End-of-Day Momentum in the Cross-Section and Option Hedging

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Abstract

Hedging activities by option market makers can have a nontrivial impact on the price of the underlying. In this study, we show that delta-hedging their single stock option inventories, options market makers elicit temporary price pressure on the underlyings' stock prices in the last half hour of a trading day. Our estimated effect is economically large. Establishing delta-neutrality around the market close causes return momentum or reversal of 18 basis points for each one percentage point move in the underlying until half an hour before trading close. The direction is determined by the interaction between the aggregated gamma exposure of option market makers and the return until 30 minutes before market close. Interestingly, our results are more pronounced for stocks with high market capitalization. Information-based explanations are not driving our results, suggesting a non-informational channel through which option markets affect underlying stocks.

JEL classification: G12, G13, G14, G23

Keywords: Intraday Momentum, Cross-Sectional Momentum, Gamma Exposure, Option Market Maker

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1. Introduction

The hedging activity of option market makers has recently garnered a lot of attention, and has attracted negative press coverage for increasing selling pressure during already turbulent times.[1] Just recently, the hedging activity of option market makers was blamed to increase the violent stock swings during the March 2020 Covid-19 selloff. The Wall Street Journal wrote:

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

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

While a growing academic literature has evolved around the effects of option market activity on the price of the underlying, much is left unexplained. For example, while it is by now widely understood that options are non-redundant and may directly influence the price of the underlying (Black, 1975), we lack a clean quantification of these effects in individual stocks, and how they relate to intraday effects. Option market makers' hedging rules mostly relate to neutrality to movements in the underlying. That is, dynamic hedging of written option positions leads to them buying the underlying after previous price appreciation and selling it after previous price depreciation. Along the same lines, delta-hedging a purchased options positions involves selling the underlying after the price has risen and buying the underlying after the price has decreased. The most likely market participants that periodically engage in delta-hedging option positions are naturally market makers, but also certain hedge funds and volatility arbitrageurs.

We hypothesize that these delta-hedging activities occur mostly in the last half hour of a trading day, i.e. start taking place around 15:30 each day. Baltussen, Da, Lammers, and Martens (2020) provide several reasons why delta-hedging should take place close to the end of the trading day. First, previous studies have indicated that it is optimal to only partially hedge after a large intraday price movement, hence requiring additional hedging afterwards (Clewlow and Hodges, 1997). Second, liquidity and volume patterns are attractive at the open and close, as previous studies have documented a U-shape intraday volume pattern (Andersen and Bollerslev, 1997). Third, delta-hedging might reduce overnight positions in the underlying and thereby overnight or gap risks. Fourth, regulations such as BIS capital requirements make it costly to hold overnight positions due to higher capital costs and investment frictions. And lastly, investment products that seek to deliver a multiply of the underlying market's daily movement, e.g. leveraged

[1] See for example Davies (2019).

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

ETFs, are benchmarked at closing prices. The pattern of option market makers' selling and buying within the last half hour implies that hedging short option positions leads to a continuation of the price movement of the day during the last half hour. Contrarily, hedging purchased options induces price movement reversals.

We start by showing that individual stocks exhibit intraday return momentum when considering returns in the last half hour of a trading day to the return until 15:30, which includes the overnight return. This effect is highly significant statistically and economically large. Next, we link this intraday return momentum to a measure of market maker hedging pressure, quantifying the amount an option market maker would have to trade in the stock to stay neutral to future movements in the underlying, given the price change until 15:30. Consistent with theory, a negative Γ-exposure of the market maker in stock i is associated with exacerbated intraday momentum for that same stock. Likewise, for a positive net Γ-exposure, we observe a dampening return effect in form of relative mean reversion.

The effects of market maker hedging on the price of the underlying are more pronounced for large stocks. The market size of the underlying stock seems to play a significant role in understanding market maker hedging. We argue this to be driven by a lack of direct hedging with the underlying of position sizes in smaller issues. Instead, market makers may choose to opt for a beta-hedge with the help of some broader market index, which directly covers multiple stocks on the book and may be cheaper to implement. We further show that the size of the underlying market, measured as the average trading volume in USD relative to the market capitalization, is inversely related to the magnitude of our effects, with little change in the statistical significance. Likewise, the dollar open interest relative to the market capitalization also shows an inverse relationship. These findings suggest that the effects of a market maker hedging pressure of similar magnitude has stronger price effects for a) stocks with relatively little trading, and b) for stocks with a shallower option market. Larger and deeper option markets may be characterized by more dispersion in the trade intent, which ultimately leads to more buyer-writer pairs arising between end customers, leaving less inventory to be absorbed by market makers and arbitrageurs. This in turn would of course also decrease the amount of required intraday hedging by these investor groups.

We further check the validity of our identification procedure of likely market maker hedging of their option portfolios, by contrasting our finding with option market predictors previously proposed by the literature. Roll, Schwartz, and Subrahmanyam (2010) propose the trading volume in the option relative to the market of the underlying as a predictor of future stock returns, and Blau, Nguyen, and Whitby (2014) find predictive power for the put-to-call ratio. Neither predictor explains the explanatory power of market maker hedging pressure, suggesting that the hedging channel is a novel way through which option trading temporarily affects stock returns.

To establish that we are picking up trading effects not driven by information processed in the options market, but rather mechanical returns due to hedging with the underlying, we investigate the persistence of these effects. The returns are more than reversed in the first half trading hour of the next day, making clear that the phenomenon is temporary. As a second step, we include the value-weighted market return until 15:30 on a target day as a secondary predictor. We find that the intraday momentum pattern is in fact an average market momentum, driving all stocks simultaneously, while individual stock returns exhibit mean reversion *relative to the market return.* This unites the literature on cross-sectional mean reversion by Heston, Korajczyk, and Sadka (2010), and time-series market momentum, as in Gao, Han, Zhengzi Li, and Zhou (2018) and Baltussen et al. (2020). We can reconcile the seemingly contradictory evidence provided by the two strands of literature, in that the two phenomena are one and the same – a benefit of our panel regression setup. The impact of market maker hedging activity is untouched by this detour.

To rule out other explanations and better understand the intraday hedging phenomenon we undertake a battery of robustness and sanity checks. Results are relatively homogeneous across different industries, and stronger in size during recessions. The same effect is observed during the great financial crisis. Focusing on the dissemination of earnings and company news, we find little effect of both, ruling out that our findings are related to the prevailing information density about individual stock returns.

While our statistical results are strong and robust, the economic significance remains unanswered. For this, we employ a trading strategy, which contrasts a long-only investment during the last half hour of a trading day to investments conditional on the cross-sectional dispersion of our hedging pressure proxy. We find a significant outperformance relative to a simple buy-and-hold strategy in the last half hour of a trading day, with an annualized Sharpe-ratio above 4 and a 2/3 chance of a successful trade. These results are more significant than in the case of Equity Futures, as discussed in Baltussen et al. (2020), but require investments in large baskets of stocks, conditioned on the magnitude of their Γ-imbalance, which may prove difficult in a realistic market environment. For a partial remedy of this observation, we redo our trading analysis for the subset of the 20% largest stocks, and achieve comparable returns. Once we take the impact of transaction costs into account following Frazzini, Israel, and Moskowitz (2018), results vanish, as expected for a strategy with 100% daily turnover. This is still suggestive of the economic magnitude that market maker hedging activity poses on the underlying's price.

Our work relates to the literature concerned with effects of option markets on the underlying stock price dynamics. The literature generally distinguishes between two channels through which option trading may have an impact on the price of the underlying. Hu (2014) provides evidence that the information found in market makers' initial delta-hedges is impounded in and significantly alters the price of the underlying. Other studies advocating an informational channel are Cremers and Weinbaum (2010) and Pan and Poteshman (2006). 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, Pearson, Poteshman, and White (2020) analyze the effects of Γ-imbalance on absolute returns and the autocorrelation of returns, based on theoretical models that predict a negative relation between stock volatility and Γ-imbalance.[3] Whereas Ni et al. (2020) resort to daily data, Barbon and Buraschi (2020) concentrate on intraday price paths. They find that Γ-imbalance is negatively related to intraday volatility and intraday autocorrelation of returns in case of single stocks and stock indices. Moreover, they document an impact of Γ-imbalance on the frequency and magnitude of flash crashes. Finally, Baltussen et al. (2020) show that intraday momentum in many Futures contracts concentrates on days with negative Γ-exposure of option market makers.

A different, but related portion of the literature deals with the effects of market maker inventory. 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 usage of S&P 500 index option and conclude that unspanned crash risk drives much of their demand. Continuing this investigation, Jacobs and Mai (2020) find a tight integration between both prices and demand in S&P 500 and VIX options. What is still missing in this direction, is a comprehensive study of the integration between index and equity options. In the study at hand, we deal with the impact of market maker inventory management on the underlying for the case of single equities.

We also tie into the literature on intraday return patterns. We find high-frequency return continuation in the cross-section of stock returns, consistent with evidence provided by Gao et al. (2018) and Baltussen et al. (2020). Both studies focus on aggregate investment vehicles, such as ETFs and index Futures. Gao et al. (2018) show that their effects are stronger on days with elevated volatility, which are typically also accompanied by higher trading volume. In the cross-section of stocks, Komarov (2017) finds that stocks performing best in the first half of the day will likely lose in the second half if controlled for market returns. In line with this, we find the intraday momentum pattern we pick up to be connected to momentum in the aggregate market composite. Another study on short-term return reversals is Heston et al. (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

[3]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).

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. Further studies analyzing the high-frequency behavior of stock returns are Bogousslavsky (2020), Hendershott, Livdan, and Rösch (2020) and Lou, Polk, and Skouras (2019), with an emphasis on the distinction between overnight and trading periods.

