Liquidity Provision to Leveraged ETFs and Equity Options Rebalancing Flows

Evidence from End-of-Day Stock Prices*

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Abstract

Rebalancing of leveraged ETFs and delta-hedging of equity options are two distinct and economically significant sources of order flow and liquidity demands. We show that they induce significant end-of-day momentum and mean-reversion in stock returns, while the effects dissipate within the next trading day. While gamma effects are persistent throughout our sample, those stemming from leveraged ETFs are decreasing significantly over time. We argue that these dynamics arise from different intermediation structures, generating heterogeneous levels of information asymmetry on rebalancing flows. While leveraged ETF providers generate perfectly predictable flows because of their strict mandate, option delta-hedgers have flexibility in deciding the strategic timing of their rebalancing, resulting in less predictable flows. Consistent with this view, we find that leveraged ETF flows attract more liquidity provision and that their effect on prices is shorter-lived. Our findings suggest that information disclosure is beneficial for market liquidity.

JEL classification: G12, G13, G14, G23

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1. Introduction

The role of options markets and leveraged ETFs on the dynamics of the underlying stock prices has recently received significant attention, attracting negative press coverage for potentially contributing to market volatility during already turbulent times. 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[1]

In this paper, we investigate the effects of portfolio rebalancing on the intraday dynamics of stock prices at the end of the trading day, arising from two distinct derivative instruments.

The first channel relates to the options market, where market makers and broker/dealers provide liquidity to clients who want to take positions in stock options. As they have institutional incentives to avoid directional exposures, they typically 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 resulting flows depends on their initial gamma imbalance and the price movement of the underlying asset. Suppose, for instance, that the price of a stock experiences a positive jump, driven by positive unexpected news about future cash flows. If the aggregate gamma of market makers is initially negative, maintaining delta-neutrality requires the purchase of additional shares in the underlying stock. On the contrary, a positive gamma exposure requires selling the underlying asset. Thus, if the aggregate gamma of market makers is significantly negative, delta-hedging can give rise to significant net buying, contributing to end-of-day momentum. Symmetrically, if the aggregate gamma imbalance of market makers were positive, delta-hedging would have a stabilizing effect in the form of an end-of-day reversal.[2]

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

[2] Derivative markets are by construction in zero net demand since 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, some market participants are likely not involved in delta-hedging – think of retail investors or mutual funds – because of different incentives. This implies that the flows arising by delta-hedging activity may not be trivial.

The second channel relates to leveraged ETFs, that is, synthetic instruments that rely on total return swaps, and whose notional principal is a multiple of the value of a referenced index. Different from a standard ETF, a price appreciation of the underlying index has the compounded effect of increasing both the referenced portfolio and the required notional value of the swap. As a consequence, any price change gives rise to an imbalance between the required and effective notional amount of the swap. The swap counterparty has to manage her risk exposure, 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) argue that the portfolio rebalancing of leveraged ETFs may have an impact on intraday prices.

Figure 1 illustrates the rebalancing effects caused by delta-hedgers and leveraged ETFs towards the end of the trading day. The upper panel shows the intraday return path for Tesla's 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. Indeed, 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 shares are an important constituent for leveraged ETFs. At the same time, the aggregate gamma of delta-hedgers was close to zero at the beginning of the trading day. By 15:30, Apple shares had dropped by -2.24%. As a consequence, leveraged ETF swap counterparties had to sell large quantities of Apple shares to rebalance their portfolios for an estimated amount equal to 8.85% of the average trading volume in Apple shares. Possibly as a result, the price dropped further by -1.22%.

The timing of option delta-hedging and portfolio rebalancing by leveraged ETFs can be different. Figure 1 (bottom panel) illustrates the potential effect of this heterogeneity on the price dynamics. On 23 June 2016, the gamma imbalance of delta-hedgers on Amazon stock options was large and positive. At the market opening, the price dropped by almost 4%. The implied hedging demand by delta-hedgers required purchasing shares for approximately 50% of the average dollar volume in the last half trading hour in Amazon shares. Consistently, the share price started to mean revert at 15:30, albeit not completely. Leveraged ETF swap counterparties had to rebalance, which caused further

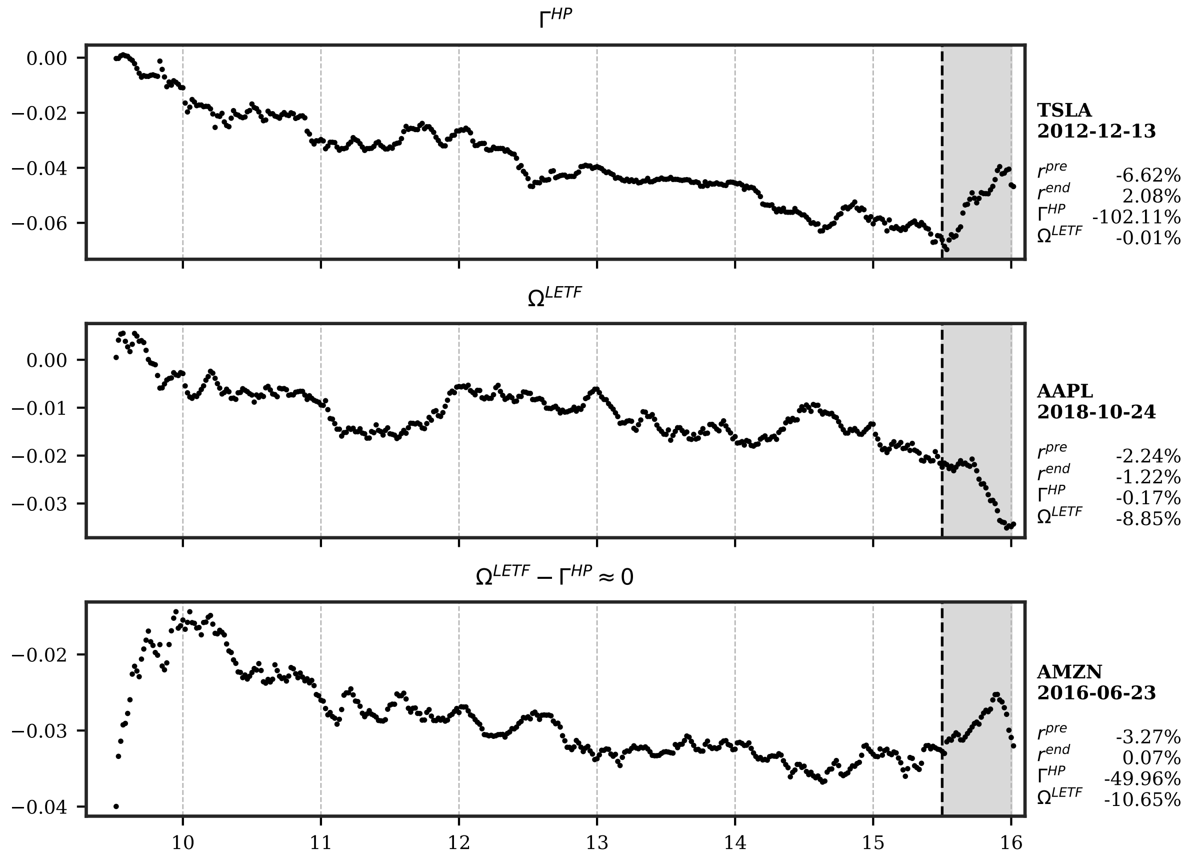

Fig. 1. **Delta-Hedging and Leveraged ETF Rebalancing Effects**
The figure depicts the effects of delta-hedging and leveraged ETF rebalancing on three days in our sample for Tesla (TSLA), Apple (AAPL), and Amazon (AMZN) stock, respectively. r^{pre} denotes the return from the previous day's close price 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 month.

downward pressure as it emerged shortly before the market closing.

We start our analysis by testing whether the above-described price effects have empirical support. To do so, we build a novel dataset merging data from several options exchanges, including 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 delta-hedgers and the rebalancing demand of leveraged ETFs, we merge with

NYSE TAQ data to get intraday prices of equity stocks. To the best of our knowledge, this is is the most comprehensive dataset covering options and leveraged ETFs – both in the cross-section and in the time series. Confirming previous findings from the literature (Tuzun, 2014; Shim and Todorov, 2021; Baltussen, Da, Lammers, and Martens, 2021; Ni, Pearson, Poteshman, and White, 2020), we find that both sources of mechanical flows are significantly related to stock returns in the last 30 minutes of the trading day. A standard-deviation increase in Γ depresses end-of-day returns by -113% of the average return in the last thirty minutes of a trading day, while a 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, the impact of both rebalancing sources is amplified when controlling for the magnitude of the other.

These results are robust to a battery of control variables suggested in the literature, such as the trading volume in the option relative to the equity market (Roll, Schwartz, and Subrahmanyam, 2010), the put/call ratio (Blau, Nguyen, and Whitby, 2014), implied volatility, the riskiness of the underlying stock, and the release of fundamental news.

Next, we turn our attention to the institutional differences between the two channels and their implications. On the one hand, leveraged ETFs are subject to a strict mandate, which requires replicating the underlying index returns at the close multiplied by a leverage factor on a daily basis. This forces leveraged ETF providers to rebalance only a few minutes before the end of the trading day, with little room for discretion. On the other hand, option delta-hedgers enjoy some degree of flexibility with regards to the timing of their rebalancing strategy. Moreover, while leveraged ETF holdings are fully disclosed and constant over a single trading day, the intraday inventory of delta-hedgers potentially changes and is not readily available. These different sets of rules and incentives may generate a heterogeneous degree of information asymmetry regarding flows for the two channels.

An important empirical contribution of our analysis, therefore, relates to the consequences of disclosing order flow information. By exploiting the institutional differences of the two channels, we shed light on the relationship between order flow disclosure and market quality. First, do the transparency of leveraged ETFs and the predictability of their flows lead to enhanced liquidity provision or does it attract predatory trading? How does this affect the speed of reversal of stock prices after the liquidity shocks? Second, how do the effects of the two sources of mechanical order flow evolve over time? Do liquidity providers improve their ability to accommodate shocks over time? And does such a learning process depend on the availability of information on flows?

