Does Option Trading Have a Pervasive Impact on Underlying Stock Prices?☆

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Abstract

The question of whether and to what extent option trading impacts underlying stock prices has been a focus of interest since options began exchange-based trading in 1973. Recent research presents evidence of an informational channel through which option trading impacts stock prices by showing that option market makers' delta hedge trades to hedge new options positions cause the information reflected in option trading to be impounded into underlying equity prices. This paper provides evidence of a non-informational channel by showing that option market maker hedge rebalancing impacts both stock return volatility and the probability of large stock price moves.

JEL Classification: G12, G13, G14, G23

Keywords: Option trading, option open interest, delta-hedging, pinning, stock return volatility

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Does Option Trading Have a Pervasive Impact on Underlying Stock Prices?

Abstract

The question of whether and to what extent option trading impacts underlying stock prices has been a focus of interest since options began exchange-based trading in 1973. Recent research presents evidence of an informational channel through which option trading impacts stock prices by showing that option market makers' delta hedge trades to hedge new options positions cause the information reflected in option trading to be impounded into underlying equity prices. This paper provides evidence of a non-informational channel by showing that option market maker hedge rebalancing impacts both stock return volatility and the probability of large stock price moves.

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1. Introduction

Ever since individual equity options began trading in 1973, investors, exchange officials, and regulators have been concerned that underlying stock prices might be affected by options trading.[1] Despite a substantial effort to identify such impact, only recently has the literature begun to develop convincing evidence that option trading has important impacts on stock prices. A growing literature presents evidence suggesting that options play a role in the price discovery process (for example, Pan and Poteshman, 2006; Ni, Pan, and Poteshman, 2008; Cremers and Weinbaum, 2010; Xing, Zhang, Zhao, 2010; Lin and Lu, 2015; Ge, Lin, and Pearson, 2016; and Cremers, Fodor, and Weinbaum, 2017). Notably, Hu (2014) presents evidence of an informational channel through which option trading impacts stock prices by showing that option market makers' initial delta hedge trades to hedge new options positions cause the information reflected in option trading to be impounded into underlying equity prices. Turning to a non-informational channel, Ni, Pearson, and Poteshman (2005) and Golez and Jackwerth (2012) show that rebalancing and unwinding of option market makers' delta hedges on or near option expiration causes the prices of individual stocks and stock index futures, respectively, to cluster or "pin" at option strike prices on option expiration dates.[2]

The findings in Ni, Pearson, and Poteshman (2005) and Golez and Jackwerth (2012) that re-hedging of option positions just before expiration produces measurable deviations in stock price paths leads naturally to the question of whether re-hedging away from expiration also changes stock price movements. The potential mechanism is that dynamic hedging of written option

[1] See Whaley (2003) for an account of the early period of exchange traded options.
[2] Avellaneda and Lipkin (2003) model this mechanism, focusing on the role of the time derivatives of option deltas. Due to these time derivatives, as time passes delta-hedgers who have net purchased (written) option positions will sell (buy) stock when the stock price is above the option strike price and buy (sell) stock when the price is below the strike price, tending to drive the stock price toward the option strike price.

positions involves buying the underlying asset after its price has increased and selling it after its price has decreased. This pattern of buying and selling potentially causes the underlying asset to be more volatile than it otherwise would have been. Similarly, dynamic hedging of purchased option positions potentially causes volatility to be lower than it otherwise would have been. The magnitude of the buying and selling volume to rebalance hedges is determined by the option gamma of the net options position of delta hedgers, leading to the prediction that stock return volatility will be decreasing in the gamma of delta hedgers' net options position.[3] We find that it is. Thus, we show that option market maker hedge rebalancing has a pervasive effect on stock prices in that it impacts stock return volatility at all times, not just on or near option expiration dates.