2. Data and summary statistics

Our analysis requires merging multiple databases to analyze the high-frequency impact of market maker hedging activity. We provide a discussion of our data sources and the variables of interest, and talk about summary statistics.

2.1. Data sources

We use standard data sources throughout our analyses. We obtain daily U.S. individual stock options via Ivy DB US from OptionMetrics from January 1996 to June 2019. Our options data set includes the daily bid and ask quotes, implied volatility, trading volume, open interest and Greeks for each option contract. As individual stock options are of American type, implied volatility and Greeks are calculated via binomial trees by OptionMetrics.

Trading volume, shares outstanding and closing prices of the underlying stocks are taken from the Center for Research on Security Prices (CRSP). We restrict our analysis to stocks with CRSP share code 10 and 11, where the primary exchange is either NYSE, AMEX or NASDAQ, and the exchange code is 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.

Intraday stock price data is obtained from TAQ. We use standard cleaning procedures and match intraday trade prices with CRSP to obtain PERMNOs as unique identifiers. More details are given in Appendix A. Equipped with intraday prices, we calculate intraday returns relative to the previous day's closing price. Following standard practice in the literature (see Lou et al., 2019), we assume that corporate events that mechanically impact prices, e.g. dividend payments and stock splits, take place overnight and are realized at the time of the first trade on the target date. If a delisting occurs as reported by CRSP, we assume that the delisting amount is realized at the respective day's close. In an alternative specification, we calculate overnight returns as reported by CRSP, keeping the intraday information found in the TAQ database untouched. This does not alter our results.

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

Finally, we use the Dow Jones version of Ravenpack News Analytics and its sentiment scores to identify days with significant news for each underlying. We restrict our news sample to articles which are highly relevant for a particular stock, i.e. a reading of 100 for Ravenpack's relevance score. Furthermore, we only include news which are highly positive (sentiment score above 0.75) or highly negative (sentiment score below 0.25).

Our sample comprises 6,541 individual stocks and 5,912 trading days. As underlying stocks enter our sample once they are tradable *and* optionable, our final panel is unbalanced by construction with a total of 12.3 million observations.

2.2. Gamma Imbalance

We measure the market maker's Gamma imbalance by looking at the aggregate open interest for options on underlying i. Let $V(t, S)$ denote the value of an option contract. $\Delta(t, S) = \frac{\partial V(t,S)}{\partial S}$ is 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. In case option market participants want to neutralize their exposure to movements in the underlying due to a an outstanding option position in the portfolio, they engage in delta-hedging, which requires buying or selling $-\Delta(t, S)$ shares of the underlying. As $\Delta(t, S)$ changes over time and with the level of S, the hedge has to be adjusted periodically. If $\Gamma(t, S)$ is low, $\Delta(t, S)$ moves only slightly, and adjustments to maintain delta-neutrality require little trading in the underlying. However, if $\Gamma(t, S)$ is highly negative or positive, $\Delta(t, S)$ is very sensitive to movement in the underlying, and the amount of trading in the underlying required to stay delta-neutral increases.

In principle, derivative markets are zero-sum games. For each option, there exists a buyer and a seller. Therefore, the aggregated $\Gamma(t, S)$ on each option is zero across the purchaser and seller. However, we assume that one party in each option transaction pursue an economic intention preventing it from delta-hedging. This entails investors buying puts as a hedge against downside risks or writing calls to generate income on existing stock positions. In fact, a large craze since the financial crises were so-called call overwriting strategies, which have also been popular among large pension funds, and now fallen out of favor.[4]. We refer to these market participants as end customers. The counterparty to end customers are market makers, which are obliged to uphold liquidity in the options market and facilitate the efficiency of trades. Contrary to end customers,

[4] `https://www.bloomberg.com/news/articles/2020-08-06/a-once-booming-options-strategy-on-wall-street-is-misfiring`

we assume that option market makers engage in delta-hedging, with daily adjustments to their hedges. Precisely, we assume that all option trades are facilitated by option market makers and the latter hedge their option delta-exposure.

To estimate a stock-by-stock Γ imbalance, we follow Barbon and Buraschi (2020) in the assumption that end customers are typically long in Put options and short in Call options for individual equities.[5] The authors provide convincing evidence that option strategies used by insurance companies follow this scheme. Lakonishok, Lee, Pearson, and Poteshman (2006) provide evidence that call writing is more prominent than purchasing calls across all option market participants except for market makers. Furthermore, Cici and Palacios (2015) analyse option positions of mutual funds and find that the majority of their option positions are written single stock calls, followed by purchases in single stock put options.

As counterparties to end customers, we therefore assume that market makers are long in call and short in put options. As $\Gamma(t, S)$ varies with time to maturity T and strike K, we first compute the dollar gamma for each option contract. For a call (C) option on day t with strike price K and maturity T, the dollar gamma $\Gamma^{\$}(t, S)^C$ is calculated as

$$\Gamma^{\$}(t, S)^C_{K,T} = \Gamma(t, S)^C \times OI^C_{K,T} \times 100 \times S, \tag{1}$$

where $\Gamma(t, S)^C$ is the option's gamma, $OI^C_{K,T}$ denotes the open interest, 100 is the contract multiplier of the option, and S is the time-t price of the underlying.

Similarly, for a put (P) option on day t with strike price K and maturity T, the dollar gamma $\Gamma^{\$}(t, S)^P$ for the maker maker is calculated as

$$\Gamma^{\$}(t, S)^P_{K,T} = -1 \times \Gamma(t, S)^P \times OI^P_{K,T} \times 100 \times S, \tag{2}$$

where $\Gamma(t, S)^P$ is the option's gamma, $OI^P_{K,T}$ denotes the open interest, 100 is the contract multiplier of the option, and S is the time-t price of the underlying. Note that we multiply by -1 to reflect the net-short position of market makers in put options.

For the aggregated gamma imbalance for stock i at time t, denoted by $\Gamma^{IB}_i(t, S)$, we take the sum over all calls and puts in the market, i.e.

$$\Gamma^{IB}_i(t, S_i) = \underbrace{\left(\sum_{K,T} \Gamma^{\$}(t, S_i)^C_{K,T} + \sum_{K,T} \Gamma^{\$}(t, S_i)^P_{K,T} \right)}_{(\star)} \times \frac{S_i}{100} \times \frac{1}{ADV_{i,t}}. \tag{3}$$

$(\star)$ in Equation (3) denotes the dollar gamma imbalance, aggregated over all option contracts for stock i and time t. Precisely, it is the dollar amount option market makers need to trade in stock i for each one-dollar move in stock i's price. By multiplying $(\star)$

[5] Baltussen et al. (2020) make the same assumption in case of S&P 500 options.

with the underlying's price divided by 100, we express the dollar gamma imbalance for a one percent move in S_i. This facilitates comparison in our cross-sectional analyses. Finally, we scale by the average dollar trading volume, $ADV_{i,t}$, computed over the last month.[6] Thereby, we express the market maker's gamma imbalance as a portion of the typical trading in the stock to obtain a timely proxy for the potential price impact of hedging adjustments.

Consider the case that $\Gamma^{IB}_{i,t}$ for stock i at time t is negative and option market makers want to maintain a delta-neutral position, i.e. the overall delta of their options portfolio and the underlying stock should equal zero. As the gamma imbalance is negative, option market makers need to sell the underlying if the underlying has declined as the option delta has decreased, and buy the underlying if it has appreciated as the option delta has increased. Along the same lines, delta-hedging a positive gamma position leads to selling the underlying if it appreciated and buying it after it has decreased. An illustration of the four cases is given in Table 1. In our baseline specification, we assume that option market makers engage in re-hedging their positions in the last half hour of a trading day.[7] If the aggregate gamma for a stock is negative, delta-hedging contributes to intraday momentum in a stock, that is, if the return until 15:30 is negative (positive), hedging has the effect of continuing the downward (upward) movement in the last half hour. On the contrary, if gamma is positive in the aggregate, delta-hedging leads to intraday reversal, dampening the return movement until hedging begins.

Table 1: **Effect of Γ^{HP} on last half hour's return**
The table depicts the interaction of gamma imbalance Γ^{IB} and the return until the last hour of the trading day. It visualizes the effect of gamma hedging pressure, as defined in Equation (4), on the return in the last half hour of the trading day.

	$r_{close-1\to 15:30} > 0$	$r_{close-1\to 15:30} < 0$
$\Gamma^{IB}(t-1,S) > 0$	$\Gamma^{HP} > 0 \Rightarrow r_{15:30\to close} \searrow$	$\Gamma^{HP} < 0 \Rightarrow r_{15:30\to close} \nearrow$
$\Gamma^{IB}(t-1,S) < 0$	$\Gamma^{HP} < 0 \Rightarrow r_{15:30\to close} \nearrow$	$\Gamma^{HP} > 0 \Rightarrow r_{15:30\to close} \searrow$

We join the information of Γ^{IB} and $r_{close-1\to 15:30}$ to assess the total trading relative to the average dollar volume market makers would have to undertake to adjust their hedge positions to regain delta neutrality at market close. We define the hedging pressure of

[6]As Appendix B shows, it is inconsequential to our main results if we compute the average dollar trading volume over weekly or quarterly horizon.

[7]Anecdotal evidence in favor of this assumption is given in Li (2019).

stock i as the interaction between Γ^{IB} and $r_{close-1 \to 15:30}$, expressed in percent:

$$\Gamma^{HP}_{i,t} = 100 \times \Gamma^{IB}_i(t-1, S_i) \times r^i_{close-1 \to 15:30}. \quad (4)$$

Γ^{HP} is our main variable of interest. It effectively combines the information of the aggregate position adjustment in hedge positions to maintain delta-neutrality, and the signal in form of intraday returns, which determines how much hedging is actually required. As Table 1 visualizes, the negative reading of Γ^{HP} is thus directly interpretable as additional *buying pressure* originating from market makers, while a positive reading implies additional *selling pressure* in the last half trading hour.