We begin by investigating how quickly option delta-hedgers 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 almost exclusively at the end-of-day. We note that these results can explain why the regression coefficient on leveraged ETFs flow is almost four times larger than its options-based counterpart. Leveraging on a numerical simulation, we show that the wedge may result from the measurement errors on our proxy for gamma imbalance – arising from the discretion of the rebalancing strategy of delta-hedgers.

Next, we show that the price effects of both channels are on average fully reversed, but with heterogeneous speed. While leveraged ETF-induced price pressure evaporates at the next-day opening, that arising from delta-hedging is significantly longer-lived and requires almost a full trading day to be reversed. We also find that for leveraged ETFs the price impact coefficient is lower for larger flows, while it does not change significantly for gamma-related flows. As in Brøgger (2021), we interpret these findings as evidence of enhanced liquidity provision for the more predictable leveraged ETF-based flows.

Finally, we exploit the length of our sample to analyze the time-series evolution and persistence of the two channels, using rolling-window regressions. The findings clearly indicate that the magnitude of the price effects stemming from leveraged ETFs is declining over time, being barely statistically significant in the last part of the sample. On the contrary, the importance of gamma-induced price effects is persistent throughout the sample and, if anything, has been increasing over time. The high and increasing fragmentation of the U.S. options market potentially causes the difference in the statistical performance over time, as it hinders market participants from constructing a precise measure of the true inventory positions of delta-hedgers.

Overall, these results suggest that liquidity providers can better identify shocks coming from leveraged ETFs, thus incrementally limiting their impact on asset prices over time. On the contrary, the price effects due to gamma imbalances and delta-hedging of options exposures persist throughout the sample, suggesting that liquidity provision is impeded by information asymmetry.

Related Literature

Our work relates to several streams of the literature. The first concerns the role of order flow information disclosure in microstructure dynamics (Madhavan, 2000). A number of theoretical works suggest that transparency is positively associated with market quality. Forster and George (1992) and Benveniste, Marcus, and Wilhelm (1992) model the effects of anonymity in financial markets and show that spreads and price impact are lower when dealers are partially informed about the direction of liquidity trades. Admati and Pfleiderer (1991) propose a model of sunshine trading, showing that liquidity traders who can pre-announce their order flow enjoy better liquidity provision but increase adverse selection costs for others who cannot. Other models, however, argue in favor of opaqueness. For instance, Madhavan (1995) provides a theoretical setting featuring market segmentation where large institutional investors benefit from non-disclosure of their liquidity trades. The empirical evidence on the subject has not yet settled the issue. Porter and Weaver (1998) study the effects of increased transparency on the Toronto Stock Exchange, concluding that spreads widen after an increase in transparency. Gemmill (1996), analyzes the consequences of an increase in post-trade transparency on the London Stock Exchange, finding no significant impact on market liquidity. By exploiting the heterogeneous impact of two sources of mechanical intraday rebalancing, our results shed new light on the issue, providing evidence that order flow transparency leads to better liquidity provision. We argue that, as the institutional mandate of leveraged ETFs forces them to act under full transparency, they collectively enjoy a positive equilibrium with lower spreads during their rebalancing operations. Conversely, the freedom of options delta-hedgers to partially control their rebalancing strategy generates a less desirable equilibrium with higher transaction costs and reduced price efficiency.

The second stream studies the feedback effects of options trading on the underlying stock price dynamics. The literature generally distinguishes between two channels through which options 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.[3] 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

[3]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).

stock volatility and Γ-imbalance.[4] 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 et al. (2021) 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 the inventory of option market makers. Gârleanu, Pedersen, and Poteshman (2009) have provided path-breaking 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 behind the use of S&P 500 index options and conclude that unspanned crash risk drives much of their demand. Relatedly, 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 part of the literature studies intraday return patterns. We find high-frequency return continuation in the cross-section of stock returns, consistent with the evidence provided by Gao, Han, Zhengzi Li, and Zhou (2018) and Baltussen et al. (2021). 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

[4]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).

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 a 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 stream 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 outsized returns.

2. Data and Measurements

To conduct our empirical analysis we source data from several databases, including information for single stocks, 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 to study their potential impact on stock prices.

2.1. Data Sources

Options Market. 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.

Each of the five exchanges provides four categories of volume for each option series: open buy, open sell, close buy, and close sell. Each category is further broken down into different types of market participants: *broker/dealer*, *proprietary*, and *customer*.[5] 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. We also gather daily bid and ask quotes, implied volatility, trading volume, open interest, and Greeks for each option contract 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 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.

Table OA3.1 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 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 Market. 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 codes 10 and 11, and exchange codes 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

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

trade prices with CRSP to obtain PERMNOs as unique identifiers. More details are given in Online Appendix OA1. 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.

To summarize, our sample across optionable stocks and leveraged ETFs comprises 1,882,332 stock-day observations from January 2012 through December 2019.[6]

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 option market 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 $Volume_{o,t}^{CloseSell,I}$

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

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 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 yields 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.[7] 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 $Mult_o = 100$).[8]

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. 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

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

[8] 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.

us to obtain a timely proxy for the potential price impact of hedging adjustments.

$\Gamma^{IB}_{j,t}$ 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 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}.

2.3. Measuring Leveraged ETF 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 $S_{t+1} = L \times A_{t+1} = L \times A_t \times (1 + L \times r^{bench}_{t+1})$. However, the actual exposure of the total return swaps at $t+1$ is $E_{t+1} = S_t \times (1 + r^{bench}_{t+1}) = L \times A_t \times (1 + r^{bench}_{t+1})$. The difference between the required and the actual notional is the rebalancing amount, equal to $S_{t+1} - E_{t+1} = L \times (L-1) \times A_t \times r^{bench}_{t+1}$. 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.[9] 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

[9] 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.

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 $r^{\text{pre}}_{i,t;bench}$ 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:

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

We scale by the average dollar volume in the last half hour ($\text{ADV}^{\text{end}}_{t-1}$) to compare the impact of rebalancing with the average amount of trading at the end of the trading day.

2.4. Summary Statistics

In this section, we provide summary statistics for the gamma hedging pressure and leveraged ETF rebalancing quantity.

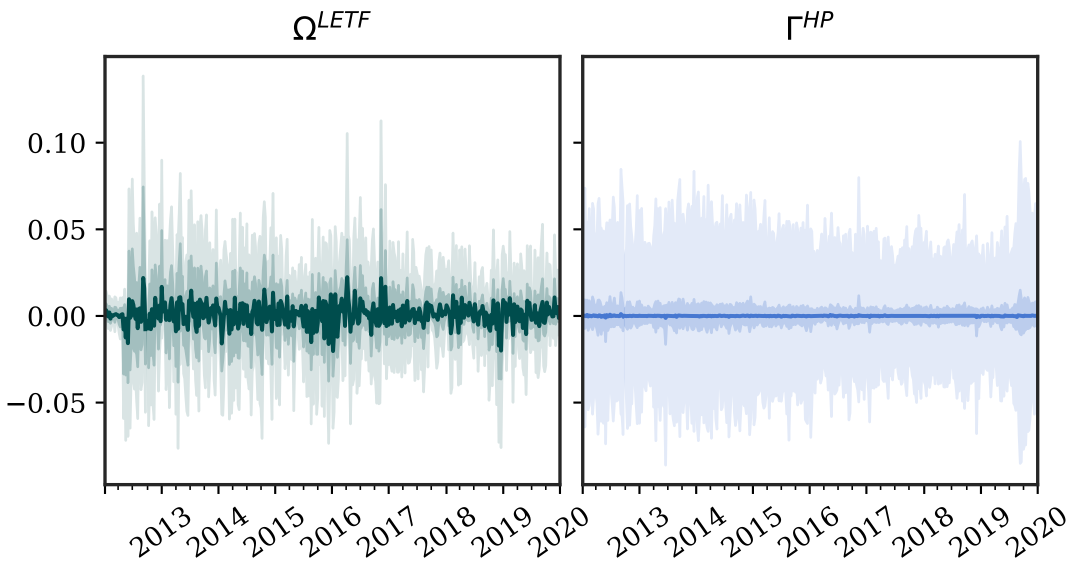

Fig. 2. **Time Series Cross-sectional Distribution of Ω^{LETF} and Γ^{HP}**
This figure shows weekly averages of the cross-sectional distribution of the demand pressure from the rebalancing of leveraged ETFs (Ω^{LETF}) and Gamma imbalance (Γ^{HP}). The dark line represents the cross-sectional median, the dark-colored area the 25th/75th percentile, and the light-colored area the 5th/95th percentile.

Figure 2 shows the cross-sectional distribution of Ω^{LETF} over time and compares it with the distribution of Γ^{HP}. While both are time-varying, the distribution of Γ^{HP} is wider, with a larger interquartile range, suggesting that on the same day delta-hedgers can have a large negative gamma imbalance on some stocks and, at the same time, a large positive gamma imbalance on another stock. Table A1 in the Appendix provides more granular summary statistics on Γ^{HP} and Ω^{LETF}. Table A1 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: **The Cross-Section of Demand Pressure from Gamma and Leveraged ETF 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

Table 1 documents the economic significance of the demand pressure arising from the rebalancing activity of the leveraged ETFs and the delta hedging activity 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 of the average dollar volume in the last 30 minutes of the trading day (ADV^{end}), depicted in the first column. 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 end-of-day 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 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 dominates for large total rebalancing flows.

2.5. Abnormal Order Flow

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

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

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

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

where m denotes the minutes within the hedging window for target day t.[10]

3. Empirical Results

3.1. Main Results

Consider the case in which $\Gamma_{j,t}^{IB}$ 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, leading to additional momentum. Instead, for a positive $\Gamma_{j,t}^{IB}$, the delta-hedgers have to buy the underlying stock, trading against its previous price change, which gives rise to intraday reversals. Following Equation (6), rebalancing of the swap portfolios replicating the exposure of leveraged ETFs will always be in the same direction as the previous movement of the benchmark ETF, potentially leading to momentum for a large number of stocks. Another important difference between the two rebalancing sources is in the cross-section. Since Γ^{HP} can greatly differ across stocks even on the same day t, the effect is inherently stock-specific. For Ω^{LETF} in contrast, all stocks that belong to

[10]We scale by $\text{ADV}_{t-1}^{\text{end}}$ to make the signed volume comparable across stocks and over time.

the same benchmark index are exposed to the same price pressure, proportional to their weighting in the index.

