Inelastic Hedging Demand and Intraday Momentum

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Abstract

Delta-neutral hedging in options with short gamma exposure can result in nonlinear losses that make the demand for underlying assets inelastic. The inelastic hedging demand exacerbates intraday momentum and price fluctuations. With a large sample of stock options, we demonstrate that inelastic demand arises outside the break-even ranges of hedging short gamma exposure, strengthening intraday momentum for the underlying stock. Using the data on options holdings, we show that intraday momentum is stronger when active option traders have short gamma exposure. We also find that the market makers often maintain delta-neutral hedging instead of unwinding their option positions when the underlying prices hit the break-even ranges. Overall, this paper provides evidence of how the inelastic demand of financial intermediaries generates excessive price volatility via delta-neutral hedging.

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1 Introduction

Inelastic demand can generate large fluctuations in asset prices (Gabaix and Koijen (2022)). Recent research shows low demand elasticity in the U.S. stock markets, and ongoing research explores the causes of this phenomenon. The known causes include financial frictions and regulations. We posit the question of whether the design of trading mechanisms could cause elastic demand. We start with the findings in Baltussen, Da, Lammers, and Martens (2021) that hedging demand in the options market creates intraday momentum for the underlying asset prices and make the point that hedging in options can result in nonlinear losses that make the demand for underlying stocks inelastic when stock prices have large fluctuations. This mechanism was illustrated in the recent events that have reignited the urgency in understanding how options trading could destabilize underlying stock markets.[1] We aim to examine whether demand inelasticity induced by option hedging demand exists persistently and pervasively in the US stock markets.

The causes of extreme price fluctuations in the GME episode include the traditional short-sale squeeze and the notable surge in gamma hedge demand from delta-neutral traders, such as market makers (MMs) in the options market, leading to a so-called "gamma squeeze."[2] During that time, options trading volume and open interest (OI) recorded highs, and so the delta-neutral trader who held the majority of the counterpart position against the end user faced a larger size of the short OI and, subsequently, a larger size of short gamma exposure. This short gamma position could force them to make trend-following trading on the underlying stock in the same direction as its initial movement.[3]

More importantly, the book losses of the delta-neutral hedging could increase nonlinearly

[1]On January 27, 2021, Gamestop (GME) stock recorded a +1,744% year-to-date increase, which was triggered by crowds of retail investors gathered on social media.

[2]A staff report from SEC (2021) 'Staff Report on Equity and Options Market Structure Conditions in Early 2021' released on October 14, 2021, from the Securities and Exchange Commission attributes this surge, in part, to what is known as a "squeeze," a phenomenon where heightened short-sale interest can trigger a massive buyback when share prices rise.

[3]Section 2.1(a) explains in detail its behavior. Generally speaking, if the underlying market moves up, the MMs carrying short gamma need to buy the underlying asset at an unfavorable higher price to neutralize their delta position changed by their short gamma exposure. Conversely, they need to sell at an unfavorable lower price in response to the underlying asset moving down. Although MM carries long gamma more commonly, as shown in Gârleanu, Pedersen, and Poteshman (2009) and Christoffersen, Goyenko, Jacobs, and Karoui (2017), short gamma position, even with less frequent cases, can have potentially catastrophic consequences, providing a compelling reason to study this topic more deeply.

because of the mechanics in option pricing.[4] Therefore, when having a short gamma exposure, the delta-neutral traders face exponential losses with large upside (downside) movements in the underlying stock prices and are forced to buy (sell) more stocks to keep the delta-neutral positions by the end of the day. In other words, their short gamma exposure from option markets, combined with large price movements in the underlying assets, generates inelastic demand for the underlying assets. Our research question emerges: How does the inelastic demand for delta hedging by option traders impact the returns of the underlying asset?

Unlike the straightforward process of a short squeeze, which originates from a short-sale position, the inelastic trading demand driven by a gamma squeeze operates through a more complex mechanism. This mechanism can potentially repeat multiple times, influenced by the magnitude of movement in the underlying asset, and the required size of trades may also fluctuate over time or due to the moneyness of the options. Understanding their impact on underlying assets is, therefore, crucial for studying excessive volatility. Additionally, over the past decade, the volume of option delta-neutral traders has surged alongside the growth of retail investors[5], highlighting the urgency for further academic study on this topic.

In this paper, inelastic demand arises from delta-neutral hedging profit and loss (PnL), which varies according to options' gamma and theta exposure. The key to identifying inelastic demand is the nonlinear relationship between the hedging PnL and underlying stock returns caused by infrequent delta rebalancing.[6] To capture this nonlinear relationship, this paper designs a novel measure, called the break-even range, by examining the breakeven points of gamma loss (profit) and theta profit (loss). When delta-neutral traders maintain a short gamma imbalance in their option positions, any market movement generates negative gamma PnL and a positive theta PnL. Consequently, there are two breakeven points between gamma and theta PnL in both directions on each trading day. Beyond these gamma-theta breakeven ranges (GTBR), net PnL turns negative in a nonlinear manner, compelling delta-neutral traders to rebalance their delta positions to avoid dramatic losses, as shown in Figure 2. This rebalancing pattern creates inelastic demand for the underlying asset. Building upon the methodology of Gao, Han, Li, and Zhou (2018), this paper

[4]See Figure 2.

[5]See `https://qz.com/1969196/citadel-securities-gets-almost-as-much-trading-volume-as-nasdaq`

[6]The infrequent rebalancing by delta-neutral option traders can be caused by transaction costs, trading objectives, jumps in the underlying asset prices, model uncertainty, among others.

empirically tests whether the GTBRs serve as inflection points for exacerbated intraday momentum.

The first main finding from empirical testing is that when the stock price breaks the GTBR, stock market intraday momentum surges. In addition, on average, when the ranges are hit, option MMs do not unwind their short gamma positions but rather maintain delta hedging positions, contributing to a larger momentum effect. This finding expands the current literature on demand-based asset pricing by investigating the impact on asset prices via the inelastic demand of option MMs, a financial intermediary. Secondly, it finds that intraday momentum via MMs' gamma imbalance does not exist even when they hold a short gamma position, as long as the underlying stock prices do not hit these breakeven points. This finding is significant because earlier work mainly focused on MMs' contribution to intraday momentum merely through gamma imbalance, but this study provides a clearer picture of the mechanism. Lastly, this paper demonstrates that the hedging demand of MMs interacts with the demand of active option traders in that the MMs' hedging demand is more likely to turn inelastic when the active option traders also have short gamma exposure. This finding adds to the demand-based asset pricing literature studying passive institutions' inelastic demand by providing evidence of the inelastic demand of active institutions, which can behave strategically to impact asset prices.

This paper adds to a large body of literature on price processes such as momentum, price discovery using derivatives market data, intermediary asset pricing, and demand-based asset pricing. First, a significant body of literature has investigated excessive volatility in price processes. Christensen, Oomen, and Renò (2022) investigates the occurrence of short-lived locally explosive trends in the price pathways of financial assets, whereas Andersen, Todorov, and Zhou (2023) proposes a detector involving violations of the usual Ito semimartingale assumption. This paper finds that the intraday momentum accelerates after the stock prices break the breakeven range in the option book PnL. In addition, since Jegadeesh and Titman (1993) documented abnormal returns from the strategy of long winners and short losers, research on market momentum has expanded to encompass a broader range of asset classes and countries.[7] Recently, there has been a growing body of literature focusing on intraday momentum. Studies such as Heston, Korajczyk, and Sadka (2010)

[7] Griffin, Martin, and Ji (2001) demonstrates the economic significance of global momentum profits. Additionally, various scholars have investigated different sources of momentum. For example, Hong, Lim, and Stein (1998) examines the effects of size and analyst coverage on momentum, while Moskowitz and Grinblatt (1999) identifies the industry component of stock return momentum.

explore the intraday predictability of cross-sectional returns, Gao et al. (2018) document intraday momentum trends, and Li, Sakkas, and Urquhart (2021) analyze intraday time-series momentum. This paper adds to this literature by documenting one of the major sources of intraday abnormal returns under an option-related condition within the context of MMs' inelastic demand.

Secondly, asset price discovery using information from the derivatives market has been extensively studied due to its significance in determining asset prices. Poteshman and Pan (2004) find that information from option volume predicts stock prices. However, Muravyev, Pearson, and Paul Broussard (2013) argues that option price quotes do not provide useful information regarding future stock prices. Recent studies have expanded this literature by examining the impact of delta and gamma hedging on underlying prices. While existing literature mainly focuses on MMs' gamma imbalance position, this study contributes by identifying the triggering range of gamma hedging derived from MMs' inelastic demand created by the book PnL.

Thirdly, the literature on asset price discovery by intermediary participants has been growing. He and Krishnamurthy (2013) find that risk premia rise when intermediaries face capital scarcity, emphasizing the importance of intermediaries' actions. This paper supports this argument by showing how the gamma loss over theta profit could potentially trigger capacity scarcity for intermediaries.

Finally, this paper contributes to the literature on demand system-based asset pricing (see, for example, (Koijen & Yogo, 2019);Gabaix and Koijen (2022);(Davis, Kargar, & Li, 2025)). While previous studies demonstrate that inelastic demand from passive institutions influences asset prices, this work shows that MMs' inelastic demand, created by PnL restrictions, impacts intraday asset prices, and it's more pronounced when active institutions have demands in those options. Furthermore, the discovery of the GTBR and its significance has practical implications. Firstly, it can aid market participants in decision-making. Secondly, the GTBR can serve as an important threshold for firms or regulators to assess risk management metrics dynamically, based on option-implied information, which is particularly useful in fast-changing financial market conditions. Thirdly, the frequency of breaking this range can be utilized to estimate MMs' OI limit or underlying market capacity.

In the following Section 2, this paper explains in detail the process of delta-neutral hedge managing short gamma to maintain a delta-neutral position during a day, as well as the profile of gamma PnL versus theta PnL. The article then elaborates on why the break-even range is crucial for delta-neutral traders like MMs and its importance as a threshold for intraday momentum. Section 3 outlines the data sources for empirical testing and the methods used for data cleansing. In Section 4, the empirical analysis of the break-even range is discussed.

2 Inelastic Demand and Gamma-Theta Breakeven Range (GTBR)

This section provides a detailed explanation of how inelastic demand in short gamma hedging relates to GTBR before showing the testing results. Starting with the review of the dynamic hedge to understand the circumstance which option MM faces upon carrying short gamma imbalance in Section 2.1, Section 2.2 use an example of MMs' gamma hedge to explain the motivations behind delayed delta rebalancing (for the rest of the paper, gamma hedge and delta rebalancing are used interchangeably). Section 2.3 explains how to find the GTBR and when the underlying stock price hits the GTBR, inelastic demand for the underlying stocks arises.

2.1 Dynamic hedge review

This subsection reviews the source of the gamma PnL when the delta-neutral trader sells a call option with a relevant delta-neutral hedge. Since Black and Scholes (1973) developed the option pricing model, the option pricing method based on the dynamic hedge has been widely used by options traders and serves as a valuable guide for market makers (MMs) who provide liquidity in the options market by replicating options' payoff.[8]

[Insert Figure 1 here]

Figure 1 represents an example case where MMs have a short call option with their delta hedge position by the underlying price at 103. The blue line is the typical option value payoff that MMs should replicate (so their target payoff to replicate). The delta hedge replication (gray line) has a linear payoff as its price rises. The delta hedge performance, however, is unable to keep up with

[8]This pricing concept facilitates option traders buying or selling options from other market participants because they can hedge their long or short option position by trading their underlying assets so that they can maintain their entire portfolio risk at a neutral level. For example, if MMs sell a call option, then they buy some delta shares of its underlying asset to match the change in call option value.

the convex value growth of the option. That is, as the underlying price rises, the slope (delta) of the option value grows while the hedged asset value remains linear. This is known as the gamma effect. Therefore, MM needs to rebalance (buy more) the delta at 106 to match the higher delta requirement, and this value gap is a gamma loss (red line) in Figure 1(a). On the other hand, as time passes, the option value decays, as shown in Figure 1(b) (green line). Figure 1 shows not only a trade-off between the gamma and theta PnL but also the crucial implication that the theta PnL for a day is somewhat static while the gamma PnL, its counterpart, varies by the underlying movement. This fact is clearer in Figure 2

[Insert Figure 2 here]

Figure 2 shows a PnL profile of a delta-neutral trader carrying a short gamma position during a day starting with a spot price of 105. Total PnL (=Theta PnL (green line) + Gamma PnL (red line)) is the highest at 105, while it reduces exponentially if the spot price moves in either direction. If the spot price moves more than this range of the yellow lines, where the total PnL begins negative, then the delta-neutral trader faces an unfavorable position and is more likely to delta-hedge to stop losing money. This total PnL change comes from the heterogeneity of the payoff between the option and the option hedge instruments. The option value changes continuously and non-linearly with convexity. On the other hand, its hedge instrument (underlying stock or future) value changes linearly. Therefore, while a large upward or downward movement changes option values non-linearly, the underlying value of the hedge only moves linearly and does not catch up with the convex movement of the option.

