The Role of Leveraged ETFs and Option Market Imbalances on End-of-Day Price Dynamics*

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Abstract

Leveraged ETFs and market makers who are active in option markets must adjust imbalances arising from market movements to achieve delta-neutrality. This dynamic adjustments may cause either end-of-day return momentum or reversal depending on the size of the imbalance versus the prevailing liquidity. We find that a large and negative (positive) aggregated gamma imbalance, relative to the average dollar volume, gives rise to an economically and statistically significant end-of-day momentum (reversal). We compare this channel to the rebalancing of leveraged ETFs and find that the effect generated by leveraged ETFs is economically larger. Consistent with the notion of temporary price pressure, the documented effects quickly revert at the next day's open. Information-based explanations are unlikely to cause the results, suggesting a non-informational channel through which leveraged ETFs and option markets affect underlying stocks towards the market close.

JEL classification: G12, G13, G14, G23

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1. Introduction

We investigate the potential links between large portfolio rebalancing effects due to hedging strategies used by option market makers and leveraged ETFs, the intraday dynamics of stock prices (momentum and reversal), and abnormal changes in end-of-day volatility.

The role of the options market and leveraged ETFs on the dynamics of the underlying stock prices has recently garnered a lot of attention, attracting negative press coverage for potentially contributing to market volatility during already turbulent times.[1] Just recently, the trading activity in options was blamed to increase the violent stock swings during the February-March 2020 Covid-19 selloff. The Wall Street Journal wrote:

> *"Investors searching for clues on what drove the back-to-back drops in the stock market are pointing to the options market as a contributor, saying hedging activity by traders may have exacerbated the decline."*

Wall Street Journal, Feb. 27, 2020[2]

While it is widely accepted that options are non-redundant and may directly influence the price of the underlying (Black, 1975), we lack a clear quantification of these effects in individual stocks and how they relate to end-of-day price dynamics. We study the role of two distinct institutional channels.

The first channel relates to the activity of (option) market makers. Market makers and broker/dealers provide liquidity to clients who want to take positions in stock options. However, they have institutional incentives to avoid directional exposures and they usually delta-hedge their positions. Since the option delta changes when the value of the underlying changes, market makers need to regularly update their positions to maintain delta neutrality.

The direction of the price pressure exerted by the market maker depends on its initial gamma imbalance and the price movement of the underlying asset. Suppose, for instance, that the price of a stock has a positive jump, due to some positive unexpected fundamental news about future cash flows. If the gamma of the market maker positions is initially negative, maintaining delta-neutrality requires the purchase of additional shares in the underlying stock. On the contrary, a positive net gamma requires selling the underlying

[1] See for example Davies (2019).

[2] https://www.wsj.com/articles/the-invisible-forces-exacerbating-market-swings-11582804802

asset. Thus, if the aggregate gamma of market makers is significantly negative, delta-hedging could give rise to significant net purchase contributing to end-of-day momentum. Contrarily, if the aggregate gamma imbalance of market makers was positive, delta-hedging would have a stabilizing effect in the form of an end-of-day reversal.

Notice that derivative markets are by construction zero-sum games. For each option, there is a buyer and a seller. Therefore, the overall dollar value of aggregate gamma for each option is zero across all purchasers and sellers. However, certain market participants may have different incentives to hedge. Thus, in the cross-section one can observe a distribution of delta and gamma imbalances. Market makers are obliged to uphold liquidity in the options market and facilitate the efficiency of trades. They refrain from taking any directional bets on the underlying stocks by hedging their option delta-exposure.

The second source of institutional frictions relates to the end-of-day mechanical rebalancing of leveraged ETFs. The mechanism is simple. For a normal ETF the payoff is equal to the value of the referenced portfolio. Thus, the required notional exposure is identical to the actual exposure. Leveraged ETFs are synthetic instruments that are benchmarked at the close and created with total return swaps whose notional principal is a multiple of the value of a referenced portfolio. Thus, different than for a normal ETF, a price appreciation of the underlying asset portfolio has the compounded effect of increasing both the referenced portfolio and the required notional value of the swap. As a consequence, any price appreciation or drop gives rise to an imbalance between the required and effective notional amount of the swap. The swap counterparty has to manage her exposure to the underlying ETF, thus potentially inducing a large rebalancing of the portfolio of physical assets used to hedge the swap (see Section 2.3). Cheng and Madhavan (2010) argues that the portfolio rebalancing of leveraged ETFs may have an impact on intraday prices.

Figure 1 (top panel) illustrates the rebalancing effects caused by option market makers and leveraged ETFs towards the end of the trading day. The upper panel shows the intraday return path for Tesla stock on 13 December 2012. At the beginning of the day, the aggregate gamma was positive and economically significant. During the day, Tesla experienced a negative return equal to -6.62% by 15:30. Based on the information available, the gamma imbalance implied that delta-hedgers needed to trade an amount equal to 102.11% of the average dollar trading volume of Tesla shares in the last half-hour. As Figure 1 illustrates, a strong price reversal emerged in the last 30 minutes of the trading day, which is consistent with the large initial positive gamma imbalance.

An interesting example that relates to the role of leveraged ETFs is provided by the dynamics of Apple stock on 24 October 2018, see Figure 1 (middle panel). Apple stocks are an important constituent for leveraged ETFs. At the same time, at the beginning of the trading day the aggregate gamma of market makers was close to zero. By 15:30, Apple shares had dropped by −2.24%. As a consequence, leveraged ETF had to sell large quantities of Apple shares to rebalance their portfolio of leveraged swaps for an estimated dollar amount equal to 8.85% of the average dollar daily trading volume in Apple shares. Possibly as a result, the price dropped further by −1.22%.

The timing of delta-hedging by market makers and portfolio rebalancing by leveraged ETFs can be different. Figure 1 (bottom panel) illustrates this heterogeneity and the potential effect on the price dynamics. On 23 June 2016, the gamma imbalance of market makers on Amazon stock options was large and positive. At the opening, the price dropped by almost 4%. The implied hedging demand by likely delta-hedgers required purchasing shares for approximately 50% of the average dollar volume in Amazon shares. Consistently, the share price started to mean revert, albeit not completely. At 15:30 the share price was −3.27% lower than the previous day. Leveraged ETF had to rebalance, which caused further downward pressure as it emerged shortly before the market closing.

There are two important differences between these two channels. First, the direction of the price pressure from leveraged ETFs only depends on the return on the benchmark index which the leveraged ETF promises to track as a multiple.[3] Hence, the price pressure can support dynamics consistent with intraday momentum. On the other hand, the price pressure exerted by the rebalancing of market makers depends on the sign of their gamma imbalance, and the effect can be consistent with either a momentum or mean-reversion effect. Second, while option market makers have discretion on the execution of their hedging strategies, leveraged ETF swap counterparties are required to establish the target exposure of the fund at the close. We thus expect larger effects of leveraged ETF rebalancing on end-of-day returns.[4] Third, the demand pressure arising from leveraged ETFs is common across all stocks which are part of the index referenced by the ETF. On the other hand, the market makers' gamma imbalance is stock-specific and it can be,

[3]There are generally two types of leveraged ETFs, bull funds that promise to deliver a multiple of the underlying ETF's return, and bear funds, which are designed to generate a multiple of the opposite return of the index.

[4]While market makers should hedge continuously, whenever a large intraday price movement emerges, the existence of frictions may create incentives for them to delay their hedging and distribute implied price pressure during the day (Clewlow and Hodges, 1997). Indeed, liquidity and volume patterns are attractive at the open and close, as previous studies have documented a U-shape end-of-day volume pattern (Andersen and Bollerslev, 1997). It is certainly unusual for market makers to remain unhedged when markets are closed due to the significant overnight gap risks and regulations such as BIS capital requirements that make it costly to hold overnight positions due to higher capital costs.

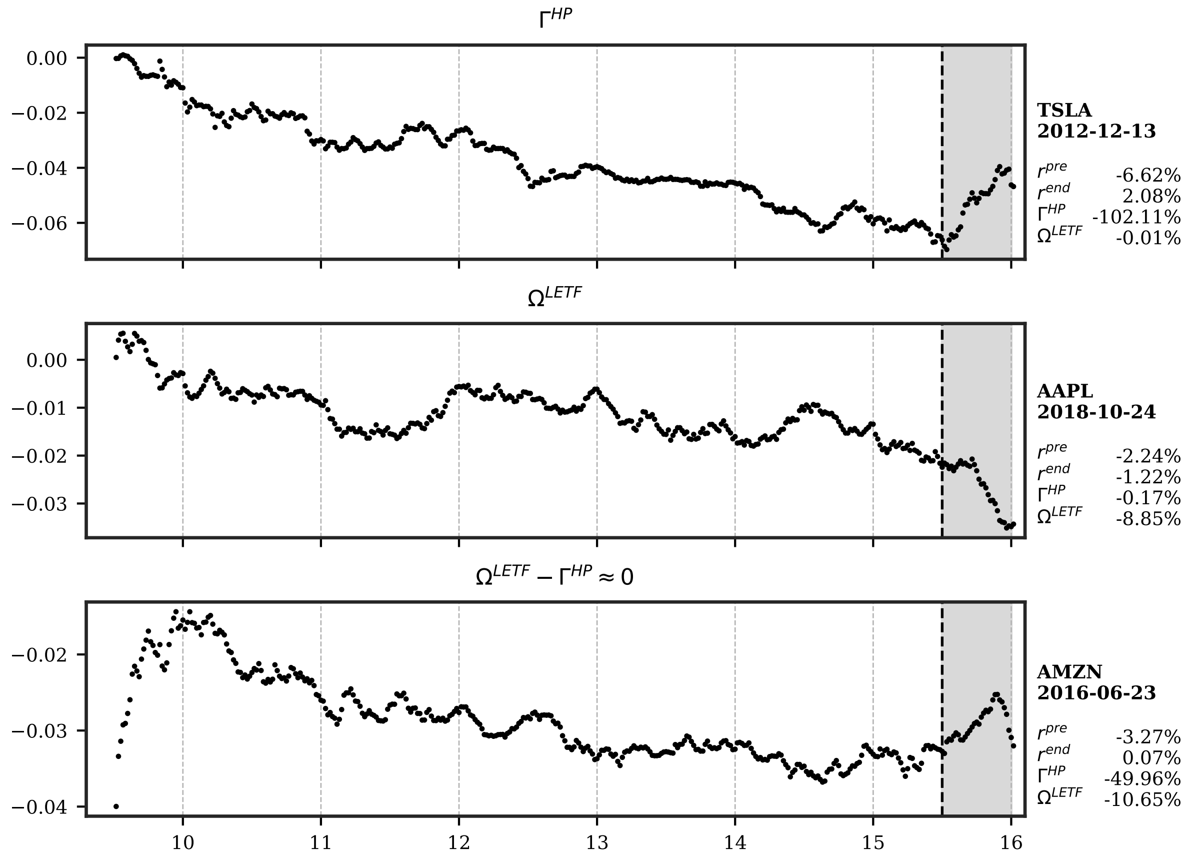

Fig. 1. **Delta-Hedging and Leveraged ETF Rebalancing Effects**
The figure depicts the effects of delta-hedging and leveraged ETF rebalancing on three days in our sample for Tesla (TSLA), Apple (AAPL), and Amazon (AMZN) stock, respectively. r^{pre} denotes the return from previous day's close price until 15:30. r^{end} denotes the return from 15:30 to close. Γ^{HP} is defined in Equation (5) and is the product of r^{pre} and the aggregate gamma imbalance, Γ^{IB}. Ω^{LETF} is the measure for leveraged ETF rebalancing, defined in Equation (6). Γ^{HP} and Ω^{LETF} are expressed in relative terms to the average dollar trading volume in the last half hour over the last quarter.

at the same time, positive for one stock and negative for another. This may generate mean-reversal for a set of stocks and intra-day momentum for others.

We build a unique dataset that merges data from several options exchanges providing the identity of all option counterparties and the portfolio composition of 72 leveraged ETFs for 24 underlying benchmark ETFs, which represents almost the whole universe of leveraged ETFs on U.S. equity indexes. After computing the gamma imbalance of market makers and the rebalancing demand of leveraged ETFs, we use intraday TAQ data to study the potential implications on intraday price dynamics. We ask three related questions: First, is there an empirical correlation between the required portfolio rebalancing of leveraged ETFs, the gamma imbalance of market makers, and end-of-day price dynamics? What is the relative importance of these two channels? Second, given the emergence of a price jump during the trading day, what is the extent to which the resulting portfolio imbalances are absorbed during the trading day and at the market closure? Third, how does the effect hold up in different subsamples and over time? Is the effect more pronounced for small or large stocks? While large stocks are often more liquid, they are more often part of those indexes that are referenced by leveraged ETFs.

First, we investigate both effects in isolation. We find that end-of-day returns and orderflow measured by signed trading volume are correlated with a measure of delta-hedging required by market makers to neutralize price changes that have occurred until 15:30. When this hedging-pressure is positive (negative), we observe abnormal selling (buying) pressure at the close, which directly translates into lower (higher) returns. This effect is robust to a series of control variables suggested in the literature, such as the trading volume in the option relative to the market (Roll, Schwartz, and Subrahmanyam, 2010), the put/call ratio (Blau, Nguyen, and Whitby, 2014), and properties of the implied volatility. Turning to the impact of rebalancing flows originating from leveraged ETF replication, we find large effects on both end-of-day orderflow and returns. The riskiness of the stock position does not drive our results.

Next, we compare the two effects on a joint dataset, comprising all stocks that are optionable and included in at least one leveraged ETF. First, the effect by leveraged ETFs on end-of-day returns is larger in terms of economic and statistical significance. A one standard-deviation increase in the Γ hedging pressure depresses end-of-day returns by -113% of the average return in the last thirty minutes of a trading day. A one standard-deviation increase in leveraged ETF rebalancing flows increases end-of-day returns by 430% of the average return in the last half hour. Moreover, we find that the impact of both rebalancing sources is amplified when controlling for the magnitude of the other. This is most evident when we condition on the set of days where both sources agree to either buy or sell the underlying stock.

To assess the economic significance of the cross-sectional impact of these rebalancing flows, we design a long-short strategy that uses as conditional signal the estimated demand pressure. We find that the average annualized return of the strategy is positive, unexplained by traditional risk factors, and orthogonal to the market return at the close. The annualized Sharpe-ratio is about 3 (5), with a success rate of 58% (62%), using a value-weighted (equal-weighted) portfolio.

A central question in our analysis regards the timing of the portfolio rebalancing. While theoretical arguments imply that hedging activity should be done instantaneously by market makers, the presence of frictions may delay the hedging activity to the end-of-day when liquidity is deeper. We empirically address this question by varying the intraday hedging window at 30 minute intervals, between 10:00 and 16:00. We find supporting evidence that a significant component of the hedging activity of option market makers takes place toward the end of the trading day (an hour before the close); at the same time, the counterparties to leveraged ETFs unequivocally implement their portfolio rebalancing at the close.

Building on this insight, we also investigate how quickly option market makers actively hedge following a large price shock in the underlying. If the large movement has occurred early during the trading day, we find that the hedging activity is almost immediate. In contrast, the rebalancing activity of leveraged ETFs is unrelated to intraday jumps and takes place solely end-of-day.

Furthermore, we find that the estimated impact of option market maker is robust to the presence or absence of fundamental news about the underlying stock. We consider both earnings announcements and the release of material news as identified by RavenPack.

If portfolio rebalancing and hedging activities substantially distorts prices at the close, we expect other market participants to correct this mispricing at the next open. Indeed, we find that more than 80% of the impact of market makers and a third of the impact of leveraged ETFs is reversed at the next open, highlighting the transitory nature of the phenomenon.

Using rolling three-year subsamples, we provide evidence that the impact of both channels has been both economically and statistically significant in all subsamples between 2012 and 2019. Additionally, we find that the impact of delta-hedging has increased over time, whereas it remained constant for leveraged ETF rebalancing.

The effects of delta-hedging on the price of the underlying are more pronounced for large stocks. This is due to the larger dollar open interest of high market capitalization stocks, which skews the Γ-imbalance distribution towards them. On the other hand, the impact of leveraged ETF rebalancing is symmetric between large and small stocks.

We provide a battery of robustness checks, relating to the empirical setup, the assumption regarding who engages into delta-hedging, different ways to measure average and risk-adjusted returns, and confirm that our results are unaffected by the respective company's industry. Furthermore, we address concerns regarding the possibility that changes in the options inventory of market makers in response to private and/or public information on end-of-day returns explain our results (see Ni, Pearson, Poteshman, and White, 2020, for the effect of delta-hedging on stock return volatility).

Related Literature

Our work relates to several streams of the literature. The first stream studies the feedback effects of option markets on the underlying stock price dynamics. The literature generally distinguishes between two channels through which option trading may have an impact on the price of the underlying. Hu (2014) provides evidence that the information found in market makers' initial delta-hedges can significantly affect the price dynamics of the underlying.[5] However, a non-informational channel may also be at work: Ni, Pearson, and Poteshman (2005) and Golez and Jackwerth (2012) document that rebalancing and unwinding of option market makers' delta hedges on or very close to expiration drive the prices of individual stocks and stock index futures towards option strike prices on option expiration dates. Lately, Ni et al. (2020) analyze the effects of Γ-imbalance on absolute returns and the autocorrelation of returns, based on theoretical models that predict a negative relation between stock volatility and Γ-imbalance.[6] Whereas Ni et al. (2020) resort to daily data, Barbon and Buraschi (2020) concentrate on intraday price dynamics. They find that Γ-imbalance is negatively related to intraday volatility and document that Γ-imbalance can affect the frequency and magnitude of flash crashes. Baltussen, Da, Lammers, and Martens (2020) show that end-of-day momentum in many futures contracts concentrates on days with negative Γ-exposure of option market makers. Finally, Chordia, Kurov, Muravyev, and Subrahmanyam (2021) propose a risk-based channel. The authors show that net buying pressure in index puts on the International Securities Exchange positively predicts subsequent S&P 500 index returns and trace the predictability to the purchase of protection when uncertainty is high.

A different, but related stream of the literature studies the effects of option market maker inventory. Gârleanu, Pedersen, and Poteshman (2009) have provided pathbreaking work on how demand pressure affects option prices. A closely related study is by Fournier and Jacobs (2020). Johnson, Liang, and Liu (2016) investigate the forces

[5]Other studies advocating an informational channel are, among others, Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), Ni, Pan, and Poteshman (2008), Cremers and Weinbaum (2010), Roll et al. (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2016).

[6]For a theoretical foundation, see among others Frey and Stremme (1997), Frey (1998), Sircar and Papanicolaou (1998), Platen and Schweizer (1998), Wilmott and Schönbucher (2000).

behind the use of S&P 500 index option and conclude that unspanned crash risk drives much of their demand. Related, Jacobs and Mai (2020) find a tight link between prices and demand in S&P 500 and VIX options. Chen, Joslin, and Ni (2019) infer financial intermediary constraints via deep out-of-the-money index put options. The authors show that a tightening of intermediary constraints is accompanied by option expensiveness and broker-dealer deleveraging.