2.3. *Cross-Sectional Hedging Pressure*

In Figure 1 we show the cross-sectional distribution over time of Γ^{IB} and Γ^{HP} side-by-side. The dark blue line represents the cross-sectional median. It is above zero for Γ^{IB} on most days, suggesting that end customers engage more in underwriting call options than they demand downside protection through equity put options. An alternative way to hedge the downside exposure through option positions is the use of index put options, which may be preferred, as they provide indirect protection of a larger portion of the portfolio. The findings by Gârleanu et al. (2009) suggest that end customers trade more in equity calls than puts, which is in direct contrast to position sizes in index options. The median for Γ^{HP} is close to zero at all times, as the cross-sectional median return until 15:30 is close to flat.

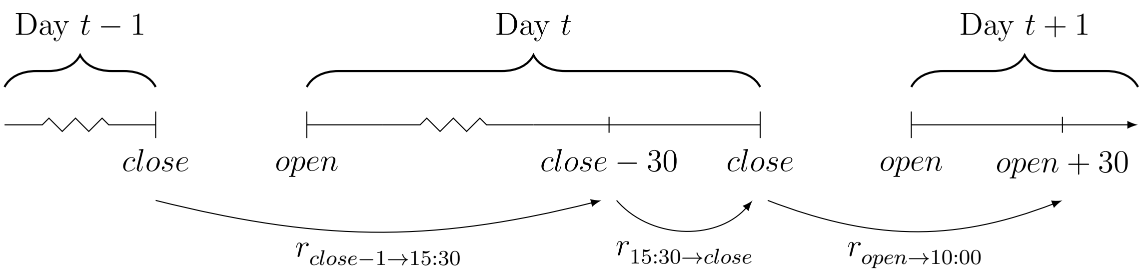
[Insert Figure 1 Near Here]

Turning to the cross-sectional dispersion, the dark teal area in Figure 1 shows the 25th and 75th percentile. For Γ^{IB} we find typical values between 0% and +1.5% again suggesting that the gamma exposure of market makers tends to be positive. Periodically we observe significant spikes and contractions, most notably after the financial crisis, which brought a general dry up of option market liquidity that is further amplified in the case of individual equity options. The light teal area represents the 10th and 90th percentile of the cross-sectional distribution. Here the spikes and contractions are more pronounced, but generally follow a similar pattern. We find negative Γ^{IB} for some stocks, ranging as low as −1%, as measured relative to the average dollar trading volume of the last month. For these stocks, end consumers request more downside protection than they engage in call underwriting. Following the line of reasoning in Section 2.2, we expect these stocks to exhibit a return continuation driven by the option market maker's gamma exposure.

The cross-sectional dispersion of Γ^{HP} is much more homogeneous over time. The 25th and 75th percentile (in dark teal) form a tight band around the cross-sectional median, ranging from -1% to around $+1\%$. Notably, we observe a slight contraction in the measure towards the end of our sample, which we attribute to less dispersion in intraday volatility patterns. The 10th and 90th percentile show more movement, contracting somewhat in 2003 and after the financial crisis. The general picture, however, is this: the cross-sectional distribution of option market maker hedging pressure is stationary over time. One would thus expect a consistent effect of their hedging activity over time, despite strong variation in the overall holdings by market makers. While holdings (and thus Γ^{IB}) contract during times of crises, the higher return volatility during these periods exacerbate the required position sizes to stay delta-neutral, which effectively offsets the reduced option inventory. Since market makers seek to be delta-neutral by the end of a trading day, and particularly over night, they lack the leeway of splitting larger share transactions over multiple days, as advocated by ...[8] Using panel regressions, we determine the impact of market maker hedging activity on the underlying's price in the next section.

3. Intraday Momentum and Market Maker Hedging

We first document in how far the intraday momentum found in Baltussen et al. (2020) transfers over to the cross-section of stock returns. To do so, we run unbalanced panel regressions of the return for stock i on target day t from 15:30 until market close on the return until 15:30, which includes the overnight return from the previous day's close. The figure below summarizes our empirical setup for target day t:



To assess the effects of $r_{close-1\rightarrow 15:30}$ on $r_{15:30\rightarrow close}$, we run regressions of the form:

$$r^i_{15:30\rightarrow close} = \beta_0 r^i_{close-1\rightarrow 15:30} + Entity_i + \varepsilon_{i,t} \tag{5}$$

Throughout our analysis, we cluster standard errors both by date and entity to account for differences in the dispersion of returns over time and across assets. Because we have a sufficient number of clusters, this procedure leads to unbiased errors (Petersen, 2008). We also account for the impact of common shocks following Thompson (2011). Returns

[8]For a further discussion of this, see Heston et al. (2010).

in the regression are weighted by each stock's market capitalization on day $t-1$ to account for stylistic differences in large and small stocks. To see why this is important, Figure 2 shows the realized annual volatility based on 5-minute returns for the two time-periods considered. To highlight the differences between large and small stocks, we split our universe by the median market cap in the last month. Intraday variance is inversely related to the size of the company. With value-weighting, we minimize the cross-sectional variance (Fama and French, 1993), yielding more precise estimates. Additionally, options are typically introduced sooner for large stocks, which puts more weight on assets for which we have more observations.[9] An alternative specification scales returns by an ex-ante measure for stock i's volatility, similar to Moskowitz, Ooi, and Pedersen (2012). We conduct this analysis, which yields comparable, albeit slightly stronger results, in Appendix C. We further include entity fixed effects in the regression, to account for differences in the mean returns of different stocks (Huang, Li, Wang, and Zhou, 2020).

We are interested in the impact of option market maker hedging pressure on the price path of the underlying. To establish whether intraday return patterns are also found in the cross-section of stocks, we follow Equation (5) and regress single stock returns in the last half hour on returns until 15:30, which include the overnight return from the previous close. Results are given in Model (1) of Table 2. Intraday momentum carries over to individual stock returns, in that we find significant evidence of a return continuation in the last half hour for the average stock. A 1% return from last day's close to 15:30 today is on average followed by an additional return of 0.66% in the last thirty minutes. Identifying a common effect across the 6551 entities considered is a very involved task, due to the existence of strong idiosyncrasies. With this in mind, the intraday momentum in single equities is remarkably strong, despite a lower estimate compared to the results on equity market futures in Baltussen et al. (2020).

[Insert Table 2 Near Here]

Since our interest lies primarily in understanding whether intraday returns are significantly altered by market maker hedging activity, we next regress the returns in the last half hour on the market maker's gamma imbalance Γ^{IB} (Model 2):

$$r^i_{15:30\rightarrow close} = \beta^{IB}\Gamma^{IB}_{i,t-1} + Entity_i + \varepsilon_{i,t}, \tag{6}$$

Γ^{IB} is the total dollar amount the option market maker would have to expense to stay Δ-neutral for a 1% move in the underlying relative to the average transacted dollar volume in the last month. While Γ^{IB} has been shown to exert significant influence on return variation (Ni et al., 2020; Barbon and Buraschi, 2020), we find no relation to

[9] Figure 3 shows histograms of the average days individual PERMNOs are included in the sample, conditional on the company size.

actual returns in the last 30 minutes. This comes as no surprise. First, signed returns are much harder to predict than measures of variation. Second, Γ^{IB} does not account for the actual return *direction*, thereby mixing the effects of buying and selling pressure due to the hedging activity of option market makers. Positive Γ^{IB} introduces additional buying pressure originating from the market maker for a negative return until 15:30, but additional selling pressure if $r_{close-1 \rightarrow 15:30} > 0$. The opposite holds for $\Gamma^{IB} < 0$. Therefore, one would expect the effects to cancel out when used to predict returns, resulting in an insignificant coefficient.

Adding Γ^{HP} as a direct measure of signed hedging pressure in the market circumvents this issue. Results are presented in Model (3):

$$r^i_{15:30 \rightarrow close} = \beta_0 r^i_{close-1 \rightarrow 15:30} + \beta^{HP} \Gamma^{HP}_{i,t-1} + Entity_i + \varepsilon_{i,t} \tag{7}$$

This way we seek to understand the effects of market maker hedging, given a certain magnitude for the returns until 15:30, $r_{close-1 \rightarrow 15:30}$. To this end, a positive (negative) reading of Γ^{HP} introduces additional selling (buying) pressure by the market maker, if regulatory and risk considerations require her to close the day delta-neutral. We again find significant evidence of intraday momentum in the cross-section of stock returns. Effects are further amplified once we account for the hedging pressure by market makers. A 1% return until 15:30 is now followed by an additional return of around 88 basis points, at a t-value of roughly 2.7. Γ^{HP} provides further information about cross-sectional returns in the last half hour of a trading day. A hedging pressure of 1% of the average trading volume in the last month depresses $r_{15:30 \rightarrow close}$ by a highly significant 18.3 basis points (t-value of -3.629). We have seen in Figure 1 that the cross-sectional 10th percentile of Γ^{HP} averages around -2.5%, introducing substantial hedging pressure for a subset of the cross-section, which markedly adds to the intraday momentum pattern we observe unconditionally. Γ^{HP} provides incremental information concerning the magnitude of intraday momentum, in that intraday momentum in individual stocks is stronger if the net Γ is negative, evident in the negative sign of Γ^{HP}. Likewise, hedging pressure by market makers reduces the magnitude of single stock intraday momentum if $\Gamma^{IB} > 0$. This conforms with the general idea that hedges by the market maker have a destabilizing effect if the market maker is Γ^{IB}-negative, and a stabilizing effect if $\Gamma^{IB} > 0$.