If the gamma loss equals or is less than the theta gain (the spot price is inside the yellow lines), the implied volatility turns out to be the same as or higher than the realized volatility. In reality, realized volatility changes frequently and moves more or less than the implied volatility. Delta rebalancing can be costly, as shown in FIGLEWSKI (1989). Many studies try to identify an optimal delta hedge strategy in extension to the Black-Scholes model.[9]

[9]For example, the stochastic volatility model has been studied since Heston (1993). On the other side, sticking with the Black-Scholes model, Hull and White (2017) examines the minimum variance delta method, considering the effect of underlying price change on implied volatility. Profit and loss (PnL) attribution of Carr and Wu (2020) has been simplified by assuming that 1) the vega PnL is negligible because gamma exposure is large at relatively shorter maturity with smaller vega exposure and implied volatility during the day does not change very frequently, unlike realized volatility; 2) portfolio delta is hedged to be neutral; and 3) funding PnL is very tiny during the day. As a result, the portfolio's PnL attribution during the day considers gamma and theta profiles as well as intraday trading. Appendix A has a detailed formulation of this simplification.

2.2 An example of intraday hedging dynamics

This subsection shows four typical cases that a delta-neutral trader, such as a market maker (MM), faces during the day when they have an open short gamma position. Through table 1, this paper draws attention to the challenge of managing. The trader can have a complex decision-making process, considering the limitations of existing option pricing models and the uncertainty in model choice in real time. In addition, the traders' incentives and beliefs can also play a role in making the decision more than a pure risk management exercise. Because of these considerations, traders' discretion in managing option portfolios is often required.

[Insert Table 1 here]

Table 1 shows that a delta-neutral trader, sold call options and bought delta shares of the underlying assets to hedge and replicate the short call position at the market close with the following details: Underlying price: \$100, Strike price: \$100, Days to expiry: 30 days, Interest rate: 3%, Notional amount: \$10 million (Mio), Volatility: 22%. This option opens the following Greeks: Delta: 0.539, Gamma: 0.046, Theta: -0.061. On the following market day, suppose that the underlying stock goes up by 1%, 180 minutes after the market opens. Then, assuming all other Greeks remain fixed, the dollar delta from the short option position will increase from \$5.38 Mio to \$6.00 Mio while the dollar delta from the long stock position will almost stay at \$5.38 Mio. As a result, the net delta of the two positions is -619.01k. If the stock does not move but stays at +1% until the market closes, then the trader must buy \$619.01k of the underlying at +1% higher price, which locks up \$3.1k gamma loss. Instead, the MM earns \$6.11k in theta profit as compensation for the gamma loss.

Case 1 shows that the underlying moves up +1% at 180 minutes (T_180m) and back down to flat at 390 minutes (390m) while the trader does not take any action for the day. Then, this would be the best scenario for the trader's current short gamma position because the total daily PnL will be +6.11k without taking any action. However, after 180m, if the underlying rises up further to +2% as in Case 2, then the trader's gamma loss would increase to -12.08k, which is greater than its theta profit (+6.11k). Therefore, MM must decide whether to begin rebalancing before the market closes so as to compensate for its gamma loss by trading PnL. Case 3 is an ideal example of early rebalancing since its total PnL ends up with +0.22k. However, for uninformed delta-neutral traders, this is a tricky decision because a wrong decision will result in trading loss, as in Case 4. In comparison to Case 1, which has the same underlying stock scenario, Case 4 loses all of the theta gains due to early delta rebalancing. This uncertainty leads MM to refrain from early or frequent reactions to the gamma hedge. This difficulty intensifies greatly when they have a large position, necessitating deeper investigation of their dynamics in conjunction with underlying asset impact, as Bates (2003) emphasizes the necessity for renewed attention on the financial intermediation of underlying risks by option market makers.

This challenge stems not only from the difficulty of forecasting future volatility but also from a trader's incentive to maximize theta profit over gamma loss when they carry a short gamma position. Behavior biases as in Odean (1998) can make traders hold on to the losing trades longer in the hope of a market reversion and against the firm's risk management goal. When traders are motivated to rebalance less frequently, the hedging demand can turn inelastic when the underlying stock price has large movements to make total PnL dramatically negative.

2.3 Delta-neutral trader's incentive on gamma-hedging at the gamma-theta breakeven range (GTBR)

This section shows that the delta-neutral trader's incentive to maximize profit leads them to gamma-hedge (delta-rebalancing) at the gamma-theta breakeven range (GTBR). First, Section 2.3.1 derives the gamma theta breakeven range (GTBR). Section 2.3.2 derives the hedge triggering point of the delta-neutral trader based on their profit-maximizing incentive. Lastly, Section 2.3.3 shows that the GTBR from Section 2.3.1 is a special case of the hedge triggering point from Section 2.3.2. Through these steps, this study finds that the hedge trader's incentive to maximize PnL leads to the hedge trigger point close to the GTBR.

2.3.1 Introducing the gamma-theta breakeven range (GTBR)

Assuming other Greeks and their PnL are fixed, by using the PnL attribution of Carr and Wu (2020)[10], the delta-neutral trader's PnL from gamma and theta exposure for a day at market close,

[10] See also Cont and Tankov (2010) and Bergomi (2015).

T, from an option is

$$PnL_T = \frac{\theta}{365} + \frac{1}{2}\Gamma \cdot 100 \cdot r \cdot r = \frac{\theta}{365} + 50\Gamma \cdot r^2$$

Let $r = GTBR$, and $PnL = 0$. Then,

$$GTBR = \pm\sqrt{-\frac{\theta}{365 \cdot 50\Gamma}} \tag{1}$$

The term Γ represents the dollar gamma, which is the change in the dollar delta for a 1% change in the underlying asset's price. It is calculated as $\Gamma = \frac{\gamma S^2}{100}$, where γ is the Black-Scholes Gamma, and S denotes the price of the underlying asset. The symbol θ stands for Theta, and r represents the percentage change in the underlying price for a day.

2.3.2 Hedge trader's perspectives: Optimal gamma hedge point

This subsection finds the optimal hedge trigger point from a trader's perspective by using their profit-maximizing incentive. The delta-neutral trader decides whether to rebalance the portfolio delta to neutral at a specific time during the day. The decision would follow their expected PnL into the close with their rebalancing impact. The trader's expected PnL for the day at a time, t, is

$$E_t[PnL_T] = E_t[50\Gamma r_{T-t}^2 + 50\Gamma r_t^2 + \theta_1 + H\{(r_{T-t} - 100k\Gamma r_t)(-100\Gamma r_t) - |100\Gamma r_t \cdot tc|\}|r_t] \tag{2}$$

The term r_T represents the percentage change in the underlying price at the market close. H indicates whether a hedge trader rebalances during the day, with a value of 1 if rebalancing occurs and 0 otherwise. The symbol t refers to the timing of when a hedge trader rebalances. The term θ_1 represents Theta for one day, calculated as $\theta_1 = \frac{\theta}{365}$. The variable k denotes the trader's expected market impact relative to the trading dollar size. Finally, tc stands for the transaction cost, expressed as a percentage.

The trader's expected PnL for the day at t consists of the expectation of five components, the gamma PnL between the end of the day and a time of the day ($50\Gamma r_{T-t}^2$); the gamma PnL by the time of the day ($50\Gamma r_t^2$); the daily theta PnL (θ_1); the trading PnL from gamma-hedge (delta rebalancing) considering its market impact ($(r_{T-t} - 100k\Gamma r_t)(-100\Gamma r_t)$) where ($-100\Gamma r_t$) is the gamma hedge size upon r_t movement of the underlying; and the transaction cost ($|100\Gamma r_t \cdot tc|$).

F.O.C for $E_t[PnL_T]$ by r_t, r_t^* is

$$r_t^* = \frac{\mu(T-t)(1+100\Gamma k)+tc'}{(1+2\cdot 100^2 k^2\Gamma^2)} \tag{3}$$

The details of the derivation are in Appendix A2. r_t^*, the gamma hedge triggering level at t varies depending on the remaining time for the day, the expected average return from a hedger, the impact cost, and the transaction cost. The gamma hedge will be triggered at the wider range if the remaining market hour is longer or if return drift, potential market impact, or transaction cost is higher.

2.3.3 Relation between GTBR and gamma hedge triggering level

From equation (1) in Section 2.3.1, GTBR is derived and can be simplified as below. The detailed step for the simplification is in Appendix A3. Also, from equation (3) in Section 2.3.2, this gamma hedge condition can have the same level as GTBR under the condition: before the market opens ($T-t=1/365$), no impact and cost ($tc'=k=0$), and a hedger believes the underlying may move as the implied volatility.

$$GTBR \approx \pm\sqrt{-\frac{\theta}{365\cdot 50\Gamma}} = \pm\frac{\sigma_{imp}}{\sqrt{365}} \approx E[r_t^*] \tag{4}$$

The delta-neutral trader's gamma hedge triggering condition would be close to the GTBR before the market opens if the hedger's belief in the average daily return is close to the daily variance. Therefore, r_t^*, the gamma hedge triggering level of the daily return at t, can be a more general condition of the GTBR. Before the underlying market opens or if the market does not move at all, a delta-neutral trader such as MM would use the GTBR as a benchmark reference level for their decision-making, and this reference range can be adjusted depending on the dollar gamma amount, its potential market impact relative to liquidity, its hedge timing, and overall reference daily return. Section 4 empirically demonstrates the significance of this range, the GTBR, as an inflection point at which the intraday momentum by delta-neutral traders impacts the intraday momentum. The data set used for the empirical analysis is introduced in Section 3.

3 Data

This paper hypothesizes that the intraday momentum driven by the option hedge demand is limited or accelerated under the special condition because the delta-neutral hedge trader does not always decide to follow the trend in every case. Therefore, this empirical testing requires a dataset to measure the underlying intraday performance, the demand for gamma hedge, and the GTBR. The following subsections describe the source and the cleansing method of the data. Appendix B1 also has the descriptive statistics of the data.

3.1 Underlying Intraday Performance: TAQ

The intraday performance of the underlying is measured by the relative return during a day. Those returns are calculated by using the mid of the best bid and the best ask quotes for every minute. This paper follows the measure of the intraday market momentum by Gao et al. (2018)'s approach using half-hour observations of a day. Baltussen et al. (2021) also shows the intraday momentum from the gamma hedge by regressing the last 30 minutes' performance on the first 30 minutes' performance.

$$r_{i\_j} = \frac{Midqoute_i}{Midqoute_j} - 1$$

Where Midquote$_i$ is the midquote of i minutes after the market opens for $i = 1, 2, \ldots, 390$, and Midquote$_0$ is the closing price of the most recent market day. The Monthly Trade and Quote (MTAQ) from SAS Cloud of Wharton Research Data Services (WRDS) is used to measure intraday midquotes. MTAQ data are cleaned by Holden and Jacobsen (2014)'s interpolated time technique, which alleviates some distorted measures of spreads driven by high-frequency quotes to replicate Daily Trade and Quote (DTAQ).