A third stream focuses on the effects of (leveraged) ETF ownership on the constituent stocks. Ben-David, Franzoni, and Moussawi (2018) show that stocks with higher ETF ownership exhibit higher volatility, as liquidity shocks caused by short-horizon traders in the ETF can be transmitted to the underlying stocks by an arbitrage mechanism. Shum, Hejazi, Haryanto, and Rodier (2016) show that the rebalancing flows of leveraged ETFs amplify end-of-day volatility in the period from 2006 to 2011.

Another stream studies intraday return patterns. We find high-frequency return continuation in the cross-section of stock returns, consistent with evidence provided by Gao, Han, Zhengzi Li, and Zhou (2018) and Baltussen et al. (2020). Both studies focus on aggregate investment vehicles, such as ETFs and index Futures. Gao et al. (2018) show that their effects are stronger on days with elevated volatility, which are typically also accompanied by higher trading volume. In the cross-section of stocks, we confirm the finding of Komarov (2017) that stocks performing best in the first half of the day will likely lose in the second half if controlled for market returns. Another study on short-term return reversals is Heston, Korajczyk, and Sadka (2010). The authors show that the returns of a half-hour period have predictive power over the same half-hour periods for up to 40 days in the future, when controlling for the impact of the market. They relate this to the usage of trade mechanisms by institutional traders, designed to limit the relative price impact of their orders. More recently, studies link investor heterogeneity on the stock-level to cross-sectional intraday and overnight return variations. Lou, Polk, and Skouras (2019) hypothesize that different investor types trade predominately at different times throughout the trading day. Empirically, the authors document high persistence in overnight and intraday return components, which they find not on single-stock basis, but also for 14 equity strategies such as size, value or profitability. Bogousslavsky (2020) focuses only on intraday returns and finds that a mispricing factor earns positive returns up to the last half hour, consistent with the idea that arbitrageurs trading on mispricing reduce their positions at the end of the trading day.

Finally, the last streams focuses on the U.S. equity market closing auction. Bogousslavsky and Muravyev (2020) show that the share of daily volume in the closing auction has more than doubled from 2010 to 2018. They attribute the increase in trading volume to the rise of indexing and ETFs. Wu and Jegadeesh (2020) examine the price impact, including ts temporary component, of closing auctions. Trading strategies based on market-on-close imbalances generate out-sized returns.

2. Data and Measurements

To conduct our empirical analysis we pull data from several databases, including stock and indices, single-name options, and leveraged ETFs. By merging these data sources we obtain a unique dataset allowing us to measure flows coming from the hedging of options and rebalancing of leveraged ETFs and study their potential impact on stock prices.

2.1. Data Sources

Option Markets. The first dataset merges option data from five different exchanges: (a) the CBOE C1 exchange, (b) NASDAQ GEMX (GEMX), (c) NASDAQ International Security Exchange (ISE), (d) NASDAQ Options Market (NOM), and (e) NASDAQ PHLX (PHLX). The dataset includes information on signed trading volume, the underlying stock, and the category of the counterparties engaged in the trade. The sample starts in May 2005, when ISE data becomes available, then it adds PHLX data, which begins in January 2009, NOM data, which starts in November 2011, GEMX data, starting in August 2013, and CBOE data, which starts at the beginning of 2010. Our sample ends in July of 2020.

Each of the five exchanges provides four categories of volume for each option series: open buy, open sell, close buy, and close sell. Each of the volume categories is further broken down into different types of market participants: *broker/dealer*, *proprietary*, and *customer*.[7]. For each type of market participant, we sum the buy and sell trades to estimate the long and short open interest at the trader-type level. The five exchanges sum up to a substantial proportion of the equity options market, delivering the most comprehensive coverage available at the moment. Nonetheless, we do not cover volume outside of these exchanges and OTC options trading.[8] We also gather daily bid and ask quotes, implied volatility, trading volume, open interest, and Greeks for each option contract

[7]In 2009, the type of *professional customer* has been introduced alongside the customer. We merge *professional customers* with *customers*.

[8]Ge et al. (2016) estimate that ISE alone covers 30% of the total trading volume on individual equity options.

from OptionMetrics. As individual stock options are of American type, OptionMetrics uses binomial trees to compute implied volatility and Greeks.

Leveraged ETFs. We obtain information on all leveraged ETFs on U.S. equity indexes from ETFGlobal from January 2012 through December 2019, including the leverage amount, the benchmark index referenced by the fund, and the assets under management of each leveraged ETF at the daily frequency. We compute the constituents of the benchmark index of each leveraged ETF and use TAQ data to calculate intraday returns of each selected benchmark referenced by the leveraged ETF. Figure 2 reports the evolution of aggregate assets under management (AUM) of leveraged ETFs. This industry has grown rather significantly from about USD 40bn in 2012 to USD 130bn in 2020 in leverage-adjusted terms. Even though the AUM in leveraged ETFs may appear insignificant when compared to the total stock market capitalization, this should not obscure its potential impact on end-of-day returns for the following reasons. First, when compared to the average dollar trading volume, which is typically several orders of magnitude smaller than the market value, the flows arising from leveraged EFTs become relevant. Second, as we argue in Section 2.3, the trading volume stemming from leveraged ETFs is concentrated in a very short time window at the end of the trading day. Third, leveraged ETFs volume is likely executed through market orders, for the positions *must* be rebalanced to avoid tracking errors.

Table OA2.1 in the Online Appendix provides an overview of the properties of leveraged ETFs included in our sample. On average, we consider 72 leveraged ETFs for 24 underlying benchmark indices, with a cross-sectional distribution that is fairly stable over time. On average, 45% of the funds we consider are inverse or bear funds. Weighted by the AUM (VW), this number drops to 33%, but fluctuates more substantially over time, with a proportion of just 16% at the 10th percentile and 63% at the 90th. The average fund is leveraged by an absolute value of 2.35.

Stock Markets. Information on individual equity stocks is obtained from the Center for Research on Security Prices (CRSP) and includes trading volume, shares outstanding, and closing prices. We restrict our analysis to stocks with CRSP share code 10 and 11, and exchange code 1, 2, 3, 31, 32, and 33. Information on any type of distribution (e.g. dividends and stock splits) is also obtained from CRSP. We match data from CRSP with our options data via the matching algorithm provided by WRDS.

High-frequency Data on Underlying Assets. Intraday stock price data and transaction volumes are obtained from TAQ. We use standard cleaning procedures and match intraday trade prices with CRSP to obtain PERMNOs as unique identifiers. More details are given

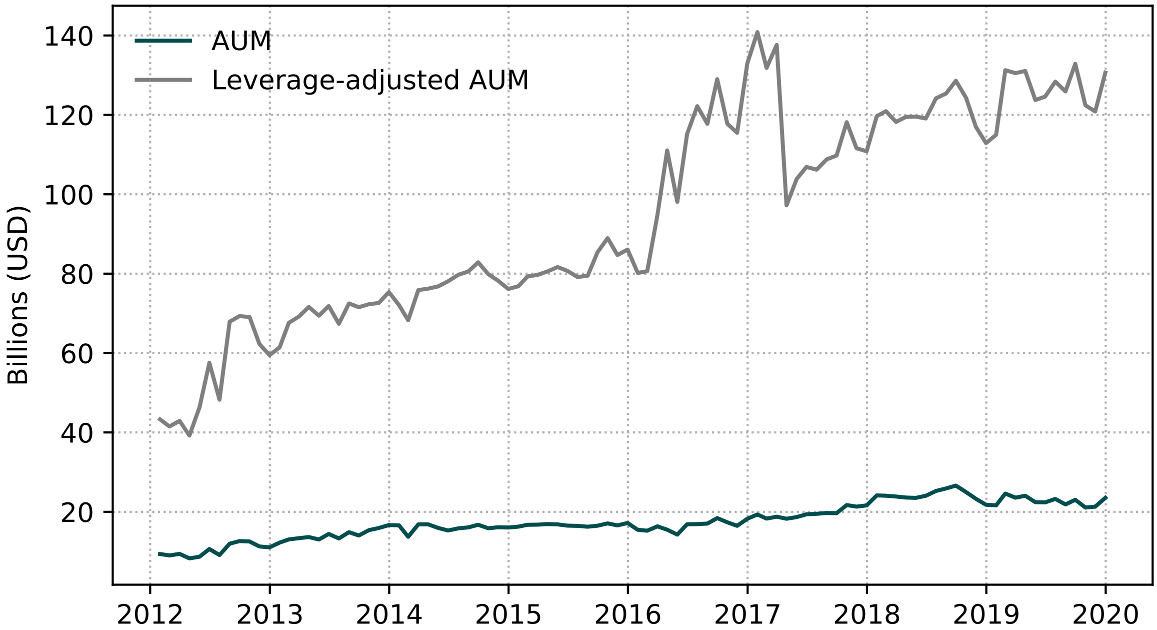

Fig. 2. **Evolution of U.S. Equity Index Leveraged ETF Assets under Management**
This figure shows the evolution of the assets under management (AUM) and leveraged-adjusted assets under management over time. Leverage-adjusted assets under management are computed by multiplying the assets under management by $L \times (L-1)$, where L denotes the leverage factor, for each LETF-day observation. The sample period is from January 2012 to December 2019.

in Appendix A. Equipped with intraday prices, we calculate intraday returns relative to the previous day's closing price. Following standard practice in the literature, (see Lou et al., 2019), we assume that corporate events that mechanically impact prices, e.g. dividend payments and stock splits, take place overnight and are realized at the time of the first trade on the target date. If a delisting occurs as reported by CRSP, we assume that the delisting amount is realized at the respective day's close.

Earnings Announcements and News. Information on earnings announcement days is obtained from Compustat and I/B/E/S. Whenever the announcement date for the same stock differs between Compustat and I/B/E/S, we follow Dellavigna and Pollet (2009) and use the earlier date. Compustat and I/B/E/S are matched to our CRSP data via the matching algorithms provided by WRDS.

Finally, we use the Dow Jones version of Ravenpack News Analytics and its sentiment scores to identify days with significant news for each underlying. We restrict our news sample to articles that are most relevant for a particular stock, i.e. a relevance score of 100. Furthermore, we only include news that is highly positive (sentiment score above

0.75) or highly negative (sentiment score below 0.25).

To summarize, our sample includes 3,428,010 observations on optionable stocks from May 2005 through July 2020, and 4,448,494 observations of stocks included in leveraged ETFs from January 2012 through December 2019. To study the relative importance of the two channels, we also consider a *joint sample* obtained from the intersection of these two.[9] This comprises 1,979,544 observations from January 2012 through December 2019.

2.2. Measuring Gamma Hedging Pressure

Let $V(t,S)$ denote the value of an option contract and $\Delta(t,S) = \frac{\partial V(t,S)}{\partial S}$ be the first derivative of the option price with respect to the underlying, whereas $\Gamma(t,S) = \frac{\partial^2 V(t,S)}{\partial S^2}$ measures the change of $\Delta(t,S)$ for changes in S. When $\Gamma(t,S)$ is not zero, $\Delta(t,S)$ changes depending on time to maturity and the level of S and, consequently, any hedging position has to be adjusted periodically. If $\Gamma(t,S)$ is large in absolute terms, $\Delta(t,S)$ is very sensitive to movements in the underlying and it implies a large amount of rebalancing for the market maker to remain delta-neutral.

Since makers and broker/dealers have similar hedging incentives, we classify both as "delta-hedgers". Consequently, we categorize proprietary and customers as non-delta-hedgers and refer to them jointly as "end-customers" in the remainder of the paper.

To obtain the gamma imbalance of delta-hedgers, we proceed as follows. Let $OI_{o,t}^{Buy,I}$ be the open interest of investors of type I in long positions in option o at time t, which is related to daily volume as follows (see Ni et al., 2020):

$$OI_{o,t}^{Buy,I} = OI_{o,t-1}^{Buy,I} + Volume_{o,t}^{OpenBuy,I} - Volume_{o,t}^{CloseSell,I} \tag{1}$$

$$OI_{o,t}^{Sell,I} = OI_{o,t-1}^{Sell,I} + Volume_{o,t}^{OpenSell,I} - Volume_{o,t}^{CloseBuy,I}, \tag{2}$$

where $Volume_{o,t}^{OpenBuy,I}$ and $Volume_{o,t}^{OpenSell,I}$ denote the volume from investors type I to open new long and short option positions, and $Volume_{o,t}^{CloseBuy,I}$ and $Volume_{o,t}^{CloseSell,I}$ refer to volumes with which investors of type I closed existing long and short positions, respectively.

Second, we calculate the delta-hedgers' net open interest in option series o at date t's

[9] To appear in the joint sample, each stock has to be optionable and included in one or more leveraged ETFs.

close as

$$netOI_{o,t} = -\left[OI_{o,t}^{Buy,Customer} - OI_{o,t}^{Sell,Customer} + OI_{o,t}^{Buy,Proprietary} - OI_{o,t}^{Sell,Proprietary}\right], \tag{3}$$

where $netOI_{o,t}$ is measured in units of option contracts and $OI_{o,t}^{D,I}$ is the open interest of direction D (either buy or sell) by market participant type I (either customer or proprietary) in option series o at the close of date t. The net open interest of market makers is the opposite of the sum of the remaining market participant types. Assuming that broker/dealers are also delta-hedgers, we arrive at Equation (3).

Let $\Gamma_o(t, S)$ denote the gamma of option series o on stock j at day t and underlying price S, expressed in shares of the underlying.[10] To compute the day t delta-hedger dollar gamma imbalance in option series o, we take the product of $\Gamma_o(t, S)$ with the stock price S at 15:30 on the target day and multiply by the contract multiplier $Mult_o$ of o (typically $Mult_o = 100$). [11]

To obtain the aggregated gamma imbalance on an underlying stock j for trading day t, denoted by $\Gamma_{j,t}^{IB}$, we compute the sum over all options on the underlying:

$$\Gamma_{j,t}^{IB} = \underbrace{\left(\sum_o netOI_{o,t-1} \times \Gamma_o(t-1, S_{j,t-1}^{close}) \times S_{j,t}^{15:30} \times Mult_o\right)}_{(\star)} \times \frac{S_{j,t-1}^{close}}{100} \times \frac{1}{\text{ADV}_{j,t-1}^{\text{end}}}. \tag{4}$$

The term $(\star)$ in Equation (4) denotes the total dollar gamma imbalance for a given stock at day t. It is the dollar amount delta-hedgers need to trade in the underlying for each one-dollar move in the underlying stock price S. By multiplying $(\star)$ by the underlying price divided by 100, we obtain the dollar gamma imbalance for a one percent move in S. This facilitates comparison over time and in the cross-section. Finally, we scale by the average dollar volume in the last half hour of a trading day, $\text{ADV}_{t-1}^{\text{end}}$, computed over the last month.[12] Thereby, we express the delta-hedgers' gamma imbalance in a given stock as a fraction of the typical trading taking place in the last half hour, which allows us to obtain a timely proxy for the potential price impact of hedging adjustments.

[10]OptionMetrics calculates the gamma of an option as the absolute change in delta given a \$1.00 change in the underlying.

[11]Since we cannot observe intraday variations of the net open interest, we assume that $\Gamma(t, S)$ only changes due to innovations in the stock price. We hence use the observed stock price at 15:30 on day t to compute the best possible estimate of the amount to be traded by delta-hedgers.

[12]As Table OA3.1 shows, it is inconsequential to our main results if we compute the average dollar trading volume over a weekly or quarterly horizon.

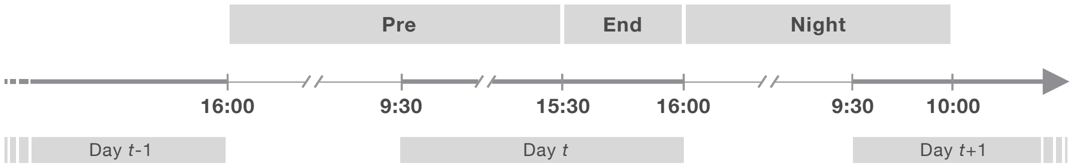

Fig. 3. **Timeline.** This diagram shows how returns over different periods of the trading day are calculated. We denote by $r^{\text{pre}}_{j,t}$ the cumulative return of stock j from the closure of day $t-1$ to 15:30 of day t, and by $r^{\text{end}}_{j,t}$ its return during the last half-hour of day t, i.e. from 15:30 to 16:00.

$\Gamma^{IB}_{j,t}$ denotes the amount of hedging market makers would have to do for a 1%-move in the underlying stock j at time t. We combine this measure with information on how much the underlying has moved before the start of the hedging window. The timeline is illustrated in Figure 4. The return from the close of day $t-1$ to the start of the hedging window at 15:30 is denoted as $r^{\text{pre}}_{j,t}$. The percentage hedging pressure is thus the interaction between $\Gamma^{IB}_{j,t}$ and $r^{\text{pre}}_{j,t}$:

$$\Gamma^{HP}_{j,t} = 100 \times \Gamma^{IB}_{j,t} \times r^{\text{pre}}_{j,t}. \tag{5}$$

Γ^{HP} is our main variable of interest. It directly captures the amount of hedging required for delta-hedgers to remain delta-neutral after observing intraday return r^{pre}.

We acknowledge that our proxy for the delta hedging amount has some limitations. First, we cover only about 50-70% of the transacted volume in equity options and, second, we rely solely on Gamma to approximate changes in the hedging amount. In an ideal setting, we would be able to track intraday changes in the inventories of delta-hedgers, obtain intraday changes in deltas, and a complete list of hedging times. These limitations introduce errors in our estimates but, as Ni et al. (2020) shown, bias regression coefficients toward zero. We hence argue that our analysis provides a lower bound for the real impact of gamma imbalance on stock prices.

2.3. Measuring LETF Rebalancing Pressure

To understand how leveraged ETFs may contribute to intraday price momentum, let L be the fund's leverage factor, say -3 for a bear and $+3$ for a bull fund, and A_t the leveraged ETF's assets under management (AUM). The required notional amount of total return swaps at day t is $S_t = L \times A_t$. Hence, if the return on the index at time $t+1$ is r^{bench}_{t+1}, then $A_{t+1} = A_t \times (1 + L \times r^{bench}_{t+1})$. Therefore, the required notional amount of total return swaps at $t+1$ becomes $S_{t+1} = L \times A_{t+1} = L \times A_t \times (1 + L \times r_{t+1}^{bench})$. However, the actual exposure of the total return swaps at $t+1$ is $E_{t+1} = S_t \times (1 + r_{t+1}^{bench}) = L \times A_t \times (1 + r_{t+1}^{bench})$. The difference between the required and the actual notional is the rebalancing amount, equal to $S_{t+1} - E_{t+1} = L \times (L-1) \times A_t \times r_{t+1}^{bench}$. Given that the required hedging multiple $L \times (L-1)$ is strictly positive for $L \in \mathbb{R} \setminus [0,1]$, leveraged ETF swap counterparties always have to trade in the same direction as the return of the underlying index, which may induce an end-of-day return momentum effect in the stocks included in the index referenced by the leveraged ETF.[13] Unlike the gamma imbalance effect, hedging demand by leveraged ETFs for a given stock is not necessarily proportional to the return of that specific stock but, rather, to the return of the underlying index. Therefore, leveraged ETFs rebalancing may induce return momentum in a stock, even if its return in the first part of the trading day is zero.