For completeness, we include returns until 15:30, Γ^{IB} and the interaction between the two, Γ^{HP}, in a single regression framework in Model (4):

$$r^i_{15:30 \rightarrow close} = \beta_0 r^i_{close-1 \rightarrow 15:30} + \beta^{IB} \Gamma^{IB}_{i,t-1} + \beta^{HP} \Gamma^{HP}_{i,t-1} + Entity_i + \varepsilon_{i,t} \tag{8}$$

We find only marginal changes compared to Model (3). The inclusion of Γ^{IB} seems to be of lesser importance to understand the effects of market maker hedging compared to the previous return. Since Γ^{HP} is the interaction between $r_{close-1\rightarrow 15:30}$ and Γ^{IB}, we will nonetheless from here on compare Models (1) and (4), i.e. unconditional intraday momentum in the cross-section and the impact of market maker hedging pressure.

In a last step, we try to understand whether effects are driven by the magnitude of the market maker's gamma imbalance Γ^{IB} or merely its sign. To do so, add dummy $\Gamma^{IB} \leq 0$ and interact it with returns until 15:30, $r_{close-1\rightarrow 15:30}$. We expect to see more pronounced effects for the interaction, suggesting that market maker hedging activity has a stronger impact on the price of the underlying if the aggregate gamma is negative. Referring back to Table 1, the coefficient for $r_{close-1\rightarrow 15:30}$ now picks up differential effects of the intraday return pattern in the first row ($\Gamma^{IB} \leq 0$), while the interaction with dummy $\Gamma^{IB} > 0$ naturally corresponds to additional effects if the market maker is on average net short gamma, i.e. for the second row in the table. The regression takes the following form:

$$r^i_{15:30\rightarrow close} = \beta_0 r^i_{close-1\rightarrow 15:30} + \beta^{IB<0}(\Gamma^{IB} \leq 0) \times r^i_{close-1\rightarrow 15:30} + Entity_i + \varepsilon_{i,t} \qquad (9)$$

The empirical results strongly support our hypothesis: the inclusion of the dummy interaction suppresses the statistical significance of outright intraday momentum and nearly halves its coefficient, which is now at 0.398 (t-value of 1.8). This suggests only marginally significant intraday momentum for positive Γ^{IB}, i.e. a positive gamma exposure of option market makers. The interaction is statistically significant at, suggesting very large intraday momentum for underlyings in which the option market maker is negative in the aggregate. Summing the two coefficients yields the average intraday momentum slope for a negative gamma exposure. It amounts to a large return continuation of the return until 15:30 (coefficient of 1.605).

The five regression specifications provide convincing evidence of the effects of market maker hedging activity on individual stock momentum. We confirm a stabilizing effect for a positive Γ-exposure, and a further acceleration of the return direction if the Γ-exposure of market makers in individual stocks is negative. The intraday momentum pattern in the last half hour is thus intimately linked to the existence and magnitude of market maker hedging activity. In fact, intraday momentum is concentrated in stocks with $\Gamma^{IB} < 0$. Next, we will discuss potential drivers of this connection.

3.1. Market Capitalization, Market Size, and Γ-Effects

We are interested in whether the influence of option market maker hedging pressure differs for stocks with different characteristics. As a first test, we examine differences in the effects of hedging pressure for stocks of different market sizes. Large caps not only exhibit lower volatility on average, but the cross-sectional dispersion of volatility is also lower compared to small stocks (see Figure 2). At the same time, large caps are more likely to enjoy a liquid and deep options market. We therefore seek to understand whether our results that the hedging pressure of option market makers influence underlying stock returns is connected to the size of the underlying stock, and the size of the option market.

In Table 3 we compare intraday momentum and market maker hedging effects between small and large stocks, with a cutoff at the median market capitalization in the last month. From column (1) we learn that intraday momentum also exists for small stocks, with a slightly smaller magnitude on average (coefficient of +0.594). This effect is still highly significant with a t-value of 3.721. Once again we observe a slight increase in this coefficient once we include Γ^{HP}, which itself is statistically significant at the 5%-level. Interestingly, the magnitude of the coefficient is much lower at -0.047, or about a third of what we observe for the full sample. A plausible explanation for this is that market makers opt to hedge baskets of smaller issues jointly, through the use of index options. The coefficient of Γ^{IB} is once again insignificant.

[Insert Table 3 Near Here]

Our results that market maker hedging pressure exerts an influence on the price of the underlying is driven by the impact of large caps. Not only is the intraday momentum coefficient larger, at +0.662% without the inclusion of Γ^{HP} and +0.908% with the inclusion, the impact of Γ^{HP} itself is more pronounced as well. A 1% hedging pressure leads to additional selling pressure in the underlying of -0.193%, which is highly significant with a t-value of roughly -3.6. While many cross-sectional effects are concentrated in smaller stocks, intraday momentum, and more importantly the impact of market maker hedging, is more pronounced in the returns of large stocks. In section 4 we examine the economic significance of trading on Γ^{HP}, and note that the large stocks for which we find a highly significant impact, are also those which enjoy more frequent trading, at higher liquidity.

We next turn to the influence of the size of the market of the underlying and the corresponding option market relative to the cross-section. In columns (1) & (2) of Table 4 we split the sample first by the cross-sectional median dollar volume transacted in the underlying over the last twelve months. A larger market for the underlying should buffer the relative price impact of market maker hedging pressure, leading to smaller coefficient estimates. In columns (3) & (4) we do a similar median sample split, this time with respect to the dollar open interest relative to the market capitalization of the underlying, to gauge the size of the options market for stock i.[10] A larger option market in general has an ambivalent impact on our results. On the one hand, larger option markets may exert more pronounced hedging pressure by the market maker, if she has to absorb an absolutely larger amount of option positions. This should make the impact of intraday hedging pressure on returns of the underlying more severe. On the other hand, this larger

[10]This measure is defined as $\frac{\sum_{K,T} OI_{K,T} \times 100 \times S}{MarketCap}$. We use the average over the last year to limit the influence of outliers and thereby limit the amount of migration at the split point.

option market may also be characterized by more trade between end customers. This would alleviate some of the hedging pressure, which could in turn also lead to smaller coefficients of Γ^{HP}.

[Insert Table 4 Near Here]

We first reject the idea that a larger trade volume in the underlying increases the impact of market maker delta-hedging. Instead, the coefficient in the "High $Vol" sub-sample is about 50% larger compared to the low underlying dollar volume sample. Both are highly significant with t-values below -3. The intraday momentum follows a similar pattern in that it is more pronounced for larger underlying markets. With respect to the relative dollar open interest, we find much more pronounced effects in the "Low $OI" sample, with a coefficient of -0.44 vs. -0.176 for the "High $OI" sample. Both are highly significant with t-values of -4.3 and -3.5. This is in line with the second part of our hypothesis about the effects of the option market size. Larger option markets are *not* characterized by stronger hedging pressure on the underlying, but the opposite. Other specifications of the (relative) size of the underlying and option market have led to similar conclusions that, contrary to the concentration in large caps, the market size has little impact on the existence of hedging pressure on the underlying's price, but determines the size of the effect.

3.2. Reversal at the Next Open

If the impact of market maker hedging is driven mechanically and does not reflect fundamental information about the underlying, we should expect to see a reversal of the effects at the next open. In fact, even without explicitly considering market maker hedging pressure, Baltussen et al. (2020) find significant reversal in multiple Futures markets on the following three days. Here, we also include the impact of Γ^{HP} on day $t-1$ as an additional explanatory variable besides returns in the last half hour, to directly analyze the reversal due to the hedging activity by market makers. We seek to explain the return in the first half hour until the open of trading day $t+1$, to capture information processing by the remaining market participants, under the assumption that the mechanically-driven return movement by market makers is reversed relatively quickly. Our regressions follow Equations 5 – 8.

[Insert Table 5 Near Here]

The results in Table 5 show clear evidence of such a reversal in the cross-section of stock returns. Not only is the closing return on day t significantly negatively related to the return in the first half hour of the following day[11], but the hedging pressure, Γ^{HP} now also shows a positive slope coefficient of comparable size to that in Table 2. Both of these effects are highly significant at any conventional level of significance. The empirical evidence suggests that the effects of market maker hedging are reversed at the start of the next trading day, constituting a temporary drift from the fundamental value of the underlying – the *non-information channel* of option trading. This drift is reversed at the next open.

3.3. Market vs. Cross-Sectional Momentum

We have seen that individual stocks exhibit intraday momentum, when returns in the last half hour are compared to returns until 15:30. This time-series intraday momentum is similar to the effects found in Gao et al. (2018) and Baltussen et al. (2020) in the case of Equity ETFs and Futures, but differs from the analysis in Heston et al. (2010). The authors are interested in cross-sectional differences in returns and find patterns of half-hour returns significantly predicting returns of the same half-hour up to 40 days in the future. To determine whether the cross-sectional intraday momentum is driven by an *average* momentum, i.e. a time-series momentum, or by cross-sectional differences as advocated by Heston et al. (2010), we include the returns on a value-weighted market proxy as an explanatory variable.[12]

[Insert Table 7 Near Here]

Consistent with the idea that intraday momentum in individual stocks is driven by an *average* time-series momentum, the coefficient to the market return is large and highly significant (see Table 7). At the same time, the coefficient to $r_{close-1\rightarrow 15:30}$ switches signs, from positive to negative, indicating a reversal in the last half hour *relative to the market return.* This corroborates the study by Heston et al. (2010) that returns exhibit intraday reversals if the market impact is accounted for. This switch in sign, however, has no implications for our result that the market maker hedging pressure significantly and negatively impacts individual stock returns in the last half hour of a trading day. The information inherent in Γ^{HP} seems largely unrelated to the overall market return until 15:30, and impacts both the cross-sectional and time-series dimension of individual stock returns.