3.2 Demand for gamma hedge: ISE

Delta-neutral traders' demand for the underlying asset on a day is a function of the dollar gamma positions carried by them. That dollar gamma position is the summation of each dollar gamma position from all options listed for the underlying. Estimating the dollar gamma position of the delta-neutral trader at each underlying for each day is a difficult task because the trading volume and open interest (OI) data available publicly do not specify an investor group or their purpose for positioning. Nevertheless, their position can be estimated fairly accurately by using the fact that MM is one of the most representative delta-neutral traders. MMs' daily position is estimated from the daily open and close position data provided by the NASDAQ International Securities Exchange (ISE). ISE data includes 'Opening Buy/Sell' and 'Closing Buy/Sell' quantities for 'Firm,' 'Customer,' 'Broker/Dealer,' 'Proprietary,' and 'Professional Customer' levels. The difference between the total buy and total sell per day is their daily net trading quantity. For 'Firm' on the day t, the net daily trading quantity of the option i of an underlying is

$$FirmNetTradQty_{t,i} = OpenBuy_{t,i} - OpenSell_{t,i} + CloseBuy_{t,i} - CloseSell_{t,i}$$

The cumulative sum of each option from its listing date is the open interest (OI). For 'Firm' by the day T after the option i's listing date, the open interest of the option i of the underlying is

$$FirmOI_{T,i} = \sum_{t=1}^{T} FirmNetTradQty_{t,i}$$

The next step is to find the MMs' OI based on the OI of 'Firm', 'Customer', 'Broker/Dealer', 'Proprietary', and 'Professional Customer'. This paper follows the approach of S. X. Ni, Pearson, Poteshman, and White (2020). It estimates the total MMs' OI by the sum of 'Firm', and 'Customer' OI multiplied by -1.

$$MM\_OI_{T,i} = -1 \cdot (FirmOI_{T,i} + CustomerOI_{T,i})$$

This method assumes that MMs' usual counterparties are 'Firm' and 'Customer' accounts. This assumption is reasonable, and it allows this test to yield more conservative results. One might argue that some of the 'Firm' or 'Customer' are also delta-neutral traders, as is MM. However, in this case, if MM has a short gamma, the other party is likely to have a long gamma position. If the empirical test of MMs' short gamma position reveals significant results despite the presence of long gamma delta hedgers (which mitigate the short gamma effect) at the counterpart side, the original argument that the short gamma delta hedge has a significant impact on market intraday trend will be strengthened. [11] Therefore, MMs' dollar gamma position for a day T for the 'option i' of the underlying is

$$MM\_\Gamma_{T,i} = MM\_OI_{T,i} * \frac{\gamma_i \cdot MidQoute_T^2}{100} \cdot ContractSize$$

where γ_i: Black-Scholes gamma for the option i. Also, MMs' dollar gamma position for a day T for the 'underlying' is

$$MM\_\Gamma_T = \sum_{i=1}^{I} MM\_\Gamma_{T,i}, \qquad i = \{1, 2, ...I\}$$

At this stage, MMs' estimated gamma position for each underlying for each day is added in a new column to the dataset from the previous section. [12]

3.3 Gamma-Theta Breakeven Range: OptionMetrics

GTBR can be calculated in two ways, as shown in Sections 2.3 and 2.5. Both methods should produce nearly identical statistics. [13] GTBR can be calculated for each option because a GTBR is determined by each gamma and theta Greek of each option, respectively. Because there are multiple options with multiple strikes and tenors for each underlying, the most accurate estimate of the average GTBR for each underlying for each day would be calculating the MMs' dollar gamma weighted average for each underlying for each day. Instead, as a reference to Greeks and volatility, this paper employs the at-the-money (ATM) with 30-day tenor option from the Standardized option data table in Ivy DB US of OptionMetrics. The OptionMetrics' Standardized

[11] Some literature estimates MMs' OI by put option OI based on the assumption that MM has counter positions against heavy put option demands from end-users. Gârleanu, Pedersen, and Poteshman (2005) finds it for OTM put options thanks to the special data identifying aggregate positions for dealers and end consumers. However, given that the gamma position varies by strikes and is exponentially high at ATM, this assumption is not perfect. Hence, using ISE data, which identifies the OI by groups, provides a more accurate estimate of the MMs' gamma exposure.

[12] The first 250 days of the data for each underlying are deleted based on the assumption that the first row of the cumulative OI data window does not include previous cumulative data. For example, if the first row of the OI data for an underlying is on 2 January 2006, then the cumulative sum of OI on 2 January 2006 does not include the cumulative data of the previous year. The best estimate would be to find its relevant listing date and filter out the biased data. However, for convenience and simplicity, the current version of the analysis assumes that the significant net open trade began a year ago cumulatively. Therefore, the first 250 days (approximately a year) of the cumulative data are removed as they can be biased. Then, 1% and 99% of the outliers are winsorized.

[13] Their means are 0.02101 and 0.02063, while both standard deviations are 0.01138. The empirical analysis primarily uses the 2.3 method.

Option data are ATM forward options with interpolated tenor from fixed expiry. They are widely used for empirical testing due to their convenience and representativeness. This simplified approach assumes that ATM option with 30 days tenor as a representative option structure in measuring the gamma impact because 1) ATM gamma and theta are exponentially higher than other longer strikes; 2) there's only a minor gamma effect from far OTM and deep ITM options in both downside and upside; 3) due to volatility skew, relatively small GTBR difference from higher volatility in downside and lower volatility in upside would even be averaged out; 4) longer tenor options do not have much gamma but mostly used to build a vega position; and 5) using 30 days standardized tenor would result in a more conservative effect in this empirical analysis purpose.[14] Therefore, using Greeks and volatility from the ATM option with 30 30-day tenor is an excellent reference for Greeks and volatility in measuring the impact of gamma hedges. At this stage, daily GTBR data are calculated and added in new columns to the dataset of the previous section.

4 Empirical Analysis

This section tests the hypotheses to show the effect of delta-neutral hedging on the intraday momentum of the underlying asset when the inelastic demand arises outside the GTBR. Sections 4.1 to 4.5 demonstrate the existence of intraday momentum, which becomes pronounced when the underlying price hits the PnL-driven range, GTBR. In Sections 4.4 to 4.7, we explore the various subsamples of observations in terms of the source of hedging demand. We show that intraday momentum strengthens when active option traders have negative gamma exposure, when the underlying asset price declines, or when short gamma is concentrated in lower strike prices. Finally, we assess the impact of option expiry on our findings and an out-of-sample R-square analysis.

4.1 Does Impact of Gamma Hedge Rise at GTBR?

By regressing the last half-hour return, r_{390_360}, on the first half-hour return r_{30_0}, Gao et al. (2018) reveals an intraday momentum pattern. Utilizing this specification, Baltussen et al. (2021) demonstrates that the market's intraday momentum exists significantly more prominently on days with negative Net Gamma Exposure (NGE). This section tests the hypothesis that the effect of

[14] Besides, the small error of the reference volatility impact is minimal as $GTBR = \frac{\sigma}{\sqrt{365}}$.

hedging demand of delta-neutral traders on intraday momentum is stronger when the underlying stock prices break the GTBR. In other words, we test whether the GTBR being broken or not during a day is an important inflection point for intraday momentum. We construct several indicator variables in our regression analysis. At time t, $D\_GTBR\_Hit_t$ is set to 1 if the intraday return breaks out of the GTBR, and 0 otherwise. The variable D_Short_Gamma is set to 1 if the option market makers carry a negative dollar gamma position from the previous day and 0 otherwise. The following regressions test the hypothesis that at GTBR, intraday momentum is accelerated.

$$r_{390\_360} = \alpha + \beta_1 \cdot r_{30\_0} + \beta_2 \cdot r_{30\_0} \cdot D\_Short\_Gamma + \beta_3 \cdot r_{30\_0} \cdot D\_GTBR\_Hit_{360} + Controls + \epsilon$$

[Insert Table 2 here]

Table 2 presents the results of the intraday momentum regression of the last 30 minutes' return on the first 30 minutes return. We report Newey and West's (1986) t-statistics, and all coefficients are multiplied by 100. The firm-level fixed effect is included. The regression in column (1) shows that there is intraday momentum, as documented in the earlier study by Gao et al. (2018). Additionally, the regression in column (2), including D_Short_Gamma, reveals that the short gamma sign has a substantial explanation for market intraday momentum, which extends the findings in Baltussen et al. (2021) to individual stocks. Column (3), including $D\_GTBR\_Hit_{360}$, demonstrates that breaking GTBR is a significant factor, a test of the main hypothesis on the hedging demand of delta-neutral traders. Column (4), including both D_Short_Gamma and $D\_GTBR\_Hit_{360}$, shows that the effect of breaking GTBR on intraday momentum is beyond the effect of the short gamma exposure. This result indicates that the delta-neutral trading in the options market extends beyond the market makers, so intraday stock momentum is exacerbated by breaking out of the GTBR for both MMs and other delta-neutral traders. The inelastic demand from underlying delta rebalancing triggered by the variations in the PnL between gamma profit and theta loss contributes to stock intraday momentum. In terms of the magnitudes, the MMs' short gamma exposures add to intraday momentum by 68% (=0.71/1.05) on average, and the GTBR breakings add 91% (=0.96/1.05) on average.

Column (5) adds two controls, the earning impact and implied volatility impact, which interact with r_{30_0}. $D\_Earning$ equals one if an earning is announced 24 hours before the 360th minute of a day and zero otherwise. The result shows that the coefficient of the main variable, $D\_GTBR\_Hit_{360}$, even increases from 0.96 to 1.18 with large t-statistics. On the other hand, the control variable, earnings announcement impact on intraday momentum, shows a negative coefficient of -2.41, indicating that it works as an intraday reversion force. This result is in line with Milian (2015)'s findings that earnings announcements have a negative correlation with price action for firms with actively listed options. The second control variable, implied volatility, shows a strong and significant impact on intraday momentum, and it subsumes the impact from the momentum coefficient r_{30_0}. We also find that implied volatility reduces the effect of short gamma exposure, $D\_Short\_Gamma \cdot r_{30\_0}$, partly because of high correlations, 89%, between implied volatility and the short gamma exposure.

We hypothesize that the GTBR matters to the hedging demand for all delta-neutral traders, with the MMs as the most representative group. If this is the case, the MMs' short gamma exposure should have a strong (weak) effect on intraday stock momentum when the underlying stock price does (not) break the GTBR. To examine this hypothesis, we repeat the above regression analysis for the subsamples conditional on whether $D\_GTBR\_Hit_{360}$ is zero or one. The results are reported in Table 3. Columns (1) and (2) show the results of the subsample with $D\_GTBR\_Hit_{360} = 0$, and Columns (3) and (4) with $D\_GTBR\_Hit_{360} = 1$. Consistent with our argument, the effect of MMs' short gamma exposure on intraday momentum remains only when the underlying stock price breaks the GTBR. When the stock price stays within the GTBR, the effect of MMs' short gamma exposure becomes statistically insignificant and much smaller in magnitude.

[Insert Table 3 here]

Our baseline analysis demonstrates that the GTBR affects the hedging demand of delta-neutral traders. We nonetheless acknowledge that the exact PnL inflection point might be different for the marginal delta-neutral traders. However, the further deviation of the stock price from the GTBR, the more likely elastic hedging demand arises. We next investigate the severity of the breakouts of the GTBR.

4.2 Does the Severity of GTBR Breaking Impact Intraday Momentum?

This section analyzes the severity of breaking GTBR and the effect of gamma size by sorting data. The variable, $D\_GTBR\_Hit_{360}$, has the limitation that it lacks cumulative occurrence on breaking GTBR and only considers the price location at a specific time. The delta-neutral traders are more likely to be pressured for delta-rebalancing if the GTBR breaking occurs more frequently during the trading hours before the market close.[15] For example, hitting GTBR at only the 360th minute of the day would be very different from hitting GTBR for every minute by the 360th minute during the same trading day. To measure this effect, we define the cumulative GTBR breaking measured by the cumulative sum of the past number of breaking GTBR at every minute:

$$Cumul\_GTBR\_Hit_t = \sum_{m=1}^{t} D\_GTBR\_Hit_m$$

The data is then classified as 0, 1 to 89, 90 to 179, 180 to 269, 270 to 359, and 360 times the number of breaking GTBR for 360 minutes.

Additionally, we refine the measure of MMs' gamma exposure by using dollar gamma exposure quintiles. To make gamma exposure comparable over time and across firms, the dollar gamma size is normalized by the average of the last seven days of the underlying volume multiplied by the $MidQuote$. The data is then sorted by quintile:

$$NormGamma_t = \frac{\Gamma_t}{MidQuote_t \frac{1}{7} \sum_{d=t-6}^{t} V_d}$$

[Insert Table 4 here]

Table 4 shows the results of the regression identifying the intraday momentum by sorted groups, and its result reinforces that both short Gamma and GTBR are important contributors to intraday momentum in Table 2. The first column $NormGamma^1$ shows the regression result from the data having the largest short gamma exposure, while the last column $NormGamma^5$ shows the regression result from the data having the largest long gamma exposure. The first row ($Cumul\_Hit\_GTBR = 0$) represents the regression results from data with non-breaking GTBR

[15] Psychological factors guiding traders' expectations for the rest of the trading hours would be influenced by the history of intraday price patterns and their cumulative status, potentially influencing the hedging demand.

for 360 minutes, while the last row ($Cumul\_Hit\_GTBR = 360$) shows the regression results from data with 360 times of breaking GTBR for 360 minutes. The result of the first row shows the regression results of the data where the underlying market has never broken the GTBR, and there is no significant intraday market momentum, despite that the MM has the highest short gamma in the first column. This evidence explains that the GTBR is a significant factor in determining the intraday momentum. Furthermore, the last column explains that when the MM carries the highest long gamma, there is a significant market intraday 'reversion' (-1.25). This implies that MMs' long gamma position pushes back the intraday movement to reverse as a contrarian when the underlying market is within the range. Besides, in other cases where the GTBR is hit more frequently, there is no clear intraday momentum and reversal, but a mild intraday reversal. From the rows with the cases ($1 \leq Cumul\_Hit\_GTBR \leq 359$), and from the columns where the MM carries a short gamma position, the data shows that the GTBR being hit has more intraday momentum than zero hits. Interestingly, we observe some nonlinear effects across $Cumul\_Hit\_GTBR$ for each gamma quintile. A potential explanation is that when the stock prices are out of the GTBR during most of the trading day, MMs could decide to start delta rebalance earlier during the day and spread out over the day rather than wait for the last 30 minutes.