In Table 2, we investigate the impact of the rebalancing activity of delta-hedgers and leveraged ETF swap counterparties on the order-flow and returns of individual stocks in the last half hour before the close. To do so, we employ two types of panel regressions:

$$\text{RSVOL}_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Gamma_{j,t}^{HP} + \beta_2 \Omega_{j,t}^{LETF} + FE_j + FE_t + \epsilon_{j,t}, \tag{9}$$

$$r_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Gamma_{j,t}^{HP} + \beta_2 \Omega_{j,t}^{LETF} + FE_j + FE_t + \epsilon_{j,t}. \tag{10}$$

including asset (FE_j) and date fixed effects (FE_t).[11] Standard errors are double-clustered by day and asset, and return observations weighted by the stock's market capitalization in the previous month to rule out that our results are driven by microstructure issues in small stocks.

Table 2: **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 option hedging pressure Γ^{HP} and leveraged ETF rebalancing quantity Ω^{LETF} following Equation (9). 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)	(5)
Dependent	$\text{RSVOL}_t^{\text{end}}$	r_t^{end}	$\text{RSVOL}_t^{\text{end}}$	r_t^{end}	r_t^{end}
Γ_t^{HP}	-9.438**	-9.464***			-10.960***
	(-2.116)	(-4.709)			(-5.521)
Ω_t^{LETF}			109.572***	43.394***	46.738***
			(5.450)	(4.797)	(5.198)
r_t^{pre}	-1.263***	-0.757***	-1.512***	-0.902***	-0.820***
	(-5.111)	(-6.907)	(-5.640)	(-8.139)	(-7.452)
Observations	1,882,332	1,882,332	1,882,332	1,882,332	1,882,332
R^2 (%)	0.141	0.284	0.234	0.325	0.370
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]

[11]In Appendix C, we add control variables $\boldsymbol{X}_{j,t}$ to Equation (9) to rule out that neither informational channels nor risk-based explanations are driving our results.

Gamma Hedging Pressure Column (1) shows that Γ^{HP} negatively impacts $\text{RSVOL}_t^{\text{end}}$ with a coefficient of -9.44 (t-value: -2.12), which establishes a significant link between the gamma-induced trading activity of delta-hedgers and end-of-day order flow. At the same time, this additional directed volume has a direct impact on end-of-day returns (column 2). Specifically, the slope coefficient of Γ^{HP} is negative and highly significant at -9.46 (t-value: -4.71), suggesting that a negative shock to Γ^{HP} (additional buying pressure) amplifies end-of-day returns. We furthermore control for the impact of other momentum-based intraday effects by including the previous return from last day's close to the start of the supposed hedging window at 15:30. While the estimated slope coefficient is negative and significant, its inclusion does not materially change the estimated impact of Γ^{HP} on end-of-day returns.

In Online Appendix OA7, we mitigate concerns that investors might trade options based on past information which is correlated with future intraday returns. Our results remain quantitatively and qualitatively the same when replacing Γ^{HP} with an estimate based on older option inventories of delta-hedgers following Ni et al. (2020).

Leveraged ETFs If the rebalancing pressure from leveraged ETFs is sufficiently large, we should find that it positively relates to end-of-day order flow, as well as returns. Column (3) shows how a positive shock to Ω^{LETF} clearly leads to additional buying pressure at the close. The slope coefficient is estimated at 109.57 and is highly significant (t-value: 5.45). The ensuing buying pressure also translates to higher end-of-day returns with a coefficient of 43.40 (t-value: 4.80), as shown in column (4).

Joint Rebalancing 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 expected selling from leveraged ETFs, she may have revised her prediction.

In column (5) of Table 2 we estimate a model accounting for the two channels jointly, resulting in increases of both coefficients in absolute magnitude to -10.96 for Γ^{HP} and 47.74 for Ω^{LETF}, both of which are significant at the 1%-level. A one standard deviation decrease in Γ^{HP} is associated with a 113% increase in the magnitude of end-of-day returns relative to the stock-level mean return during that period, while a standard deviation increase in Ω^{LETF} corresponds to an increase of 430%.

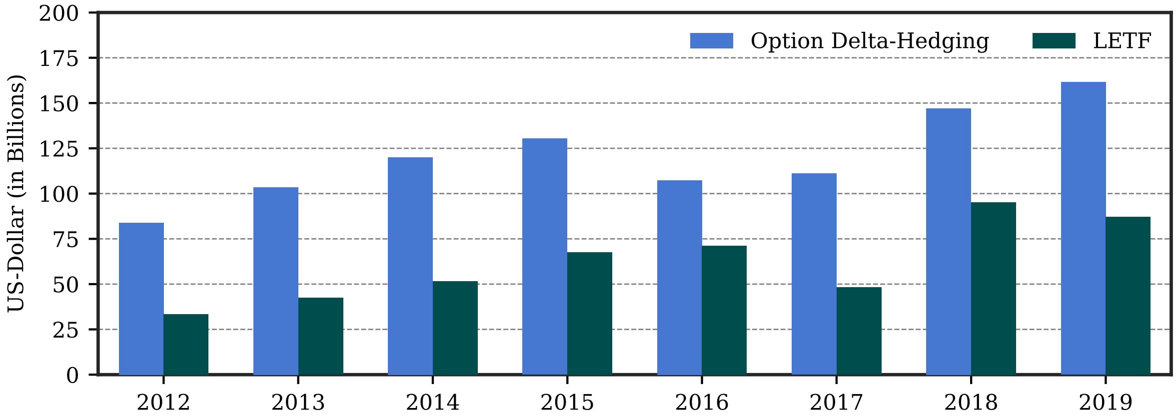

Fig. 3. **Year-by-Year Rebalancing Flows**
The figure shows the estimated overall absolute rebalancing flows from leveraged ETFs and option delta-hedging for each year in the sample in billion USD.

We find that a shock to the buying pressure coming from leveraged ETF rebalancing flows is estimated to impact end-of-day returns of a target stock two to four times as much as a similarly-sized shock from option delta-hedgers. But how do the estimated rebalancing amounts stack up when considered across all stocks in the universe of optionable stocks, which are also included in leveraged ETFs? Figure 3 shows the absolute year-by-year rebalancing amount in billion USD, summed across the entire cross-section of stocks in our sample. For each year, the total amount that would have to be traded in the underlying stocks to assure delta-neutrality exceeds that required by leveraged ETF counterparties. In fact, in most years the total rebalancing flows from delta-hedgers are at least twice as large. We find that the total trading amount for both rebalancing sources has increased over time, from approximately 80 billion USD in 2012 for Γ^{HP} to 160 billion USD in 2019 – a twofold increase. This growth has two reasons: first, the general growth in options trading. Second, the staggered introduction of weekly options on single equities, which, due to their short lifespan and corresponding large gamma values, have a large impact on the overall gamma position of delta-hedgers, potentially prompting larger rebalancing trading. The total amount of rebalancing from leveraged ETFs has increased even more dramatically, starting at 35 billion USD in 2012 and growing to 85 billion USD in 2019, which mimics the rapid growth of the industry.

Information Quality of Rebalancing Proxies Why do gamma hedging flows have a seemingly smaller impact on end-of-day order flow and returns, despite being larger in terms of USD traded? It is well known that noise in the explanatory variable biases regression estimates towards zero, which potentially explains the seemingly smaller one-to-one impact of gamma rebalancing. In this section, we investigate the role of uncertainty attached to acquiring the information necessary to determine the amount of rebalancing flows from option delta-hedgers. As a counterpoint, consider the estimation of the rebalancing pressure from leveraged ETFs in Equation (6). To quantify Ω^{LETF} we need to know the leverage factor, the assets-under-management, the return on the benchmark ETF before hedging begins, and the weight of the target stock in the benchmark ETF. All of these inputs are readily observable. Furthermore, leveraged ETFs are mandated to provide a daily multiple exposure to the benchmark, forcing their swap counterparties to trade near the market close. Consequently, all necessary information to determine their rebalancing activity is observed with little uncertainty.

In contrast, the information used to quantify the total amount of rebalancing from delta-hedgers is more uncertain for a number of reasons: first, we only observe approximately 50-70% of the transacted volume in equity options. In fact, the fragmented exchange landscape of equity options trading contributes to the opacity of rebalancing flows. Only a fraction of exchanges reports on detailed volume data by type of market participant, while the remainder is invariably unobservable. Second, delta-hedgers are not explicitly required to rebalance at the close, but may do so at different times during the day, or even hold on to some directional risk overnight. Third, the inventory data provides only an end-of-day snapshot of the delta-hedgers portfolio, which disregards intraday changes in the gamma imbalance.

To understand the impact of information uncertainty on the estimation of how Γ^{HP} influences end-of-day returns, we resort to a simulation study, outlined in detail in Appendix B. Figure 4 shows the results for two levels of $\pi \in [10\%, 50\%]$, which denotes the probability that delta-hedgers rebalance at a different time than between 15:30 and 16:00. We also vary the amount of unobserved fluctuation $\sigma(\Delta)$ in the empirically observed gamma imbalance, relative to the fluctuation of the true value, which addresses the influence of intraday shifts in the delta-hedger's portfolio, as well as the unobserved portion of the total option inventory.

Given the evidence in Figure 3 that the cumulative amount of rebalancing is much larger for Γ^{HP} than it is for Ω^{LETF}, we set the true impact of Γ^{HP} on end-of-day returns to the empirical estimate for Ω^{LETF} of -41 as a conservative estimate in the simulation. This true value is shown by the green line. We also highlight our empirical estimate of around -11. The blue line denotes the average estimated coefficient for 1,000 simulations over 2,000 time steps, the blue-shaded area the 95% confidence bounds.