Specifically, we investigate whether the net gamma of delta-hedging investors is indeed negatively related to the volatility of the underlying stock by using daily net open interest and signed volume data of different investors that allow us to compute (for 1990-2001) or estimate (for 2002-2012), respectively, for each underlying stock the gamma of the net options position of likely delta hedgers. We find a highly significant negative relation between the gamma of the net options position of likely delta-hedgers and the absolute return of the underlying stock. The finding is robust to controlling for persistence in stock volatility and for the possibility that the option positions of likely delta-hedgers are changed as the result of investors trading options to profit from information about the future volatility of underlying stocks. In addition, the finding is present

[3] In the theoretical literature, Jarrow (1994), Frey and Stremme (1997), Frey (1998), Platen and Schweizer (1998), Sircar and Papanicolaou (1998), Frey (2000), and Schönbucher and Wilmott (2000) model the effect of the delta-hedging of derivative positions on underlying assets that are not perfectly liquid. These models predict that when the gamma of the net option position on an underlying stock of delta-hedging investors is positive (negative), hedge re-balancing will reduce (increase) the volatility of the stock.

for both large and small and high and low liquidity underlying stocks in both the 1990-2001 and 2002-2012 sample periods, when we define likely delta hedgers to include firm proprietary traders as well as options market makers, and when we use the change in the absolute return as the dependent variable in the regression analyses. We also show that the rebalancing of hedges on individual stocks helps explain the return volatility of the S&P 500 index. Hence, we provide evidence that option market activity has a pervasive impact on the volatility of underlying stocks.

The effect of hedge rebalancing on volatility is economically significant. The stocks' average daily absolute returns are 303 and 220 basis points during the 1990-2001 and 2002-2012 sample periods, respectively. A one standard deviation shock to the key gamma variable is associated with a 28.8 (29.6) basis point change in absolute return in the first (second) period. Consequently, 9.5 percent (= 28.8/303) of the daily absolute return of optioned stocks in the first period, and 13.4 percent (= 29.6/220) in the second period, can be attributed to option market participants re-balancing the hedges of their option positions. Similar calculations indicate that a one standard deviation shock to the average of the key gamma variable is associated with a 4.6% (7.0%) change in the absolute daily return of the S&P 500 index in the first (second) sample period.

As indicated above there is another channel, informational trading, through which option trading impacts stock prices. For example, Pan and Poteshman (2006) show newly established options positions predict underlying stock returns, consistent with option trading containing information that is only later reflected in stock prices. Hu (2014) uses option order imbalances to estimate the stock order imbalances stemming from options market makers' delta hedge trades and finds that the stock order imbalances due to the delta hedge trades predict stock returns. This paper complements Hu (2014) by documenting the existence of a non-informational channel through which option hedge trading, in our case hedge rebalancing, impacts stock prices. Recognizing that hedging by options market makers is a mechanism through which they manage their inventories of options positions, the results are also related to the work of Hendershott and Menkveld (2014) showing that equity market makers' inventory management practices distort stock prices.

Since stock trading due to hedge rebalancing is not related to information, its impact on stock prices should be temporary. Dynamic delta hedgers managing negative gamma options positions buy after stock price increases and sell after stock price decreases. These demand pressures can push stock prices to be higher or lower than the levels justified by fundamentals, so stock prices are more likely to reverse compared to the case when delta hedgers' gammas are positive or close to zero. Indeed, we show that when the key net gamma variable is negative stocks have lower return autocorrelations on the following days.

Our results also shed light on the literature that investigates whether option introduction (that is, the existence of option trading) leads to an overall increase or decrease in the variability of underlying stock returns. Bansal, Pruitt, and Wei (1989), Conrad (1989), and Skinner (1989) all find that being optioned yields a decrease in the volatility of underlying stock prices. However, Lamoureux and Panikkath (1994), Freund, McCann, and Webb (1994), and Bollen (1998) demonstrate that the apparent decrease in volatility is probably rooted in the fact that exchanges tend to introduce options after increases in volatility, as they show that the decrease in volatility that occurs after option introduction is also observed in samples of matched control firms that lack option introduction. We show, by contrast, that volatility increases or decreases depending upon the sign of the net gamma of delta-hedging investors. Consequently, even though option trading changes the variability of underlying stock returns, it is not surprising that there is no evidence of an unconditional increase or decrease of volatility associated with option trading.

The remainder of the paper is organized as follows. Section 2 develops our empirical predictions. The third section describes the data. Section 4 presents the results, and Section 5 briefly concludes.