To compute the amount of rebalancing affecting an individual stock, let stock j be included in the underlying of a leveraged ETF i with a weight of $w_{i,j,t}$ on day t. If the swap counterparty starts rebalancing their exposure at 15:30, and $r_{i,t;bench}^{\text{pre}}$ denotes the return on the benchmark ETF up until that moment, the relative amount of rebalancing required in stock j is the sum over all leveraged ETFs in which stock j is included in:

$$\Omega_{j,t}^{LETF} = \frac{\sum_{i=1}^{N_{i,t}} L_i \times (L_i - 1) \times A_{i,t-1} \times w_{i,j,t-1} \times r_{i,t;bench}^{\text{pre}}}{\text{ADV}_{j,t-1}^{\text{end}}} \tag{6}$$

We scale by the average dollar volume in the last half hour (ADV^{end}) to compare the impact of rebalancing with the average amount of trading at the close.

2.4. Summary Statistics

In this Section, we provide summary statistics for the gamma imbalance and leveraged ETF hedging pressure.

Figure 4 shows the cross-sectional distribution of Ω^{LETF} over time and compares it with the distribution of Γ^{HP} in the joint sample. While both are time-varying, the distribution of Γ^{HP} is wide, with a larger interquartile range, suggesting that on the same day market makers can have a large negative gamma imbalance on some stocks and, at the same time, a large positive gamma imbalance on another stock. Table B1 in

[13] We assume that returns swap providers (or their counterparties) ultimately need to hold a quantity of the underlying stock proportional to the size of the swap contract. If some of the swaps are based on other instruments or on correlated assets, this would introduce noise in our proxy and bias our results toward zero.

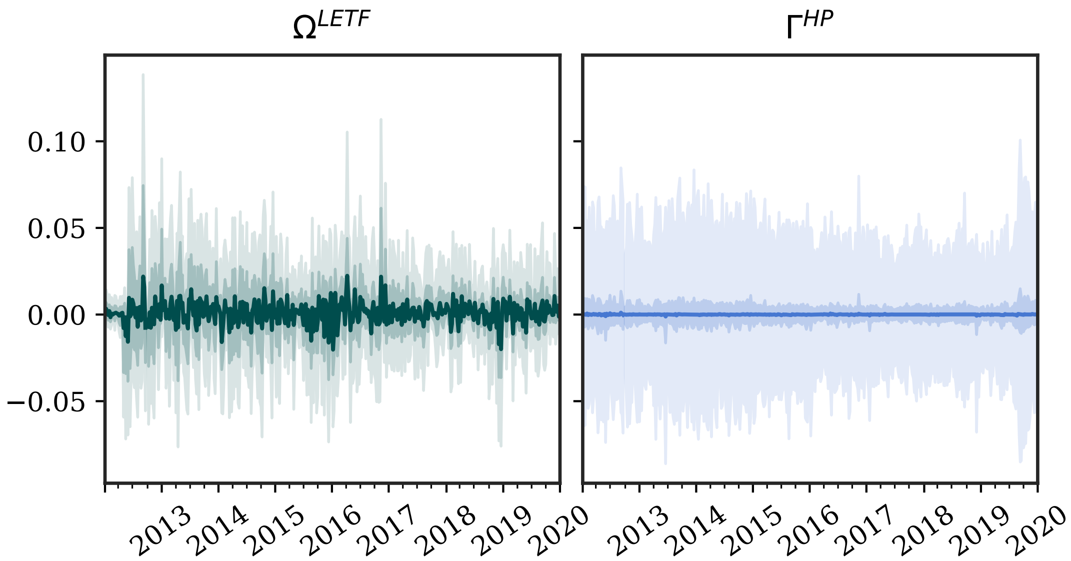

Fig. 4. **Time Series Cross-sectional Distribution of Ω^{LETF} and Γ^{HP}**
This figure shows weekly averages of the cross-sectional distribution of the demand pressure from the rebalancing of leveraged ETFs (Ω^{LETF}) and Gamma imbalance (Γ^{HP}). The dark line represents the cross-sectional median, the dark-colored area the 25th/75th percentile, and the light-colored area the 5th/95th percentile.

the Appendix provides more granular summary statistics on Γ^{HP} and Ω^{LETF}. Table B1 shows that the aggregate pressure arising from leveraged ETFs is on average higher than the one from delta-hedging, but the distribution of absolute Γ^{HP} has a heavy right tail.

Table 1 documents the economic significance of the demand pressure arising from the rebalancing activity of the leveraged ETFs and the delta hedging activity of market makers in the options market. The second column reports the average number of stocks in the joint sample for which the combined dollar rebalancing amount due to both channels exceeds a certain threshold (first column) of the average dollar volume in the last 30 minutes of the trading day (ADV^{end}). We find that, on average, for 69 (12) stocks the combined rebalancing amount exceeds the 10% (25%) threshold. For these stocks, the average rebalancing dollar amount is equal to 21.23% (49.00%) of ADV^{end}. The cross-sectional dispersion is large and for stocks in the 90th percentile (last column) the average rebalancing dollar amount exceeds 34.30% (76.72%) of the total trading volume. The fourth column provides information about the relative importance of each channel. The majority of the rebalancing amount is driven by Γ^{HP}. For the group exceeding a rebalancing threshold of 10% (25%), 71.86% (80.91%) of the average absolute combined

Table 1: **The Cross-Section of Demand Pressure from Gamma and LETFs Rebalancing**
This table reports the average daily number (N) and percentage (Share) of stocks with a combined rebalancing amount in the last 30 minutes of the trading day exceeding a certain threshold (first column), as a percentage of the average dollar volume. The fourth column (% Gamma) reports the proportion of the total demand pressure due to the Gamma imbalance Γ^{HP} relative to the combined rebalancing amount: $|\Gamma^{HP}|/(|\Gamma^{HP}| + |\Omega^{LETF}|)$. Additionally, the table reports the average mean (Mean), standard deviation (Std), and 10%- and 90%-percentile of the share of the combined rebalancing amount conditional on exceeding the specified level. The sample contains stocks that are optionable and included in the benchmark index of at least one leveraged ETF. The sample period is from January 2012 – December 2019.

	N	Share	% Gamma	Mean	Std	10%	90%
1%	601.7	60.23%	49.95%	5.11	8.29	1.30	9.81
2%	354.4	35.48%	55.76%	7.68	10.41	2.86	13.67
5%	182.6	18.28%	63.01%	12.07	13.72	5.47	20.28
10%	69.5	6.95%	71.86%	21.23	19.63	10.83	34.30
15%	34.0	3.41%	76.47%	30.50	24.34	16.43	48.97
25%	12.5	1.25%	80.91%	49.00	31.88	28.92	76.72
50%	3.4	0.34%	84.75%	94.33	44.86	72.69	122.20

rebalancing originates from the hedging activity of option market makers. Moreover, the share of Γ^{HP} in the combined rebalancing amount is monotonically increasing in the threshold level, suggesting that the demand pressure from this channel is highly non-linear and can become dominant. Thus, the relative importance of the two channels for the dynamics of asset prices is largely an open question and requires a direct empirical investigation.

2.5. Abnormal Order Flow

We define the abnormal order flow in the last 30 minutes of trading day t for stock j as

$$\text{RSVOL}^{\text{end}}_{j,t} = \text{SVOL}^{\text{end}}_{j,t} / \text{ADV}^{\text{end}}_{j,t-1} \,. \tag{7}$$

$\text{SVOL}^{\text{end}}_{j,t}$ is the difference between the trading volumes in up- and down-minutes, defined as

$$\text{SVOL}^{end}_{j,t} = \sum_{m \in 15:30 \to Close} \text{VOL}_{j,t,m} \times \mathbb{1}_{r_{j,t,m}>0} - \sum_{m \in 15:30 \to Close} \text{VOL}_{j,t,m} \times \mathbb{1}_{r_{j,t,m}<0}, \tag{8}$$

where m denotes the minutes within the hedging window for target day t.[14]

3. Empirical Results

Consider the case in which $\Gamma^{IB}_{j,t}$ for stock j at time t is negative. If delta-hedgers want to maintain delta-neutrality, they have to sell the underlying stock if it has depreciated intraday. Additionally, if $\Omega^{LETF}_{j,t}$ is negative, rebalancing of leveraged ETFs will cause further downward price pressure. Table 2 provides an overview of these two effects. Accordingly, our empirical study revolves around the following two hypotheses:

$H0^{\Gamma}$: *Positive (negative) Gamma hedging pressure leads to additional selling (buying) at the end of the trading day and, consequently, to negative (positive) end-of-day stock returns.*

$H0^{\Omega}$: *If the previous day return on the benchmark index was positive (negative), the rebalancing activity of leveraged ETFs adds to buying (selling) at the close and, consequently, to positive (negative) end-of-day stock returns.*

An important difference between $H0^{\Gamma}$ and $H0^{\Omega}$ is in the cross-section. Since Γ^{HP} can greatly differ across stocks even at the same time t, the effect is stock-specific. For Ω^{LETF}, in contrast, all stocks that belong to the same referenced index are exposed to the same price pressure.

3.1. Discretionary Rebalancing: Gamma Hedging Pressure

Order Flow

The first part of $H0^{\Gamma}$ predicts that Γ^{HP} is negatively related to the order flow of the underlying stock. To test this hypothesis we run panel regressions of the following form:

$$\mathrm{RSVOL}^{\mathrm{end}}_{j,t} = \beta_0 \Gamma^{HP}_{j,t} + \boldsymbol{\gamma}' \boldsymbol{X}_{j,t} + FE_j + FE_t + \epsilon_{j,t}, \tag{9}$$

including asset (FE_j) and date fixed effects (FE_t), and allowing for additional control variables $\boldsymbol{X}_{j,t}$, depending on the specification. $H0^{\Gamma}$ predicts that the sign of β_0 is negative.

[14] We scale by $\mathrm{ADV}^{\mathrm{end}}$ to make the signed volume comparable across stocks in the cross-section and over time.

Table 2: **The Impact of Γ^{HP} and Ω^{LETF} on End-of-Day Returns**
The table depicts the effects of Γ^{HP}, as defined in Equation (5), and Ω^{LETF}, as defined in Equation (6), on end-of-day returns. $RSVOL$ denotes the relative signed trading volume, as defined in Equation (7). The upper half of the table visualizes the interaction of gamma imbalance Γ^{IB} and the return until the last hour of the trading day, r_t^{pre}. The lower half of the table visualizes directly the impact of Ω^{LETF} on r_t^{pre}.

	$r_t^{\text{pre}} > 0$	$r_t^{\text{pre}} < 0$
$\Gamma_{t-1}^{IB} > 0$	$\Gamma_t^{HP} > 0 \Rightarrow$ RSVOL $\searrow \Rightarrow r_t^{\text{end}} \searrow$	$\Gamma_t^{HP} < 0 \Rightarrow$ RSVOL $\nearrow \Rightarrow r_t^{\text{end}} \nearrow$
$\Gamma_{t-1}^{IB} < 0$	$\Gamma_t^{HP} < 0 \Rightarrow$ RSVOL $\nearrow \Rightarrow r_t^{\text{end}} \nearrow$	$\Gamma_t^{HP} > 0 \Rightarrow$ RSVOL $\searrow \Rightarrow r_t^{\text{end}} \searrow$
$\Omega_{t-1}^{LETF} > 0$	RSVOL $\nearrow \Rightarrow r_t^{\text{end}} \nearrow$	RSVOL $\nearrow \Rightarrow r_t^{\text{end}} \nearrow$
$\Omega_{t-1}^{LETF} < 0$	RSVOL $\searrow \Rightarrow r_t^{\text{end}} \searrow$	RSVOL $\searrow \Rightarrow r_t^{\text{end}} \searrow$

Results are reported in Table 3 with standard errors double-clustered by day and asset, as it is done throughout the paper. Column (1) provides support for our hypothesis, reporting that the coefficient on Γ^{HP} is -13.37 (t-value: -3.89). The estimate is significantly different from zero at the 1% confidence level, suggesting a link between the hedging pressure of market makers due to their gamma imbalance and the order flow in the underlying stock.

Nevertheless, this unveiled empirical relationship may be consistent with alternative hypotheses. In particular, it may arise from intraday oscillations in the level of risk, for volatility-target investors might rebalance their portfolio away from risky assets towards the end of the trading day if volatility changes, generating directional order flow. Since option demand is also a positive function of investors expectations about future volatility, changes in risk may impact the inventory of market makers and, potentially, their Γ imbalance. These two observations may generate a mechanical and negative relationship between gamma imbalance and order-flow, driven by the dynamics of expected volatility.

To rule out the above explanations, specifications in columns (2) and (3) add controls for two proxies of expected volatility, namely the level of the at-the-money implied volatility (IV) on day $t-1$ and a forecast of future variance using an EGARCH model,

Table 3: **Delta Hedging and End-of-day Order Flow**
The table reports the results of a regression of relative signed trading volume in the last half hour of a trading day on market maker hedging pressure Γ^{HP}, following Equation (7). IV_{t-1} denotes implied volatility at time $t-1$. $\hat{RV}_t^{end}$ denote the square root of predicted realized variance for the time period from 15:30 to 16:00. PC_{t-1} is the put-call-ratio and $O/S_{t-1}^{\$}$ denotes the option-to-stock volume in dollar terms. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	$\text{RSVOL}_t^{\text{end}}$	$\text{RSVOL}_t^{\text{end}}$	$\text{RSVOL}_t^{\text{end}}$	$\text{RSVOL}_t^{\text{end}}$	$\text{RSVOL}_t^{\text{end}}$
Γ_t^{HP}	-13.368***	-13.369***	-13.372***	-13.378***	-13.367***
	(-3.892)	(-3.891)	(-3.890)	(-3.894)	(-3.899)
IV_{t-1}		-0.434			
		(-0.296)			
$\hat{RV}_t^{end}$			73.938		
			(0.628)		
PC_{t-1}				0.689**	
				(2.170)	
$O/S_{t-1}^{\$}$					1177.611
					(1.402)
Observations	3,331,713	3,331,713	3,331,360	3,325,116	3,331,706
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

$\hat{RV}$.[15] Results show that neither of these two controls is significant, nor does the inclusion of either materially alter the coefficient and statistical significance of Γ^{HP}.

Besides risk-based explanations, our findings may arise from information being transmitted from the options market to the market of the underlying. A stream of the literature argues that options are often used because of their implicit leverage in presence of market frictions, for instance when short selling is expensive (Ge et al., 2016). Accordingly, Blau et al. (2014) find that an increase in the put-call ratio negatively predicts future returns at the daily, weekly, and monthly frequency. Roll et al. (2010) and Hu (2014) show that the option-to-stock volume predicts options' underlying returns. We thus extend the baseline regression to control for these explanatory variables. Columns (4) and (5) sum-

[15]The EGARCH models the sum of 1-minute squared returns for each stock in the last half hour of a trading day, using historical data up until day $t-1$ (see Moskowitz, Ooi, and Pedersen (2012)).

marize the results and show that the coefficient on Γ^{HP} is unchanged both in magnitude and significance, suggesting that our results are not driven by an information channel.

End-of-day returns

Given that higher hedging pressure from the options market is associated with additional signed volume at the end of the trading day, we study the extent to which this hedging pressure affects end-of-day stock returns. To test the second half of the joint hypothesis $H0^{\Gamma}$, we regress the returns from 15:30 to the close of day t (r^{end}) onto our proxy for gamma hedging pressure (Γ^{HP}), controlling for the return from the open to 15:30 (r^{pre}). As in the previous specification, we saturate the regression model with fixed effects and other stock-specific control variables $\boldsymbol{X}_{j,t}$:

$$r_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Gamma_{j,t}^{HP} + \boldsymbol{\gamma}' \boldsymbol{X}_{j,t} + FE_j + FE_t + \epsilon_{j,t}. \tag{10}$$

The results are reported in Table 4. The slope coefficient β_1 equals -11.947 (t-value: -5.37) and is statistically significant at the 1%-level, suggesting that a negative shock to Γ^{HP} amplifies end-of-day returns. Comparing the results in column (1) to those reported in column (2)-(5), we find insignificant changes in the slope coefficient, suggesting that the results are robust to the additional control variables. While proxies for expected volatility IV and $\hat{RV}$ are both significant in the regression setup, the inclusion of neither proxy materially changes the impact of Γ^{HP}. The same applies to the proxies of informed trading.[16]

3.2. Leveraged ETFs

Order Flow

We investigate the first part of the prediction $H0^{\Omega}$, which suggests the existence of a positive relationship between end-of-day order flow in single equities and the rebalancing pressure from leveraged ETFs. Similar to Equation (9), we run the following regression:

$$\text{RSVOL}_{j,t}^{\text{end}} = \beta_0 \Omega_{j,t}^{LETF} + \boldsymbol{\gamma}' \boldsymbol{X}_{j,t} + FE_j + FE_t + \epsilon_{j,t}. \tag{11}$$

The results are summarized in Table 5. We find that signed volume in the last half hour

[16] To further rule out the possibility of informed trading driving our results, we adopt the idea of Ni et al. (2020) and compute Γ^{HP} based on "old" positions. Results from this exercise are reported in Appendix D and allow us to reject such an alternative explanation.

Table 4: **Delta Hedging and End-of-day Returns**
The table summarizes the results of regressions of returns in the last half hour of a trading day on market maker hedging pressure Γ^{HP}, after controlling for returns until 15:30 (r^{pre}), as in Equation (10). IV_{t-1} denotes implied volatility at time $t-1$; $\hat{RV}_t^{end}$ denotes the square root of predicted realized variance for the time period from 15:30 to 16:00; PC_{t-1} is the put-call-ratio and $O/S^{\$}_{t-1}$ denotes the option-to-stock volume in dollar terms. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and value-weight observations. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-11.947***	-11.916***	-11.941***	-11.954***	-11.947***
	(-5.367)	(-5.368)	(-5.344)	(-5.369)	(-5.376)
r_t^{pre}	-0.718***	-0.719***	-0.718***	-0.718***	-0.718***
	(-4.560)	(-4.573)	(-4.560)	(-4.558)	(-4.560)
IV_{t-1}		5.974***			
		(3.077)			
$\hat{RV}_t^{end}$			521.440*		
			(1.889)		
PC_{t-1}				0.354*	
				(1.736)	
$O/S^{\$}_{t-1}$					622.216
					(1.062)
Observations	3,365,367	3,365,367	3,365,009	3,358,722	3,365,359
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

of a trading day is positively correlated with Ω^{LETF}, our proxy of rebalancing pressure by leveraged ETF. Consistent with the prediction, the estimated coefficient is positive (70.206) and highly significant (t-value: 6.08).