Our results add to the literature by showing that the short gamma exposure is not the sole determinant of hedging demand, and the GTBR breaking is necessary for the short gamma effect on intraday momentum. In Appendix D, we repeat the above analysis with the same regression setup but with the cumulative number of the whole day rather than the cumulative number of the day by the last 30 minutes.

4.3 Is the GTBR the Inflection Point for Hedging Demand?

We propose that the GTBR is where the hedging demand of the delta-neutral traders turns inelastic. To provide evidence on this, we examine the intraday momentum across returns normalized by the GTBR. Specifically, the absolute returns at the 360th minute are normalized by its GTBR:

$$GTBR\_Normalized_{360} = |\frac{r_{360\_0}}{GTBR}|$$

For example, if the absolute return at the 360th minute is 0.50% while the GTBR is 1.00%, then this normalized return is calculated to be 0.50. Then, these data are sorted and grouped by deciles. For each decile, regressions with the dependent variable, r_{390_360} and the independent variables, r_{30_0} and $r_{30\_0} \cdot D\_Short\_Gamma$, are executed. The coefficient of the independent variable, r_{30_0}, which is the momentum coefficient, is estimated for each decile.

[Insert Figure 3 here]

Figure 3(a) shows the coefficients of each decile. The data point at which this normalized return equals 1 (the return at the 360th minute = GTBR) is located at the 67.7% percentile and is represented by an orange vertical line. Figures 3(b) and (c) represent the same chart, but the data are divided by the sign of the return for the first 30 minutes. In all cases, decile 1, where stocks do not move much at all at the 360th minute, does not show any momentum but reversion. The momentum coefficient clearly increases as the decile increases and jumps around the percentile where the return at the 360th minute equals the GTBR (between decile 6 and 7). This evidence supports the argument that the gamma hedge activity around the GTBR boosts the market's intraday momentum. Besides, the coefficients begin decreasing after decile 7. This reduction potentially comes from the case that MM already rebalanced its delta exposure at GTBR earlier. Hence, it does not force the delta-neutral trader to push the intraday momentum for the last 30 minutes. For example, the average of normalized returns in decile 10 is 2.51 (2.51σ), which is significantly far from the GTBR (1σ). Therefore, in this case, the gamma hedge activity would have been done earlier or spread over the day, as in the case of $Cumul\_Hit\_GTBR_{360}$ in Table 4 of Section 4.2.

4.4 Hedging Demand from Active Option Traders

Koijen and Yogo (2019) proposed an asset pricing model with asset demand from heterogeneous investors, reflecting institutional differences. This section delves into how the inelastic demand of MM is associated with option demand from active option traders. The ISE introduced a new trade category on October 1, 2009, termed 'PROFESSIONAL CUSTOMER'. This category refers to market participants who, not trading for MM or firm accounts (like banks), enter over 390 orders per day across a month. These positions typically represent active institutional demands such as hedge funds, active mutual funds, boutiques, etc.. Table 5 illustrates the examination of whether intraday momentum on an underlying asset varies when active investors engage in the options market for that asset.

[Insert Table 5 here]

We define the dummy variable $Prof\_Option\_Holding = 1$ if the professional investor's option gamma exposure is positive and 0 otherwise. Columns (1) to (3) present the results on the effects of MMs' short gamma exposure and GTBR breaking on intraday momentum when active option traders have a short gamma exposure, and Columns (4) to (6) present the results when active option traders have a long gamma exposure. We also present the coefficient differences with Walt statistics following a chi-squared distribution.

We have two interesting findings. First, the effect of GTBR remains in both subsamples, with the stronger effect when active option traders have long gamma exposure. Second, the effect of MMs' short gamma exposure disappears when the active option traders have long gamma exposure. This is consistent with the notion that MMs engage in delta rebalancing more frequently when active option traders take the opposite gamma positions.

4.5 MMs' Gamma Exposure

When the MMs carry a short gamma position and the GTBR is hit, the MMs may reduce their gamma exposure by unwinding their option positions, instead of trading the underlying stocks for delta-neutral hedging. Table 6 presents the testing results of the hypothesis that MMs buy back options when the underlying asset moves over the range frequently (in other words, the underlying return hits GTBR frequently). The dependent variable is an open interest of MMs for a day, denoted as $MM\_OI_{T,i}$, and it's regressed by the frequency of hitting the range. The same regressions are conducted on four different subsets grouped by the sign of gamma position and direction of underlying asset return.

[Insert Table 6 here]

The results indicate that when MMs carry short gamma positions, upon frequent hitting of the GTBR (meaning that there is a greater chance that the hedger has more restricted times in terms of PnL perspective, and so a greater chance that inelastic hedging demand arises), they do not buy back options. This suggests that to keep their delta-neutral positions, they have to conduct delta rebalancing by trading the underlying asset. This supports the argument that MMs' short gamma exposure strengthens intraday momentum because they do delta rebalancing rather than buying back the options.

On the other side, when MMs have long gamma positions, they actually buy more options in response to GTBR breaking. If they expand their long gamma exposure, they should further hedge their long gamma positions by contrarian trades in contrast to momentum trades for short gamma positions. This finding supports the findings in Table 4, which imply that when maintaining long gamma positions, there is no momentum in the underlying asset.

4.6 Asymmetric Impact of Short Gamma Exposure on Intraday Momentum

This section conducts a similar regression to Section 4.1 but divides the data into two groups to explore whether the GTBR behaves differently depending on the underlying return direction. The first group comprises data where the underlying stock moves up 30 minutes after opening, while the second group includes data where the underlying stock moves down 30 minutes after opening.

[Insert Table 7 here]

Table 7 presents panel (a) for the moving-up case of underlying asset return and panel (b) for the moving-down case of underlying asset return. The results indicate that intraday momentum exists in both directions. However, in panel (a), both interaction variables in regression (3) and (4) are insignificant, while in panel (b), these interaction variables are significant. This suggests that the contribution to intraday momentum from short gamma and breaking the range is more pronounced when the underlying asset moves downward in the first 30 minutes.

4.7 The Sources of Short Gamma Exposure

This section examines the sources of gamma positions, such as gamma positions from call options, put options, upside strike options, and downside strike options. Table 8 presents three panels: Panel (a) includes all data, Panel (b) includes data where the underlying asset rises in the first 30 minutes, and Panel (c) includes data where the underlying asset moves down in the first 30 minutes. *D_Short_Gamma_Calls* (*D_Short_Gamma_Puts*) equals 1 if the MMs have a short gamma position from call (put) options, and 0 otherwise. *D_Short_Gamma_Upsides* (*D_Short_Gamma_Downsides*) equals 1 if the MMs have a short gamma position from upside strike (downside strike) options, and 0 otherwise.

[Insert Table 8 here]

Panel (a) reveals that short gammas from calls, puts, and downside strikes contribute to the intraday momentum of the underlying market. This suggests that short gamma positions from both call and put options have a similar impact on intraday momentum. However, the strike range of the source of the short gamma position emerges as a crucial factor for momentum impact. Gamma positions from strikes above the underlying price show no impact on intraday momentum, while gamma positions from downside strikes exhibit a significant impact. The analysis extends to two subsamples, mirroring Section 4.6. Regardless of the underlying movement in the first 30 minutes, short gamma positions from call and put options significantly affect intraday momentum. Additionally, the contribution to momentum from downside strike options is stronger during the first 30 minutes of the underlying market movement.

This finding supports the main argument of this paper that MMs' gamma position and hitting the breakeven range explain underlying intraday momentum more precisely. Short gamma positions from both short calls with long underlying and short puts with short underlying compel delta-neutral traders to trade the underlying instrument in the same direction as the underlying asset in their dynamic hedge activity. Thus, short gamma positions from both call and put options have a clear gamma impact on intraday momentum. Furthermore, the asymmetrical result between downside strike options and upside strike options suggests that delta-neutral traders have more inelasticity in demand for gamma hedge in the downside when holding short gamma positions from downside strikes.

4.8 Option Expiry and Non-Expiry Weeks

S. Ni, Pearson, and Poteshman (2005) illustrated that the hedge impact from option market makers tends to cluster around the expiration date at optionable strikes. As the option contract's duration shortens, the gamma imbalance of traders aiming to maintain delta neutrality becomes more evident. Consequently, the underlying stock price experiences increased volatility, attributed to the actions of delta rebalancing traders. Someone may argue that the gamma hedge impact on intraday momentum just comes from strong expiry week data. To investigate this idea, this section conducts a similar test to Section 4.1, using a subset of data consisting solely of the expiry week and another subset of data excluding the expiry week.

[Insert Table 9 here]

The results depicted in Table 9 demonstrate that intraday momentum in the underlying market price is significantly present during both the expiry week and non-expiry weeks. This finding supports the idea that hitting the breakeven range exerts a robust effect on the intraday momentum of the underlying asset return, regardless of whether it's during the expiration week or other time periods.

4.9 Out-of-Sample Prediction with the GTBR

This subsection assesses the Out-of-Sample R^2 (OOSR2) to gauge the predictive capability of the GTBR. Given the inconsistency in the performance of factors, as noted by Goyal and Welch (2007), OOSR2, proposed by Campbell and Thompson (2008), has become widely adopted to evaluate out-of-sample predictability, aiming to mitigate the overfitting issue. Baltussen et al. (2021) and Gao et al. (2018) also employ OOSR2 to assess the intraday predictability in their analyses.

$$OOSR2 = 1 - \frac{\sum_{t=1}^{T}(r_{390\_360,t} - \hat{r}_{390\_360,t})^2}{\sum_{t=1}^{T}(r_{390\_360,t} - \bar{r}_{390\_360,t})^2}$$

A positive OOSR2 suggests predictability, indicating that the predictive model exhibits a smaller average mean squared error in prediction compared to the historical average. Following regression at each underlying level, the OOSR2s are computed.

[Insert Table 10 here]

Table 10 displays the summary statistics of R^2 and OOSR2 from regressions conducted for each underlying. Initially, the data are grouped by underlying, and then at each underlying level, the last 30 minutes' return is regressed on the first 30 minutes' return. Columns (1), (2), (3), and (4) represent different regressions for r_{390_360}, akin to Table 2. Column (1) features regression (1) with only r_{30_0}, column (2) adds D_Short_Gamma interaction to regression (1), column (3) adds D_GTBR_hit interaction to regression (1), and column (4) includes all variables. Underlying stock returns with fewer than 250 observations are excluded in this test. On average, R^2 and OOSR2 are highest in regression (4), which accounts for the GTBR effect combined with short gamma exposure. Moreover, all OOSR2 values are positive, with even the lowest OOSR2 from an underlying regression being positive. This suggests that the GTBR effect significantly contributes to prediction at each underlying level.

5 Conclusion

For the last decade, delta-neutral option traders such as option MMs have seen the exponential growth of retail investors. Therefore, understanding MMs' behavior and impact is crucial. This study provides new evidence that the inelastic hedging demand of delta-neutral traders impacts the underlying asset prices.

The empirical findings support the presence of specific breakeven points (GTBR) from gamma loss and theta profit, which serve as critical inflection points that intensify MMs' trading activities in the underlying asset. These points mark thresholds where market dynamics compel MMs to execute delta rebalancing trades, thereby creating inelastic demand for underlying assets. Moreover, the paper adds to the literature on demand-based asset pricing by incorporating the role of active institutions in shaping market conditions. Unlike previous research predominantly focused on passive institutional impacts, this study highlights how gamma imbalances of option MMs and active traders contribute significantly to asset price movements. Our findings also contribute to a deeper understanding of how derivative markets influence underlying asset prices through hedging strategies.

References

Andersen, T. G., Todorov, V., & Zhou, B. (2023, July 20). Real-time detection of local no-arbitrage violations. Retrieved from `https://ssrn.com/abstract=4516075` doi: 10.2139/ssrn.4516075

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

Barbon, A., Beckmeyer, H., Buraschi, A., & Moerke, M. (2021). The role of leveraged etfs and option market imbalances on end-of-day price dynamics. *ERN: Other Econometric Modeling: Capital Markets - Asset Pricing (Topic)*.

Barbon, A., & Buraschi, A. (2020). Gamma fragility. *University of St.Gallen School of Finance Research Paper Series*.