[11] The larger estimates arise as we are now comparing half-hour to half-hour returns, instead of 6-hours to half-hour returns as in the analyses before

[12] Note that this procedure effectively forces the market effect to average across all stocks in the sample, disregarding differences in sensitivities (βs). In unreported analyses we run the same regression with CAPM residuals, for stocks with at least 500 occurrences in our sample. The results are comparable.

3.4. *Discussion of Our* Γ *Proxy*

As we approximate Γ^{HP} by the open interest in call and put options on the stock level, our measure might pick up another driver of intraday return patterns. Although shown to work in the cross-section of stocks, a natural candidate is the O/S ratio by Roll et al. (2010), which represents the option-to-stock-volume ratio. Moreover, Blau et al. (2014) show that the unsigned put volume relative to total option volume is negatively related to next-day returns. We re-run our baseline model in Equation (8), but include separately the O/S and put-call ratio as control variables. We measure the O/S ratio either in share or dollar terms. Instead of the raw O/S ratios, we consider the log of it, as it highly dispersed in the cross-section and time-series.

[**Insert Table 6 Near Here**]

As Table 6 shows, our results are not driven if we include any of the additional covariates to our baseline specification. Precisely, the economic and statistically significance of our variable of interest, Γ^{HP}, remains unchanged.

4. Economic Significance

In the preceding section, we have established the importance of market maker hedging pressure as a driver of single stock returns in the last half hour of a trading day. Next, we assess the usefulness of the predictability by means of a trading strategy. Therefore, we use the return up to the last half hour and the gamma imbalance of each single stock as timing signals. More specifically, we calculate Γ^{HP} for each single stock at 15:30 on each trading date. Subsequently, we construct decile portfolios based on Γ^{HP} and take a long (short) position in the lowest (highest) decile. Stocks exhibiting a very negative reading of Γ^{HP} on 15:30 exhibit either a positive return combined with a negative gamma imbalance or a negative return combined with a positive gamma imbalance. In the first case, we expect a return continuation until market close as option market markers hedge by buying the underlying as the underlying has risen beforehand. In the latter case, we assume that the underlying stock mean-reverts in the last half hour. In both cases though, we anticipate a positive return. A similar reasoning applies to take a short position into the highest decile portfolio.

Mathematically, our strategy can be expressed as follows:

$$\eta(\Gamma^{HP}) = \sum 1_{\{\Gamma_i^{HP} < q(0.05,\Gamma^{HP})\}} \times w_i \times r_{close,i} - 1_{\{\Gamma_i^{HP} > q(0.95,\Gamma^{HP})\}} \times w_i \times r_{close,i}, \quad (10)$$

where $q(\alpha, \Gamma^{HP})$ denotes the α-percentile of Γ_i^{HP} of available stocks at day t. We choose w_i to be either equally or value weighted within each decile porfolio.

Panel A of Table 8 reports summary statistics on returns of our strategy. The average total excess return is 14.74% on an annual basis when stocks are equally weighted. In case of value weighting, the strategy yields annual excess returns of 11.99%.[13] In order to get a better understanding of the performance, we consider a benchmark strategy *Always long* which takes long positions in all stocks at the beginning of the last half hour and closes all positions at the market close on each trading day. As Panel of A Table 8 reveals, *Always long* yields an annual return of 7.34% for equalling weighting the stocks. The performance drops sharply for value-weighting to 1.49% being not significantly different from zero. The superiority of our strategy remains in place when we take risk into consideration. Panel A of Table 8 documents the standard deviation and Sharpe ratio. Our equally-weighted strategy generates a Sharpe ratio of 6.23, nearly five times larger than the comparable benchmark strategy. It exhibits also a high positive skewness of 1.18 versus 0.53 for *Always long*.

To show robustness, but also address concerns about the implementation of our strategy, Panel B in Table 8 repeats the above analysis, but is restricted to stocks in the highest market capitalization quintile. As shown, the results also hold for this subsample of stocks.

Our trading strategies have so far neglected trading costs. However, this is an important aspect as our intraday strategy exhibits by construction a turnover of 100%. Frazzini et al. (2018) document trading costs in the range of 5bp using a large trade record over nearly the same time span as our sample. This figure marks roughly the break-even point for our trading strategy as the value-weighted strategy across the high market cap quintile stocks earns 5.3bp per day.

[**Insert Table 8 Near Here**]

5. Understanding Market Maker Hedging Pressure

To emphasize the mechanism through which market maker hedging pressure influences cross-sectional stock returns, we carry out a battery of additional robustness tests. More precisely, we are interested in how far our findings relate to differing (option-)market characteristics across industries, and how results comove with the business cycle and the great financial crisis. Additionally, we mitigate concerns that our results may be driven by an informational channel.

[13] Although we effectively hold our positions only for half an hour on each trading day, i.e. one thirteenth of a trading day, we scale by 252 to compare to once-per-day investments.

5.1. *Industry Sectors*

Lakonishok et al. (2006) provide evidence that option trading activity of certain market participants, e.g. retail investors, reveal preferences for special stock characteristics. Israelov and Nielsen (2014) also suggest that option trading activity might vary with the underlying assets' attributes. The authors list the attractiveness of high-volatility stocks for call-writing strategies as one of eight myths about call-writing. We conjecture that the option demand of certain trader types might manifest themselves on an aggregate industry level. We therefore assign each stock in our sample to one industry where the classification is based on SIC codes and follows Kenneth French's website. Subsequently, we run our baseline specification in Equation (8) for each industry sample.

Table 9 summarizes the empirical results. There are several noteworthy observations. First, statistically robust intraday momentum is only apparent in Business, Health, and Other industry sectors. The economic magnitude of intraday momentum varies across the three industries. It is strongest for the sector Other. Second, the effect of Γ^{HP} on the last half hour returns is statistically significant at least at the 5% confidence level in all five industries. Moreover, it is statistically significant at the 1% confidence level for three out of five industries. Third, the economic magnitude of the delta-hedging activities of market makers on the return in the last half hour of the trading day is strong across all industries. It is most pronounced in the sectors Health and Other, where option market maker lead to a momentum or reversal, depending on their aggregate gamma imbalance, of more than 23 basis points per one percentage point move in the underlying from the previous day's close until 30 minutes before the close. Γ^{HP} is weakest in economic terms in the sectors Consumer and Business, but with approximately 13 basis points still meaningful. Our results show that delta-hedging has a pervasive impact on the underlying stock price dynamics, regardless of the industry considered.

[**Insert Table 9 Near Here**]

5.2. *Different Market Conditions*

Chordia and Shivakumar (2002) have stressed the importance of the business cycle on momentum returns. As the authors show, momentum strategies yield positive returns only in expansionary periods, whereas returns during recessions are negative. Motivated by these findings, we investigate the effect of Γ^{HP} on the last half hour return under various market conditions. Therefore, we split the entire sample along the business cycle into recession and expansion days, and into the financial crisis and non-crisis periods. As in Gao et al. (2018), we set the financial crisis from 2$^{\text{nd}}$ December 2007 to 30$^{\text{th}}$ June 2009, whereas recession and expansion dates are taken from the National Bureau of Economic Research.

[Insert Table 10 Near Here]

First, we estimate Equations (5) and (8) either for NBER recession days or expansion days and report results in Table 10. As evident from Table 10, the effect of the hedging pressure on the last half-hour return is economically stronger during recession days compared to expansion days. During expansions, option market makers hedging activities induce a momentum or reversal of 11 basis points per one percent move in the underlying until 15:30. During recessions, the effect increases more than six-fold, up to 76 basis points. The coefficient on Γ^{HP} remains significant in both subsamples, though at the 10% level during recessions, whereas at the 1% level during expansions. The change in the level of significance might be driven by the small sample of recession days, as these make up only 6% of the days in our sample.

As Table 11 summarizes, the results remain qualitatively and quantitatively the same if we either exclude or focus on the financial crisis. The effects of intraday momentum and market maker hedging pressure are amplified in times of distress, which is in direct contrast to the findings of Chordia and Shivakumar (2002) for monthly momentum strategies.

[Insert Table 11 Near Here]

5.3. Fundamental News

We have highlighted a non-informational channel through which option prices influence the dynamics of the underlying for the case of individual stocks. In related research, several studies have pointed towards an informational channel. Black (1975) reasons that the higher leverage inherent in derivatives makes their use appealing to investors. Pan and Poteshman (2006) provide evidence of informed trading in options markets and its impact on the underlyings' stock prices. Lin and Lu (2015) suggest that analysts play an important role in the price discovery process between option and stock markets. The authors point towards analyst increasing the use of option trading around analyst-related news as a driver of the options predictability on stock returns. In a recent study, Cremers, Fodor, and Weinbaum (2020) analyse how informed traders transact in the options market around news announcement. Overall, the authors document that informed option trading remains profitable even after transaction costs. Consequently, one may argue that our results are ultimately due to an informational channel if they are subsumed by periods of earnings and news announcement releases.

In an effort to mitigate concerns about this informational channel of options trading, we first collect earnings announcement dates from I/B/E/S and Compustat, as earnings announcements constitute the most influential regularly occurring corporate news events. Second, we use the Dow Jones version from RavenPack News Analytics to identify days with fundamental news releases for each firm in our sample. RavenPack assigns each news article a relevance and sentiment score, among others. We keep only records where the relevance score equals 100. Thereby we ensure that news are highly relevant for a company. Based on the sentiment score, we classify each news record either as positive or negative news. Having identified date t as either an earnings announcement or news day for stock i, we focus on a symmetric two-week window around t to investigate the effects of earnings and news releases on the connection between intraday hedging pressure by market makers and returns. We re-run our baseline specification in Equation (8) by excluding or concentrating on days with earnings announcements or news releases in Table 12.