After controlling for ex-ante forecasts of realized volatility before ($\hat{RV}^{\text{pre}}$) and at the close ($\hat{RV}^{\text{end}}$), the slope coefficients for Ω^{LETF} are unchanged.

End-of-day returns

For the second part of $H0^{\Omega}$, we analyze whether the documented order flow arising from leveraged ETF rebalancing translates into additional price pressure. The regression setup

Table 5: **ETF Rebalancing and End-of-day Order Flow**
The table reports the results to regressing the relative signed trading volume in the last half hour of a trading day on leveraged ETF rebalancing quantity Ω^{LETF} following Equation (11). $\hat{RV}_t^{end}$ ($\hat{RV}_t^{pre}$) denote the square root of predicted realized variance for the time period from 15:30 to 16:00 (from previous day's close to 15:30) on day t. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)
Dependent	$\text{RSVOL}_t^{\text{end}}$	$\text{RSVOL}_t^{\text{end}}$	$\text{RSVOL}_t^{\text{end}}$
Ω_t^{LETF}	70.206***	70.096***	70.137***
	(6.075)	(6.065)	(6.064)
$\hat{RV}_t^{pre}$		-46.954*	
		(-1.873)	
$\hat{RV}_t^{end}$			10.641
			(0.063)
Observations	4,359,817	4,342,509	4,342,509
Entity FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]

takes the following form:

$$r_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Omega_{j,t}^{LETF} + \boldsymbol{\gamma}' \boldsymbol{X}_{j,t} + FE_j + FE_t + \epsilon_{j,t}. \tag{12}$$

The results are summarized in Table 6 and show that the impact of leveraged ETF rebalancing on signed order flow is positive and significant with a coefficient equal to 33.214 (t-value: 5.42).

The estimated coefficient increases in magnitude and becomes even more significant once we control for stock-level returns up to 15:30 (r^{pre}), suggesting that the effect we are capturing indeed arises from ETF-level order-flow pressure, rather than from stock-specific dynamics. Moreover, as columns (3) and (4) report, the coefficient on Ω^{LETF} is unaffected by the inclusion of measures of single-stock riskiness (Heston et al., 2010; Gao et al., 2018; Baltussen et al., 2020).

Table 6: **ETF Rebalancing and End-of-day Returns**
The table reports the results of regressions of returns in the last half hour of a trading day on the leveraged ETF rebalancing quantity Ω^{LETF}, after controlling for the returns until 15:30 (r^{pre}) as in Equation (12). $\hat{RV}_t^{15:30\rightarrow close}$ ($\hat{RV}_t^{close-1\rightarrow 15:30}$) denote the square root of predicted realized variance for the time period from 15:30 to 16:00 (from previous day's close to 15:30) on day t. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}	33.214***	41.350***	41.386***	41.358***
	(5.421)	(6.752)	(6.751)	(6.745)
r_t^{pre}		-0.900***	-0.908***	-0.909***
		(-9.897)	(-10.031)	(-10.032)
$\hat{RV}_t^{pre}$			36.481**	
			(2.484)	
$\hat{RV}_t^{end}$				408.311***
				(4.165)
Observations	4,403,855	4,403,855	4,386,322	4,386,322
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]

3.3. Assessing Rebalancing Jointly

The two rebalancing channels may affect closing stock returns in different ways. In the example reported in the Introduction, for instance, an investor considering only Gamma hedging flows would have predicted positive returns for Amazon on June 23rd, 2016, given the large and negative magnitude of Γ^{HP}. Had she also known about the significant amount of selling expected from leveraged ETFs, she may have revised her prediction. In this section, we discuss in more detail the relative importance of these two channels. To conduct this analysis, we consider a joint sample, which comprises all stocks that are included in at least one leveraged ETF and for which options are traded on one of the five exchanges we consider. Then, we run the following panel regression:

$$r^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Gamma_{j,t}^{HP} + \beta_2 \Omega_{j,t}^{LETF} + FE_j + FE_t + \epsilon_{j,t} \qquad (13)$$

The results are summarized in table Table 7, showing that the slope coefficients of both Γ^{HP} and Ω^{LETF} are statistically significant. The slope coefficient of Γ^{HP} is equal to -9.16 (t-value: -4.53); the slope coefficient of Ω^{LETF} is equal to 44.36 (t-value: 4.56). In column (3) we estimate a model accounting for the two channels jointly, resulting in increases of both coefficients in absolute magnitude to -10.677 for Γ^{HP} and 47.611 for Ω^{LETF}. Accounting for the mean of each explanatory variable in the sample, the average impact of leveraged ETF rebalancing is about 4 times larger than that of Γ^{HP}. It is important to notice that the joint sample restricts the universe to larger stock, given the two requirements of being optionable and included in leveraged ETFs. For these stocks, we find that the end-of-day effect of leveraged ETF rebalancing is about twice as large as the effect of the gamma hedging pressure. More precisely, a standard deviation decrease in Γ^{HP} is associated with a 1.13-times increase in the magnitude of end-of-day returns relative to the stock-level median, while a standard deviation increase in Ω^{LETF} corresponds to a 4.31-times increase.

To further investigate the relative importance of the two channels, we construct four variables, which capture the amount of price pressure in four distinct states. We define the first state as one in which $\Gamma_{i,t}^{HP} < 0$ and $\Omega_{i,t}^{LETF} > 0$. We label this state as "BB". The first letter denotes the trade direction for option market makers (B for buy, S for sell) and the second letter the trade direction for the rebalancing of leveraged ETFs. We define the other three states in a similar way:

$$
\begin{aligned}
\text{BB} &= (\Omega_{i,t}^{LETF} - \Gamma_{i,t}^{HP}) \times \mathbb{1}_{(\Gamma_{i,t}^{HP}<0),\,(\Omega_{i,t}^{LETF}>0)} \\
\text{SS} &= (\Gamma_{i,t}^{HP} - \Omega_{i,t}^{LETF}) \times \mathbb{1}_{(\Gamma_{i,t}^{HP}>0),\,(\Omega_{i,t}^{LETF}<0)} \\
\text{BS} &= (\Omega_{i,t}^{LETF} - \Gamma_{i,t}^{HP}) \times \mathbb{1}_{(\Gamma_{i,t}^{HP}<0),\,(\Omega_{i,t}^{LETF}<0)} \\
\text{SB} &= (\Omega_{i,t}^{LETF} - \Gamma_{i,t}^{HP}) \times \mathbb{1}_{(\Gamma_{i,t}^{HP}>0),\,(\Omega_{i,t}^{LETF}>0)} \qquad (14)
\end{aligned}
$$

Thus BB restricts to scenarios with joint buying pressure in the last half hour, when both option dealers and leveraged ETFs swap counterparties are forced to buy additional shares of the underlying stock. This should lead to a larger effect on end-of-day volumes and returns. Symmetrically, SS captures states in which both sources of rebalancing induce selling pressure at the close. Conversely, BS (SB) is non-zero in situations in which option market makers have to buy (sell) shares, while the rebalancing of leveraged ETFs requires the sale (purchase) of additional shares.[17] To gauge the effects of rebalancing on

[17]In our sample, BB occurs for 24.4%, SS for 20.3%, BS for 23.8 and SB for 29.0% of observations.

Table 7: **Joint Impact of Delta-Hedging and Leveraged ETF Rebalancing**
The table reports the results to regressing the returns in the last half hour of a trading day on returns until 15:30 (r^{pre}), on options market maker hedging pressure Γ^{HP} and leveraged ETF rebalancing quantity Ω^{LETF} following Equation (13). We also consider the impact of joint rebalancing activity using the variables defined in Equation (14) in the regression setup proposed in Equation (15). T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is 2012 – December 2019.

	(1)	(2)	(3)	(4)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-9.164***		-10.677***	
	(-4.531)		(-5.324)	
Ω_t^{LETF}		44.357***	47.611***	
		(4.563)	(4.935)	
r_t^{pre}	-0.821***	-0.959***	-0.882***	
	(-6.982)	(-8.172)	(-7.479)	
BB				41.412***
				(5.183)
SS				-44.044***
				(-3.747)
BS				-24.422***
				(-2.949)
SB				19.074***
				(2.619)
Observations	1,940,150	1,940,150	1,940,150	1,940,150
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	-
SEs	[t;j]	[t;j]	[t;j]	[t;j]

end-of-day stock returns in under these different circumstances, we estimate the following regression model:

$$r^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \text{BB}_{j,t} + \beta_2 \text{SS}_{j,t} + \beta_3 \text{BS}_{j,t} + FE_j + FE_t + \epsilon_{j,t} \quad (15)$$

Given that the estimated effect of Ω^{LETF} is larger, we expect it to dominate the joint effect of the two sources of rebalancing disagree in the trade direction. However, a reduction of the estimated coefficient suggests that a) our identification approach is working and b) that knowing about Gamma flows is still useful in these cases.

Results, reported in column (4) of Table 7, show that joint buying pressure (BB) is associated with significantly positive returns in the last half hour of a trading day. The coefficient on BB is 41.41 (t-value: 5.18) and is highly significant both statistically and economically. Similarly, the coefficient on SS is roughly comparable and estimated at -44.044 (t-value: -3.747). These results imply that a one standard deviation increase in the joint rebalancing amount from leveraged ETF and option market makers on BB (SS) days amplifies (depresses) end-of-day returns by 1.53 bps (-1.68 bps). These effects are not trivial, since the median return at the close amounts to only 0.32 bps, suggesting a 4.8-times (5.25-times) return multiple. This underlines the importance of identifying multiple sources of rebalancing activity at the close. As expected, we find smaller absolute coefficients for BS and SB. Once again, we find evidence supporting the idea that the impact of leveraged ETF rebalancing outweighs the impact of Γ^{HP}. Indeed, the coefficient on BS is negative (t-value: 2.95) and the one of SB is positive (t-value: 2.62). A one standard deviation increase in the joint rebalancing leads to additional returns of 0.65 bps (0.49 bps) on BS (SB) days, highlighting the relative dominance of leveraged ETF rebalancing effects.

3.4. Trading Strategy

Next, we study the extent to which the excess return generated by a long-short strategy based on Γ^{HP} and Ω^{LETF} are related to traditional risk factors. First, we construct a long-short portfolio based on Γ^{HP}. Specifically, on each day at 15:30, we sort our stock sample according to Γ^{HP} into decile portfolios. Subsequently, we build a long-short strategy, denoted by LmH^{Γ}, by taking a long (short) position in the lowest (highest) decile portfolio. We close our positions at the market close of the same trading day, such that we effectively hold the securities in our strategy for 30 minutes each day.

In a second strategy, HmL^{Ω}, we use Ω^{LETF} as a timing signal. We construct decile portfolios based on Ω^{LETF} and take a long (short) position in the highest (lowest) decile.

Finally, we use both Γ^{HP} and Ω^{LETF} as signals in a combined strategy. For each stock at 15:30, we compute its cross-sectional rank according to Γ^{HP} and Ω^{LETF}, respectively.[18] We sum the individual ranks to obtain a combined ranking. Based on the combined ranking, we once again build decile portfolios and go long (short) the highest (lowest) decile portfolio.

[18] In the combined strategy, we reverse the Γ^{HP} ranking, such that a higher rank denotes buying pressure.

Table 8: Γ^{HP} **and** Ω^{LETF} **Based Trading Strategies**
The table reports the economic value of timing the last half-hour market return using Γ^{HP}, Ω^{LETF} and a joint signal based on both. The Γ^{HP}-strategy, LmH^{Γ}, takes a long (short) position in a stock when the stock's Γ^{HP} is in the lowest (highest) decile. The Ω^{LETF}-strategy, HmL^{Ω}, takes a long (short) position in a stock when the stock's Ω^{LETF} is in the highest (lowest) decile. The combined strategy, $\text{HmL}^{\Gamma,\Omega}$, computes a cross-sectional rank according to Γ^{HP} and Ω^{LETF} and takes a long (short) position in a stock when the stock's aggregated ranking is in the highest (lowest) decile. As a benchmark, $\text{Market}^{\text{end}}$ denotes investing in all stocks from 15:30 to 16:00. We consider equally-weighted (EW) and value-weighted (VW) portfolios, including for $\text{Market}^{\text{end}}$. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (Sharpe), skewness, kurtosis, and success rate (Success). The returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is January 2012 – December 2019.

	Avg ret	Std dev	Sharpe	Skewness	Kurtosis	Success
Panel A: Equally Weighted						
LmH^{Γ}	5.16***	1.25	4.13	0.33	3.48	62.34
HmL^{Ω}	11.82***	2.54	4.65	0.46	2.98	60.81
$\text{HmL}^{\Gamma,\Omega}$	11.00***	2.16	5.09	0.22	3.10	61.91
$\text{Market}^{\text{end}}$	0.62	3.29	0.19	-0.61	6.18	54.02
Panel B: Value Weighted						
LmH^{Γ}	5.20***	1.36	3.83	0.17	3.00	61.07
HmL^{Ω}	5.78***	2.31	2.51	0.13	3.54	56.29
$\text{HmL}^{\Gamma,\Omega}$	6.21***	1.98	3.14	0.31	3.21	58.13
$\text{Market}^{\text{end}}$	-1.39	3.26	-0.43	-1.05	12.27	51.92

Table 8 reports summary statistics of the resulting strategies for the joint sample.[19] In Panel A, decile portfolios are equally-weighted, whereas Panel B shows results for value-weighted portfolios. LmH^{Γ} yields average total excess returns of 5.16% per year, which are significant at the 1%-level. The results are robust to using either equally- or value-weighted returns within each portfolio (Panel B). For matters of comparison, we consider a benchmark strategy $\text{Market}^{\text{end}}$ which takes a long position in all available stocks at the beginning of the last half hour of a trading day and closes each position at the close. For our sample from 2012 through 2019, $\text{Market}^{\text{end}}$ yields an insignificant annual return of 0.62%.

When we compare LmH^{Γ} with HmL^{Ω}, we find that equally-weighted average returns of

[19] Appendix OA7 in the Internet Appendix reports summary statistics for LmH^{Γ} and HmL^{Ω} in their respective sample periods.

Table 9: **Risk-adjusted Returns of Γ^{HP} and Ω^{LETF} Trading Strategies**
The table reports the estimation results from regressing returns of strategies timing the last half-hour based on Γ^{HP}, Ω^{LETF} and a combination of both on the returns of all stocks from 15:30 to 16:00 (Market$^{\text{end}}$), the equity market excess return (MKT), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), momentum (MOM), and an intermediary capital asset pricing factor (IC, proposed by He et al., 2017). The Γ^{HP}-strategy, LmH$^{\Gamma}$, takes a long (short) position in a stock when the stock's Γ^{HP} is in the lowest (highest) decile. The Ω^{LETF}-strategy, HmL$^{\Omega}$, takes a long (short) position in a stock when the stock's Ω^{LETF} is in the highest (lowest) decile. The combined strategy, HmL$^{\Gamma,\Omega}$, computes a cross-sectional rank according to Γ^{HP} and Ω^{LETF} and takes a long (short) position in a stock when the stock's aggregated ranking is in the highest (lowest) decile. We consider equally weighted (EW) and value-weighted (VW) portfolios. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is January 2012 – December 2019.

	Intercept	Market$^{\text{end}}$	MKT	SMB	HML	RMW	CMA	MOM	IC	R2	R2 adj
Panel A: Equally Weighted											
LmH$^{\Gamma}$	5.15	0.01								0.10%	0.05%
	(9.51***)	(1.27)									
	5.10		0.92	-0.29	-1.00	3.06	4.59	1.12	0.77	0.78%	0.36%
	(9.00***)		(0.99)	(-0.24)	(-0.59)	(1.52)	(1.90*)	(1.33)	(1.08)		
HmL$^{\Omega}$	11.83	-0.02								0.04%	-0.01%
	(8.56***)	(-0.72)									
	12.92		-0.45	3.77	-1.64	2.62	-1.07	-1.47	1.00	0.33%	-0.09%
	(8.49***)		(-0.21)	(1.48)	(-0.42)	(0.62)	(-0.20)	(-0.80)	(0.64)		
HmL$^{\Gamma,\Omega}$	11.01	-0.01								0.02%	-0.03%
	(9.96***)	(-0.45)									
	11.54		0.58	3.67	-1.54	5.07	-0.84	-0.28	0.70	0.46%	0.03%
	(9.26***)		(0.29)	(1.63)	(-0.49)	(1.50)	(-0.19)	(-0.17)	(0.55)		
Panel B: Value Weighted											
LmH$^{\Gamma}$	5.21	0.01								0.03%	-0.02%
	(9.37***)	(0.42)									
	4.84		1.24	1.11	0.46	2.89	0.89	2.13	0.72	0.88%	0.45%
	(7.99***)		(1.00)	(0.88)	(0.27)	(1.58)	(0.31)	(2.10**)	(0.86)		
HmL$^{\Omega}$	5.77	-0.01								0.02%	-0.03%
	(6.07***)	(-0.30)									
	6.22		0.24	0.93	-1.11	-4.98	1.03	-4.06	-1.04	0.72%	0.29%
	(5.87***)		(0.09)	(0.42)	(-0.36)	(-1.27)	(0.25)	(-2.87***)	(-0.61)		
HmL$^{\Gamma,\Omega}$	6.19	-0.02								0.07%	0.02%
	(7.44***)	(-0.58)									
	6.58		-1.86	1.54	-4.23	0.67	2.44	-1.46	1.65	0.36%	-0.07%
	(6.92***)		(-0.91)	(0.80)	(-1.62)	(0.23)	(0.68)	(-0.96)	(1.36)		

the latter are twice as high. Risk-adjusted returns are also slightly higher, with a Sharpe-ratio of 4.65 for HmL$^{\Omega}$ vs. 4.13 for LmH$^{\Gamma}$. Here, however, we document that the average and risk-adjusted-performance is halved if we weigh observations by the company's market capitalization. This suggests that the effect of leveraged ETF rebalancing is outsized for smaller stocks.

Finally, Table 8 includes the summary statistics of the trading strategy that combines Γ^{HP} and Ω^{LETF} as trading signals. The combined strategy yields an annualized average return of 11.00%, with an improved annual Sharpe ratio of 5.09.[20] $\text{HmL}^{\Gamma,\Omega}$ also shows the best performance when stocks are value-weighted, with an average annual return of 6.21% and a Sharpe-ratio of 3.14. At the same time, the success rates of all three strategies are high, above 56% and highest for LmH^{Γ}, with values upwards of 61%.[21]

Table 9 summarizes the results of regressions of LmH^{Γ}, HmL^{Ω}, and $\text{HmL}^{\Gamma,\Omega}$ on the market model ($\text{Market}^{\text{end}}$) and the Fama-French five-factor model (Fama and French, 2015), augmented by a momentum factor and an intermediary capital asset pricing factor (He et al., 2017).[22,23] We find that neither the market nor the augmented five-factor model explains the properties of LmH^{Γ}, HmL^{Ω}, and $\text{HmL}^{\Gamma,\Omega}$. The R^2s of these regressions is small on average. The only factor that is statistically significant is MOM. This is interesting since it suggests that part of MOM returns correlate with intraday dynamics related to institutional frictions. Notwithstanding the significance of this factor, the alphas of these regressions are very large and significant.