Bates, D. S. (2003). Empirical option pricing: a retrospection. *Journal of Econometrics*, *116*(1), 387-404. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0304407603001131` (Frontiers of financial econometrics and financial engineering) doi: https://doi.org/10.1016/S0304-4076(03)00113-1

Bergomi, L. (2015). Introduction. In *Stochastic volatility modeling* (First ed.). Chapman and Hall/CRC, an imprint of Taylor and Francis.

BIS. (2000). Stress testing by large financial institutions: Current practice and aggregation issues. *Bank For International Settlement (BIS)*.

Black, F., & Scholes, M. S. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*, 637 - 654.

Breeden, D. T., & Litzenberger, R. H. (1978). Prices of state-contingent claims implicit in option prices. *The Journal of Business*, *51*(4), 621–651.

Campbell, J., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*, 1509-1531.

Carr, P., Madan, D. B., & Stanley, M. (2001). Option pricing, interest rates and risk management: Towards a theory of volatility trading..

Carr, P., & Wu, L. (2020). Option profit and loss attribution and pricing: A new framework. *Journal of Finance*.

Chetty, R., & Szeidl, A. (2006). Consumption commitments and risk preferences. *NBER Working Paper Series*.

Christensen, K., Oomen, R., & Renò, R. (2022). The drift burst hypothesis. *Journal of Econometrics*, *227*(2), 461-497. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0304407620303912` doi: https://doi.org/10.1016/j.jeconom.2020.11.004

Christoffersen, P., Goyenko, R., Jacobs, K., & Karoui, M. (2017, 11). Illiquidity Premia in the Equity Options Market. *The Review of Financial Studies*, *31*(3), 811-851.

Cont, R., & Tankov, P. (2010). Gamma hedging. In R. Cont (Ed.), *Encyclopedia of quantitative finance* (1st ed.). Wiley.

Davis, C., Kargar, M., & Li, J. (2025). Why do portfolio choice models predict inelastic demand? *Journal of Financial Economics*, *172*, 104096. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0304405X25001047` doi: https://doi.org/10.1016/j.jfineco.2025.104096

FIGLEWSKI, S. (1989). Options arbitrage in imperfect markets. *The Journal of Finance*, *44*(5), 1289-1311. Retrieved from `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1989.tb02654.x` doi: https://doi.org/10.1111/j.1540-6261.1989.tb02654.x

Gabaix, X., & Koijen, R. S. J. (2022). In search of the origins of financial fluctuations: The inelastic markets hypothesis. *Swiss Finance Institute Research Paper*(No. 20-91). doi: http://dx.doi.org/10.2139/ssrn.3686935

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

Gârleanu, N., Pedersen, L. H., & Poteshman, A. M. (2005). Demand-based option pricing. *The Review of Financial Studies*.

Goyal, A., & Welch, I. (2021). A comprehensive look at the empirical performance of equity premium prediction ii. *The Review of Financial Studies*.

Griffin, J. M., Martin, J. S., & Ji, S. (2001). Momentum investing and business cycle risk: Evidence from pole to pole. *Journal of Finance*.

Gârleanu, N., Pedersen, L. H., & Poteshman, A. M. (2009, 02). Demand-Based Option Pricing. *The Review of Financial Studies*, *22*(10), 4259-4299.

He, Z., & Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*.

Heston, S. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies*, *6*, 327-343.

Heston, S., Korajczyk, R. A., & Sadka, R. (2010). Intraday patterns in the cross-section of stock returns. *Journal of Finance*.

Holden, C. W., & Jacobsen, S. (2014). Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions: Liquidity measurement problems in fast, competitive markets. *Journal of Finance*, *69*, 1747-1785.

Hong, H. G., Lim, T., & Stein, J. C. (1998). Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies. *Journal of Finance*.

Hull, J. (2006). *Options, futures, and other derivatives*. Pearson Prentice Hall.

Hull, J., & White, A. H. (2017). Optimal delta hedging for options. *Journal of Banking and Finance*.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*, 65-91.

Jorion, P. (2001). *Value at risk: The new benchmark for managing financial risk*. McGraw-Hill.

Koijen, R. S. J., & Yogo, M. (2019). A demand system approach to asset pricing. *Journal of Political Economy*, *127*(4), 1475-1515. doi: 10.1086/701683

Li, Z., Sakkas, A., & Urquhart, A. (2021). Intraday time series momentum: Global evidence and links to market characteristics. *Journal of Financial Markets*.

Milian, J. A. (2015). Unsophisticated arbitrageurs and market efficiency: Overreacting to a history of underreaction? *Journal of Accounting Research*, *53*, 175-220.

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum. *Journal of Finance*, *54*, 1249-1290.

Muravyev, D., Pearson, N. D., & Paul Broussard, J. (2013). Is there price discovery in equity options? *Journal of Financial Economics*, *107*(2), 259-283.

Newey, W., & West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix. *Econometrica*.

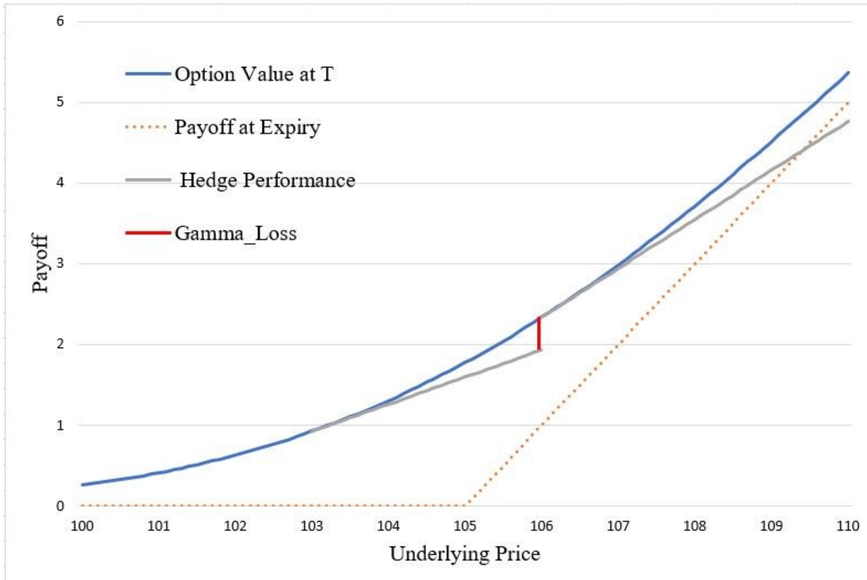
Ni, S., Pearson, N. D., & Poteshman, A. M. (2005). Stock price clustering on option expiration dates. *Journal of Financial Economics*.

Ni, S. X., Pearson, N. D., Poteshman, A. M., & White, J. S. (2020). Does option trading have a pervasive impact on underlying stock prices? *The Review of Financial Studies*.

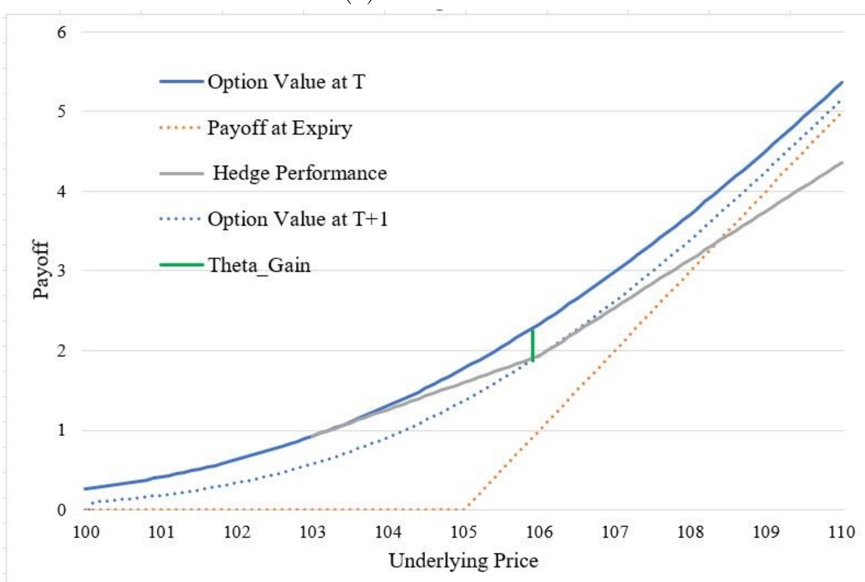
Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*.

Poteshman, A. M., & Pan, J. (2004). The information of option volume for future stock prices. *Review of Financial Studies*.

SEC. (2021). Staff report on equity and options market structure conditions in early 2021. *The Securities and Exchange Commission (SEC)*.



(a) Gamma Loss



(b) Theta Gain

Figure 1: Delta neutral portfolio to replicate a call option position

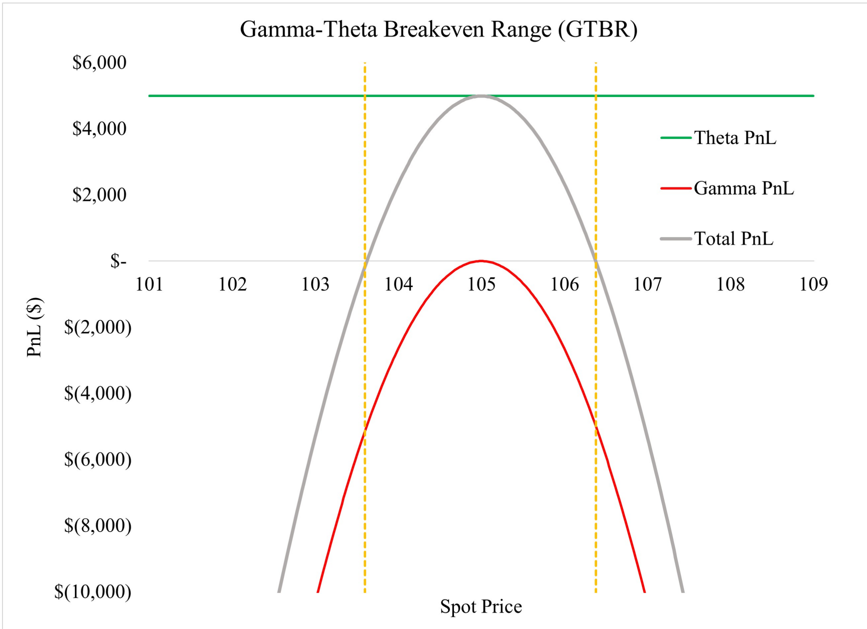
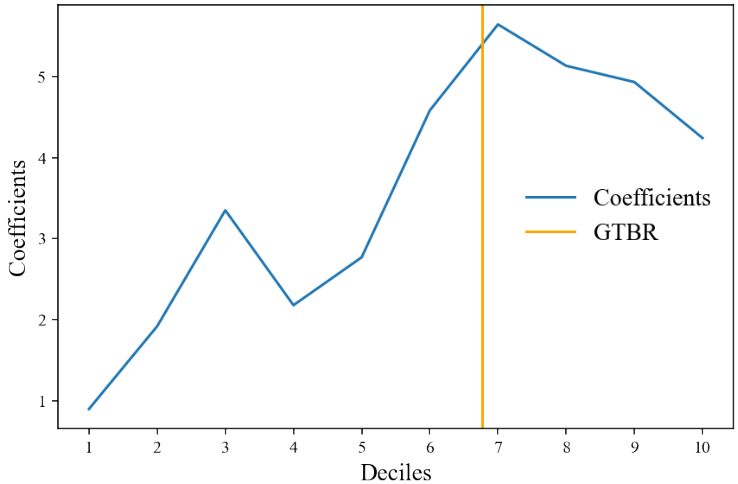
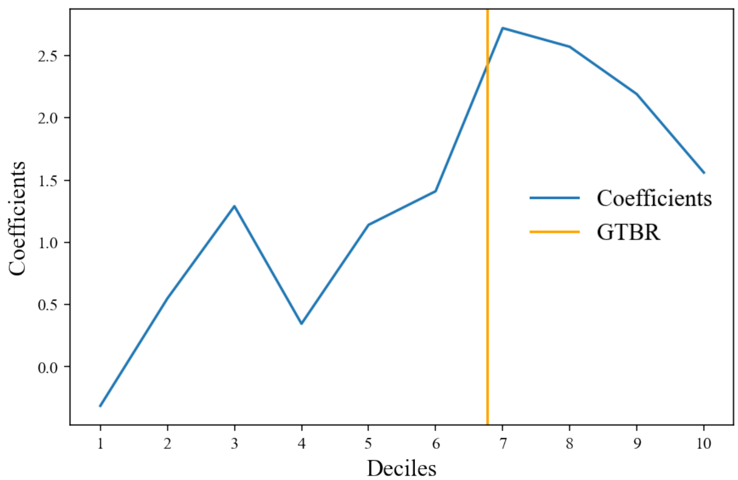