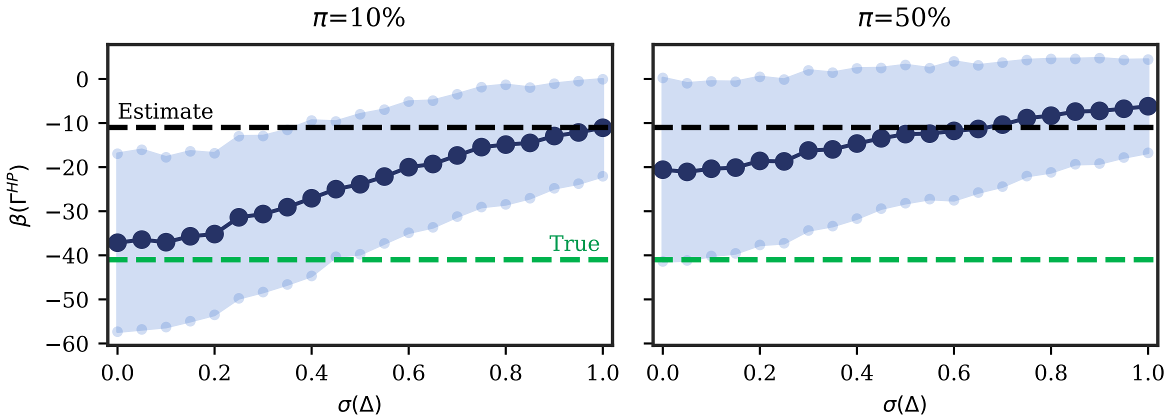

Fig. 4. **Simulating Error Sources in Γ^{HP}**
The figure shows the impact of unobserved fluctuation in the empirical gamma estimate $\sigma^{(}\Delta)$ and the probability with which option delta-hedgers may decide to rebalance their exposure at a different time than at the close, denoted as π. The setup of the simulation study is outlined in Appendix B. The green line shows the true slope coefficient of Γ^{HP} in the simulation, which we fix at -41, the black line highlights our empirical estimate from Table 2. The blue line denotes the average estimated coefficient for 1,000 simulations over 2,000 time steps, the blue-shaded area the 95% confidence bounds.

For a low level of $\pi = 10\%$ we find that we would require a very high level of $\sigma(\Delta)$, about as high as the fluctuation of its true value. If we increase the probability that delta-hedgers establish delta-neutrality of their positions at their own discretion and may deviate from the supposed hedging window at the close to 50%, we find average coefficients much closer to our empirical estimate of ≈ -11. In fact, an uncertainty level $\sigma(\Delta)$ of around 0.6 generates the empirically-observed impact of Γ^{HP} on end-of-day returns. In the following section, we empirically investigate the level of discretion of delta-hedgers, which can severely impede the estimation of its true impact as shown in the simulation.

3.2. Discretionary Rebalancing Times

Intraday jumps potentially present occasions where delta-hedgers are incentivized to deviate from end-of-day hedging. Consequently, we focus on the price effects of rebalancing activities following large price movements. 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 stock intervals where the returns exceed the top or bottom 2.5th percentile as jump events. 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 3 we separately report results for jump events occurring either before noon or between noon and 15:00.

As evident in column (1), we find large and significantly negative coefficients for jumps before noon in the case of Γ^{HP} (-44.42, t-value: -1.98). This suggests that option delta-hedgers rebalance their exposure shortly after particularly large price movements. We do not find any effect for jumps in the second part of the trading day. In stark contrast to these results, the impact for leveraged ETF rebalancing is insignificant and economically negligible at all times, regardless of whether we consider jumps before or after noon (columns (3) and (4)).

To further investigate how option delta-hedgers exploit the discretionary nature of their re-hedging needs, we focus on the gamma imbalance accumulated only after a jump event. For this, we assume the delta-hedger hedges her accrued exposure right after the jump, and hedges the remainder once more at the close. The remaining exposure consequently amounts to

$$\Gamma_{j,t}^{HP} = 100 \times \Gamma_{j,t-1}^{IB} \times r_{j,t}^{\text{after jump}}, \tag{11}$$

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

The results reported in columns (5) and (6) in Table 3 provide evidence of end-of-day rebalancing on identified jump-days only for jumps that happen after noon. In fact, the pattern of significance and the magnitude of coefficients inversely match the pattern for the impact of hedging directly after large price movements. Taken together, we conclude that delta-hedgers tend to rapidly rebalance after early jumps, but 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).

Although we find substantial evidence that end-of-day rebalancing by delta-hedgers impacts stock prices, the results presented here highlight the significant uncertainty regarding the timing of the rebalancing activity. As the simulation study shows, this uncertainty introduces errors in the empirical measurement of Γ^{HP}, which attenuates its estimated impact on end-of-day returns, driving coefficients towards zero.

Table 3: **Rebalancing Flows on Jump Days**
The table reports the results to regressing intraday jump returns on returns in the subsequent 30-minute interval. For Γ^{HP}, we identify jumps in the underlying stock returns. For Ω^{LETF}, 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. Jumps can take place before noon or after noon, but before 3pm. 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 (9). 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^{end}	r_t^{end}
Γ_t^{HP}	-44.416**	0.251			-34.546	-77.316***
	(-1.984)	(0.013)			(-1.575)	(-2.668)
Ω_t^{LETF}			-0.220	-0.493		
			(-0.686)	(-0.642)		
$r_t^{\text{incl. jump}}$	-0.952***	-1.288***	-0.711**	-0.266		
	(-4.240)	(-6.311)	(-2.083)	(-1.561)		
$r^{\text{after jump}}$					-0.825***	-1.176***
					(-3.678)	(-3.955)
Observations	339,552	305,694	500,036	293,872	339,552	305,694
R^2 (%)	0.160	0.199	0.057	0.029	0.101	0.112
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	Pre-Noon	After-Noon	Pre-Noon	After-Noon	Pre-Noon	After-Noon

3.3. Reversal

If the mechanical rebalancing activities of delta-hedgers and leveraged ETF swap counterparties move prices sufficiently far from fundamental values, we should observe a quick reversal of these effects at the next open as other market participants enter the market and correct these deviations. Consequently, 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 regression

$$r^{\text{night}}_{j,t} = \beta_0 r^{\text{end}}_{j,t} + \beta_1 \Gamma^{HP}_{j,t} + \beta_2 \Omega^{LETF}_{j,t} + FE_j + FE_t + \epsilon_{j,t}, \tag{12}$$

where $r^{\text{night}}_{j,t}$ is the return from the close of day t to 10:00 on day $t+1$.

Table 4: **Next-Day Reversal**
The table reports the results to regressing returns from closure of day t to 10:00 on day $t+1$ on returns until 15:30, r^{pre}, on option hedging pressure Γ^{HP} and leveraged ETF rebalancing quantity Ω^{LETF} following Equation (9). We also consider the return from 15:30 of day t to 10:00 on $t+1$, $r^{\text{end+night}}$, and the 24h return from day t's 15:30 to day $t+1$'s 15:30, $r^{\text{end+next pre}}$, as dependent variables. 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.

Dependent	(1) r^{night}_t	(2) r^{night}_t	(3) r^{night}_t	(4) $r^{\text{end+night}}$	(5) $r^{\text{end+next pre}}$
r^{pre}_t	0.951**	1.268***	1.057***	0.235	-0.626
	(2.444)	(3.126)	(2.737)	(0.585)	(-1.163)
Γ^{HP}_t	25.573***		28.118***	17.132*	13.316
	(3.208)		(3.427)	(1.844)	(1.551)
Ω^{LETF}_t		-70.943***	-79.521***	-32.584	-40.628
		(-3.382)	(-3.634)	(-1.515)	(-1.402)
Observations	1,882,234	1,882,234	1,882,234	1,882,234	1,879,754
R^2 (%)	0.030	0.028	0.040	0.007	0.006
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 4 highlights the relatively swift reversal of the impact of Γ^{HP} and Ω^{LETF}: the coefficient on Γ^{HP} in column (1) is positive at 25.57 (t-value: 3.28), while that on Ω^{LETF} in column (2) is negative at -70.95 (t-value: -3.38). In column (3), we include both rebalancing flows jointly and show a magnification of the proposed reversal effects for both.

In order to assess if the initial price impact is fully reverted over night, we substitute the overnight return in Equation (12) by the return from 15:30 of day t to 10:00 on $t+1$, $r^{\text{end+night}}$. A full reversal of the effect would render the impact of Γ^{HP} and Ω^{LETF} on $r^{\text{end+night}}$ insignificant. As column (4) in Table 4 shows, this is the case for Ω^{LETF}. However, the coefficient on Γ^{HP} is statistically significant at the 10% level, suggesting that rebalancing flows from delta-hedgers take more time to be fully reversed. Indeed, we observe a full reversal effect for the impact of gamma rebalancing when considering the return from t's 15:30 to $t+1$'s 15:30, $r^{\text{end+next pre}}$, as shown in column (5).

3.4. Liquidity Provision

How do market participants react when delta-hedgers or leveraged ETF swap counterparties have to trade particularly large quantities of a certain stock? Strategic traders could engage in predatory trading by amplifying the rebalancing activities from option delta-hedgers and leveraged ETF swap counterparties (Brunnermeier and Pedersen, 2005). Predators initially buy (sell) the underlying while rebalancing flows exert significant buying (selling) pressure and unwind their position as the rebalancing concludes. Contrarily, strategic traders may provide liquidity instead, which Admati and Pfleiderer (1991) term a *sunshine equilibrium.* In this scenario, the price impact of rebalancing flows is minimized.

To investigate how strategic traders react to large rebalancing flows, we augment Equation (9) with a dummy interaction for days when the rebalancing flow exceeds a certain percentile:

$$r_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \mathcal{F}_{j,t} + \beta_2 \mathcal{F}_{j,t} \times \text{L}_{j,t,x} + FE_j + FE_t + \epsilon_{j,t}, \tag{13}$$

where $\mathcal{F}$ is one of our two proxies for order flow, and $\text{L}_{j,t,x}$ is a dummy variable that is equal to 1 if the absolute magnitude of the respective rebalancing flow of stock j exceeds the xth cross-sectional percentile. We consider three thresholds for x, i.e, $x \in \{95, 97.5, 99\}$.