Figure 5 depicts the performance and drawdown curves of the trading strategies between 2012 and 2019. Neither of the two trading strategies experiences significant fluctuations, nor do we visually spot any structural breaks. Instead, cumulative returns are fairly smooth over time. No strategy except for $\text{Market}^{\text{end}}$ exhibit a maximum drawdown in excess of −2%. The maximum drawdown is smaller for the combined strategy compared to the Ω^{LETF} strategy.

[20] The daily return $\text{HmL}^{\Gamma,\Omega}$ equates to 4.36 basis points on average. This compares well to Bogousslavsky (2020) who documents that a mispricing factor earns an alpha of −2.43 basis points in the last 30 minutes of the trading day.

[21] To put this in context, Jiang, Kelly, and Xiu (2020) use convolutional neural networks on price path images to predict the future return direction. They achieve a success rate of up to 53.6%.

[22] Data on the Fama-French five-factor model and the momentum factor is taken from Kenneth French's website, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`, whereas data on the intermediary capital asset pricing factor is obtained from Zhiguo He's website, `https://voices.uchicago.edu/zhiguohe/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/`.

[23] Appendix OA8 in the Internet Appendix reports results for LmH^{Γ} and HmL^{Ω} on their respective sample periods.

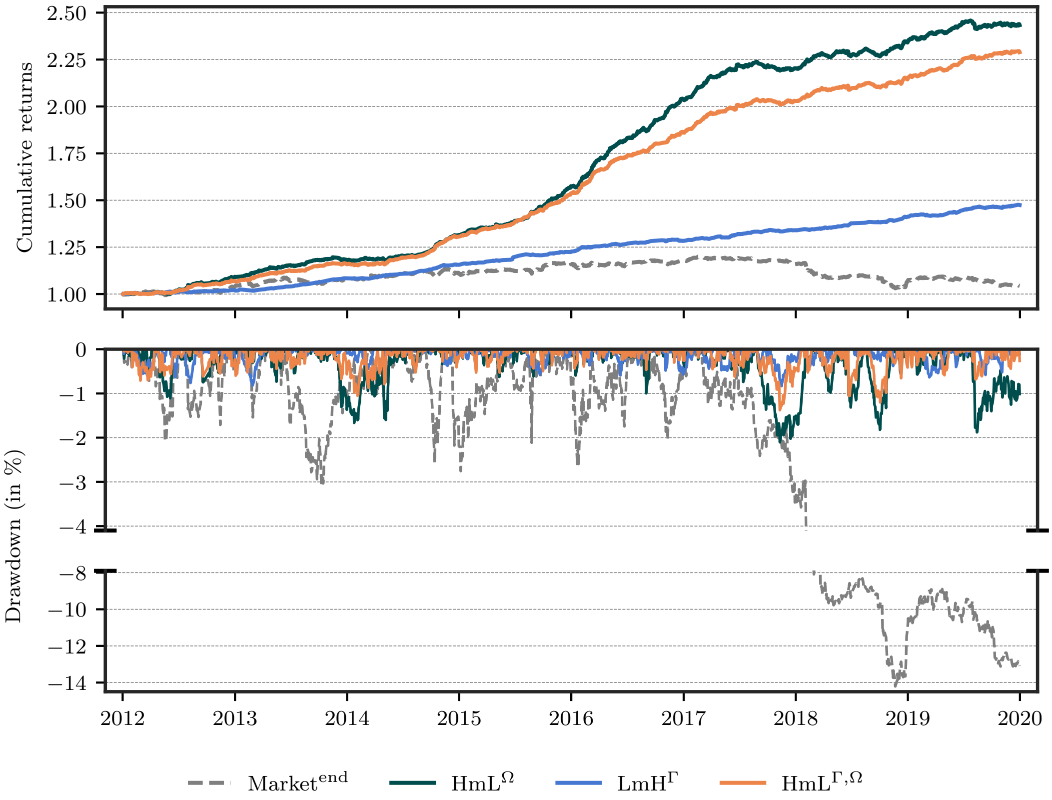

Fig. 5. **Performance and Drawdown Curves of Γ^{HP} and Ω^{LETF} Trading Strategies**
The figure shows the cumulative performance of a one-dollar investment (top panel) into as well as the drawdown curve in percent (bottom panel) for trading strategies based on Γ^{HP} and Ω^{LETF}. The Γ^{HP}-strategy, LmH$^{\Gamma}$, takes a long (short) position in a stock when the stock's Γ^{HP} is in the lowest (highest) decile. The Ω^{LETF}-strategy, HmL$^{\Omega}$, takes a long (short) position in a stock when the stock's Ω^{LETF} is in the highest (lowest) decile. The combined strategy, HmL$^{\Gamma,\Omega}$, computes a cross-sectional rank according to Γ^{HP} and Ω^{LETF} and takes a long (short) position in a stock when the stock's aggregated ranking is in the highest (lowest) decile. As a benchmark, Market$^{\text{end}}$ denotes investing in all stocks from 15:30 to 16:00. The sample period is January 2012 – December 2019.

4. Characteristics of Delta-Hedging and Leveraged ETF Rebalancing

In this section, we investigate the effects of delta-hedging and leveraged ETF rebalancing in more detail.

4.1. Hedging Windows

Throughout the paper, our working assumption is that rebalancing occurs during the last 30 minutes of the trading day. We now challenge this assumption and explore rebalancing effects on alternative hedging windows W, one for each 30-minute interval between 10:00 and the close at 16:00. We compute cumulative returns from the previous day's close until the beginning of interval W, and recalculate Γ^{HP} and Ω^{LETF} based on the new values for r^{pre} and r^{pre}_{bench}, following Equation (5) and Equation (6).

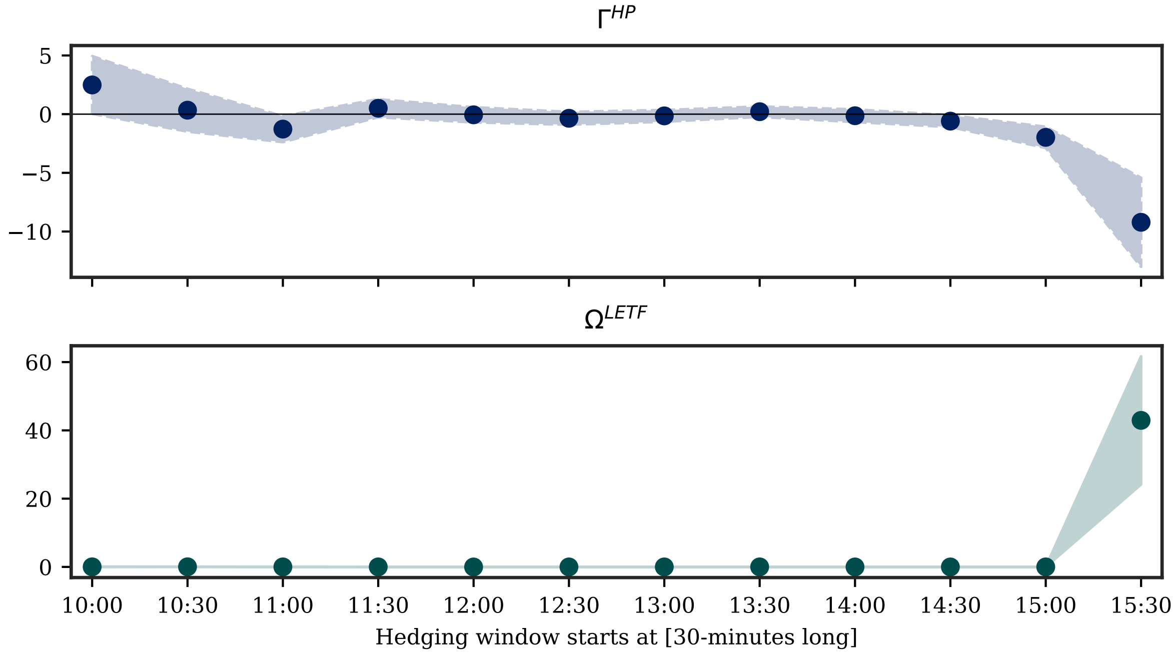

Fig. 6. **Alternative Delta-Hedging and Leveraged ETF Hedging Windows**
The figure shows the effect on Γ^{HP} and Ω^{LETF} when varying the time interval over which r^{pre} is measured. The x-axis displays the time until we measure the cumulative return from the previous trading day's close price. For the Γ^{HP}-analysis, we take returns of the underlying stock (r^{pre}), whereas we take the returns of the LETF benchmark indices for the Ω^{LETF}-analysis (r^{pre}_{bench}). We also record returns in the subsequent 30-minute time interval (r^{next}). Next, we reconstruct Γ^{HP} and Ω^{LETF} with the new values for r^{pre} and r^{pre}_{bench} following Equation (5) and Equation (6), respectively. Finally, we re-estimate Equation (10) and Equation (12)using r^{next} as the dependent variable and plot the estimated coefficients for each window. The filled areas denote 95% confidence bounds.

Figure 6 shows the resulting intraday evolution of the impact of Gamma and leveraged ETF rebalancing flows on end-of-day returns. For Γ^{HP} (upper panel), we find significantly negative coefficients only for the last two hedging windows, suggesting that some rebalancing may already take place an hour before the market closes. Nonetheless, the bulk of rebalancing seems to occur between 3:30 pm and 4 pm, when the coefficient is the largest in absolute magnitude at roughly -10. We find no significant effect during the other hedging windows apart from 10 am to 10:30 am, where the estimated coefficient is only marginally significant. For leveraged ETFs (lower panel), we find virtually no impact of rebalancing for any hedging window different from the last one. Only the end-of-day coefficient is significantly different from zero. In conjunction, these results support the view that option market makers enjoy some level of discretion regarding the timing of their rebalancing activity. Market makers for swaps replicating leveraged ETFs, in contrast, are bound by their contractual obligation to deliver a multiple exposure at the market close, and time their rebalancing activity accordingly.

4.2. Discretionary vs. non-discretionary

The previous section has indicated that some rebalancing activity of option market makers may occur before the close. In order to investigate in how far they act at their own discretion with regards to the timing of these activities, we focus on the price effects of rebalancing activities following large price movements. Intuitively, a market maker may be inclined to hedge her directional exposure immediately after observing substantial jumps in the underlying. Given the evidence above, we would assume that this applies only to option market makers.

We detect price jumps for the underlying stocks in the case of Γ^{HP} and the benchmark ETF for Ω^{LETF}. For this, we compare the return in each 30-minute interval of a given trading day with the return distribution of the same interval over the last year. We denote as "jump events" those stock intervals where this metric is in the top or bottom 2.5% of the distribution. We then record the cumulative return from the previous day close up to the end of the interval when the jump has occurred ($r_t^{\text{incl. jump}}$) and relate it to the return in the subsequent 30-minute interval (r_t^{next}), and to Γ^{HP} and Ω^{LETF} computed using $r_t^{\text{incl. jump}}$. In Table 10 we separately report regressions for jump events occurring on expanding portions of a trading day, from those observed until 12:00 in columns (1) and (4), to those observed until 15:00 in columns (3) and (6). The underlying idea is that market makers may want to hedge large price movements only if they occur early during the day, and wait for favorable market conditions at the close otherwise. Notice that we intentionally leave out the last 30 minutes of the trading day from this exercise to avoid conflating the results presented here with the end-of-day evidence.

For Γ^{HP} we find large and significant negative coefficients, indicating a stronger effect than in our baseline specification. This suggests that option market makers aggressively rebalance their exposure after particularly large price movements. Interestingly, the effect

Table 10: **Delta-Hedging and Leveraged ETF Rebalancing After Intraday Jumps**
The table reports the results to regressing the intraday jump returns on returns in the subsequent 30-minute interval. For delta-hedging, we identify jumps in the underlying stock returns. For leveraged ETF rebalancing, we identify jumps in the benchmark of the leveraged ETF. To detect jumps, we compare each non-overlapping 30-minute return with returns of the same interval over the last year. If the return is higher (lower) than the 97.5% (2.5%) percentile, we regard the return as a jump. Next, we record the return from yesterday's close until the end of the 30-minute interval, where the jump has occurred ($r_t^{\text{incl. jump}}$). We collect also the return of the subsequent 30-minute interval (r_t^{next}) on the stock level. In the case of leveraged ETFs, we select all stocks in leveraged ETFs for which a jump in the benchmark index of the leveraged ETF has occurred. Finally, we disregard jumps that have occurred after a certain time (given in row "Jumps Until"). Equipped with $r_t^{\text{incl. jump}}$, r_t^{next}, and the intraday return of the benchmark index, we reconstruct Γ_t^{HP} and Ω_t^{LETF} for each affected stock j. Subsequently, we run Equation (10) and Equation (12). T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}
Γ_t^{HP}	-44.416**	-41.310*	-31.825			
	(-1.984)	(-1.875)	(-1.492)			
Ω_t^{LETF}				-0.220	-0.349	-0.405
				(-0.686)	(-1.099)	(-1.312)
$r_t^{\text{incl. jump}}$	-0.952***	-0.965***	-0.951***	-0.711**	-0.596**	-0.596**
	(-4.240)	(-4.883)	(-4.947)	(-2.083)	(-2.322)	(-2.559)
Observations	339,552	559,520	645,246	500,036	716,298	795,337
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Jumps Until	12:00	14:00	15:00	12:00	14:00	15:00

is stronger for jumps in the first part of the trading day, supporting the idea that option market makers may decide to wait to re-hedge after late jump events to take advantage of favorable liquidity patterns at the close (Lou et al., 2019; Andersen and Bollerslev, 1997). The impact for leveraged ETF rebalancing, instead, is not significantly different from zero in all specifications. These results confirm Figure 6, indicating that leveraged ETFs market makers rebalance *only* at the very end of the trading day, even if large price swings occurr intraday.

To further investigate how option market makers exploit the discretionary nature of their re-hedging needs, we focus on the gamma imbalance accumulated only during

Table 11: **End-of-day Delta-Hedging on Identified Jump Days**
The table reports the effect of end-of-day delta-hedging on end-of-day returns, conditional on the occurrence of an intraday jump. Precisely, we reset the Gamma exposure of option market makers at the time the jump has occurred and re-estimate the aggregate Gamma exposure of option market makers at 15:30, (Γ_t^{HP}), given by the product of the return after the jump until 15:30 ($r^{\text{after jump}}$) and the gamma imbalance. We vary times until we consider jumps (Jumps Until). T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-34.546	-43.904**	-46.904**
	(-1.575)	(-2.069)	(-2.330)
$r^{\text{after jump}}$	-0.825***	-0.832***	-0.862***
	(-3.678)	(-3.762)	(-3.953)
Observations	339,552	559,520	645,246
Entity FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]
Jumps Until	12:00	14:00	15:00

and after a jump event. We thus assume that the market maker re-hedges her accrued directional exposure after the jump in stock j on day t, such that the remaining exposure amounts to

$$\Gamma_{j,t}^{HP} = 100 \times \Gamma_{j,t-1}^{IB} \times r_{j,t}^{\text{after jump}}, \tag{16}$$

where $r^{\text{after jumps}}$ measures the return of the underlying after the identified jump period until 15:30.

The results reported in Table 11 provide evidence of end-of-day rebalancing on identified jump-days only for jumps that happen relatively late during a trading day. In fact, the pattern of significance and the magnitude of coefficients inversely match the pattern in Table 10 for the impact of hedging directly after large price movements. The later the identified jump, the less likely will a market maker rebalance her exposure right away. Adding to the considerations of Clewlow and Hodges (1997), we find that market makers tend to rapidly rebalance after *early* jumps, while they tend to wait until trading closes for *later* jumps.[24]

[24]We show that the rebalancing impact after jumps differs between large and small stocks in our

Considering the amount of trading on identified jump days corroborates this idea. In Figure 7 we show the trading volume for the average stock in our sample, relative to the intraday volume pattern we observe on a typical day (also shown in the last panel of the Figure). From the plot we can make three observations: First, if a jump occurs on a given day, the 30 minutes immediately after the jump and the last 30 minutes of the trading day experience the most trading activity. Second, if the jump occurred early in the day (before 13:30) we find the trading activity in the 30 minutes after the jump to occasionally exceed that end-of-day. Third, if we instead consider late jumps (after 13:30), most trading happens in the last half hour. Together, these results are consistent with the idea that option market makers hedge mostly early jumps immediately.

4.3. Mechanical

We hypothesize that rebalancing activities of option market makers and leveraged ETF swap counterparties do not reflect fundamental values, but solely originate from the existence of derivatives markets. If this is the case, neither source of rebalancing should depend on the current market environment or the reason why stocks and benchmark ETFs moved before the hedging window.

Index versus Stock Specific Effects

While Gamma rebalancing activity depends on the return of the underlying stock, the rebalancing amount for leveraged ETFs instead depends on the return of the benchmark index of the leveraged ETF. We exploit this unique structure of the rebalancing flows from leveraged ETFs, by conditioning on those stocks for which the return until hedging begins is near zero (below 10 bps). Given that the impact of rebalancing flows is mechanical, we still expect an effect of Ω^{LETF} in roughly the same magnitude as for the full sample. This approach allows us to investigate the impact of leveraged ETF rebalancing without being conflated by other intraday return phenomena (Heston et al., 2010; Lou et al., 2019; Bogousslavsky, 2020), or option rebalancing in the form of Γ^{HP}. The results in Table 12 confirm our prior.

sample in Tables OA6.1 – OA6.3 in the Internet Appendix.