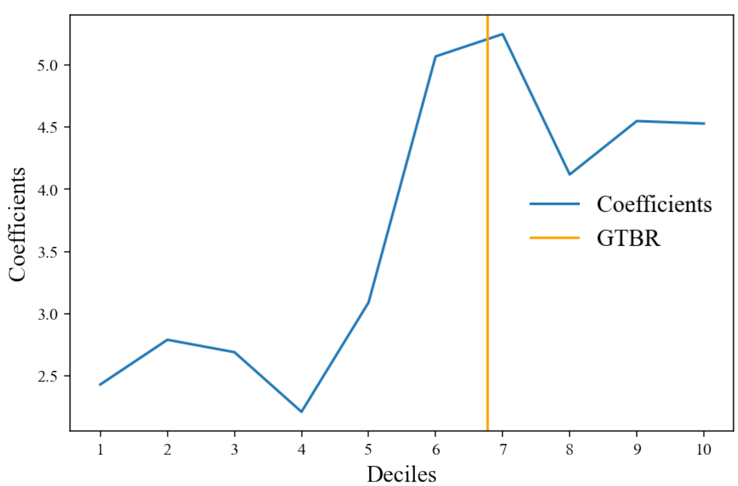
Figure 2: Intraday PnL change by spot price movement
NOTE: MM has a short option leg with its delta hedge leg at the underlying price of 105



(a) By using all data



(b) By using data with **positive** return for the first 30 minutes



(c) By using data with **negative** return for the first 30 minutes

Figure 3: Momentum coefficient from deciles

Table 1: An example of a delta-neutral trader's dilemma

At the market close on T-1 , MM has a delta-neutral portfolio by \$10 mio short call options and delta-hedged position. The call option has the following specifications: Underlying price: \$100, Strike price: \$100, Days to expiry: 30 days, Interest rate 3%, Notional amount: \$10 million (mio), Volatility: 22%. This option opens the following Greeks: delta: 0.539, gamma: 0.046, Theta: -0.061. All cases below consider the underlying moves up 1%, 180 minutes (180m) after market opens, but MM takes different actions.

Case 1:	Underlying moves up 1% at 180m and down back to flat at 390m MM does nothing						
		Delta\$	Gamma\$	Gamma PnL	Theta PnL	Trading PnL	Total PnL
T-1 close		0.00k	-461.64k	0.00k	0.00k	0.00k	0.00k
T_180m	+1%	-619.01k	-448.95k	-3.10k	6.11k	0.00k	2.15k
T_390m	**+0%**	0.00k	-461.64k	0.00k	6.11k	0.00k	6.11k

Case 2:	Underlying moves up 1% at 180m and up further to 2% at 390m MM does nothing						
		Delta\$	Gamma\$	Gamma PnL	Theta PnL	Trading PnL	Total PnL
T-1 close		0.00k	-461.64k	0.00k	0.00k	0.00k	0.00k
T_180m	+1%	-619.01k	-448.95k	-3.10k	6.11k	0.00k	2.15k
T_390m	**+2%**	-1207.93k	-426.16k	-12.08k	6.11k	0.00k	-5.97k

Case 3:	Underlying moves up 1% at 180m and up further to 2% at 390m MM rebalances at 180m						
		Delta\$	Gamma\$	Gamma PnL	Theta PnL	Trading PnL	Total PnL
T-1 close		0.00k	-461.64k	0.00k	0.00k	0.00k	0.00k
T_180m	+1%	-619.01k	-448.95k	-3.10k	6.11k	0.00k	2.15k
T_390m	**+2%**	-588.91k	-426.16k	-12.08k	6.11k	6.19k	0.22k

Case 4:	Underlying moves up 1% at 180m and up further to 2% at 390m MM rebalances at 180m						
		Delta\$	Gamma\$	Gamma PnL	Theta PnL	Trading PnL	Total PnL
T-1 close		0.00k	-461.64k	0.00k	0.00k	0.00k	0.00k
T_180m	+1%	-619.01k	-448.95k	-3.10k	6.11k	0.00k	2.15k
T_390m	**+0%**	+619.01k	-461.64k	0.00k	6.11k	-6.19k	-0.08k

Table 2: Stock intraday momentum, short gamma exposure, and GTBR

This table reports the regression of the last 30 minutes by the first 30 minutes with the interactive variables. D_Short_Gamma equals 1 if the MM has a short gamma position and 0 otherwise. D_GTBR_hit equals 1 if the underlying breaks the Gamma-Theta Breakeven Range (GTBR) at 360 minutes after the market opens and 0 otherwise. Newey and West (1986) t-statistics are in parentheses. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively and coefficients are multiplied by 100.

	Dependent: r_{390_360}				
Independent	(1)	(2)	(3)	(4)	(5)
r_{30_0}	1.82***	1.64***	1.22***	1.05***	-1.16***
	(18.06)	(14.82)	(7.93)	(6.49)	(-4.20)
$r_{30\_0} \cdot D\_Short\_Gamma$		0.72***		0.71***	0.56**
		(2.98)		(2.97)	(2.32)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			0.95***	0.96***	1.18***
			(5.01)	(5.00)	(6.07)
$r_{30\_0} \cdot D\_Earning$					-2.41***
					(-5.40)
$r_{30\_0} \cdot ImpliedVol$					3.66***
					(7.84)
$Adj.R^2(\%)$	0.02	0.02	0.02	0.02	0.03
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Observations	342,264	342,264	342,264	342,264	342,185

Table 3: Stock intraday momentum and short gamma exposure conditional on GTBR breaking

This table reports the regression of the last 30 minutes by the first 30 minutes with the interactive variables. D_Short_Gamma equals 1 if the MM has a short gamma position and 0 otherwise. D_GTBR_hit equals 1 if the underlying breaks the Gamma-Theta Breakeven Range (GTBR) at 360 minutes after the market opens and 0 otherwise. Newey and West (1986) t-statistics are in parentheses. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively and coefficients are multiplied by 100.

	Dependent: r_{390_360}			
	$D\_GTBR\_hit_{360} = 0$		$D\_GTBR\_hit_{360} = 1$	
	(1)	(2)	(3)	(4)
r_{30_0}	1.129***	-0.302	1.963***	-0.540*
	(6.56)	(-0.83)	(14.13)	(-1.69)
$r_{30\_0} \cdot D\_Short\_Gamma$	0.413	0.286	0.900***	0.723**
	(1.09)	(0.76)	(2.99)	(2.41)
$r_{30\_0} \cdot D\_Earning$		-3.060**		-2.196***
		(-2.13)		(-4.71)
$r_{30\_0} \cdot ImpliedVol$		2.419***		4.522***
		(3.55)		(7.37)
Firm FE	Yes	Yes	Yes	Yes
Adj. R^2	-0.001	-0.000	0.003	0.006
N	231785	231755	110479	110430

Table 4: Stock intraday momentum: double sort by cumulative GTBR breaking and MMs' Gamma exposure

This table reports the regression of the last 30 minutes on the first 30 minutes with the sorted data set. After measuring the hitting GTBR every minute, $Cumul\_Hit\_GTBR_{360}$ is calculated by the cumulative hit number for the first 360 minutes and then categorized by the number. $NormGamma$ is the normalized dollar gamma, and they are categorized by quintile. $NormGamma^1$ has the strongest short gamma while $NormGamma^5$ has the strongest long gamma. The $Cumul\_Hit\_GTBR$ has been sorted first, and then the $NormGamma$ is categorized. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively and coefficients are multiplied by 100.

r_{390_360} on r_{30_0}	**(Short Gamma)**				**(Long Gamma)**
	$NormGamma^1$	$NormGamma^2$	$NormGamma^3$	$NormGamma^4$	$NormGamma^5$
$Cumul\_Hit\_GTBR_{360} = 0$	0.23	1.42**	-0.20	-0.29	-1.25**
	(0.40)	(2.52)	(-0.55)	(-0.41)	(-2.73)
$0 < Cumul\_Hit\_GTBR_{360} < 90$	2.25***	3.57***	0.91**	0.23	0.21
	(4.31)	(6.96)	(2.02)	(0.51)	(0.52)
$90 \leq Cumul\_Hit\_GTBR_{360} < 180$	2.16***	3.77***	2.19***	0.61	0.98*
	(4.32)	(5.40)	(3.30)	(0.91)	(1.65)
$180 \leq Cumul\_Hit\_GTBR_{360} < 270$	2.21***	4.51***	2.72***	0.91	0.20
	(3.19)	(6.74)	(4.24)	(1.52)	(0.34)
$270 \leq Cumul\_Hit\_GTBR_{360} < 360$	3.09***	3.70***	1.59***	1.06***	-0.49*
	(8.23)	(9.85)	(4.56)	(3.22)	(-1.59)
$Cumul\_Hit\_GTBR_{360} = 360$	1.04**	3.88***	1.87***	1.13***	-0.03
	(2.10)	(6.99)	(3.96)	(2.71)	(-0.07)

Table 5: Stock intraday momentum and active option traders' option holdings

This table reports the regression of the last 30 minutes on the first 30 minutes by professional investors' option holdings. $Prof\_Option\_Holding = 1$ if the active professional investor's option gamma exposure is positive and 0 otherwise. D_Short_Gamma equals 1 if the MM has a short gamma position and 0 otherwise. D_GTBR_hit equals 1 if the underlying breaks the Gamma-Theta Breakeven Range (GTBR) at 360 minutes after the market opens and 0 otherwise. Newey and West (1986) t-statistics are in parentheses. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ for the regressions (1) to (6), respectively, and coefficients are multiplied by 100. The statistics for the difference is the Wald statistic following chi-squared distribution.

	Dependent: r_{390_360}								
	$Prof\_Option\_Holding = 0$			$Prof\_Option\_Holding = 1$			$Difference$		
Independent:	(1)	(2)	(3)	(4)	(5)	(6)	(4)-(1)	(5)-(2)	(6)-(3)
r_{30_0}	1.66***	1.42***	-0.92***	1.56***	0.49***	-3.02***	0.23	-0.93***	-2.10***
	(18.99)	(11.75)	(-4.63)	(14.38)	(2.93)	(-10.62)	(0.23)	(8.76)	(12.44)
$r_{30\_0} \cdot D\_Short\_Gamma$	0.83***		0.76***	-0.02		-0.40	-0.84		-1.16**
	(4.92)		(4.51)	(-0.06)		(-1.42)	(2.51)		(4.78)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$		0.76***	0.94***		1.66***	1.98***		0.90**	1.04***
		(4.95)	(6.08)		(7.97)	(9.42)		(5.29)	(6.96)
$r_{30\_0} \cdot D\_Earning$			-2.16***			-3.04***			-0.88
			(-5.59)			(-6.14)			(0.97)
$r_{30\_0} \cdot ImpliedVol$			3.29***			7.59***			4.30***
			(14.05)			(15.79)			(11.87)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	241,086	241,086	241,025	101,178	101,178	101,160	342,264	342,264	342,185

Table 6: MMs' option trading and gamma imbalance

This table reports the regression of the open interest of MM on the cumulative hit number of GTBR by the direction of the market and previous MMs' gamma imbalance. $Cumul\_Hit\_GTBR_{390}$ is the cumulative hit number of GTBR for a day and $MM\_OI_{T,i}$ is the open interest of MM for a day. Newey and West (1986) t-statistics are in parentheses. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively

Independent: $Cumul\_Hit\_GTBR_{390}$	Dependent: Dependent: $MM\_OI_{T,i}$	
	MMs' gamma imbalance	
	Long	**Short**
Underlying moves		
Up	0.27***	-0.13
	(8.94)	(-1.18)
Down	0.12***	0.04
	(3.60)	(0.43)
Firm F.E	Yes	Yes
Observations	266,150	71,453

Table 7: Stock intraday momentum and market price direction

This table reports the regression of the last 30 minutes on the first 30 minutes with the interactive variables. Regressions in Table (a) run with the data where the market rises in the first 30 minutes, while regressions in Table (b) run with the data where the market moves down in the first 30 minutes. D_Short_Gamma equals 1 if the MM has a short gamma position and 0 otherwise. D_GTBR_hit equals 1 if the underlying breaks the Gamma-Theta Breakeven Range (GTBR) at 360 minutes after the market opens and 0 otherwise. Newey and West (1986) t-statistics are in parentheses. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively and coefficients are multiplied by 100.