Columns (1) to (3) of Table 5 report the results for Γ^{HP}, whereas columns (4) to (6) do so for Ω^{LETF}. The estimated coefficients for the interaction terms are positive, but not statistically significant for Γ^{HP}, implying that we neither find evidence in favor of predatory trading nor in favor of a sunshine equilibrium. On the contrary, the estimated coefficients for Ω^{LETF} rebalancing flows are negative and highly significant for large flows that exceed the 95th percentile of Ω^{LETF}. We find a monotonic increase in β_2 in the threshold used to identify large leveraged ETF rebalancing flows. This pattern is consistent with a sunshine equilibrium in the spirit of Admati and Pfleiderer (1991), in which other market participants accommodate the liquidity needs by large rebalancing flows from leveraged ETFs.

Table D3 in the Appendix provides supporting evidence using the change in the bid-ask spread of individual stocks. A shock to the absolute value of Γ^{HP} prompts market

Table 5: **Liquidity Provision Around Large Rebalancing Flows**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30 on delta-hedging and leveraged ETF rebalancing flows including dummy variables for large rebalancing flows. $\mathrm{L}_{j,t,x}$ is a dummy variable that is equal to 1 if the size of the respective rebalancing flow of stock j exceeds the xth cross-sectional percentile of the absolute rebalancing flow. We consider three thresholds for x, i.e, $x \in \{95, 97.5, 99\}$. 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.

	(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}	-11.588***	-11.294***	-10.333***			
	(-3.407)	(-4.358)	(-4.114)			
$\Gamma_t^{HP} \times \mathrm{L}_{t,x}$	2.828	3.252	2.696			
	(1.081)	(1.373)	(0.855)			
Ω_t^{LETF}				57.027***	53.729***	49.683***
				(4.803)	(5.230)	(5.672)
$\Omega_t^{LETF} \times \mathrm{L}_{t,x}$				-22.267**	-26.226***	-30.561***
				(-2.327)	(-2.725)	(-3.111)
r_t^{pre}	-0.754***	-0.753***	-0.755***	-0.909***	-0.908***	-0.908***
	(-6.905)	(-6.902)	(-6.894)	(-8.212)	(-8.183)	(-8.187)
Observations	1,882,332	1,882,332	1,882,332	1,882,332	1,882,332	1,882,332
R^2 (%)	0.284	0.285	0.284	0.334	0.335	0.333
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]
xth perc.	95.0	97.5	99.0	95.0	97.5	99.0

makers in the underlying stock to increase the corresponding spreads in advance. In contrast, we find no such evidence for rebalancing flows from leveraged ETFs. Together with the results regarding large flows in Table 5, we find convincing evidence in favor of a better liquidity provision for the flows of leveraged ETF counterparties, driven by a greater transparency on their timing and of their magnitude. Conversely, market makers in the underlying stocks face the risk of adverse selection from the flows of option market makers due to their opaque nature and discretionary timing.

3.5. Trading Strategies

Next, we quantify the economic significance of these frictions by studying trading strategies that use Γ^{HP} and Ω^{LETF} as timing signals. First, we construct a long-short portfolio based on Γ^{HP}. On each trading 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 the strategy is active for only 30 minutes each day. In the 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 sort our stock sample according to their aggregate imbalance $\Omega^{LETF} - \Gamma^{HP}$ into decile portfolios and subsequently build a long-short strategy, denoted by $\text{HmL}^{\Gamma,\Omega}$.

Table 6: **Γ^{HP} and Ω^{LETF} Based Trading Strategies**
The table reports the economic value of timing the last half-hour market return using 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. Portfolios are value-weighted, including for $\text{Market}^{\text{end}}$. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (Sharpe), Sharpe ratio assuming an effective spread of 25% of the quoted bid-ask spread (Net 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	Net Sharpe	Skewness	Kurtosis	Success
LmH^{Γ}	5.20***	1.36	3.83	1.76	0.17	3.00	61.07
HmL^{Ω}	5.78***	2.31	2.51	0.05	0.13	3.54	56.29
$\text{HmL}^{\Gamma,\Omega}$	6.63***	1.54	4.29	1.77	0.27	2.80	62.70
$\text{Market}^{\text{end}}$	-1.39	3.26	-0.43	-0.43	-1.05	12.27	51.92

Table 6 reports summary statistics of the resulting strategies using value-weighted portfolios. LmH^{Γ} yields an average total excess return equal to 5.20% per year which are significant at the 1%-level. Although HmL^{Ω} yields a slightly higher average total excess return per year, 5.78%, LmH^{Γ} exhibits a higher Sharpe ratio (3.83 vs. 2.51). Similarly, we observe higher success ratios for LmH^{Γ} compared to HmL^{Ω} (61% vs. 56%).

The combination of the two signals Ω^{LETF} and Γ^{HP} reduces the noise and improves the success ratio with an increase in the average return to 6.62% per year, which is significant at the 1%-level. Consistent with this, the combined strategy exhibits the highest (gross) Sharpe ratio of 4.29 and a success rate of 62%. It is notable that the skewness of the three strategies are positive, compared to the negative skewness of the return on the market. [12]

Table 7: **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. Portfolios are value-weighted. 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
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$^{\Gamma,\Omega}$	6.66	0.02								0.2%	0.1%
	(10.24***)	(1.82*)									
	6.30		3.05	0.19	-0.38	-0.02	4.79	1.30	-0.02	1.10%	0.70%
	(8.70***)		(2.62***)	(0.12)	(-0.19)	(-0.01)	(1.55)	(1.14)	(-0.02)		

Because of the significant turnover ratio required in such a strategy, it is important to investigate the potential impact of transaction costs if an trader were to implement such a strategy. We assume an effective spread of 25% of the quoted bid-ask spread at 15:30 as a measure for transaction costs. As evident from Table 6, we find that the trading strategy based on Γ^{HP} continues to yield high risk-adjusted performance with a net Sharpe ratio of 1.76. On the other hand, the net Sharpe ratio for HmL$^{\Omega}$ is reduced to 0.05. The strategy that combines the two signals HmL$^{\Gamma,\Omega}$ generates the highest net

[12] 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%.

Sharpe ratio, which is equal to 1.77. This confirms that the economic frictions generated by these two channels jointly are indeed economically significant, although Γ^{HP} plays a greater role.

How much of these strategies' end-of-day returns are explained by exposure to well-established risk factors? Table 7 summarizes the results of regressing LmH^{Γ}, HmL^{Ω}, and $\text{HmL}^{\Gamma,\Omega}$ on the end-of-day market return ($\text{Market}^{\text{end}}$) and the full-day Fama-French five-factor model (Fama and French, 2015), augmented by a momentum as well as an intermediary capital asset pricing factor (He et al., 2017).[13] We find that neither the market nor the augmented five-factor model can explain the returns of LmH^{Γ}, HmL^{Ω}, and $\text{HmL}^{\Gamma,\Omega}$. The R^2 is small on average. The only factor that is statistically significant for the joint strategy is MKT, the other factors in the extended five-factor model are not significant. Notwithstanding the statistical importance of MKT, the alphas of these regressions are statistically significant and virtually unchanged and account for almost the entire average gross excess return.

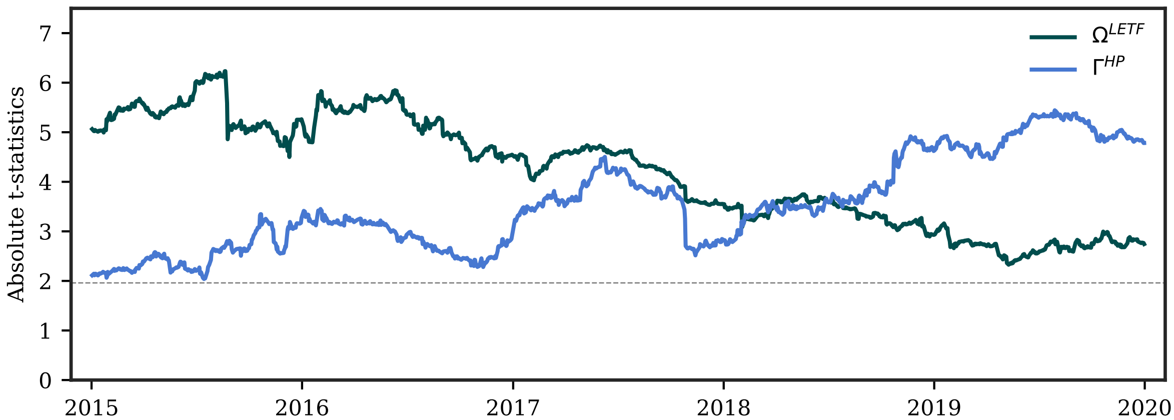

Fig. 5. **Rolling Regressions**
The figure shows the absolute t-statistics of estimated Γ^{HP} and Ω^{LETF} coefficients over time, as measured on a rolling basis for each three year-period starting in January 2012. Specifically, we estimate Equation (9) for the first three years in our sample, shift the starting and end date by one day and repeat this for all days in the sample (January 2012 – December 2019).

[13]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/`.

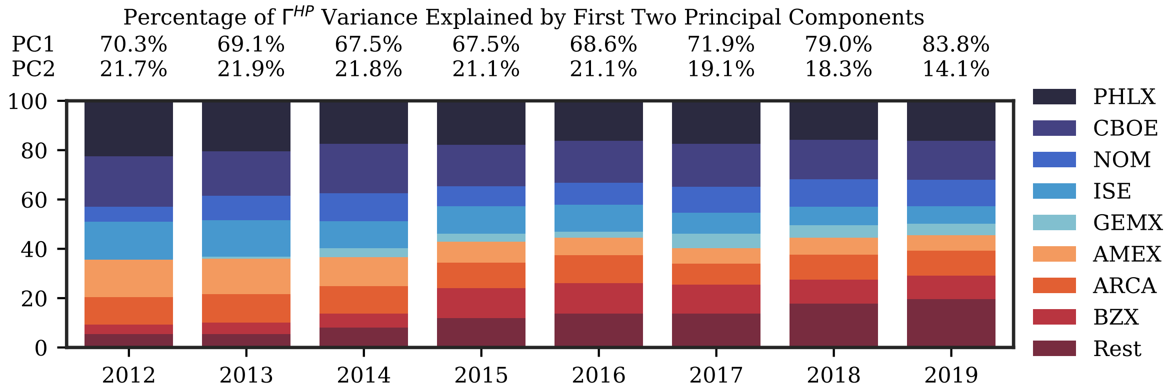

Fig. 6. **Market Share of Option Exchange Volume**
The figure shows the annual share of transacted volume in equity options on each U.S. options exchange. The market share is given for the five option exchanges in our sample (PHLX, CBOE, NOM, ISE, and GEMX), as well as the three largest exchanges among the remainder (AMEX, ARCA, and BZX). *Rest* combines volumes on exchanges BOX, BXO, C2, EDGX, EMLD, MERC, MIAX, and PEARL. The upper part of the figure shows the percentage of Γ^{HP} variance explained by the first two principal components across all option exchanges in our sample on a year-by-year basis. PC1 and PC2 denote the first and second principal component, respectively.