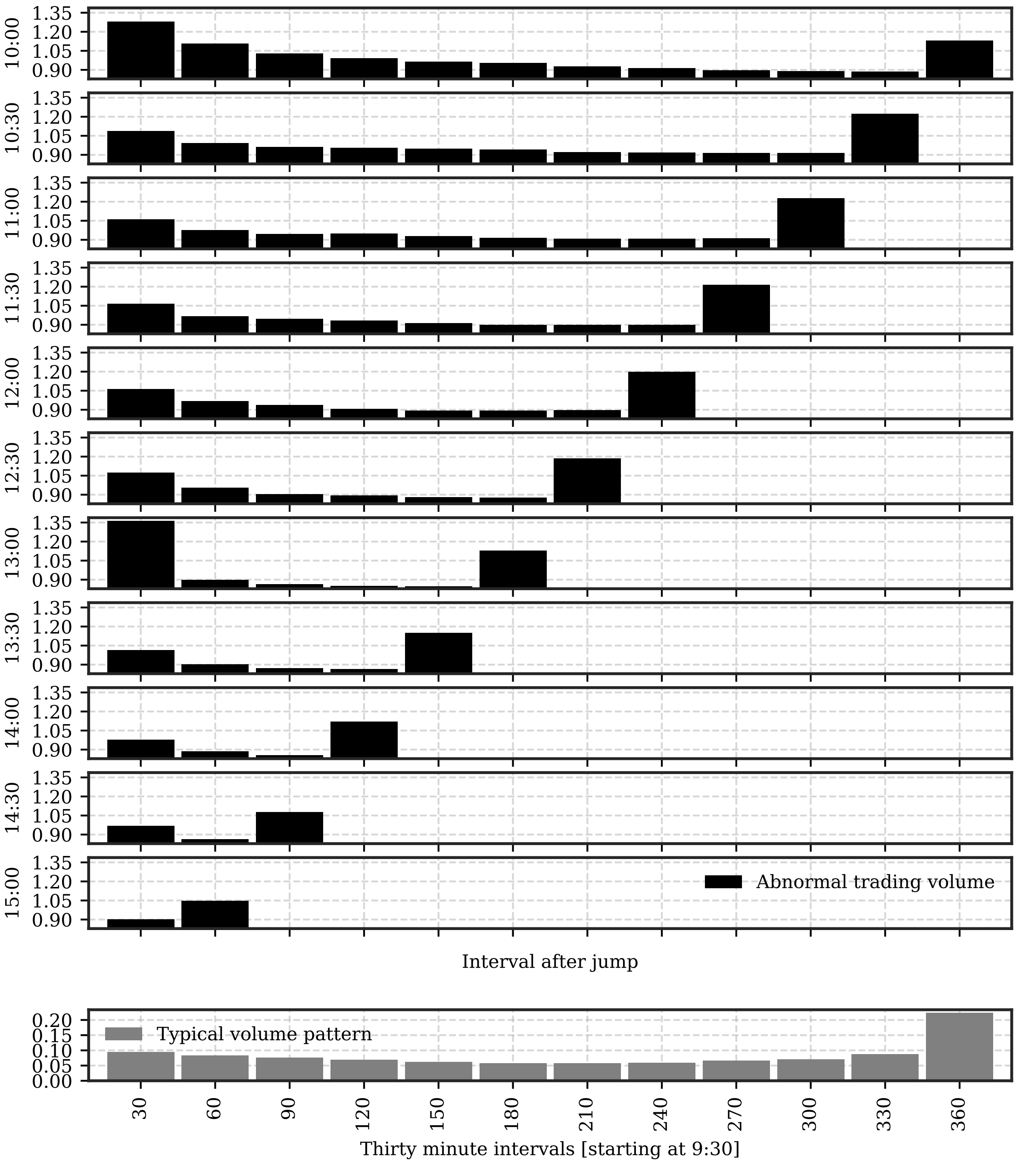

Fig. 7. **Volume Patterns on Jump Days**
The figure shows the intraday volume pattern for the average stock in our sample between 2012 and 2019 on identified jump days. The intraday volume pattern is expressed relative to the average volume pattern on a typical day, which is shown in the last panel in gray. The other panels show the relative trading activity conditional on when the jump in the underlying stock occurred, varying between all but the last possible thirty-minute interval.

Table 12: **Near Zero Returns of the Underlying Stock**
The table reports the results to regressing the returns in the last half hour of a trading day on the Leveraged ETF rebalancing quantity Ω^{LETF}. We have included only stock-day observations for which the absolute return from the previous day's close until 15:30 of stock j is below 10 basis points. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}		71.441***	71.697***
		(5.212)	(5.246)
r_t^{pre}	-0.912		-1.242
	(-0.427)		(-0.579)
Observations	123,737	123,737	123,737
Entity FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]

What is the role of news on fundamentals?

To test that delta-hedging effects are unrelated to fundamental news on the underlying stock, we perform sample splits on earnings announcements and material news. We identify the two weeks centered around earnings announcements and the releases of material news as indicated by RavenPack for each stock in our sample. The estimated coefficients for stocks with and without material news releases or earnings announcements in Table 13 barely differ, confirming the mechanical nature of Γ^{HP}-flows.

4.4. *Transitory versus Persistent Components*

If the rebalancing activity of market makers exerts enough pressure to push prices from fundamental values, other market participants should pick up on this mispricing and quickly correct it. We, therefore, expect to see a quick reversal of these effects at the next open. If the impact of rebalancing activity is indeed transitory, we expect returns on the following market open to relate positively to Γ^{HP} and negatively to Ω^{LETF}. To test this hypothesis, we run the panel regressions

$$r_{j,t}^{\text{night}} = \beta_0 r_{j,t}^{\text{end}} + \beta_1 \Gamma_{j,t}^{HP} + \beta_2 \Omega_{j,t}^{LETF} + FE_j + FE_t + \epsilon_{j,t}, \tag{17}$$

Table 13: **Impact of Fundamental Information**
The table reports the results to regressing the returns in the last half hour of a trading day on returns until 15:30, r^{pre}, and gamma hedging pressure Γ^{HP}. The regression results are reported for several subsamples where we focus on or exclude days with fundamental information, either earnings announcements (EA) or fundamental news releases identified by RavenPack. Specification (1) uses the subsample for which Compustat and/or I/B/E/S do not report earnings announcements (EA). Specification (2) excludes day-asset observations for which Compustat and/or I/B/E/S report earnings announcements. In specification (3) we exclude asset-day observations for which RavenPack documents either at least one negative (score $\geq$ 25) or one positive (score $\leq$ 75) news appearance, whereas specification (4) includes only these observations. Whenever earnings announcements or fundamental news are released on day t for asset j, we exclude also a window of 5 trading days around t for asset j. t-statistics are in parentheses below. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-9.430***	-9.274**	-9.589***	-9.386***
	(-4.713)	(-2.317)	(-5.968)	(-2.716)
r_t^{pre}	-0.746***	-0.933***	-0.728***	-0.897***
	(-6.454)	(-5.034)	(-6.268)	(-5.407)
Observations	1,639,105	301,045	1,603,389	336,761
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]
Subsample	Excluding EA	Only EA	Excluding News	Only News

where $r_{j,t}^{\text{night}}$ is the return from the close of day t to 10am on day $t+1$.

Table 14 provides evidence for the reversal of Γ^{HP} and Ω^{LETF} effects at the next open. In specifications (1) and (2), the coefficient on Γ^{HP} is positive at 31.868 (t-value: 3.53), while that on Ω^{LETF} is negative at -45.959 (t-value: -2.108), suggesting that price effects from the previous day are short-lived. In column (3), where both channels are considered jointly, the estimated reversal effects are even stronger. Returns at the open are about four times as dispersed as end-of-day returns when measured by the respective standard deviation. In economic terms, we, therefore, find that on average 84% of the impact of delta-hedging and a third of the impact of leveraged ETF rebalancing is reversed at the next open.

Table 14: **Impact of Joint Rebalancing – Transitory Impact**
The table reports the results to regressing returns from closure of day t to 10am on day $t+1$ on returns until 15:30, r^{pre}, on option market maker hedging pressure Γ^{HP} and leveraged ETF rebalancing quantity Ω^{LETF} following Equation (13). We also consider the impact of joint rebalancing activity using the variables defined in Equation (14) in the regression setup proposed in Equation (15). T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)
Dependent	r_t^{night}	r_t^{night}	r_t^{night}
Γ_t^{HP}	31.868***		34.339***
	(3.532)		(3.734)
Ω_t^{LETF}		-45.959**	-59.984***
		(-2.108)	(-2.685)
r_t^{end}	-12.439***	-12.553***	-12.364***
	(-4.902)	(-4.927)	(-4.887)
Observations	1,939,895	1,939,895	1,939,895
Entity FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]

4.5. Subsample Analysis

We re-run our baseline regression for the first three years in our sample, shift the starting and end date by one day, and repeat this procedure for all years in the joint sample (2012–2019). The resulting coefficients for Γ^{HP} are provided as the blue line in Figure 8, while those for Ω^{LETF} are provided as the green line. Corresponding t-statistics are presented in the lower panel. The impact of Γ^{HP} has stayed nearly unchanged until the end of 2016 at an estimated coefficient of roughly -9 but has started to increase in absolute magnitude afterward. In fact, during 2019 the magnitude of the effect has increased to a coefficient of -16. The estimated coefficient for Ω^{LETF} stayed within the same ballpark over time, fluctuating between 40 and 60, with a mean of around 50 for the years 2012 through 2019. The impact of both rebalancing activities was statistically highly significant throughout our sample.

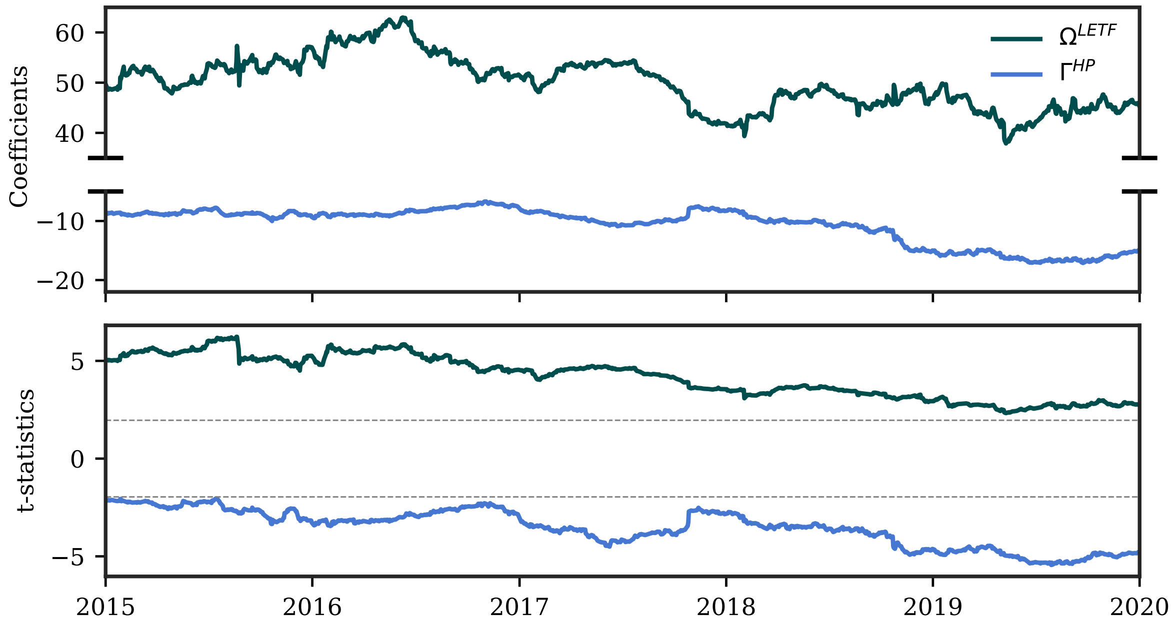

Fig. 8. **Rolling Regressions**
The figure shows the impact of Γ^{HP} and Ω^{LETF} over time, as measured on a rolling basis for each three year-period starting in January 2012. Specifically, we estimate Equation (10) and Equation (6) for the first three years in our sample, shift the starting and end date by one day and repeat this for all days in our joint sample (January 2012 – December 2019). The upper panel depicts the estimated coefficients for Γ^{HP} and Ω^{LETF}, whereas the lower panel shows the corresponding t-statistics.

4.6. Market Capitalization Effects

The impact of rebalancing flows may differ between stocks of different market capitalization. On the one hand, we might find a stronger impact for small stocks, given that the same amount of nominal trading potentially influences prices more, as a result of their limited liquidity. On the other hand, large stocks are typically included in multiple leveraged ETFs and enjoy a bigger and more liquid options market. The results in Table 8 have already hinted towards roughly constant effects of Γ^{HP} for stocks of differing market size, but outsized effects of Ω^{LETF} on small issues. To investigate this more formally, we split our sample by the prevailing cross-sectional median of last month's average market capitalization and redo the regression in Equation (13) for each subsample. The results are shown in Table 15. The estimated coefficient of Γ^{HP} is elevated for small stocks. In economic terms, a one standard deviation decrease in Γ^{HP} amplifies end-of-day returns by 0.48 bps (0.33 bps) for small (large) stocks. At the same time, however, small stocks are known to be more volatile (Fama and French, 1993), such that the impact measured in units of return-per-risk is amplified for large stocks.

Table 15: **Impact of Joint Rebalancing – Small vs. Large Caps**
The table reports the results to regressing the returns in the last half hour of a trading day on returns until 15:30, r^{pre}, on options market maker hedging pressure Γ^{HP} and leveraged ETF rebalancing quantity Ω^{LETF} following Equation (13). We also consider the impact of joint rebalancing activity using the variables defined in Equation (14) in the regression setup proposed in Equation (15). T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity-fixed effects in all specifications and value-weight observations. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-14.997***		-14.748***	-7.917***		-9.424***
	(-5.542)		(-5.461)	(-3.826)		(-4.602)
Ω_t^{LETF}		47.120***	46.951***		41.185***	44.714***
		(8.366)	(8.342)		(3.663)	(3.977)
r_t^{pre}	-0.253***	-0.271***	-0.265***	-0.955***	-1.090***	-1.012***
	(-3.191)	(-3.435)	(-3.358)	(-7.083)	(-8.177)	(-7.487)
Observations	970,574	970,574	970,574	969,576	969,576	969,576
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Market Cap	Small	Small	Small	Large	Large	Large

In contrast, while the estimated coefficient for Ω^{LETF} is roughly the same between the larger and smaller stocks in our sample, the resulting return impact is much larger for small stocks (1.75 bps vs. 0.76 bps). The larger fluctuation of end-of-day returns of small stocks is offset by a comparably large increase in the fluctuation of Ω^{LETF}.

4.7. Other Robustness Tests

The Online Appendix contains a battery of additional robustness tests. Our results are robust to the choice of the look-back window to compute ADV^{end} (Appendix OA3) or to using scaled returns following Moskowitz et al. (2012) (Appendix OA4). Furthermore, delta-hedging and leveraged ETF rebalancing are present across all industries (Appendix OA5).

5. Conclusion

A growing literature focuses on cross-sectional intraday return variation, linking it to investor heterogeneity on the stock level. In this paper, we provide novel insights into how derivative markets add to cross-sectional variation towards the end of the trading day. By drawing upon a unique dataset merging data from several exchanges identifying types of market participants in U.S. stock options and the portfolio composition of U.S. equity-focused leveraged ETFs, we document large price pressure on end-of-day returns when option market makers engage in delta-hedging and leveraged ETF swap counterparties rebalance their positional exposure.

We show that delta-hedging and leveraged ETF rebalancing exert an economically large price pressure on end-of-day returns. Whereas leveraged ETFs contribute to a market-wide momentum effect, delta-hedging can either have a stabilizing effect in the form of end-of-day reversal, but also exaggerate intraday momentum. The direction is determined by the previous return of the underlying and the aggregate option inventory of market makers. Moreover, our results reveal that option market makers have discretion on the execution of their hedging strategies, especially after intraday jumps. On the contrary, leveraged ETF swap counterparties are required to establish the target exposure of the fund at the close. We find that both rebalancing effects are mechanical, that is, they do not impound new fundamental information into prices. Given that the impact of rebalancing is mechanical in nature, we also document that it is transitory, as the effects reverse at the next open. Our results furthermore suggest that especially the impact from option market imbalances continues to increase over time, leading to potentially erratic moves at the close and subsequent reversals the next day.

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Appendix A. Cleaning of High-Frequency Data

To analyze intraday momentum effects in individual stocks, we rely on the NYSE Trades and Quote (TAQ) database for January 1996 through July 2019. Since the NYSE provides the raw tape of all trades performed on the included exchanges, multiple cleaning steps are required. Additionally, we merge the TAQ database with CRSP to use the PERMNO as a unique identifier per common share of any company.

A.1. Cleaning Procedure

We retain only trades with trade correction indicators “00” an “01”, which refer to correctly recorded trades, and those that have been subsequently altered, but reflect the actual trade price at the time. We further keep only trades with trade sale corrections ”Z”, ”B”, ”U”, ”T”, ”L”, ”G”, ”W”, ”K”, and ”J”, as well as an accompanying ”I” reflecting odd lot trades. To rely on trade prices during regular trading hours only, we discard all observations before 9:30 and after 16:01. We explicitly include the minute of 4pm, as many closing trades (denoted by sale conditions ”6” or ”M”) fall within the first few seconds afterwards.

If multiple trades occur at exactly the same point in time, we take the median price as the “correct price”. To make sure that prices are consistent by Ticker, we employ a bounce-back filter following Andersen, Bondarenko, and Gonzalez-Perez (2015), which effectively checks whether any trade’s price deviates by more than 15 times the median absolute deviation of the day. If this is the case, we will kick this observation if we observe a reversion to the previous price within the next five minutes, or 10 trades, whichever encompasses more trades. We also drop price observations which deviate by more than two times $|\log(p_t/\hat{p})|$, where $\hat{p}$ is the median for the day. We choose trade-based filters to check for the internal consistency, instead of relying on the Quote database also provided by the NYSE, as some observations are falsely recorded in both. Afterwards, we span a minute-by-minute grid between 9:30 and 16:01 and map trades to these trading minutes, taking the volume-weighted average price within each minute to limit the impact of microstructure noise and single trades.

A.2. Merge with CRSP

The TAQ database provides intraday trade prices, but lacks information about distributions, mergers, and delistings. We obtain this information from CRSP, as the lowfrequency database in financial economics.

We use the PERMNO provided by CRSP as an identifier that is unique over time. In a first step, we merge the historical CUSIP by CRSP (NCUSIP) with the CUSIPs in the master file taken from TAQ. In some occasions, we cannot merge available tickers in the trade file this way, and in a second step merge the two databases by the root ticker and ticker suffix, which indicates different share classes. We keep only stocks with share codes 10 and 11, denoting common shares, as well as exchange codes 1, 2, 3, 31, 32 and 32, representing the NYSE, AMEX and NASDAQ, respectively. Using this procedure, we can merge most stocks for which we have intraday data available and cover most of the CRSP sample. Since we are interested in the impact of market maker hedging activity, we retain only those stocks that are optionable, i.e. for which options have traded between May 2005 and July 2020.

Appendix B. Detailed Summary Statistics on Γ^{HP} and Ω^{LETF}

Table B1 provides detailed summary statistics on the main variables of interest in the main paper. Panel A in Table B1 provides the summary statistics for the joint sample, that is, every stock in the joint sample is optionable and included in a benchmark index of at least on leveraged ETF. Panel B in Table B1 provides the summary statistics for the sample of optionable stocks. Panel C in Table B1 provides the summary statistics for the sample of stocks included in benchmark indices of leveraged ETFs.

Table B1: **Summary Statistics**
The table reports means, standard deviations, and quantiles for the gamma, leveraged ETF variables and returns used in the regression models. The descriptive statistics are first computed for each day and subsequently averaged across all days. r^{pre}, r^{night} and r^{end} are denoted in basis points. ADV^{end} is given in million USD. Γ^{IB}, Γ^{HP}, Ω^{LETF} and their corresponding absolute values are given percentage. The sample periods and data sets are given in the panel titles.