(a) The underlying stock price **up** at the first 30 minutes

Independent	Dependent: r_{390_360} (1)	(2)	(3)	(4)	(5)
r_{30_0}	3.98***	3.81***	3.91***	3.75***	2.82***
	(20.45)	(18.68)	(13.08)	(12.02)	(5.43)
$r_{30\_0} \cdot D\_Short\_Gamma$		0.61*		0.61*	0.60*
		(1.83)		(1.83)	(1.80)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			0.09	0.08	0.40
			(0.31)	(0.29)	(1.35)
$r_{30\_0} \cdot D\_Earning$					-4.20***
					(-6.78)
$r_{30\_0} \cdot ImpliedVol$					1.59***
					(2.12)
Firm F.E	Yes	Yes	Yes	Yes	Yes
Observations	170,868	170,868	170,868	170,868	170,847

(b) The underlying stock price **down** at the first 30 minutes

Independent	Dependent: r_{390_360} (1)	(2)	(3)	(4)	(5)
r_{30_0}	1.02***	0.78**	-0.03	-0.28	-5.16*
	(5.22)	(3.78)	(-0.09)	(-0.88)	(-10.65)
$r_{30\_0} \cdot D\_Short\_Gamma$		1.35***		0.95***	0.74***
		(4.55)		(2.86)	(2.23)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			1.35***	1.37***	1.65***
			(4.55)	(4.57)	(5.51)
$r_{30\_0} \cdot Earning$					-0.56
					(-0.86)
$r_{30\_0} \cdot ImpliedVol$					6.77***
					(10.41)
Firm F.E	Yes	Yes	Yes	Yes	Yes
Observations	168,256	168,256	168,256	168,256	168,298

Table 8: Stock intraday momentum and gamma exposure decomposition

This table reports the regression of the last 30 minutes on the first 30 minutes with Gamma positions from calls, puts, upside strikes, and downside strikes by the direction of the first 30 minutes. Regressions in Table (a) run with all data. Regressions in Table (b) run with the data where the market rises in the first 30 minutes, while regressions in Table (c) run with the data where the market moves down in the first 30 minutes. *D_Short_Gamma_Calls* (*D_Short_Gamma_Puts*) equals 1 if the MM has a short gamma position from call (put) options and 0 otherwise. *D_Short_Gamma_Upsides* (*D_Short_Gamma_Downsides*) equals 1 if the MM has a short gamma position from upside strike (downside strike) options and 0 otherwise. *D_GTBR_hit* equals 1 if the underlying breaks the Gamma-Theta Breakeven Range (GTBR) at 360 minutes after the market opens and 0 otherwise. Newey and West (1986) t-statistics are in parentheses. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively and coefficients are multiplied by 100.

(a) All data

	r_390_360									
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
r_{30_0}	1.82***	1.65***	1.62***	1.85***	1.62***	1.22***	1.06***	1.03***	1.25***	1.02***
	(18.06)	(15.01)	(15.01)	(17.18)	(14.62)	(7.93)	(6.57)	(6.34)	(7.90)	(6.33)
$r_{30\_0} \cdot D\_Short\_Gamma\_Calls$		0.71***		0.70***						
		(2.86)		(2.85)						
$r_{30\_0} \cdot D\_Short\_Gamma\_Puts$					0.82***	0.81***				
					(3.47)	(3.42)				
$r_{30\_0} \cdot D\_Short\_Gamma\_Upsides$							-0.29	-0.32		
							(-1.04)	(-1.15)		
$r_{30\_0} \cdot D\_Short\_Gamma\_Downsides$									0.87***	0.87***
									(3.54)	(3.54)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			0.96***	0.96***		0.96***		0.97***		0.96***
			(5.01)	(5.01)		(5.00)		(5.03)		(5.01)
Observations	342,264	342,264	342,264	342,264	342,264	342,264	342,264	342,264	342,264	342,264

(b) The underlying **up** at the first 30 minutes

	r_390_360									
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
r_{30_0}	3.98***	3.85***	3.76***	3.98***	3.83***	3.91***	3.78***	3.70***	3.91**	3.77***
	(20.45)	(18.89)	(18.23)	(19.83)	(18.76)	(13.08)	(12.43)	(12.08)	(12.95)	(12.39)
$r_{30\_0} \cdot D\_Short\_Gamma\_Calls$		0.51		0.51						
		(1.51)		(1.50)						
$r_{30\_0} \cdot D\_Short\_Gamma\_Puts$					0.83**	0.82**				
					(2.55)	(2.55)				
$r_{30\_0} \cdot D\_Short\_Gamma\_Upsides$							0.01	0.01		
							(0.04)	(0.03)		
$r_{30\_0} \cdot D\_Short\_Gamma\_Downsides$									0.57	0.57
									(1.70)	(1.70)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			0.08	0.08		0.09		0.08		0.08
			(0.29)	(0.27)		(0.31)		(0.29)		(0.29)
Observations	170,868	170,868	170,868	170,868	170,868	170,868	170,868	170,868	170,868	170,868

(c) The underlying **down** at the first 30 minutes

	r_390_360									
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
r_{30_0}	1.02***	0.75***	0.79***	1.04***	0.73***	-0.03	-0.31	-0.26	-0.01	-0.34
	(5.22)	(3.65)	(3.83)	(5.19)	(3.57)	(-0.09)	(-0.98)	(-0.82)	(-0.03)	(-1.09)
$r_{30\_0} \cdot D\_Short\_Gamma\_Calls$		1.13***		1.13***						
		(3.29)		(3.32)						
$r_{30\_0} \cdot D\_Short\_Gamma\_Puts$					0.85***	0.86***				
					(2.61)	(2.64)				
$r_{30\_0} \cdot D\_Short\_Gamma\_Upsides$							-0.23	-0.32		
							(-0.57)	(-0.78)		
$r_{30\_0} \cdot D\_Short\_Gamma\_Downsides$									1.23***	1.27***
									(3.67)	(3.77)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			1.35***	1.37***		1.36***		1.37***		1.38***
			(4.55)	(4.57)		(4.56)		(4.57)		(4.63)
Observations	168,256	168,256	168,256	168,256	168,256	168,256	168,256	168,256	168,256	168,256

Table 9: Stock intraday momentum: option expiration

This table reports the regression of the last 30 minutes by the first 30 minutes with the interactive variables. D_Short_Gamma equals 1 if the MM has a short gamma position and 0 otherwise. D_GTBR_hit equals 1 if the underlying hit the Gamma-Theta Breakeven Range (GTBR) at 360 minutes after the market opens and 0 otherwise. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively, and coefficients are multiplied by 100. All regressions use the firm-fixed effect.

(a) With the subset of **the expiry week**

Independent	Dependent: r_{390_360} (1)	(2)	(3)	(4)	(5)
r_{30_0}	2.17***	1.88***	1.18***	0.89***	-4.28***
	(10.60)	(8.19)	(3.84)	(2.76)	(-7.66)
$r_{30\_0} \cdot D\_Short\_Gamma$		1.22**		1.22**	0.94*
		(2.47)		(2.47)	(1.90)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			1.65***	1.65***	1.91***
			(4.25)	(4.25)	(4.87)
$r_{30\_0} \cdot D\_Earning$					-1.34
					(-1.38)
$r_{30\_0} \cdot ImpliedVol$					8.46***
					(8.75)
$Adj.R^2(\%)$	0.34	0.36	0.38	0.40	0.91
Firm F.E	Yes	Yes	Yes	Yes	Yes
Observations	79,281	79,281	79,281	79,281	79,261

(b) With the subset of **the non-expiry week**

Independent	Dependent: r_{390_360} (1)	(2)	(3)	(4)	(5)
r_{30_0}	1.74***	1.60***	1.24***	1.10***	-0.31*
	(15.30)	(12.77)	(7.00)	(5.93)	(-1.00)
$r_{30\_0} \cdot D\_Short\_Gamma$		0.57**		0.57**	0.46*
		(2.10)		(2.09)	(1.69)
$r_{30\_0} \cdot D\_GTBR\_hit_{360}$			0.79***	0.79***	0.99***
			(3.61)	(3.60)	(4.45)
$r_{30\_0} \cdot D\_Earning$					-2.72***
					(-5.43)
$r_{30\_0} \cdot ImpliedVol$					2.37***
					(4.56)
$Adj.R^2(\%)$	0.24	0.24	0.25	0.25	0.33
Firm F.E	Yes	Yes	Yes	Yes	Yes
Observations	262,983	262,983	262,983	262,983	262,924

Table 10: Summary statistics of the R^2 and OOSR2 from the predictive regressions of stock returns

This table represents the summary statistics of the R^2 and OOSR2 from the regression by each underlying. The data are first grouped by underlying, and then at each underlying level the last 30 minute return is regressed by the first 30 minute return. The column (1), (2), (3), and (4) shows the different regressions for r_{390_360}. The column (1) is the regression by only r_{30_0}, the regression (2) adds D_Short_Gamma interaction to the regression (1), the regression (3) adds D_GTBR_hit interaction to the regression (1), and the regression (4) includes all indicators.

	R^2				OOSR2			
Stat	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Mean	0.87	1.34	1.18	1.82	1.34	1.54	1.57	1.78
StdDev	1.52	2.75	1.79	3.14	7.24	9.80	7.87	10.06
Min	0.00	0.00	0.00	0.00	-1.21	-1.68	-1.31	-1.71
$25^{th} Percentile$	0.10	0.20	0.20	0.50	0.45	0.62	0.59	0.77
Median	0.30	0.60	0.50	1.00	0.90	1.20	1.09	1.40
$75^{th} Percentile$	0.90	1.40	1.30	2.00	1.91	2.34	2.31	2.63
Max	9.90	35.10	12.10	39.10	23.26	27.49	26.82	28.72

Appendices

A1. Simplifying daily PnL attribution

From Carr and Wu (2020), the instantaneous PnL of the option position is,

$$\begin{aligned} dPnL =& Theta * dT + Delta * dS + Vega * dI \\ &+ \frac{1}{2}Gamma(dS)^2 + \frac{1}{2}Volga(dI)^2 + \frac{1}{2}Vanna(dS)(dI) + J_T \end{aligned}$$

where dS, dI, and J_T represent an underlying price change, an implied volatility change, and a PnL change by higher orders. MMs' delta-neutral portfolio begins a day with delta-neutral and rebalances its delta by the end of the day. Therefore, in the delta-hedged portfolio, the delta PnL of the option can be deleted. Also, assuming that there's no significant change in higher order PnL during the day, a daily PnL attribution is

$$Daily\ PnL = \frac{Theta}{365} + \frac{1}{2}Gamma(\Delta S)^2 + Trading\ PnL$$

Vega, Volga, and Vanna PnL is negligible compared to gamma PnL in the scope of this study because gamma exposure is significant at relatively shorter maturity. In short maturity, vega volga, and vanna are relatively small and implied volatility during the day does not change significantly very frequently.

A2. The optimal hedge trigger point for a trader's perspective

This equation can be rewritten as below.

$$\begin{aligned} E_t[PnL_T] &= E_t[50\Gamma r_{T-t}^2 + 50\Gamma r_t^2 + H\{(r_{T-t} - 100k\Gamma r_t)(-100\Gamma r_t) - |100\Gamma r_t \cdot tc|\}|r_t] + \theta_1 \\ &= E_t[50\Gamma r_{T-t}^2|r_t] + 50\Gamma r_t^2 + E_t[H\{(r_{T-t} - 100k\Gamma r_t)(-100\Gamma r_t) - |100\Gamma r_t \cdot tc|\}|r_t] + \theta_1 \end{aligned}$$

Let $r_{T-t} = \mu(T-t) + \sigma(W(T) - W(t)) + Hk(-100\Gamma r_t)$ where μ is a hedger's belief for average return, $W(t)$ is a brownian. Then,

$$\begin{aligned} =& 50\Gamma\mu^2(T-t)^2 + 50\Gamma\sigma^2(T-t) + H^2k^2 100^2\Gamma^2 r_t^2 - 100^2\Gamma^2\mu(T-t)Hkr_t + 50\Gamma r_t^2 \\ &+ H\mu(T-t)(-100\Gamma r_t) - |100\Gamma r_t \cdot tc| + \theta_1 \end{aligned}$$

Assume that MM tries to find the rebalancing timing ($H = 1$), then

$$\begin{aligned}=&50\Gamma\mu^2(T-t)^2 + 50\Gamma\sigma^2(T-t) + k^2 100^2\Gamma^2 r_t^2 - 100^2\Gamma^2\mu(T-t)kr_t + 50\Gamma r_t^2 \\ &+ \mu(T-t)(-100\Gamma r_t) - |100\Gamma r_t \cdot tc| + \theta_1\end{aligned} \tag{5}$$

A delta-neutral trader maximizes the expected PnL,

$$max\ E_t[PnL_T]$$

F.O.C for $E_t[PnL_T]$ by r_t, r_t^* is

$$2k^2 100^2\Gamma^2 r_t^* - 100^2\Gamma^2\mu(T-t)k + 100\Gamma r_t^* + \mu(T-t)(-100\Gamma) - |100\Gamma \cdot tc| = 0$$

$$r_t^* = \frac{\mu(T-t)(1+100\Gamma k) + tc'}{(1 + 2 \cdot 100^2 k^2 \Gamma^2)} \tag{6}$$

where $tc' = tc$ if $\Gamma >= 0$, and $tc' = -tc$ if $\Gamma < 0$.

r_t^* is the gamma hedge triggering level of the hedge trader or MM at t. This level would vary depending on the remaining time for the day, return drift, the impact cost, and the transaction cost.