3.6. The Evolution of the Imbalance and its Price Impact

We investigate how the price impact of Γ^{HP} and Ω^{LETF} changed over time by running our baseline regression using a rolling window of three years. Figure 5 displays the absolute t-statistics of the coefficients for Γ^{HP} (blue line) and for Ω^{LETF} (green line). We find that the statistical significance of Γ^{HP} has stayed nearly unchanged until the end of 2016 and has since then further increased. On the other hand, the estimated significance for Ω^{LETF} has decreased over time. Figure E1 in Appendix E shows that the difference in statistical significance over time is also reflected in the performance of the timing strategies based on Γ^{HP} and Ω^{LETF}.

A probable reason for the difference in the statistical performance over time lies in the high fragmentation of the U.S. options market, which reduces the availability and quality of information about the inventory positions of delta-hedgers.[14] This limits the ability of arbitrageurs to construct a precise measure of the rebalancing demand of delta-hedgers. Figure 6 shows the year-by-year market share for the five exchanges in our sample, as well as the three largest remaining exchanges, measured by volume in 2019. The figure shows a trend towards higher dispersion of option volumes across exchanges. This was helped by the opening of new exchanges in recent years, which allows market makers to

[14]See Andersen, Archakov, Grund, Hautsch, Li, Nasekin, Nolte, Pham, Taylor, and Todorov (2021) for a current account on the history of the U.S. options market.

strategically hide information about their inventory positions. At the start of the sample, there were nine active option exchanges; since then, seven new exchanges have been opened (Andersen et al., 2021). These new exchanges represent about a fifth of the entire volume in equity options in 2019. Moreover, not all option venues provided information useful to approximate the inventory of delta-hedgers. For example, AMEX and ARCA, which correspond to roughly 30% of traded options volume at the start of our sample, started reporting a detailed breakdown of option volumes in March of 2022 (NYSE, 2022). The latter informational friction can be mitigated if option inventories of delta-hedgers are highly correlated across option exchanges. We run a principal component decomposition of the gamma imbalance across the option exchanges for which we observe the data. We find that the first principal component can explain between 67% and 84% of the total variance of the gamma imbalance. The second principal component explains between 14% and 22%, suggesting that information from multiple exchanges is indeed needed to obtain a precise proxy of the aggregate gamma imbalance. We also find that the average 3-year rolling correlations range from 30% to 80% and are decreasing for ISE and CBOE over time (see Figure OA4.1). These results suggest the presence of an informational friction that may explain why the abnormal excess returns earned by strategies based on Γ^{HP} have been large and persistent.

4. 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 basket-wide momentum effect, delta-hedging can either have a stabilizing effect in the form of end-of-day reversal, but may 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. This institutional flexibility translates into information asymmetry faced by liquidity providers, constituting a friction for liquidity provision. Consistent with the assumption that the impact of rebalancing is mechanical in nature, we also document that it is transitory, as the effects fully reverse during the next trading day. Such a reversal materializes in a shorter time frame for leveraged ETFs price pressure than for that induced by gamma imbalances.

We finally show that the effect of option market imbalances is persistent over the years, while that of leveraged ETFs is significantly decreasing, further suggesting a key role of information asymmetry as the main friction underlying their dynamics.

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

Table A1 provides detailed summary statistics on the main variables of interest in the main paper.

Table A1: **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$^{\text{end}}$ is given in million USD. RSVOL$^{\text{end}}$, Γ^{IB}, Γ^{HP}, Ω^{LETF} and their corresponding absolute values are given percentage. The sample period is from January 2012 to December 2019.

	Mean	Std	2.5%	10%	25%	50%	75%	90%	97.5%
r^{pre}	4.75	203.33	-379.68	-187.53	-81.11	4.67	89.38	194.47	394.41
r^{end}	0.02	35.56	-73.4	-38.44	-17.9	-0.53	17.21	38.98	77.24
r^{night}	4.16	167.3	-249.0	-117.38	-50.88	2.97	57.01	125.12	267.0
ADV$^{\text{end}}$	21.72	59.1	0.25	0.78	2.19	6.79	19.94	47.4	136.93
RSVOL$^{\text{end}}$	0.56	41.86	-86.08	-48.77	-23.39	0.49	24.45	50.03	87.63
Γ^{IB}	0.52	3.0	-3.96	-1.32	-0.26	0.08	0.93	2.91	6.99
$\|\Gamma^{IB}\|$	1.45	2.67	0.0	0.03	0.14	0.55	1.67	3.76	8.03
Γ^{HP}	0.04	3.27	-7.0	-2.25	-0.48	0.0	0.51	2.37	7.28
$\|\Gamma^{HP}\|$	1.61	2.86	0.0	0.02	0.1	0.48	1.75	4.51	10.38
Ω^{LETF}	0.15	1.79	-2.97	-1.72	-0.86	0.1	1.11	2.08	3.48
$\|\Omega^{LETF}\|$	1.65	1.75	0.03	0.16	0.42	1.03	2.37	3.92	6.25
$\Omega^{LETF} - \Gamma^{HP}$	0.11	3.81	-7.99	-3.29	-1.27	0.1	1.52	3.56	8.1
$\|\Omega^{LETF} - \Gamma^{HP}\|$	2.64	3.14	0.05	0.22	0.61	1.63	3.48	6.25	11.43

Appendix B. Errors in Measuring Γ^{HP} – A Simulation Study

We simulate returns from last day's close to 15:30 (r^{pre}) and during the last half hour of a trading day (r^{end}), as well as the true Gamma imbalance of market makers for $N = 1000$ stocks, over a total of $T = 2000$ time steps, mirroring the eight years of daily data in our sample.

We allow the delta-hedger to deviate from hedging at the close. She will hedge during a different time with probability π, i.e. $p \sim \text{Bern}(\pi)$, such that the true Gamma hedging pressure for stock j on day t equals

$$\Gamma_{j,t}^{HP}(*) = r_{j,t}^{\text{pre}} \times \Gamma_{j,t}^{IB}(*) \times p,$$

where $r_{j,t}^{\text{pre}} \sim \mathcal{N}\left(0, \sigma^{\text{pre}} = 0.08\right)$. The choice of whether the market maker hedges end-of-day is inherently unobservable to other market participants. At the same time, $\Gamma^{IB}(*)$ may only be approximated with the market maker's inventory measured at the end of the *last* trading day. Intraday changes in the Gamma profile are likewise unobservable. Consequently, the empirically-observed hedging pressure is measured with error:

$$\Gamma_{j,t}^{HP} = r_{j,t}^{\text{pre}} \times (\Gamma_{j,t}^{IB}(*) + \varepsilon^{\Gamma})_{j,t},$$

where $\varepsilon^{\Gamma} \sim \mathcal{N}[0, \sigma^{\Delta} \times (\sigma^{\text{pre}} + \sigma^{\text{post}})\sqrt{2}]$, such that the standard deviation is scaled as a fraction of the variation of the true but unobservable $\Gamma^{IB}(*)$.

Next, imply a direct relationship between end-of-day returns and $\Gamma^{HP}(*)$,

$$r_{j,t}^{\text{end}} = \beta^{\Gamma}(*) \times \Gamma_{j,t}^{HP}(*) + \varepsilon_{j,t}^{\text{post}},$$

with $\varepsilon^{\text{post}} \sim \mathcal{N}\left(0, \sigma^{\text{post}}\right)$ and $\sigma^{\text{post}} = 0.04$. We set the true slope coefficient $\beta^{\Gamma}(*)$ to -41, mimicking the impact of leveraged ETF rebalancing. Empirically, we can estimate the impact of Gamma rebalancing on end-of-day returns only through the noisy proxy Γ^{HP}:

$$r_{j,t}^{\text{end}} = \beta^{\Gamma} \times \Gamma_{j,t}^{HP} + \varepsilon_{j,t}^{\text{post}},$$

We are consequently interested in how the degree of noise (σ^{Δ}) and probability of discretionary trading at a different time than the close (π) impact the empirical estimate of the slope coefficient, β^{Γ}. Results to this are shown in Figure 4.

Appendix C. Controlling for Risk- and Information-based Alternative Explanations

The 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 (1) to (3) in Table C2 add controls for proxies of expected volatility, namely the level of the at-the-money implied volatility (IV) on day $t-1$ and forecasts of future variance using an EGARCH model, $\hat{RV}^{end}$ and $\hat{RV}^{pre}$. 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).

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} and Ω^{LETF}.

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) summarize the results and show that the coefficients on Γ^{HP} and Ω^{LETF} are unchanged both in magnitude and significance, suggesting that our results are not driven by an information channel.