[**Insert Table 12 Near Here**]

As the first two columns show, the effect of Γ^{HP} remains statistically highly significant on days with or without earnings announcements. Furthermore, the Γ^{HP} coefficient obeys roughly the same order of magnitude for all specifications considered. Columns three to five confirm that also either including or excluding the days with the most significant fundamental news do not change our conclusions with respect to the economic magnitude and statistically significance of Γ^{HP}. In column (3) we rerun our main analysis restricting the sample to start in 2000, for which we were able to obtain RavenPack data.

6. Conclusion

This paper adds to the emerging literature documenting a non-informational channel through which option markets affect the underlying stock's price dynamics. We find evidence for a significant link between the returns in the last half hour of a trading day and the aggregated dollar amount option market makers need to trade in the underlying stocks to establish delta-neutrality. This link supports the hypothesis that end-of-day delta-hedging of market makers elicit price pressure on the underlying stock market. This price pressure is temporary, as the effect reverts at the next day's open. Our results are economically large. We measure a return continuation or reversal of 18 basis points per one percentage point move in the underlying from previous day's close to half an hour before trading close. Return momentum or reversal is determined by the sign of the return until 30 minutes before trading close and the sign of the aggregate gamma exposure of option market makers. An added benefit is that our results concentrate for stocks with high market capitalization, which generally enjoy more liquid trading.

Our results are not restricted to specific industries or time periods. They are neither explained by information based alternative hypotheses. We believe that our findings are of relevance not only for option and stock market participants, but also regulatory bodies, as negative gamma exposure and negative previous returns can lead to downward price spirals. This effect intensifies during periods of general market distress, such as recessions. Our results add to the literature on the effects of the option market.

References

Andersen, T. G., Bollerslev, T., 1997. Intraday periodicity and volatility persistence in financial markets. Journal of Empirical Finance 4, 115–158.

Andersen, T. G., Bondarenko, O., Gonzalez-Perez, M. T., 2015. Exploring return dynamics via corridor implied volatility. The Review of Financial Studies 28, 2902–2945.

Baltussen, G., Da, Z., Lammers, S., Martens, M., 2020. Hedging demand and market intraday momentum. Journal of Financial Economics Forthcoming.

Barbon, A., Buraschi, A., 2020. Gamma fragility. Working paper, University of St.Gallen, School of Finance Research Paper.

Black, F., 1975. Fact and Fantasy in the Use of Options. Financial Analysts Journal 31, 36–41+61–72.

Blau, B. M., Nguyen, N., Whitby, R. J., 2014. The information content of option ratios. Journal of Banking and Finance 43, 179 – 187.

Bogousslavsky, V., 2020. The Cross-Section of Intraday and Overnight Returns. Working paper.

Chordia, T., Shivakumar, L., 2002. Momentum, business cycle, and time-varying expected returns. The Journal of Finance 57, 985–1019.

Cici, G., Palacios, L.-F., 2015. On the use of options by mutual funds: Do they know what they are doing? Journal of Banking and Finance 50, 157 – 168.

Clewlow, L., Hodges, S., 1997. Optimal delta-hedging under transactions costs. Journal of Economic Dynamics and Control 21, 1353–1376.

Cremers, M., Fodor, A., Weinbaum, D., 2020. Where Do Informed Traders Trade (First)? Option Trading Activity, News Releases, and Stock Return Predictability. Working paper.

Cremers, M., Weinbaum, D., 2010. Deviations from put-call parity and stock return predictability. The Journal of Financial and Quantitative Analysis 45, 335–367.

Davies, P. J., 2019. Markets are calm, then suddenly go crazy. some investors think they know why. Wallstreet Journal, July 9, 2019.

Dellavigna, S., Pollet, J. M., 2009. Investor Inattention and Friday Earnings Announcements. The Journal of Finance 64, 709–749.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3 – 56.

Fournier, M., Jacobs, K., 2020. A Tractable Framework for Option Pricing with Dynamic Market Maker Inventory and Wealth. Journal of Financial and Quantitative Analysis 55, 1117–1162.

Frazzini, A., Israel, R., Moskowitz, T. J., 2018. Trading costs. Working paper.

Frey, R., 1998. Perfect option hedging for a large trader. Finance and Stochastics 2, 115–141.

Frey, R., Stremme, A., 1997. Market volatility and feedback effects from dynamic hedging. Mathematical Finance 7, 351–374.

Gao, L., Han, Y., Zhengzi Li, S., Zhou, G., 2018. Market intraday momentum. Journal of Financial Economics 129, 394–414.

Golez, B., Jackwerth, J. C., 2012. Pinning in the s&p 500 futures. Journal of Financial Economics 106, 566 – 585.

Gârleanu, N., Pedersen, L. H., Poteshman, A. M., 2009. Demand-Based Option Pricing. Review of Financial Studies 22, 4259–4299.

Hendershott, T., Livdan, D., Rösch, D., 2020. Asset pricing: A tale of night and day. Journal of Financial Economics 138, 635 – 662.

Heston, S. L., Korajczyk, R. A., Sadka, R., 2010. Intraday patterns in the cross-section of stock returns. The Journal of Finance 65, 1369–1407.

Hu, J., 2014. Does option trading convey stock price informationα. Journal of Financial Economics 111, 625–645.

Huang, D., Li, J., Wang, L., Zhou, G., 2020. Time series momentum: Is it there? Journal of Financial Economics 135, 774 – 794.

Israelov, R., Nielsen, L. N., 2014. Covered call strategies: One fact and eight myths. Financial Analysts Journal 70, 23–31.

Jacobs, K., Mai, A. T., 2020. The role of intermediaries in derivatives markets: Evidence from vix options. Working paper.

Johnson, T., Liang, M., Liu, Y., 2016. What Drives Index Options Exposures?*. Review of Finance 22, 561–593.

Komarov, O., 2017. Intra-day momentum. Working paper.

Lakonishok, J., Lee, I., Pearson, N. D., Poteshman, A. M., 2006. Option Market Activity. The Review of Financial Studies 20, 813–857.

Li, Y., 2019. There's a strange phenomenon reportedly influencing the direction of the stock market each day, Retrieved 2021-01-07, from https://www.cnbc.com/2019/07/09/theres-a-strange-phenomenon-reportedly-influencing-the-direction-of-the-stock-market-each-day.html.

Lin, T. C., Lu, X., 2015. Why do options prices predict stock returns? Evidence from analyst tipping. Journal of Banking and Finance 52, 17–28.

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

Moskowitz, T. J., Ooi, Y. H., Pedersen, L. H., 2012. Time series momentum. Journal of Financial Economics 104, 228 – 250, special Issue on Investor Sentiment.

Ni, S. X., Pearson, N. D., Poteshman, A. M., 2005. Stock price clustering on option expiration dates. Journal of Financial Economics 78, 49–87.

Ni, S. X., Pearson, N. D., Poteshman, A. M., White, J., 2020. Does Option Trading Have a Pervasive Impact on Underlying Stock Prices? The Review of Financial Studies Hhaa082.

Pan, J., Poteshman, A. M., 2006. The Information in Option Volume for Future Stock Prices. Review of Financial Studies 19, 871–908.

Petersen, M. A., 2008. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. The Review of Financial Studies 22, 435–480.

Platen, E., Schweizer, M., 1998. On feedback effects from hedging derivatives. Mathematical Finance 8, 67–84.

Roll, R., Schwartz, E., Subrahmanyam, A., 2010. O/s: The relative trading activity in options and stock. Journal of Financial Economics 96, 1 – 17.

Sircar, K. R., Papanicolaou, G., 1998. General black-scholes models accounting for increased market volatility from hedging strategies. Applied Mathematical Finance 5, 45–82.

Thompson, S. B., 2011. Simple formulas for standard errors that cluster by both firm and time. Journal of Financial Economics 99, 1 – 10.

Wilmott, P., Schönbucher, P. J., 2000. The feedback effect of hedging in illiquid markets. SIAM Journal on Applied Mathematics 61, 232–272.

Table 2: **Intraday Return Regressions**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1\rightarrow 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$
$r_{close-1\rightarrow 15:30}$	0.656**		0.878***	0.879***	0.398*
	(2.280)		(2.694)	(2.698)	(1.797)
Γ^{IB}		0.010		0.022	
		(0.362)		(0.791)	
Γ^{HP}			-0.183***	-0.184***	
			(-3.628)	(-3.629)	
$(\Gamma^{IB} \leq 0) \times r_{close-1\rightarrow 15:30}$					1.207**
					(2.467)
Observations	12,283,918	12,283,918	12,283,918	12,283,918	12,283,918
Entity FE	Yes	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust	Robust

Table 3: **Small vs. Large Stocks**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1\rightarrow 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. The sample is split by the cross-sectional median market capitalization over the last month. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$
$r_{close-1\rightarrow 15:30}$	0.594***	0.621***	0.662**	0.908***
	(3.721)	(3.689)	(2.183)	(2.624)
Γ^{IB}		0.011		0.023
		(0.706)		(0.836)
Γ^{HP}		-0.047**		-0.193***
		(-2.002)		(-3.580)
Observations	6,159,679	6,159,679	6,124,239	6,124,239
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust
Market Size	Small	Small	Large	Large

Table 4: **Stocks with Varying Sizes of the Underlying/Option Market**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1 \to 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. The sample is split by the cross-sectional median trading volume in the underlying over the last twelve months in columns (1) and (2). In columns (3) and (4) we split by the median relative option market size over the last twelve months, expressed as $\frac{\sum_{K,T} OI_{K,T} \times 100 \times S}{MarketCap}$. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{15:30 \to close}$	$r_{15:30 \to close}$	$r_{15:30 \to close}$	$r_{15:30 \to close}$
$r_{close-1 \to 15:30}$	0.540	1.219***	0.833**	0.930***
	(1.205)	(4.385)	(2.282)	(2.772)
Γ^{IB}	0.053	-0.010	-0.002	0.028
	(1.498)	(-0.503)	(-0.034)	(1.048)
Γ^{HP}	-0.229***	-0.083**	-0.440***	-0.176***
	(-3.348)	(-2.021)	(-4.279)	(-3.542)
Observations	6,501,921	5,781,997	6,506,838	5,777,080
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust
Subsample	Low $Vol	High $Vol	Low $OI	High $OI

