD3<0]		-0.46	-0.46	-0.45	-0.42	-0.41	-0.43	-0.43
		-2.95	-2.90	-2.70	-2.67	-2.64	-2.92	-2.85
β_{mkt}			0.87	0.88	0.85	1.18	1.19	1.36
			0.49	0.50	0.49	0.65	0.66	0.72
RV				0.03	0.02	0.02	0.03	0.03
				0.38	0.34	0.34	0.40	0.38
SREV					-4.01	-3.72	-3.81	-3.73
					-1.15	-1.10	-1.11	-1.11
MOM						0.65	0.38	0.14
						1.42	0.78	0.25
ILQ							-2116.73	48.17
							-1.30	1.05
MIS								-0.08
								-1.17
Obs.	323K	323K	323K	323K	323K	323K	323K	321K
R^2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table 12:

Changes in retail volume (pre-decimalization).

This table reports the slope estimates obtained from regressing the last hour retail order imbalance obtained from TAQ pre-decimalization. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between Jan 1993 till December 2000 with share code 10 or 11, and prices above $5 as of the portfolio formation.Stocks with a market capitalization below the 10th NYSE percentile are excluded. Observations are weighted by their previous' day market capitalization. All regression specifications include both time - and firm fixed effects. T-statistics, adjusted for clustering in time and firm dimensions, are reported between parenthesis. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

	c1	c2	c3	c4	c5	c6	c7	c8
ROD3	-0.26	0.45	0.40	0.40	0.30	0.30	0.30	0.26
	-4.80	7.74	7.01	7.01	4.76	4.71	4.69	4.64
ROD3×I[ROD3<0]		-1.52	-1.48	-1.48	-1.31	-1.31	-1.31	-1.28
		-10.20	-10.11	-10.11	-8.81	-8.79	-8.79	-9.31
β_{mkt}			4.15	4.15	3.69	3.64	3.65	3.94
			2.77	2.77	2.47	2.39	2.40	2.49
RV				-0.00	-0.00	-0.00	-0.00	-0.00
				-0.00	-0.21	-0.22	-0.24	-0.00
SREV					-14.34	-14.44	-14.85	-22.00
					-2.81	-2.76	-2.93	-9.29
MOM						-0.23	-0.21	-1.37
						-0.47	-0.43	-3.50
ILQ							12.30	12.31
							4.09	8.54
MIS								-0.21
								-3.27
Obs.	2.70M	2.70M	2.48M	2.48M	2.48M	2.48M	2.48M	2.32M
R^2	0.02%	0.11%	0.21%	0.21%	0.63%	0.63%	0.65%	1.02%

7 Appendix

7.1 Additional tables and figures

Figure A.1:

Predicting 30 minute returns (without 30-minute skip).

The top figure shows the estimated univariate coefficients obtained from fixed effects panel regression, where we predict the 30 minute return on its previous 13-period interval return. On the y-axis, we report the slope coefficient (multiplied by 100) and on the x-axis the dependent variable is stated. Around the coefficients, 95% confidence intervals are shown. Standard errors are adjusted for clustering in both 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 all specifications.

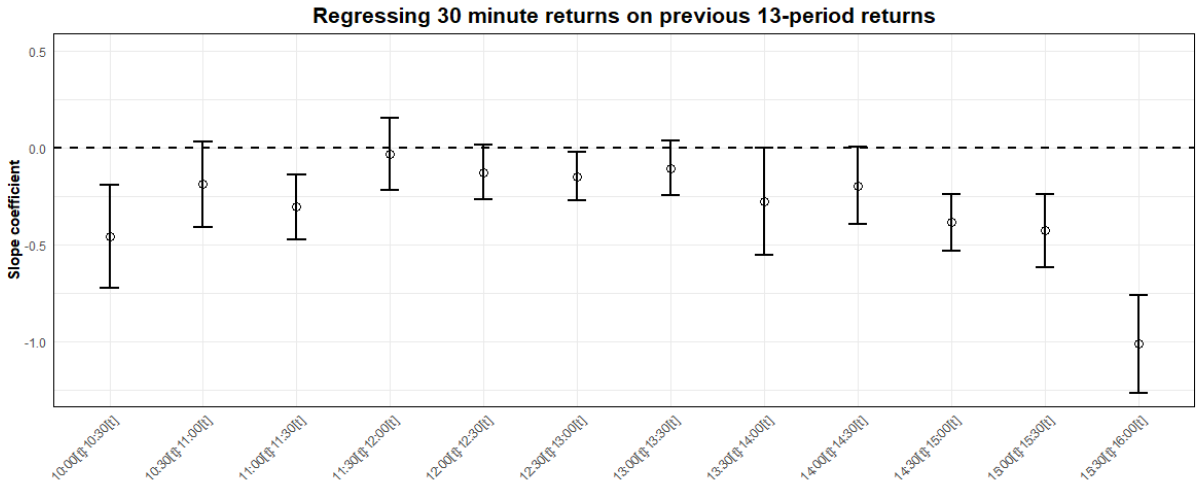


Table A.1:

Firm earnings and firm news.

This table shows the estimated coefficients obtained from panel regressions, whereby the LH return is regressed on the $ROD3$ return, an earnings date dummy, and the interaction between the earnings dummy and the $ROD3$ return in panel A. In panel B, we replace the earnings date dummy with a 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 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, and prices above $5 as of the portfolio formation. Observations are weighted by their previous' day market capitalization. The reported t-statistics are adjusted for clustering in the time and PERMNO dimension. Coefficients are multiplied by 100. Asterisks are used to indicate significance at a 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%

7.2 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 and Buraschi (2020). 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:

$$NGE^c_{i,s,m,t} = \Gamma^c_{i,s,m,t} \times OI^c_{i,s,m,t} \times 100 \times S_t$$

Where $\Gamma^C_{i,s,m,t}$ denotes the option's gamma, $OI^c_{i,s,m,t}$ 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:

$$NGE^p_{i,s,m,t} = \Gamma^p_{i,s,m,t} \times OI^p_{i,s,m,t} \times (-100) \times S_t$$

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:

$$NGE_{i,t} = \left(\sum_{s \in S^c} \sum_{m \in M^c} NGE^c_{i,s,m,t} + \sum_{s \in S^p} \sum_{m \in M^p} NGE^p_{i,s,m,t} \right) \times \left(\frac{S_t}{100 \times VOL_{i,t-1}} \right) \tag{3}$$

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.

7.3 Market-level Net Gamma Exposure and intraday returns

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 3. 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

7.4 Leveraged ETFs

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.

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