Table C2: **Controlling for Risk-based and Informational Channels**
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 (9). IV_{t-1} denotes implied volatility at time $t-1$. $\hat{RV}_t^{end}$ ($\hat{RV}_t^{pre}$) 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. 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 2012 – 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}	-10.925***	-10.958***	-10.938***	-10.961***	-10.961***	-10.914***
	(-5.513)	(-5.522)	(-5.507)	(-5.521)	(-5.523)	(-5.503)
Ω_t^{LETF}	46.832***	46.768***	46.790***	46.755***	46.738***	46.835***
	(5.208)	(5.202)	(5.198)	(5.195)	(5.198)	(5.204)
r_t^{pre}	-0.822***	-0.820***	-0.820***	-0.820***	-0.820***	-0.821***
	(-7.460)	(-7.453)	(-7.452)	(-7.453)	(-7.452)	(-7.454)
IV_{t-1}	4.463***					4.040***
	(5.079)					(5.086)
$\hat{RV}_t^{pre}$		19.132				-28.421*
		(1.065)				(-1.754)
$\hat{RV}_t^{end}$			414.582***			336.520***
			(3.156)			(2.777)
PC_{t-1}				0.005		-0.003
				(0.030)		(-0.019)
$O/S_{t-1}^{\$}$					255.550	100.469
					(0.782)	(0.321)
Observations	1,882,332	1,882,236	1,882,236	1,879,828	1,882,327	1,879,753
R^2 (%)	0.388	0.371	0.380	0.370	0.370	0.393
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]

Appendix D. Liquidity Provision: Evidence from Spreads

This appendix provides additional evidence of impeded liquidity provision for Gamma rebalancing flows, which potentially arises because of their opacity. To do so, we measure the relative change in the bid-ask spread on each stock as

$$\widehat{S}_t = \frac{S_t^{16:00:00} - S_t^{15:30:00}}{\sum_{\tau=09:30:00}^{15:00:00} S_t^{\tau}/12}, \qquad \text{with} \quad S_t = ask_t - bid_t,$$

and regress it on rebalancing flows Γ^{HP} and Ω^{LETF}. Table D3 shows that market makers active in the stocks underlying options with large rebalancing flows increase the corresponding spreads to alleviate the issue of adverse selection. We find no such evidence for rebalancing flows from leveraged ETFs.

Table D3: **Spreads and Rebalancing Flows**
The table reports the results to regressing the relative change in the bid-ask spread on Γ^{HP} and Ω^{LETF}. We measure the relative change in the spread as $\widehat{S}_t = \frac{S_t^{16:00:00} - S_t^{15:30:00}}{\sum_{\tau=09:30:00}^{15:00:00} S_t^{\tau}/12}$, where $S_t = ask_t - bid_t$ using consolidated national best bid and offer quotes from the NYSE TAQ database (Holden and Jacobsen, 2014). 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.

	(1)	(2)	(3)
Dependent	$\widehat{S}_t$	$\widehat{S}_t$	$\widehat{S}_t$
$\lvert\Gamma_t^{HP}\rvert$	6.081**		5.555*
	(2.058)		(1.876)
$\lvert\Omega_t^{LETF}\rvert$		16.353	14.572
		(0.843)	(0.750)
r_t^{pre}	0.026	0.029	0.025
	(0.235)	(0.259)	(0.228)
Observations	1,863,111	1,863,111	1,863,111
R^2 (%)	0.008	0.006	0.013
Entity FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]

Appendix E. Performance of Trading Strategies Over Time

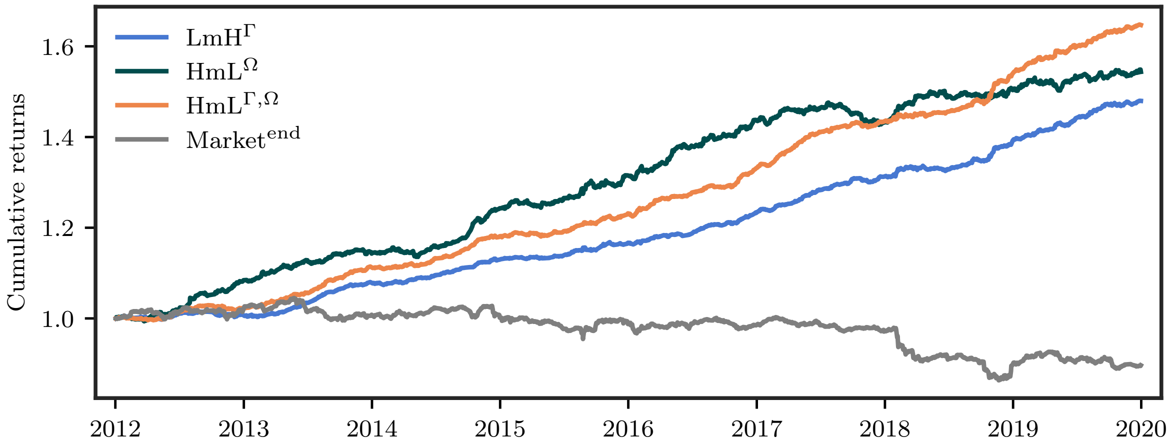

Fig. E1. **Performance of Trading Strategies Over Time**
The figure shows the cumulative performance of a one-dollar investment into trading strategies based on Γ^{HP} and Ω^{LETF}. The Γ^{HP}-strategy, LmH^{Γ}, takes a long (short) position in a stock when the stock's Γ^{HP} is in the lowest (highest) 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, $\mathrm{HmL}^{\Gamma,\Omega}$, takes a long (short) position in a stock when the stock's $\Omega^{LETF} - \Gamma^{HP}$ is in the highest (lowest) decile. As a benchmark, $\mathrm{Market}^{\mathrm{end}}$ denotes investing in all stocks from 15:30 to 16:00. The sample period is January 2012 – December 2019.

Liquidity Provision to Leveraged ETFs and Equity Options Rebalancing Flows

Evidence from End-of-Day Stock Prices

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.

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Appendix OA1. 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.

OA1.1. 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.

OA1.2. 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 low-frequency 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.

Appendix OA2. Summary Statistics of the Underlying

Table OA2.1: **Industry Distribution of Underlying Stocks**
The table reports time-series averages of industry distributions of the Fama-French 12-industry classification. For comparability to the CRSP universe, the distribution of the full CRSP sample is included.

FF-12 Industry	Our sample	CRSP sample
Consumer durables	0.44%	0.19%
Consumer nondurables	4.57%	2.71%
Manufacturing	10.23%	4.78%
Energy	5.64%	3.4%
Chemicals	3.22%	1.26%
Business Equipment	15.68%	8.62%
Telecom	2.38%	1.95%
Utilities	3.73%	1.9%
Wholesale	11.75%	4.91%
Healthcare	10.64%	5.51%
Finance	10.31%	44.15%
Other	21.41%	20.62%

Table OA2.2: **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. The sample period is January 2012 – December 2019.

	Mean	Std	10-Pctl	Q1	Median	Q3	90-Pctl
Panel A: Time-Series Distribution							
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							
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 OA3. Summary Statistics of Leveraged ETFs

Table OA3.1: **Summary Statistics of 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 OA4. Correlation of Exchange Specific Γ^{HP} and Total Γ^{HP}

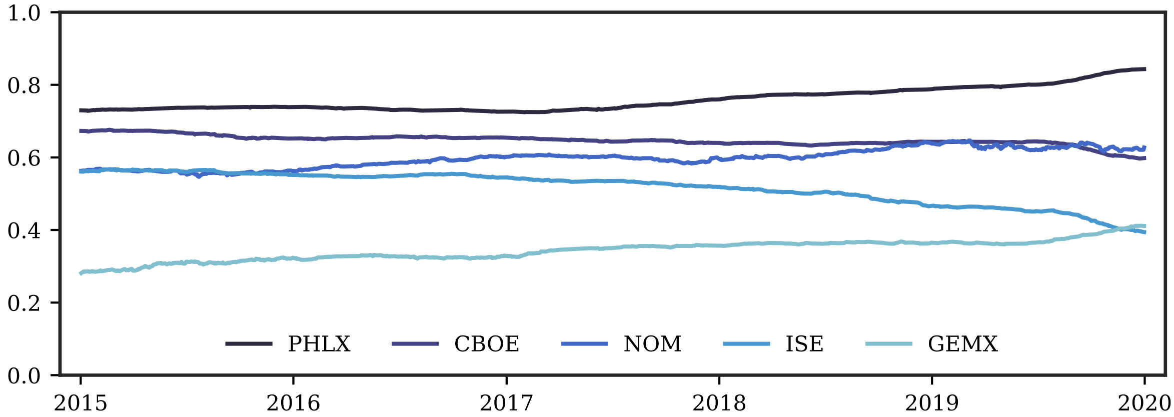

Fig. OA4.1. **Average Three-year Rolling Γ^{HP} Correlations**
The figure shows average three-year rolling correlations between Γ^{HP} based on the delta-hedgers option inventory of one single exchange (either PHLX, CBOE, NOM, ISE, or GEMX) and Γ^{HP} based on the pooled delta-hedgers option inventory across all exchanges in our sample.

Appendix OA5. Different ADV Measures

We investigate whether the choice of the time period over which we calculate the average dollar volume (ADV) effects our results. We calculate ADV over the previous week (W) or previous quarter (W) and using the last half hour of a trading day (I) or the entire daily trading volume (D). As Table OA5.1 shows, the choice of denominator for Γ^{HP} and Ω^{LETF} has little impact on our results.

Table OA5.1: **Effect of Different ADV Measures**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, r^{pre}, gamma hedging pressure Γ^{HP}, and leveraged ETF rebalancing flows Ω^{LETF} following Equation (9). 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 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}	-10.006***	-55.821***	-10.960***	-59.616***	-10.976***	-60.342***
	(-5.518)	(-7.094)	(-5.521)	(-6.949)	(-5.244)	(-6.763)
Ω_t^{LETF}	41.180***	177.953***	46.738***	190.533***	48.616***	201.118***
	(4.658)	(6.015)	(5.198)	(6.094)	(5.084)	(6.099)
r_t^{pre}	-0.817***	-0.803***	-0.820***	-0.804***	-0.824***	-0.809***
	(-7.430)	(-7.176)	(-7.452)	(-7.148)	(-7.501)	(-7.227)
Observations	1,882,332	1,882,332	1,882,332	1,882,332	1,882,332	1,882,332
R^2 (%)	0.363	0.380	0.370	0.382	0.376	0.391
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 OA6. Different Sets of Delta-Hedgers

In the main part of the paper, we assume that delta-hedgers are composed of market makers and broker/dealers. We exchange the set of delta-hedgers to include only market makers (Table OA6.1) or to include market makers, broker/dealers, and firm proprietary traders (Table OA6.2). The choice of the set of likely delta-hedgers has little impact on our results.