Table 5: **Reversal of Hedging Effects at Next Open**
The table reports the economic value of timing the last half-hour market return using our gamma measure. The strategy takes a long position in a stock when the stock's gamma exp is in the upper vigintile and a short position when it is in the lower vigintile. As a benchmark, Always long denotes investing in all stocks. We consider equally weighted (EW) and value weighted (VW) portfolios. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (Sharpe), skewness, kurtosis, and success rate (Success). The returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from January 1996 to June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{open \to 10:00}$	$r_{open \to 10:00}$	$r_{open \to 10:00}$	$r_{open \to 10:00}$
$r_{15:30 \to close}$	-13.019***		-12.998***	-12.996***
	(-6.247)		(-6.233)	(-6.234)
Γ^{IB}		-0.106**		-0.123**
		(-1.964)		(-2.316)
Γ^{HP}			0.280***	0.284***
			(4.580)	(4.620)
Observations	12,281,258	12,281,258	12,281,258	12,281,258
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust

Table 6: **Discussion of Γ-Proxy**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1 \rightarrow 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equation 8. Specification (1) adds to the baseline model in Table 2 the log of O/S-$ as a control variable, where O/S-$ is the dollar option-to-stock volume ratio, as in Roll et al. (2010). In specification (2), we include the log of O/S, where O/S denotes the option-to-stock volume ratio, expressed in shares, as in Roll et al. (2010). Specification (3) adds the put-call-ratio (PC ratio) as in Blau et al. (2014) as a control variable to our baseline model. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)
Dependent	$r_{15:30 \rightarrow close}$	$r_{15:30 \rightarrow close}$	$r_{15:30 \rightarrow close}$
$r_{close-1 \rightarrow 15:30}$	0.892***	0.891***	0.892***
	(2.701)	(2.699)	(2.704)
Γ^{IB}	0.021	0.029	0.024
	(0.811)	(1.136)	(1.018)
Γ^{HP}	-0.186***	-0.186***	-0.186***
	(-3.622)	(-3.622)	(-3.623)
log O/S-$	0.001***		
	(3.565)		
log O/S		-0.002***	
		(-3.929)	
PC ratio			0.005
			(0.591)
Observations	9,551,686	9,551,686	9,551,686
Entity FE	Yes	Yes	Yes
SEs	Robust	Robust	Robust

Table 7: **Impact of Market Returns**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30 for the stock, $r_{close-1\to 15:30}$, and the market, $r^M_{close-1\to 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$
$r_{close-1\to 15:30}$	-0.884***		-0.659***	-0.658***	-1.074***
	(-6.473)		(-4.050)	(-4.043)	(-7.165)
r_market_vw_prev	6.419***	5.535***	6.422***	6.422***	6.382***
	(7.270)	(6.090)	(7.313)	(7.312)	(7.351)
Γ^{IB}		0.013		0.024	
		(0.493)		(0.926)	
Γ^{HP}			-0.186***	-0.187***	
			(-3.948)	(-3.956)	
$(\Gamma^{IB} \leq 0) \times r_{close-1\to 15:30}$					0.930**
					(2.177)
Observations	12,283,918	12,283,918	12,283,918	12,283,918	12,283,918
Entity FE	Yes	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust	Robust

Table 8: **Market Timing**
The table reports the economic value of timing the last half-hour market return using our gamma measure. The strategy takes a long position in a stock when the stock's gamma exp is in the upper vigintile and a short position when it is in the lower vigintile. As a benchmark, Always long denotes investing in all stocks. We consider equally weighted (EW) and value weighted (VW) portfolios. For each strategy, we report the average return (Avg ret), standard deviation (Std dev), Sharpe ratio (Sharpe), skewness, kurtosis, and success rate (Success). The returns are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses, and significance at the 1%, 5%, or 10% level is denoted by ***, **, or *, respectively. The sample period is from January 1996 to June 2019.

	Avg ret	Std dev	Sharpe	Skewness	Kurtosis	Success
Panel A: All stocks						
Strategy (EW)	14.74***	2.37	6.23	1.18	16.30	66.97
	(28.34)					
Always long (EW)	7.34***	5.44	1.35	0.53	23.27	56.25
	(7.03)					
Strategy (VW)	11.99***	2.82	4.25	0.59	19.32	65.39
	(20.32)					
Always long (VW)	1.49	5.33	0.28	-0.23	18.51	52.21
	(1.43)					
Panel B: High Market Cap Quintile						
Strategy (EW)	9.83***	2.68	3.67	0.54	38.03	63.34
	(17.72)					
Always long (EW)	2.22**	5.14	0.43	-0.15	19.82	52.94
	(2.22)					
Strategy (VW)	13.53***	3.22	4.20	0.54	17.23	65.09
	(19.92)					
Always long (VW)	0.84	5.45	0.15	-0.30	17.87	51.63
	(0.79)					

Table 9: **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, $r_{close-1\to15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. 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`. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$
$r_{close-1\to15:30}$	-0.111	0.693	1.010***	0.625*	1.472***
	(-0.418)	(1.173)	(2.967)	(1.648)	(3.146)
Γ^{IB}	0.010	0.041	0.061	0.022	-0.040
	(0.383)	(1.290)	(1.604)	(1.129)	(-1.217)
Γ^{HP}	-0.132***	-0.201**	-0.132**	-0.260***	-0.232***
	(-3.439)	(-1.992)	(-2.396)	(-3.244)	(-3.166)
Observations	2,189,511	2,497,523	2,886,271	1,367,762	3,342,851
Entity FE	Yes	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust	Robust
Industry	Consumer	Manuf.+Energy	Business	Health	Other

Table 10: **Impact of Recessions and Expansions**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1\to 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. The regression results are reported for NBER expansions and recessions, respectively. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$
$r_{close-1\to 15:30}$	0.306	0.478**	2.386**	2.651**
	(1.389)	(2.036)	(2.075)	(2.171)
Γ^{IB}		0.028		-0.041
		(1.018)		(-0.237)
Γ^{HP}		-0.124***		-0.772**
		(-3.752)		(-2.011)
Observations	11,220,090	11,220,090	1,063,828	1,063,828
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust
Subsample	Expansion	Expansion	Recession	Recession

Table 11: **Impact of Financial Crisis**
The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1 \to 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. The regression results are reported for the financial crisis and the non-crisis period, respectively. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{15:30 \to close}$	$r_{15:30 \to close}$	$r_{15:30 \to close}$	$r_{15:30 \to close}$
$r_{close-1 \to 15:30}$	0.211	0.365*	3.593***	3.775***
	(1.059)	(1.664)	(2.989)	(2.990)
Γ^{IB}		0.017		-0.106
		(0.566)		(-0.162)
Γ^{HP}		-0.114***		-0.661**
		(-3.786)		(-2.259)
Observations	11,454,915	11,454,915	829,003	829,003
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust
Subsample	Non-GFC	Non-GFC	GFC	GFC

Table 12: **Impact of Fundamental Information**

The table reports the results to regressing returns in the last half hour of a trading day on returns until 15:30, $r_{close-1\rightarrow 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. 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. Specification (3) uses the subset for which RavenPack data is available, i.e. from January 2000 to the end of our sample. In specification (4) 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 (5) includes only these observations. Whenever earninigs announcements or fundamental news are released on day t for asset i, we exclude also a window of 5 trading days around t for asset i. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$
$r_{close-1\rightarrow 15:30}$	1.007***	0.509*	0.981***	1.012***	0.945**
	(3.393)	(1.658)	(3.236)	(3.476)	(2.568)
Γ^{IB}	0.012	0.072	0.034	0.030	0.044
	(0.331)	(1.101)	(0.925)	(0.965)	(0.883)
Γ^{HP}	-0.172***	-0.213***	-0.191***	-0.183***	-0.198***
	(-3.872)	(-4.121)	(-4.357)	(-4.541)	(-3.504)
Observations	10,191,799	2,092,119	10,433,753	8,595,405	1,838,348
Entity FE	Yes	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust	Robust
Subsample	Excluding EA	Only EA	Full Sample since 2000	Excluding News	Only News

Fig. 1. **Hedging Pressure Over Time.**
Shows the cross-sectional distribution of the gamma imbalance Γ^{IB} and our hedging pressure proxy Γ^{HP} over time. The dark teal line represents the cross-sectional median, the teal area the 25th/75th percentile, and the light teal area the 10th/90th percentile.