A3. Simplifying the GTBR

From equation (1) in Section 2.3.1, GTBR is derived as below.

$$GTBR = \pm\sqrt{-\frac{\theta}{365 \cdot 50\Gamma}}$$

and from Black-Scholes greek, assuming zero dividend, theta is calculated to

$$\theta_{Call} = -\frac{SN'(d_1)\sigma_{imp}}{2\sqrt{T-t}} - rKe^{-r(T-t)}N(d_2)$$
$$\theta_{Put} = -\frac{SN'(d_1)\sigma_{imp}}{2\sqrt{T-t}} + rKe^{-r(T-t)}N(-d_2)$$

where σ_{imp} is implied volatility of an option. Only when the option has deep ITM moneyness do the second terms in the above equations have meaningful value. However, because deep ITM options almost never have any gamma exposure, they have no impact on a hedge trader's decision.

As a result, Black-Scholes theta as a gamma risk buffer is approximately

$$\theta \approx -\frac{SN'(d_1)\sigma_{imp}}{2\sqrt{T-t}} \tag{7}$$

Also, the dollar gamma, Γ is

$$\Gamma = \frac{\gamma S^2}{100} = \frac{N'(d_1)}{100 \cdot S\sigma\sqrt{T-t}}S^2 = \frac{SN'(d_1)}{100\sigma\sqrt{T-t}} \tag{8}$$

By plugging equation (7) and (8) into the equation (1),

$$GTBR \approx \pm\sqrt{-\frac{\theta}{365 \cdot 50\Gamma}} = \pm\sqrt{-\frac{\frac{SN'(d_1)\sigma}{2\sqrt{T-t}}}{365 \cdot 50 \cdot \frac{SN'(d_1)}{100\sigma_{imp}\sqrt{T-t}}}} = \pm\sqrt{\frac{\sigma_{imp}^2}{365}} = \pm\frac{\sigma_{imp}}{\sqrt{365}} \tag{9}$$

B1. Descriptive Statistics

Table B1: Descriptive Statistics: Raw data

(a) Summary statistics

Variable	Mean	Standard Deviation	Min	$25^{th} Percentile$	Median	$75^{th} Percentile$	Max
r_{30_0}	0.0000406	0.0168	-0.0543	-0.00792	0	0.00813	0.0549
r_{390_360}	0.0000757	0.0059	-0.0211	-0.00245	0	0.00249	0.0228
$Cumul\_GTBR\_Hit_{360}$	91.29	124.9	0	0	10	175	360
Gamma_Size	6,098	44,894	-3,501,893	68	1,587	7077	837,537

(b) Correlation among dependent variables

Correlation	r_{30_0}	D_Short_Gamma	$D\_GTBR\_Hit_{360}$	$Cumul\_GTBR\_Hit_{360}$	r_{30_0} * D_Short_Gamma	r_{30_0} * $D\_GTBR\_Hit_{360}$
r_{30_0}	1					
D_Short_Gamma	0.0008	1				
$D\_GTBR\_Hit_{360}$	0.0007	0.0061	1			
$Cumul\_GTBR\_Hit_{360}$	-0.0082	0.0048	0.7634	1		
$r_{30\_0} \cdot D\_Short\_Gamma$	0.4946	0.0033	0.0041	-0.0035	1	
$r_{30\_0} \cdot D\_GTBR\_Hit_{360}$	0.7885	0.003	0.0021	-0.003	0.3918	1

(c) Frequency of the binary variable

		$D\_GTBR\_Hit_{360}$	
		0	1
D_Short_Gamma	0	183,168	86,721
	1	48,610	23,757

Table B2: Descriptive Statistics: r_{390_360} for sorted data

r_{390_360}		$NormGamma^1$	$NormGamma^2$	$NormGamma^3$	$NormGamma^4$	$NormGamma^5$
$Cumul\_Hit\_GTBR$ (=0)	Mean	0.000069	0.000031	0.000091	0.000008	0.000049
	Std. dev.	0.006079	0.007681	0.005502	0.004420	0.003519
	Min	-0.102644	-0.14852	-0.058900	-0.052167	-0.0399991
	Max	0.132371	0.14634	0.063478	0.060193	0.104304
	Obs	28,681	28,680	28,680	28,680	28,680
$Cumul\_Hit\_GTBR$ (0 - 90)	Mean	0.000086	0.000491	0.000195	0.000141	-0.00003
	Std. dev.	0.009189	0.011207	0.008071	0.006246	0.00453
	Min	-0.132743	-0.089247	-0.097598	-0.063326	-0.09288
	Max	0.145581	0.132691	0.093366	0.110095	0.07224
	Obs	16,785	16,785	16,784	16,785	16,784
$Cumul\_Hit\_GTBR$ (90 - 180)	Mean	0.000211	-0.000027	0.000293	0.000172	-0.000042
	Std. dev.	0.0096736	0.011129	0.008037	0.006348	0.004539
	Min	-0.159223	-0.080498	-0.066062	-0.05810	-0.048345
	Max	0.096310	0.204941	0.111568	0.085424	0.061966
	Obs	6,228	6,227	6,227	6,227	6,227
$Cumul\_Hit\_GTBR$ (180 - 270)	Mean	0.000068	0.00016	0.000073	-0.000010	-0.00002
	Std. dev.	0.0008996	0.011315	0.006759	0.006584	0.004588
	Min	-0.071074	-0.14090	-0.021053	-0.17741	-0.053929
	Max	0.116999	0.189873	0.022757	0.051985	0.045179
	Obs	5,918	5,917	5,918	5,917	5,917
$Cumul\_Hit\_GTBR$ (270 - 360)	Mean	0.000104	-0.0001	-0.000023	0.000001	-0.000031
	Std. dev.	0.010278	0.011616	0.008284	0.005905	0.004652
	Min	-0.089091	-0.127197	-0.088250	-0.044040	-0.048824
	Max	0.451178	0.151724	0.130171	0.073844	0.051443
	Obs	8,714	8,714	8,714	8,714	8,714
$Cumul\_Hit\_GTBR$ (=360)	Mean	0.000285	0.0007611	0.000406	0.000376	0.000076
	Std. dev.	0.008875	0.012107	0.008880	0.006843	0.004680
	Min	-0.047458	-0.071090	-0.1358	-0.034378	-0.032619
	Max	0.084349	0.085691	0.054945	0.046577	0.029706
	Obs	2,128	2,128	2,128	2,128	2,127

Table B3: Descriptive Statistics: r_{30_0} for sorted data

r_{30_0}		$NormGamma^1$	$NormGamma^2$	$NormGamma^3$	$NormGamma^4$	$NormGamma^5$
$Cumul\_Hit\_GTBR$ (=0)	Mean	0.000154	0.000191	0.000048	0.000108	0.00011
	Std. dev.	0.00878	0.010323	0.008603	0.007373	0.006145
	Min	-0.062036	-0.086926	-0.08483	-0.065057	-0.043315
	Max	0.073018	0.083793	0.06175	0.048946	0.05006
	Obs	28,681	28,680	28,680	28,680	28,680
$Cumul\_Hit\_GTBR$ (0 - 90)	Mean	0.000182	0.000414	0.000106	0.000029	0.000132
	Std. dev.	0.015505	0.017969	0.015638	0.013389	0.010801
	Min	-0.092147	-0.164706	-0.097135	-0.078518	-0.085701
	Max	0.132202	0.166128	0.129191	0.093663	0.05749
	Obs	16,785	16,785	16,784	16,785	16,784
$Cumul\_Hit\_GTBR$ (90 - 180)	Mean	0.000103	0.000394	-0.000276	-0.00029	-0.000138
	Std. dev.	0.018389	0.020473	0.018165	0.01547	0.012727
	Min	-0.16285	-0.156803	-0.119932	-0.083798	-0.069178
	Max	0.190086	0.19790	0.126795	0.124507	0.079713
	Obs	6,228	6,227	6,227	6,227	6,227
$Cumul\_Hit\_GTBR$ (180 - 270)	Mean	-0.000472	-0.0009	-0.000423	0.000029	0.000072
	Std. dev.	0.019625	0.021898	0.019162	0.016267	0.013378
	Min	-0.115879	-0.17013	-0.170103	-0.100671	-0.079951
	Max	0.138494	0.230159	0.230159	0.112181	0.077892
	Obs	5,918	5,917	5,918	5,917	5,917
$Cumul\_Hit\_GTBR$ (270 - 360)	Mean	-0.000316	-0.000485	-0.000313	0.0006	0.000893
	Std. dev.	0.028128	0.031434	0.028048	0.024551	0.020291
	Min	-0.664048	-0.548387	-0.185007	-0.502709	-0.499252
	Max	0.206940	0.472279	0.199802	0.130492	0.131375
	Obs	8,714	8,714	8,714	8,714	8,714
$Cumul\_Hit\_GTBR$ (=360)	Mean	0.000573	-0.000156	-0.002476	-0.001387	-0.001286
	Std. dev.	0.041613	0.043701	0.042348	0.040192	0.034732
	Min	-0.899917	-0.6305725	-0.746632	-0.670929	-0.895287
	Max	17.2688	4.012389	4.0888	0.270812	0.24955
	Obs	2,128	2,128	2,128	2,128	2,127

C1. Never broken GTBR for a whole day or broken GTBR for a whole day

Unlike section 4.2, which examined the cumulative GTBR effect for 360 minutes, this appendix section investigates whether market intraday momentum exists even when the underlying never reaches the GTBR and when the underlying market opens and stays out of GTBR for the entire day. The result is shown in Table C4. The first row contains cases in which the underlying never moves out of the GTBR. According to the findings, there is no market intraday momentum but significant market 'reverse' regardless of the gamma size and sign across columns. This implies that when the underlying remains and moves within GTBR, the mean reversion trader has a stronger impact on the market than the trend follower, including the short gamma trader. Besides that, when the MM has a long gamma, the market's intraday reversal is stronger. The last row, which contains cases in which the underlying open and remains out of GTBR for the entire day, yields a similar result to the previous section. With MMs' strong short gamma position, they still have some significant intraday trends, but the overall momentum coefficient is lower than in the normal case (breaking GTBR sometimes during the day). This implies that MMs' delta hedge from short gamma exposure spreads throughout the day because the MMs' position begins with a loss and their hedge activity focus on minimizing their hedge impact. Long gamma exposure, on the other hand, works by reducing the intraday trend without changing its direction to 'reverse.' To put it another way, their delta hedge from long gamma exposure would not push the underlying return into GTBR. The MM starts by making money over theta cost and does not want to hurt the trend too much, so they have a strong incentive to leave the underlying stays out of the GTBR while they hedge. As a result, their intraday coefficient does not experience a significant 'reverse' change. This result confirms again that the market intraday impact from the option hedging demand is not only a function of the short gamma position of them, but also the one with a clear trigger point.

Table C4: Never broken GTBR for wholeday or broken GTBR for wholeday

This table reports the regression of the last 30 minutes on the first 30 minutes with the sorted data set. After measuring the hitting GTBR every minute, $Cumul\_Hit\_GTBR_{390}$ is calculated by the cumulative hit number for the whole day and then categorized by the number. NormGamma is normalized dollar gamma and they are categorized by quintile. $NormGamma^1$ has the strongest short gamma while $NormGamma^5$ has the strongest long gamma. The Cumul_Hit_GTBR has been sorted first and then $NormGamma$ are categorized. *** is $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively and coefficients are multiplied by 100.

r_{390_360} on r_{30_0}	**(Short Gamma)**				**(Long Gamma)**
	$NormGamma^1$	$NormGamma^2$	$NormGamma^3$	$NormGamma^4$	$NormGamma^5$
$Cumul\_Hit\_GTBR_{390} = 0$	-0.911***	-0.178	-1.53***	-1.13***	-2.44***
	(-2.628)	(-0.510)	(-4.514)	(-3.469)	(-7.712)
$< 0 Cumul\_Hit\_GTBR_{390} < 390$	2.58***	3.88***	1.68***	0.858***	0.0614
	(13.87)	(20.37)	(9.495)	(5.111)	(0.384)
$Cumul\_Hit\_GTBR_{390} = 390$	1.32***	3.68***	1.85***	1.57***	0.0988
	(3.505)	(8.205)	(5.001)	(4.450)	(0.344)