Table OA6.1: **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 gamma hedging pressure Γ^{HP}, following Equation (9). We assume that market makers are delta-hedgers. 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}	-10.354***	-10.292***	-10.345***	-10.312***	-10.355***	-10.355***
	(-3.094)	(-3.077)	(-3.093)	(-3.077)	(-3.094)	(-3.094)
r_t^{pre}	-0.739***	-0.741***	-0.739***	-0.739***	-0.739***	-0.739***
	(-7.034)	(-7.050)	(-7.036)	(-7.039)	(-7.035)	(-7.034)
IV_{t-1}		4.517***				
		(5.029)				
$\hat{RV}_t^{pre}$			20.913			
			(1.159)			
$\hat{RV}_t^{end}$				418.390***		
				(3.143)		
PC_{t-1}					-0.014	
					(-0.092)	
$O/S_{t-1}^{\$}$						244.126
						(0.770)
Observations	1,882,332	1,882,332	1,882,236	1,882,236	1,879,827	1,882,327
R^2 (%)	0.267	0.286	0.269	0.277	0.267	0.268
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]

Table OA6.2: **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 gamma hedging pressure Γ^{HP}, following Equation (9). We assume that market makers, broker/dealer, and firm proprietary traders are delta-hedgers. 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}	-11.014***	-10.977***	-11.005***	-10.976***	-11.014***	-11.012***
	(-6.965)	(-6.945)	(-6.968)	(-6.947)	(-6.965)	(-6.963)
r_t^{pre}	-0.706***	-0.708***	-0.706***	-0.707***	-0.706***	-0.706***
	(-6.817)	(-6.834)	(-6.818)	(-6.821)	(-6.817)	(-6.817)
IV_{t-1}		4.516***				
		(5.076)				
$\hat{RV}_t^{pre}$			18.816			
			(1.034)			
$\hat{RV}_t^{end}$				410.953***		
				(3.101)		
PC_{t-1}					-0.010	
					(-0.063)	
$O/S_{t-1}^{\$}$						280.615
						(0.832)
Observations	1,882,332	1,882,332	1,882,236	1,882,236	1,879,823	1,882,327
R^2 (%)	0.296	0.314	0.297	0.306	0.296	0.296
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]

Appendix OA7. Γ^{HP} based on Older Positions

Endogeneity concerns regarding Equation (9) 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 follow Ni et al. (2020). Precisely, we split Γ^{HP} in two parts: gamma hedging pressure originating from older 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

$$\begin{aligned}\Gamma_{j,t;\tau}^{IB} = & \left(\sum_{o=1}^{N_{t-\tau}^{t}} netOI_{o,t-1-\tau} \times \Gamma_o(t-1, S_{j,t-1}^{close}) \times S_{j,t}^{15:30} \times Mult_o \right) \\ & \times \frac{S_{j,t-1}^{close}}{100} \times \frac{1}{\text{ADV}_{j,t-1}^{\text{end}}},\end{aligned} \tag{OA1}$$

where $N_{t-\tau}^{t}$ denotes the number of options contracts on stock j that are available at time $t-\tau$ and expire after t. The difference between Equation (OA1) and Equation (4) in the main paper is that Equation (OA1) 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 (OA1) denotes the gamma imbalance at time t of old positions.

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

$$\Gamma_{j,t;\tau}^{HP} = 100 \times \Gamma_{j,t;\tau}^{IB} \times r_{j,t}^{\text{pre}}. \tag{OA2}$$

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

$$\Gamma_{j,t}^{HP} = \Gamma_{j,t;\tau}^{HP} - \Gamma_{j,t;\text{new}}^{HP}, \tag{OA3}$$

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

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

$$r_{j,t}^{\text{end}} = \beta_0 r_{j,t}^{\text{pre}} + \beta_1 \Gamma_{j,t;\tau}^{HP} + \beta_2 \Gamma_{j,t;\text{new}}^{HP} + \boldsymbol{\gamma}' \boldsymbol{X}_{j,t} + FE_j + FE_t + \epsilon_{j,t}. \tag{OA4}$$

We hypothesize that β_1 is negative and statistically significant. Table OA7.1 and Table OA7.2 show results with τ set to five and ten business days, respectively. Both tables confirm our hypothesis.

Table OA7.1: **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 gamma hedging pressure based on five 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 (OA4). 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 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}
$\Gamma^{HP}_{t;\tau}$	-16.375***	-16.324***	-16.370***	-16.366***	-16.376***	-16.372***
	(-6.954)	(-6.942)	(-6.954)	(-6.947)	(-6.954)	(-6.955)
$\Gamma^{HP}_{t;\text{new}}$	-1.107***	-1.117***	-1.110***	-1.124***	-1.107***	-1.104***
	(-2.601)	(-2.638)	(-2.611)	(-2.664)	(-2.600)	(-2.590)
r_t^{pre}	-0.810***	-0.813***	-0.811***	-0.811***	-0.810***	-0.810***
	(-6.765)	(-6.776)	(-6.767)	(-6.767)	(-6.766)	(-6.765)
IV_{t-1}		5.133***				
		(4.964)				
$\hat{RV}^{pre}_t$			22.224			
			(1.058)			
$\hat{RV}^{end}_t$				435.201***		
				(2.795)		
PC_{t-1}					0.064	
					(0.299)	
$O/S^{\$}_{t-1}$						283.201
						(0.899)
Observations	1,015,379	1,015,379	1,015,333	1,015,333	1,014,433	1,015,375
R^2 (%)	0.341	0.363	0.342	0.351	0.341	0.341
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]

Table OA7.2: **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 gamma 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 (OA4). 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 January 2012 – December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t	r^{end}_t
$\Gamma^{HP}_{t;\tau}$	-17.973***	-17.912***	-17.972***	-17.959***	-17.973***	-17.973***
	(-6.714)	(-6.694)	(-6.715)	(-6.710)	(-6.713)	(-6.715)
$\Gamma^{HP}_{t;\text{new}}$	-1.234***	-1.244***	-1.237***	-1.251***	-1.234***	-1.231***
	(-2.777)	(-2.814)	(-2.787)	(-2.839)	(-2.776)	(-2.765)
r^{pre}_t	-0.821***	-0.823***	-0.821***	-0.821***	-0.821***	-0.821***
	(-6.837)	(-6.848)	(-6.839)	(-6.838)	(-6.838)	(-6.837)
IV_{t-1}		5.138***				
		(4.969)				
$\hat{RV}^{pre}_t$			22.482			
			(1.069)			
$\hat{RV}^{end}_t$				435.447***		
				(2.791)		
PC_{t-1}					0.064	
					(0.302)	
$O/S^{\$}_{t-1}$						287.581
						(0.910)
Observations	1,015,379	1,015,379	1,015,333	1,015,333	1,014,433	1,015,375
R^2 (%)	0.332	0.354	0.334	0.343	0.332	0.333
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]

Appendix OA8. Scaled Returns as in Moskowitz et al. (2012)

Instead of using simple returns and value-weighted observations, Moskowitz et al. (2012) propose the use of scaled returns, which expresses returns in terms of units of expected risk:

$$\hat{r} = \frac{r}{\sigma_r}, \tag{OA5}$$

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.

As shown in Table OA8.1, scaling returns does not alter our results.

Table OA8.1: **Using Scaled Returns**
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 gamma hedging pressure Γ^{HP}, following Equation (9). The regression setup follows that of Table 2 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)
Dependent	r_t^{end}	r_t^{end}	r_t^{end}
Ω_t^{LETF}		165.089***	173.968***
		(4.936)	(5.233)
Γ_t^{HP}	-29.157***		-34.042***
	(-3.501)		(-4.167)
r_t^{pre}	-0.060***	-0.068***	-0.063***
	(-7.644)	(-8.695)	(-7.948)
Observations	1,882,236	1,882,236	1,882,236
R^2 (%)	0.487	0.536	0.563
Entity FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
SEs	[t;j]	[t;j]	[t;j]

Appendix OA9. Mechanical Flows

Index versus Stock Specific Effects

While Γ^{HP} rebalancing activity depends on the return of the underlying stock, the rebalancing amount for leveraged ETFs 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 basis points in absolute terms). 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 OA9.1 confirm our prior.

Table OA9.1: **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 in absolute 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 January 2012 – December 2019.

	(1)
Dependent	r_t^{end}
Ω_t^{LETF}	69.400***
	(4.961)
r_t^{pre}	-0.899
	(-0.434)
Observations	120,913
R^2 (%)	0.119
Entity FE	Yes
Time FE	Yes
SEs	[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. 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. 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).

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 OA9.2 barely differ, confirming the mechanical nature of Γ^{HP}-flows.

Table OA9.2: **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}	-9.865***	-8.117*	-10.551***	-8.671***
	(-5.557)	(-1.879)	(-6.635)	(-2.780)
r_t^{pre}	-0.749***	-0.744***	-0.662***	-0.850***
	(-6.907)	(-4.296)	(-6.824)	(-5.168)
Observations	1,607,439	274,893	1,567,086	315,246
R^2 (%)	0.263	0.335	0.219	0.390
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

Appendix OA10. 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 OA10.1 displays results. $\Gamma^{IB}-$ and $\Omega^{LETF}-$effects are present and statistically significant in all industries.

Table OA10.1: **Effects in Different Industries**
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 gamma hedging pressure Γ^{HP}, following Equation (9). 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}	-8.777***	-6.822***	-6.919*	-20.417***	-16.849***
	(-5.212)	(-3.145)	(-1.814)	(-4.111)	(-5.734)
Ω_t^{LETF}	31.260***	21.224***	47.491***	95.533***	38.054***
	(6.586)	(3.642)	(8.304)	(6.488)	(4.318)
r_t^{pre}	-0.680***	-0.839***	-0.978***	-0.959***	-0.654***
	(-5.585)	(-4.495)	(-4.630)	(-4.689)	(-3.491)
Observations	346,342	427,144	366,477	201,183	541,186
R^2 (%)	0.269	0.295	0.430	0.748	0.308
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

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