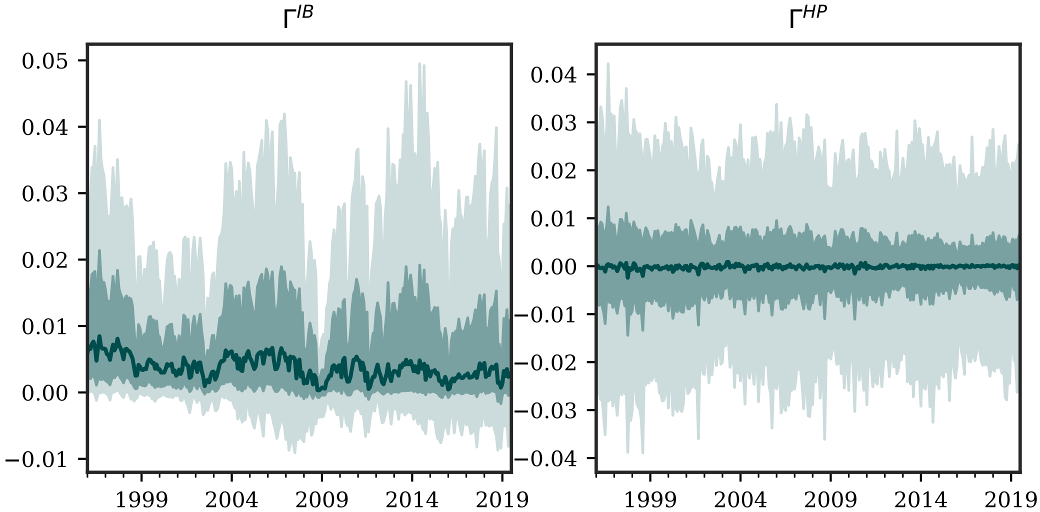


Fig. 2. **Intraday Volatility Distribution**
Shows the intraday volatility distribution of the 6551 companies in our sample from 1996 through June of 2019, split by the median market capitalization in the month before. Realized volatility is calculated as the annualized sum of 5-minute returns per stock i during the respective time period. The figure follow standard box plot convention, with the box representing the 25th and 75th percentile, the line in the box the median, and whiskers the 10th and 90th percentile.

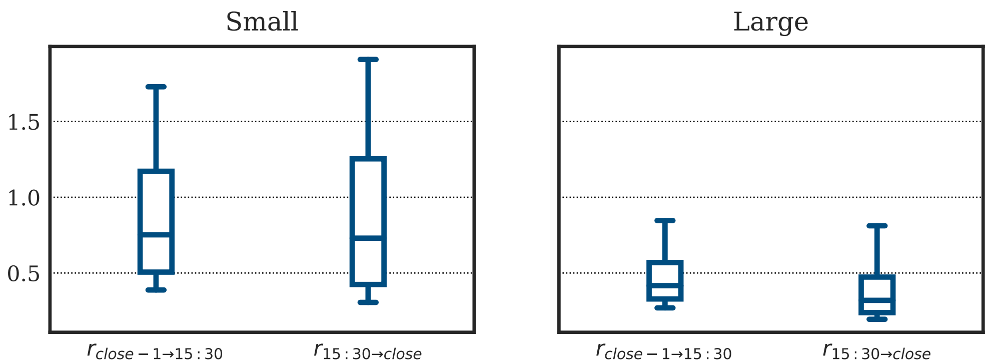
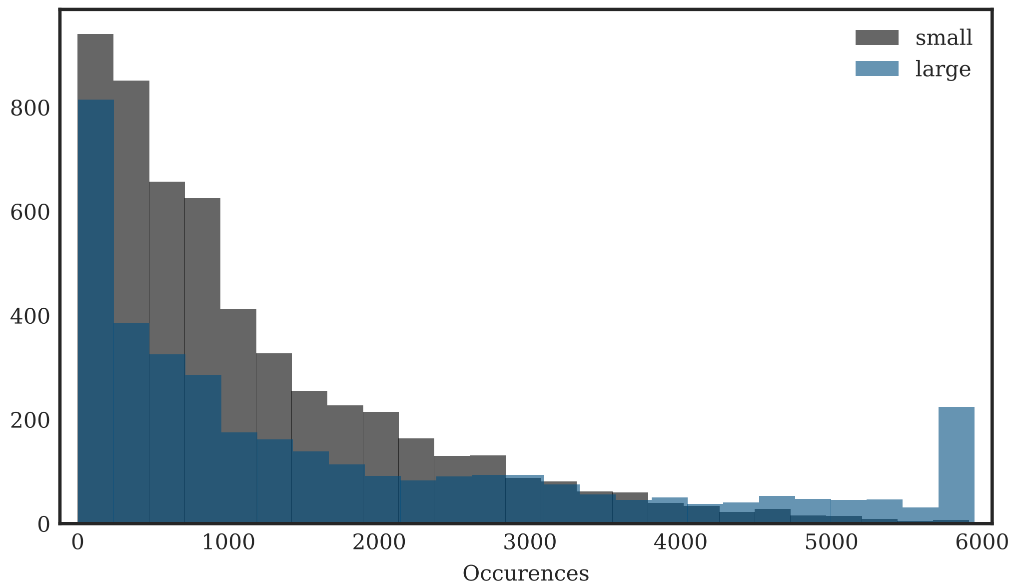


Fig. 3. **Occurrences by Size of Company**
Shows the number of occurrences individual stocks make in our sample, conditional on them falling above or below last month's median market capitalization. Since large stocks are typically included for a longer time, the histograms appear of unequal size. However, the sample sizes are the same, since the total number of occurences is the product between x- and y-values.



Appendix A. Cleaning of High-Frequency Data

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

A.1. Cleaning Procedure

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

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

A.2. Merge with CRSP

The TAQ database provides intraday trade prices, but lacks information about distributions, mergers, and delistings. We obtain this information from CRSP, as the 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. Since we are interested in the impact of market maker hedging activity, we retain only those stocks that are optionable, i.e. for which options have traded between 1996 and July of 2019.

Appendix B. Alternative Window Length for ADV

Throughout our main analyses, we have chosen a one-month time period for computing the average dollar volume (ADV) for each stock. In Table B1 and Table B2, we vary the time period to weekly and quarterly, respectively. The choice of window length is inconsequential for our results.

Table B1: **Gamma Expsoure with Weekly ADV**
The table reports the results to regressing returns in the last half hour of a trading day on Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 6 - 8. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$
Γ^{IB}	0.011		0.019	
	(0.375)		(0.624)	
$r_{close-1\to 15:30}$		0.873***	0.873***	0.398*
		(3.202)	(3.203)	(1.947)
Γ^{HP}		-0.177***	-0.177***	
		(-4.406)	(-4.417)	
$(\Gamma^{IB} \leq 0) \times r_{close-1\to 15:30}$				1.207***
				(2.973)
Observations	12,283,918	12,283,918	12,283,918	12,283,918
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust

Table B2: **Gamma Expsoure with Quarterly ADV**

The table reports the results to regressing returns in the last half hour of a trading day on Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 6 - 8. Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications and weight returns by the stock's market capitalization. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)
Dependent	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$	$r_{15:30\to close}$
Γ^{IB}	0.004		0.017	
	(0.109)		(0.406)	
$r_{close-1\to 15:30}$		0.864***	0.865***	0.398*
		(3.152)	(3.152)	(1.947)
Γ^{HP}		-0.174***	-0.174***	
		(-3.920)	(-3.928)	
$(\Gamma^{IB} \leq 0) \times r_{close-1\to 15:30}$				1.207***
				(2.973)
Observations	12,283,918	12,283,918	12,283,918	12,283,918
Entity FE	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust

Appendix C. Scaled Returns

Throughout our main analyses, returns in the regression are weighted by each stock's market capitalization on day $t-1$. In order to achieve a meaningful comparison across assets with different volatilities, Moskowitz et al. (2012) propose to scale the returns of stock i by an ex-ante measure for stock i's volatility, σ^i_{t-1}. We follow Moskowitz et al. (2012), but apply their volatility model to a higher frequency, as we are working with intraday returns. Precisely, we calculate σ^i_{t-1} as follows

$$\sigma^i_{p,t-1} = \left(\sum_{\Delta=0}^{\infty} \delta(1-\delta)^{\Delta} RV^i_{p,t-1-\Delta} \right)^{\frac{1}{2}},$$

where RV denotes the realized volatility using the five-minute returns during the respective period p over which returns on the target day are considered. As in Moskowitz et al. (2012), we set the center of mass to $\frac{\delta}{1-\delta} = 60$ days.

Subsequently, we standardize the returns as follows

$$\tilde{r}^i_{close-1 \to 15:30} = \frac{r^i_{close-1 \to 15:30}}{\sigma^i_{close-1 \to 15:30, t-1}}, \quad \text{(C1)}$$

$$\tilde{r}^i_{15:30 \to close} = \frac{r^i_{15:30 \to close}}{\sigma^i_{15:30 \to close, t-1}}. \quad \text{(C2)}$$

We use time $t-1$ volatility estimates for time t returns to circumvent any forward looking biases through scaling.

Next, we estimate Equations (5) to (8) with the scaled returns from Equations (C1) and (C2). Results are tabulated in Table C1.

Table C1: **Intraday Return Regressions with Scaled Returns**
The table reports the results to regressing scaled returns in the last half hour of a trading day on scaled returns until 15:30, $r_{close-1\rightarrow 15:30}$, Γ-imbalance Γ^{IB} and market maker hedging pressure Γ^{HP}, following Equations 5 - 8. Scaled returns are defined in Equations (C1) and (C2). Coefficients are scaled by 100 and t-statistics are in parentheses below. The t-statistics follow Thompson (2011) and cluster by time and entity, as well as account for common shocks across time. ***, **, * denotes significance at the 1%, 5%, 10% level. We include entity fixed effects in all specifications. The sample covers 1996 through June 2019.

	(1)	(2)	(3)	(4)	(5)
Dependent	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$	$r_{15:30\rightarrow close}$
$r_{close-1\rightarrow 15:30}$	2.809***		3.045***	3.045***	2.315***
	(3.397)		(3.458)	(3.460)	(3.433)
Γ^{IB}		1.963		2.290	
		(0.908)		(1.043)	
Γ^{HP}			-12.908***	-12.953***	
			(-3.471)	(-3.482)	
$(\Gamma^{IB} \leq 0) \times r_{close-1\rightarrow 15:30}$					2.074***
					(2.593)
Observations	12,282,876	12,282,876	12,282,876	12,282,876	12,282,876
Entity FE	Yes	Yes	Yes	Yes	Yes
SEs	Robust	Robust	Robust	Robust	Robust