	Mean	Std	2.5%	10%	25%	50%	75%	90%	97.5%
Panel A: Joint (2012-2019)									
r^{pre}	6.26	240.49	-405.97	-194.44	-83.0	4.92	91.94	202.79	429.13
r^{end}	0.32	45.57	-81.2	-40.28	-18.45	-0.53	17.81	41.16	87.12
r^{night}	4.25	174.25	-258.07	-119.93	-51.63	3.0	57.79	127.89	276.07
ADV^{end}	22.87	65.36	0.23	0.74	2.13	6.75	20.24	49.5	147.74
Γ^{IB}	0.55	3.66	-4.26	-1.37	-0.26	0.08	0.94	3.0	7.51
$\|\Gamma^{IB}\|$	1.56	3.34	0.0	0.03	0.14	0.56	1.72	3.95	8.82
Γ^{HP}	0.03	6.42	-8.22	-2.4	-0.49	0.0	0.53	2.53	8.51
$\|\Gamma^{HP}\|$	2.06	6.06	0.0	0.02	0.1	0.49	1.85	4.97	13.2
Ω^{LETF}	0.15	2.71	-3.54	-1.91	-0.95	0.1	1.2	2.27	4.08
$\|\Omega^{LETF}\|$	1.88	2.66	0.03	0.17	0.44	1.1	2.56	4.32	7.46
$\Omega^{LETF} - \Gamma^{HP}$	0.12	7.25	-9.8	-3.65	-1.38	0.1	1.62	3.92	9.91
$\|\Omega^{LETF} - \Gamma^{HP}\|$	3.3	6.64	0.06	0.23	0.65	1.75	3.8	7.14	15.31
Panel B: Gamma Exposure (2005-2020)									
r^{pre}	6.06	233.35	-397.66	-192.07	-83.06	4.4	91.48	200.9	421.69
r^{end}	0.42	53.35	-96.42	-46.93	-21.04	-0.47	20.64	48.06	102.65
r^{night}	3.21	168.23	-252.12	-117.57	-51.26	2.03	55.45	122.94	267.22
ADV^{end}	13.93	49.65	0.08	0.22	0.7	2.68	9.84	29.94	97.8
Ω^{LETF}	0.36	48.13	-6.0	-3.35	-1.7	0.16	2.09	3.98	7.04
$\|\Omega^{LETF}\|$	4.83	48.11	0.02	0.2	0.61	2.1	4.38	7.51	12.95
Panel C: LETF Rebalancing (2012-2019)									
r^{pre}	3.53	260.04	-442.13	-222.4	-100.77	0.23	101.71	226.63	470.58
r^{end}	1.13	56.7	-95.23	-46.36	-21.02	0.03	21.68	48.96	104.39
r^{night}	2.4	183.8	-281.23	-138.01	-63.03	-0.05	63.75	142.38	301.99
ADV^{end}	19.51	52.36	0.26	0.79	2.14	6.27	18.0	43.17	119.79
Γ^{IB}	0.38	3.57	-4.7	-1.84	-0.53	0.05	0.95	2.87	7.01
$\|\Gamma^{IB}\|$	1.64	3.17	0.01	0.06	0.22	0.72	1.91	4.01	8.46
Γ^{HP}	0.01	6.99	-9.05	-2.87	-0.68	-0.0	0.69	2.94	9.22
$\|\Gamma^{HP}\|$	2.34	6.53	0.0	0.03	0.16	0.68	2.24	5.6	14.13

Appendix C. Different Sets of Delta-Hedgers

We investigate whether the choice of the set of delta-hedgers skews our results. In the main part of the paper, we have assumed that delta-hedgers are composed of market makers and broker/dealers. We exchange the set of delta-hedgers to include only market makers (Table C2) or to include market makers, broker/dealers, and firm proprietary traders (Table C3). The choice of the set of likely delta-hedgers has little impact on our results.

Table C2: **Market Makers as the only Delta-Hedgers**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). We assume that market makers are delta-hedgers. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-11.619***	-11.560***	-11.564***	-11.625***	-11.619***
	(-3.926)	(-3.926)	(-3.901)	(-3.928)	(-3.929)
r_t^{pre}	-0.714***	-0.715***	-0.714***	-0.713***	-0.713***
	(-4.495)	(-4.509)	(-4.497)	(-4.493)	(-4.495)
IV_{t-1}		6.095***			
		(3.153)			
$\hat{RV}_t^{end}$			540.566*		
			(1.957)		
PC_{t-1}				0.334	
				(1.629)	
$O/S_{t-1}^{\$}$					680.601
					(1.162)
Observations	3,365,367	3,365,367	3,365,008	3,358,727	3,365,359
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

Table C3: **Market Makers, Broker/Dealer, and Firm Proprietary Traders as Delta-Hedgers**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). We assume that market makers, broker/dealer, and firm proprietary traders are delta-hedgers. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-16.345***	-16.309***	-16.305***	-16.350***	-16.341***
	(-8.931)	(-8.939)	(-8.915)	(-8.934)	(-8.932)
r_t^{pre}	-0.627***	-0.628***	-0.627***	-0.626***	-0.627***
	(-3.906)	(-3.920)	(-3.908)	(-3.904)	(-3.906)
IV_{t-1}		6.010***			
		(3.104)			
$\hat{RV}_t^{end}$			525.810*		
			(1.907)		
PC_{t-1}				0.341*	
				(1.685)	
$O/S_{t-1}^{\$}$					650.340
					(1.087)
Observations	3,365,367	3,365,367	3,365,006	3,358,716	3,365,359
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

Appendix D. Γ^{HP} based on "Old" Positions

Endogeneity concerns regarding Equation (10) might be raised given that traders with public and/or private information on the return of stock j in the last 30 minutes, r_j^{end}, choose the option market to exploit this information. To mitigate any concerns, we adopt the idea of Ni et al. (2020). Precisely, we split Γ^{HP} in two parts: gamma hedging pressure originating from "old" positions held by delta-hedgers at time $t-\tau$, and gamma hedging pressure stemming from new positions between $t-\tau$ and t. Ni et al. (2020) argue that option positions which existed at $t-\tau$ cannot be established due to private and/or public information after the close at $t-\tau$. In case of short-lived private and/or public information, positions at $t-\tau$ are of no use for predicting the return in the last 30 minutes on t, r^{pre}.

To decompose Γ^{HP}, we first define the gamma imbalance for stock j at time t which is based on option positions of delta-hedgers at time $t-\tau$ as

$$\Gamma^{IB}_{j,t;\tau} = \left(\sum_{o=1}^{N^t_{t-\tau}} netOI_{o,t-1-\tau} \times \Gamma_o(t-1, S^{close}_{j,t-1}) \times S^{15:30}_{j,t} \times Mult_o \right) \times \frac{S^{close}_{j,t-1}}{100} \times \frac{1}{\text{ADV}^{\text{end}}_{j,t-1}}, \tag{D1}$$

where $N^t_{t-\tau}$ denotes the number of options contracts on stock j that are available at time $t-\tau$ and expire after t. The difference between Equation (D1) and Equation (4) in the main paper is that Equation (D1) uses the net open interest of likely delta-hedgers at time $t-\tau$ and sums over options expiring after t. However, both definitions use the gamma of option contracts at the previous trading day, $t-1$. Hence, Equation (D1) denotes the gamma imbalance at time t of old positions.

Next, we define the gamma hedging pressure due to old positions as

$$\Gamma^{HP}_{j,t;\tau} = 100 \times \Gamma^{IB}_{j,t;\tau} \times r^{\text{pre}}_{j,t}. \tag{D2}$$

We decompose Γ^{HP} at time t into the part that is due to old positions existing at time $t-\tau$, $\Gamma^{HP}_{j,t;\tau}$, and the part due to new positions, $\Gamma^{HP}_{j,t;\text{new}}$, as follows

$$\Gamma^{HP}_{j,t} = \Gamma^{HP}_{j,t;\tau} - \Gamma^{HP}_{j,t;\text{new}}, \tag{D3}$$

where $\Gamma^{HP}_{j,t;\text{new}} = \Gamma^{HP}_{j,t} - \Gamma^{HP}_{j,t;\tau}$.

Finally, we run the following specification where we control for fixed effects and other control variables, $\boldsymbol{X}_{j,t}$,

$$r_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Gamma_{j,t;\tau}^{HP} + \beta_2 \Gamma_{j,t;\text{new}}^{HP} + \boldsymbol{\gamma}' \boldsymbol{X}_{j,t} + FE_j + FE_t + \epsilon_{j,t}. \tag{D4}$$

We hypothesize that β_1 is negative and statistically significant. Table D4 and Table D5 show results with τ set to five and ten business days, respectively. Both tables confirm our hypothesis.

Table D4: **Option Hedging Pressure based on 5-Business Day Old Positions**
The table summarizes the results of regressions of returns in the last half hour of a trading day on market maker hedging pressure based on five business day old positions $\Gamma^{HP}_{t;\tau}$ and hedging pressure based on new positions, $\Gamma^{HP}_{t;\mathrm{new}}$, after controlling for returns until 15:30 (r^{pre}), as in specification Equation (D4). IV_{t-1} denotes implied volatility at time $t-1$. $\hat{RV}^{end}_t$ denote the square root of predicted realized variance for the time period from 15:30 to 16:00. PC_{t-1} is the put-call-ratio and $O/S^{\$}_{t-1}$ denotes the option-to-stock volume in dollar terms. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and value-weight observations. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t
$\Gamma^{HP}_{t;\tau}$	-16.945***	-16.893***	-16.916***	-16.958***	-16.943***
	(-7.220)	(-7.191)	(-7.188)	(-7.223)	(-7.225)
$\Gamma^{HP}_{t;\mathrm{new}}$	-0.159	-0.155	-0.144	-0.159	-0.158
	(-0.411)	(-0.401)	(-0.374)	(-0.412)	(-0.408)
r^{pre}_t	-0.835***	-0.836***	-0.835***	-0.834***	-0.835***
	(-4.738)	(-4.753)	(-4.739)	(-4.736)	(-4.738)
IV_{t-1}		7.413***			
		(3.216)			
$\hat{RV}^{end}_t$			571.432*		
			(1.793)		
PC_{t-1}				0.501*	
				(1.901)	
$O/S^{\$}_{t-1}$					511.163
					(0.893)
Observations	1,878,136	1,878,136	1,877,909	1,875,677	1,878,131
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

Table D5: **Option Hedging Pressure based on 10-Business Day Old Positions**
The table summarizes the results of regressions of returns in the last half hour of a trading day on market maker hedging pressure based on ten business day old positions $\Gamma^{HP}_{t;\tau}$ and hedging pressure based on new positions, $\Gamma^{HP}_{t;\text{new}}$, after controlling for returns until 15:30 (r^{pre}), as in specification Equation (D4). IV_{t-1} denotes implied volatility at time $t-1$. $\hat{RV}^{end}_t$ denote the square root of predicted realized variance for the time period from 15:30 to 16:00. PC_{t-1} is the put-call-ratio and $O/S^{\$}_{t-1}$ denotes the option-to-stock volume in dollar terms. T-statistics are in parentheses below and are computed using time-and-entity-clustered standard errors. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and value-weight observations. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t
$\Gamma^{HP}_{t;\tau}$	-20.419***	-20.370***	-20.407***	-20.436***	-20.424***
	(-7.924)	(-7.897)	(-7.903)	(-7.926)	(-7.927)
$\Gamma^{HP}_{t;\text{new}}$	-0.186	-0.182	-0.172	-0.187	-0.185
	(-0.481)	(-0.471)	(-0.444)	(-0.482)	(-0.478)
r^{pre}_t	-0.840***	-0.842***	-0.840***	-0.840***	-0.840***
	(-4.776)	(-4.791)	(-4.777)	(-4.774)	(-4.775)
IV_{t-1}		7.417***			
		(3.218)			
$\hat{RV}^{end}_t$			572.220*		
			(1.796)		
PC_{t-1}				0.500*	
				(1.898)	
$O/S^{\$}_{t-1}$					519.470
					(0.908)
Observations	1,878,136	1,878,136	1,877,909	1,875,677	1,878,131
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

The Role of Leveraged ETFs and Option Market Imbalances on End-of-Day Price Dynamics

Online Appendix
(not for publication)

by Andrea Barbon, Heiner Beckmeyer, Andrea Buraschi, Mathis Moerke

Abstract

This appendix provides supplementary results and additional analyses besides robustness checks not included in the paper.

Table of Contents:

- Appendix OA1 provides **summary statistics** for the **underlying stocks** in the sample.
- Appendix OA2 provides **summary statistics** for the **leveraged ETFs** in the sample.
- Appendix OA3 investigates the effect of altering the calculation of the **average dollar volume**.
- Appendix OA4 investigates the effect of **scaling returns** according to Moskowitz et al. (2012).
- Appendix OA5 investigates the effect across **different industries**.
- Appendix OA6 analyses the rebalancing activities around **intraday jumps for small and large market cap stocks**, respectively.
- Appendix OA7 provides summary statistics for **trading strategies** based on Γ^{HP} and Ω^{LETF} on their respective data samples.
- Appendix OA8 provides results for **risk-adjusted returns** of the trading strategies based on Γ^{HP} and Ω^{LETF} on their respective data samples.

Appendix OA1. Summary Statistics of the Underlying

Table OA1.1: **Industry Distribution of Underlying Stocks**
The table reports time-series averages of industry distributions of the Fama-French 12-industry classification. The industry distributions are reported for the gamma exposure, LETF and joint sample. For comparability to the CRSP universe, the distributions of the full CRSP samples for the corresponding time periods are included.

FF-12 Industry	Options sample	CRSP sample (2005-2020)	LETF sample	Joint sample	CRSP sample (2012-2019)
Consumer durables	0.58%	0.28%	0.36%	0.43%	0.19%
Consumer nondurables	5.16%	3.16%	4.35%	4.55%	2.71%
Manufacturing	11.14%	5.48%	9.12%	10.17%	4.78%
Energy	6.64%	3.49%	4.53%	5.71%	3.4%
Chemicals	3.3%	1.37%	2.74%	3.21%	1.26%
Business Equipment	13.7%	10.58%	12.79%	15.6%	8.62%
Telecom	2.27%	2.37%	2.56%	2.37%	1.95%
Utilities	4.23%	2.03%	3.46%	3.71%	1.9%
Wholesale	12.25%	5.69%	9.65%	11.73%	4.96%
Healthcare	10.26%	6.76%	8.05%	10.72%	5.51%
Finance	10.56%	40.92%	16.9%	10.29%	44.13%
Other	19.91%	17.9%	25.61%	21.64%	20.61%

Table OA1.2: **Summary Statistics of Underlying Stocks**
The table reports summary statistics on the stock-day sample for the underlying stocks. Panel A reports the time-series summary statistics and Panel B reports the time-series average of cross-sectional distributions. Percent coverage of the stock universe (EW) is the number of stocks in the sample, divided by the total number of CRSP stocks. Percent coverage of the stock universe (VW) is the total market capitalization of sample stocks divided by the total CRSP market capitalization. Percent coverage of stocks traded at NYSE or AMEX is the number of stocks in the sample trading at NYSE or AMEX, divided by the total number of stocks. The firm size percentiles are computed using the full CRSP sample. Number of LETF is the number of LETF a stock is included in.

	Mean	Std	10-Pctl	Q1	Median	Q3	90-Pctl
Panel A: Time-Series Distribution							
Gamma Exposure (2005-2020)							
Number of stocks in the sample each month	892.94	347.42	320.6	559.0	1061.0	1157.0	1221.0
Stock coverage of stock universe (EW)	12.63	4.81	4.6	8.24	15.01	16.2	17.02
Stock coverage of stock universe (VW)	44.99	9.09	30.23	34.65	50.29	51.66	52.66
Stock traded at NYSE or AMEX	43.66	5.48	36.38	39.37	43.38	44.76	52.32
LETF (2012-2019)							
Number of stocks in the sample each month	2210.98	525.92	1611.8	2295.0	2355.0	2424.0	2464.0
Stock coverage of stock universe (EW)	30.89	7.43	21.88	31.22	32.99	34.5	35.04
Stock coverage of stock universe (VW)	65.04	13.57	63.67	66.72	68.52	69.23	69.71
Stock traded at NYSE or AMEX	38.74	8.07	35.78	37.91	40.15	42.89	43.42
Joint (2012-2019							
Number of stocks in the sample each month	992.53	227.92	877.2	973.0	1043.0	1101.25	1140.0
Stock coverage of stock universe (EW)	13.86	3.17	12.43	13.65	14.57	15.26	15.92
Stock coverage of stock universe (VW)	48.79	10.17	48.47	49.76	50.92	51.85	52.72
Stock traded at NYSE or AMEX	38.74	8.07	35.78	37.91	40.19	42.88	43.42
Panel B: Time-Series Average of Cross-Sectional Distributions							
Gamma Exposure (2005-2020)							
Firm size in million	13824	37492	530	1308	3626	11011	30004
Firm size CSRP percentile	78	17	52	68	82	92	96
LETF (2012-2019)							
Firm size in million	9229	33225	286	577	1578	5084	17629
Firm size CSRP percentile	69	19	42	54	71	85	94
Number of LETF	8	3	6	6	8	10	13
Joint (2012-2019							
Firm size in million	15050	44338	454	1079	3152	11182	31883
Firm size CSRP percentile	77	17	51	66	81	92	96
Number of LETF	9	3	6	7	9	11	14

Appendix OA2. Summary Statistics of Leveraged ETFs

Table OA2.1: **Summary Statistics Underlying Leveraged ETFs**
The table reports time-series summary statistics on the underlying leveraged ETFs in our sample. Number of LETF is the number of leveraged ETFs. Number of benchmark indices is the number of unique benchmark indices underlying all leveraged ETFs. Aggregated AUM denotes the assets under management across all leveraged ETFs, in million. Aggregated leverage-adjusted AUM is the assets under management adjusted for the rebalancing leverage of each leveraged ETF. Percentage of inverse LETF (EW) is the number of inverse ETFs divided by the total number of leveraged ETFs. Percentage of inverse LETF (VW) is the assets under management weighted proportion of inverse ETFs to the total leveraged ETF sample. Average absolute leverage factor (EW) is the average absolute leverage factor. Average absolute leverage factor (VW) is the assets under management weighted absolute leverage factor. The sample period is January 2012 – December 2019.

	Mean	Std	10%	25%	50%	75%	90%
Number of LETF	71.67	11.05	66.0	72.0	74.0	76.0	79.0
Number of benchmark indices	23.72	3.7	21.0	23.0	25.0	25.0	27.0
Agg. AUM	17.71	4.69	12.03	15.29	16.92	21.33	24.43
Agg. leverage-adjusted AUM	95.33	28.55	64.23	73.01	86.97	121.12	131.71
Perc. of inverse LETF (EW)	45.29	3.38	41.67	43.24	45.07	45.95	51.28
Perc. of inverse LETF (VW)	33.14	15.66	16.31	22.75	28.48	41.77	62.64
Avg. absolute leverage factor (EW)	2.35	0.13	2.21	2.22	2.32	2.45	2.5
Avg. absolute leverage factor (VW)	2.43	0.14	2.29	2.35	2.44	2.53	2.6

Appendix OA3. Different ADV Measures

We investigate whether the choice of scaling the proposed Gamma exposure with last month's average dollar volume skews our results. To do so, we exchange the proposed ADV measure with last week's ADV and last quarter's ADV. We also check whether results change materially when using ADV of the last half hour of a trading day (I) or the entire daily trading volume (D). Table OA3.1 and Table OA3.2 present results for the gamma and LETF sample, respectively, whereas Table OA3.3 displays results for the joint data sample. The choice of denominator for Γ^{HP} and Ω^{LETF} has little impact on our results.

Table OA3.1: **Effect of Different ADV Measures in Gamma Sample**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). We exchange the standard ADV measure as the average volume in the last half trading hour over the last month by similar measures using weekly (W) and quarterly horizons (Q), as well as measures using daily volume in their constructed (denoted by "-D"). T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-11.014***	-56.466***	-11.947***	-58.915***	-12.472***	-60.231***
	(-5.047)	(-5.208)	(-5.008)	(-4.808)	(-4.721)	(-4.071)
r_t^{pre}	-0.719***	-0.716***	-0.718***	-0.717***	-0.717***	-0.718***
	(-4.337)	(-4.299)	(-4.341)	(-4.326)	(-4.360)	(-4.355)
Observations	3,365,367	3,365,367	3,365,367	3,365,367	3,365,367	3,365,367
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
ADV	W-I	W-D	M-I	M-D	Q-I	Q-D

Table OA3.2: **Effect of Different ADV Measures in LETF Sample**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). We exchange the standard ADV measure as the average volume in the last half trading hour over the last month by similar measures using weekly (W) and quarterly horizons (Q), as well as measures using daily volume in their constructed (denoted by "-D"). T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}	25.285***	152.698***	41.350***	109.642***	43.195***	180.037***
	(3.311)	(8.532)	(8.569)	(2.620)	(8.425)	(9.256)
r_t^{pre}	-0.878***	-0.892***	-0.900***	-0.875***	-0.901***	-0.897***
	(-8.654)	(-9.393)	(-9.299)	(-7.911)	(-9.253)	(-9.400)
Observations	4,403,855	4,403,744	4,403,855	4,403,854	4,403,855	4,403,855
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
ADV	W-I	W-D	M-I	M-D	Q-I	Q-D

Table OA3.3: **Effect of Different ADV Measures for Joint Sample**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). We exchange the standard ADV measure as the average volume in the last half trading hour over the last month by similar measures using weekly (W) and quarterly horizons (Q), as well as measures using daily volume in their constructed (denoted by "-D"). T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-9.536***	-53.144***	-10.677***	-56.517***	-10.708***	-57.467***
	(-4.945)	(-6.602)	(-5.324)	(-6.534)	(-4.929)	(-6.290)
Ω_t^{LETF}	42.696***	181.998***	47.611***	193.612***	50.017***	206.090***
	(4.407)	(5.721)	(4.935)	(5.803)	(4.845)	(5.767)
r_t^{pre}	-0.882***	-0.869***	-0.882***	-0.870***	-0.887***	-0.875***
	(-7.484)	(-7.309)	(-7.479)	(-7.285)	(-7.519)	(-7.330)
Observations	1,940,150	1,940,150	1,940,150	1,940,150	1,940,150	1,940,150
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
ADV	W-I	W-D	M-I	M-D	Q-I	Q-D

Appendix OA4. Scaled Returns as in Moskowitz et al. (2012)

In the main analyses we use plain returns and value-weight observations in the panel regressions. Instead, Moskowitz et al. (2012) proposes the use of scaled returns, which expresses returns in terms of units of expected risk:

$$\hat{r} = \frac{r}{\sigma_r}, \tag{OA1}$$

where σ_r is calculated using an exponentially-weighted moving average from the realized variance of using 5-minute squared returns from last close to 15:30. The half life is chosen to equal 60 days.

Table OA4.1 and Table OA4.2 present results for the gamma and LETF sample, respectively, whereas Table OA4.3 displays results for the joint data sample. Scaling returns does not alter our results.

Table OA4.1: **Using Scaled Returns for the Gamma Sample**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). The regression setup follows Table 4 but uses scaled returns. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-29.475***	-29.410***	-29.486***	-29.489***	-29.475***
	(-4.171)	(-4.166)	(-4.169)	(-4.172)	(-4.175)
r_t^{pre}	-0.071***	-0.071***	-0.071***	-0.071***	-0.071***
	(-9.206)	(-9.204)	(-9.205)	(-9.208)	(-9.206)
IV_{t-1}		12.640***			
		(3.966)			
$\hat{RV}_t^{close-1\to 15:30}$			77.456		
			(1.541)		
PC_{t-1}				0.561	
				(0.917)	
$O/S_{t-1}^{\$}$					1521.516
					(0.918)
Observations	3,365,009	3,365,009	3,365,009	3,358,408	3,365,001
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]

Table OA4.2: **Using Scaled Returns for the LETF Sample**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). The regression setup follows Table 4 but uses scaled returns. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}	54.287***	95.759***	95.753***	95.756***
	(2.761)	(5.054)	(5.055)	(5.052)
r_t^{pre}		-0.064***	-0.064***	-0.064***
		(-10.184)	(-10.183)	(-10.182)
$\hat{RV}_t^{close-1\to 15:30}$			-7.640	
			(-0.156)	
$\hat{RV}_t^{15:30\to close}$				630.649**
				(2.062)
Observations	4,386,322	4,386,322	4,386,322	4,386,322
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]

Table OA4.3: **Using Scaled Returns for the Joint Sample**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). The regression setup follows Table 4 but uses scaled returns. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}		166.908***	175.169***	
		(4.700)	(4.975)	
Γ_t^{HP}	-26.845***		-31.727***	
	(-3.201)		(-3.841)	
r_t^{pre}	-0.063***	-0.071***	-0.067***	
	(-7.883)	(-8.958)	(-8.185)	
BB				170.872***
				(5.279)
SS				-179.481***
				(-3.963)
BS				-96.936***
				(-2.874)
SB				75.525***
				(2.744)
Observations	1,940,048	1,940,048	1,940,048	1,940,048
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	-
SEs	[t;j]	[t;j]	[t;j]	[t;j]

Appendix OA5. Effects Across Industries

Investor attention for stocks in respective sectors changes over time. To compare how hedging pressure from the options market impacts end-of-day returns, we sort stocks into their respective industry following the classification on Kenneth French's website.

Table OA5.1 and Table OA5.2 present results for the gamma and LETF sample, respectively, whereas Table OA5.3 displays results for the joint data sample. $\Gamma^{IB}-$ and $\Omega^{LETF}-$effects are present and statistically significant in all industries.

Table OA5.1: **Effects in Different Industries for the Gamma Sample**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). The sample is split by the industry classification based on SIC codes, following Kenneth French's website, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is May 2005 – July 2020.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-9.646***	-6.965**	-10.429**	-14.460***	-17.307***
	(-4.789)	(-2.196)	(-2.283)	(-3.286)	(-6.063)
r_t^{pre}	-0.890***	-1.009***	-0.971***	-1.179***	-0.651***
	(-6.985)	(-3.705)	(-4.488)	(-5.006)	(-3.239)
Observations	637,729	798,830	624,852	363,951	940,005
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Industry	Consumer	Manuf.+Energy	Business	Health	Other

Table OA5.2: **Effects in Different Industries for the LETF Sample**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). The sample is split by the industry classification based on SIC codes, following Kenneth French's website, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}	40.190***	20.354***	43.533***	70.799***	48.152***
	(8.611)	(3.823)	(6.716)	(5.911)	(9.913)
r_t^{pre}	-0.766***	-0.889***	-1.075***	-0.929***	-0.780***
	(-7.154)	(-5.781)	(-6.432)	(-4.889)	(-5.734)
Observations	705,758	867,361	721,391	355,840	1,753,505
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Industry	Consumer	Manuf.+Energy	Business	Health	Other

Table OA5.3: **Effects in Different Industries for the Joint Sample**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre} and market maker hedging pressure Γ^{HP}, following Equation (10). The sample is split by the industry classification based on SIC codes, following Kenneth French's website, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. T-statistics in parentheses are derived from standard errors clustered by date and entity. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects and weight returns by the stock's market capitalization. The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-8.632***	-6.315**	-7.902*	-19.952***	-15.017***
	(-5.343)	(-2.573)	(-1.887)	(-4.262)	(-5.092)
Ω_t^{LETF}	30.339***	20.801***	50.707***	96.362***	38.856***
	(6.439)	(2.871)	(9.469)	(6.680)	(4.287)
r_t^{pre}	-0.710***	-0.955***	-1.034***	-0.963***	-0.696***
	(-5.262)	(-4.391)	(-5.054)	(-4.543)	(-3.720)
Observations	354,699	437,271	378,458	210,157	559,565
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Industry	Consumer	Manuf.+Energy	Business	Health	Other

Appendix OA6. Discretionary Rebalancing – The Case of Jumps

Table OA6.1: **Delta-Hedging After Intraday Jumps – Market Cap Effects**
The table reports the results to regressing intraday jump returns on returns in the subsequent 30-minute interval for large and small stocks in our sample. We identify jumps in the underlying stock returns. To detect jumps, we compare each non-overlapping 30-minute return with returns of the same interval over the last year. If the return is higher (lower) than the 97.5% (2.5%) percentile, we regard the return as a jump. Next, we record the return from yesterday's close until the end of the 30-minute interval, where the jump has occurred ($r_t^{\text{incl. jump}}$). We collect also the return of the subsequent 30-minute interval (r_t^{next}) on the stock-level. Finally, we disregard jumps which have occurred after a certain time (given in row "Jumps Until"). Equipped with $r_t^{\text{incl. jump}}$, r_t^{next}, and the intraday return of the benchmark index, we reconstruct Γ_t^{HP} for each affected stock j. Subsequently, we run Equation (10). The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}
Γ_t^{HP}	-71.878*	-77.413**	-72.054**	-41.922*	-39.247*	-29.792
	(-1.651)	(-2.214)	(-2.239)	(-1.813)	(-1.732)	(-1.363)
$r_t^{\text{incl. jump}}$	-0.787**	-0.925***	-0.977***	-1.016***	-1.004***	-0.976***
	(-2.419)	(-3.253)	(-3.601)	(-4.004)	(-4.517)	(-4.519)
Observations	173,131	287,164	331,109	166,421	272,356	314,137
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Jumps Until	12:00	14:00	15:00	12:00	14:00	15:00
Market Cap	Small	Small	Small	Large	Large	Large

Table OA6.2: **Leveraged ETF Rebalancing After Intraday Jumps – Market Cap Effects**
The table reports the results to regressing intraday jump returns on returns in the subsequent 30-minute interval for large and small stocks in our sample. For leverage ETF rebalancing, we identify jumps in the benchmark of the leverage ETF. To detect jumps, we compare each non-overlapping 30-minute return with returns of the same interval over the last year. If the return is higher (lower) than the 97.5% (2.5%) percentile, we regard the return as a jump. Next, we record the return from yesterday's close until the end of the 30-minute interval, where the jump has occurred ($r_t^{\text{incl. jump}}$). We collect also the return of the subsequent 30-minute interval (r_t^{next}) on the stock-level. In case of leveraged ETFs, we select all stocks in leveraged ETFs for which a jump in the benchmark index of the leverage ETF has occurred. Finally, we disregard jumps which have occurred after a certain time (given in row "Jumps Until"). Equipped with $r_t^{\text{incl. jump}}$, r_t^{next}, and the intraday return of the benchmark index, we reconstruct Ω_t^{LETF} for each affected stock j. Subsequently, we run Equation (12). The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}	r_t^{next}
Ω_t^{LETF}	-0.612	-0.707**	-0.592*	-0.304	-0.430	-0.502
	(-1.618)	(-2.075)	(-1.793)	(-0.843)	(-1.198)	(-1.428)
$r_t^{\text{incl. jump}}$	-0.280	-0.226	-0.248	-0.772**	-0.640**	-0.637**
	(-1.076)	(-1.134)	(-1.366)	(-2.052)	(-2.234)	(-2.446)
Observations	232,351	337,343	376,041	267,685	378,955	419,296
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Jumps Until	12:00	14:00	15:00	12:00	14:00	15:00
Market Cap	Small	Small	Small	Large	Large	Large

Table OA6.3: **End-of-day Delta-Hedging on Identified Jump Days – Market Cap Effects** The table reports the results to regressing intraday jump returns on returns in the subsequent 30-minute interval. For delta-hedging, we identify jumps in the underlying stock returns. For leverage ETF rebalancing, we identify jumps in the benchmark of the leverage ETF. To detect jumps, we compare each non-overlapping 30-minute return with returns of the same interval over the last year. If the return is higher (lower) than the 97.5% (2.5%) percentile, we regard the return as a jump. Next, we record the return from yesterday's close until the end of the 30-minute interval, where the jump has occurred ($r_t^{\text{incl. jump}}$). We collect also the return of the subsequent 30-minute interval (r_t^{next}) on the stock-level. In case of leveraged ETFs, we select all stocks in leveraged ETFs for which a jump in the benchmark index of the leverage ETF has occurred. Finally, we disregard jumps which have occurred after a certain time (given in row "Jumps Until"). Equipped with $r_t^{\text{incl. jump}}$, r_t^{next}, and the intraday return of the benchmark index, we reconstruct Γ_t^{HP} and Ω_t^{LETF} for each affected stock j. Subsequently, we run Equation (10) and Equation (12). The sample period is January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}	r_t^{end}
Γ_t^{HP}	-75.978**	-48.187	-51.226	-27.275	-38.879*	-42.076**
	(-2.121)	(-1.398)	(-1.498)	(-1.182)	(-1.740)	(-1.985)
$r^{\text{after jump}}$	-0.104	-0.230	-0.250	-1.001***	-0.983***	-1.015***
	(-0.440)	(-1.121)	(-1.259)	(-3.748)	(-3.765)	(-3.955)
Observations	173,131	287,164	331,109	166,421	272,356	314,137
Entity FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]	[t;j]
Jumps Until	12:00	14:00	15:00	12:00	14:00	15:00
Market Cap	Small	Small	Small	Large	Large	Large

Appendix OA7. Trading Strategy for Single Data Sets

Table OA7.1: Γ^{HP} **and** Ω^{LETF} **Trading Strategies on their respective Data Samples**
The table reports the economic value of timing the last half-hour market return using either Γ^{HP} or Ω^{LETF}. The Γ^{HP}-strategy, denoted by LmH^{Γ}, takes a long position in stock j when the stock's Γ_j^{HP} is in the upper decile and a short position when it is in the lower decile. The Ω^{LETF}-strategy, denoted by HmL^{Ω}, takes a short position in stock j when the stock's Ω_j^{LETF} is in the upper decile and a long position when it is in the lower decile. $\text{Market}^{\text{end}}$ denotes investing in all stocks from 15:30 to 16:00. We consider equally weighted (EW) and value weighted (VW) portfolios for all strategies, including $\text{Market}^{\text{end}}$. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (Sharpe), skewness, kurtosis, and success rate (Success). The returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample periods are 2005–2020 and 2012–2019 for the Γ^{HP}-strategy and Ω^{LETF}-strategy, respectively.

	Avg ret	Std dev	Sharpe	Skewness	Kurtosis	Success
Panel A: LmH^{Γ} (Equally Weighted)						
LmH^{Γ}	6.23***	1.97	3.16	1.57	28.98	58.84
$\text{Market}^{\text{end}}$	2.84**	6.09	0.47	0.55	24.37	53.22
Panel B: LmH^{Γ} (Value Weighted)						
LmH^{Γ}	5.94***	2.21	2.68	0.81	19.74	59.76
$\text{Market}^{\text{end}}$	0.45	5.89	0.08	0.32	28.75	51.29
Panel C: HmL^{Ω} (Equally Weighted)						
HmL^{Ω}	18.88***	3.23	5.85	-0.14	7.69	67.72
$\text{Market}^{\text{end}}$	0.92	3.38	0.27	-0.41	5.39	53.49
Panel D: HmL^{Ω} (Value Weighted)						
HmL^{Ω}	11.01***	2.72	4.05	-0.18	9.81	61.15
$\text{Market}^{\text{end}}$	-1.08	3.24	-0.33	-0.95	11.84	51.97

Appendix OA8. Risk-adjusted Trading Strategy Returns

Table OA8.1: **Risk-adjusted Returns for Γ^{HP} and Ω^{LETF} Trading Strategies on their respective Data Samples**
The table reports the estimation results from regressing returns of strategies timing the last half-hour based on Γ^{HP} and Ω^{LETF} on the returns of all stocks from 15:30 to 16:00 (Market$^{\text{end}}$), the equity market excess return (MKT), size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), momentum (MOM), and an intermediary capital asset pricing factor (IC, proposed by He et al., 2017). The Γ^{HP}-strategy, LmH$^{\Gamma}$, takes a long (short) position in a stock when the stock's Γ^{HP} is in the lowest (highest) decile. The Ω^{LETF}-strategy, HmL$^{\Omega}$, takes a long (short) position in a stock when the stock's Ω^{LETF} is in the highest (lowest) decile. We consider equally weighted (EW) and value weighted (VW) portfolios. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample periods are 2005–2020 and 2012–2019 for the Γ^{HP}-strategy and Ω^{LETF}-strategy, respectively.

	Intercept	Market$^{\text{end}}$	MKT	SMB	HML	RMW	CMA	MOM	IC	R2	R2 adj
Panel A: LmH$^{\Gamma}$ (Equally Weighted)											
LmH$^{\Gamma}$	6.19	0.01								0.20%	0.17%
	(9.54***)	(1.24)									
	6.30		0.33	-1.40	3.23	3.49	-0.25	1.37	0.19	0.49%	0.29%
	(9.14***)		(0.35)	(-0.86)	(1.18)	(1.76*)	(-0.07)	(1.47)	(0.22)		
Panel B: LmH$^{\Gamma}$ (Value Weighted)											
LmH$^{\Gamma}$	5.94	-0.00								0.01%	-0.02%
	(9.18***)	(-0.15)									
	5.91		1.62	-0.42	0.82	2.46	0.16	1.76	-1.09	0.59%	0.39%
	(8.65***)		(0.72)	(-0.21)	(0.30)	(1.14)	(0.04)	(1.69*)	(-0.78)		
Panel C: HmL$^{\Omega}$ (Equally Weighted)											
HmL$^{\Omega}$	18.91	-0.03								0.09%	0.04%
	(11.34***)	(-0.66)									
	20.13		-5.44	1.50	-0.83	3.56	-2.14	-1.25	2.62	0.48%	0.05%
	(11.56***)		(-1.87*)	(0.41)	(-0.19)	(0.82)	(-0.34)	(-0.63)	(1.19)		
Panel D: HmL$^{\Omega}$ (Value Weighted)											
HmL$^{\Omega}$	11.01	-0.00								0.00%	-0.05%
	(8.17***)	(-0.04)									
	12.34		-1.92	3.19	-0.16	-0.29	0.71	-2.43	1.14	0.40%	-0.02%
	(8.51***)		(-0.79)	(1.11)	(-0.05)	(-0.07)	(0.13)	(-1.38)	(0.60)		

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