2. Empirical Predictions

Dynamic trading strategies that involve delta-hedging options require buying or selling the underlying asset as the delta of the option or options portfolio changes. Unless the underlying asset is traded in a perfectly liquid market, such trading will lead to changes in the price of the underlying asset. This trading due to hedge rebalancing will either increase or decrease the volatility of the underlying asset, depending upon the nature (negative or positive gamma) of the option positions that are being hedged.

Letting $V(t, S)$ denote the value of an options portfolio, the delta is $\Delta(t, S) = \partial V(t, S)/\partial S$ and the gamma is $\Gamma(t, S) = \partial\Delta(t, S)/\partial S = \partial^2 V(t, S)/\partial S^2$. The delta of purchased (written) options increases (decreases) with stock prices. The gamma is positive for purchased options positions, and negative for written options positions. Consider an option market maker who has written (that is, investors have purchased) options and wants to maintain a delta-neutral position, that is he or she wants the delta of the combined position of options and the underlying stock to be zero. Because the option position consists of written contracts with negative gamma, to maintain delta-neutrality the market maker must buy the underlying stock after its price has increased as the written option delta has decreased, and sell it after its price has decreased as the written option delta has increased. Similarly, the trading strategy to delta-hedge a positive-gamma option position (purchased options) requires selling the underlying asset after its price has increased and buying it after its price has decreased. If the gamma of the aggregate position of market makers and other delta-hedgers is negative, then the trading due to hedge rebalancing (buying if the stock price increases, and selling if it decreases) will have the effect of increasing the volatility of the underlying stock. Conversely, if the gamma of the aggregate position of market makers and other delta-hedgers is positive, then the trading due to hedge rebalancing (selling if the stock price increases, and buying if it decreases) will have the effect of reducing the volatility of the underlying stock. This reasoning predicts that the volatility of the underlying stock will be negatively related to the gamma of the aggregate option position of the option market makers and any other delta hedgers.

As discussed in the introduction, these possible effects of the stock trading stemming from hedge rebalancing have been studied in theoretical papers by Jarrow (1994), Frey and Stremme (1997), Frey (1998), Platen and Schweizer (1998), Sircar and Papanicolaou (1998), Frey (2000), and Schönbucher and Wilmott (2000). Their models imply that the associated trading will cause the volatility of the underlying asset to be greater than or less than it would have been in the absence of such trading, depending on whether the gamma of the aggregate option position of the delta-hedgers is less than or greater than zero.

Appendix A briefly summarizes the results of the models that provide explicit formulas showing the effect of hedge rebalancing on volatility. The formulas also guide the empirical work by either requiring or suggesting rescaling the gammas of the option positions by multiplying gamma by the ratio of the stock price to the number of shares outstanding (S/M) so that the gammas are comparable across firms.[4]

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[4] This rescaling also makes the normalized gamma dimensionless. Since the dependent variable (absolute value of return) is also dimensionless, the regression coefficients are dimensionless, which allows us meaningfully to compute the cross-sectional average regression coefficients. While it is not necessary that we rescale gamma to make it *dimensionless*, it is necessary that we rescale it in some way to make the units of gamma (and thus the regression coefficients) the same across firms. Making gamma dimensionless is the most natural choice.

3. Data

The primary data consist of option open interest and signed trading volume for various groups of customers obtained from the Chicago Board Options Exchange (CBOE) and the International Securities Exchange (ISE). For the period from the beginning of 1990 through the end of 2001, the data are from the CBOE and include several categories of daily open interest for every equity option series that trades at the CBOE from the beginning of 1990 through the end of 2001.[5] When equity options on an underlying stock trade both at the CBOE and also at other exchanges, the open interest data reflect trades in the option series from all exchanges. If equity options on an underlying stock are not traded at the CBOE, then they are not included in the data.

For the period from the beginning of 2002 through the end of 2012, the data are the Open/Close data from the CBOE and ISE and include several categories of daily signed volume for the equity options that trade at the CBOE and ISE, respectively. The ISE data begin only in May 2005. When the options on an underlying stock trade both at the CBOE or the ISE and at other exchanges, the data do not include the volumes on other exchanges. During this period, the trading volume on the CBOE and ISE comprised 66% of total trading volume.

The open interest data from 1990-2001 contain four categories of open interest for each option series at the close of every trade day: purchased and written open interest by public customers and purchased and written open interest by firm proprietary traders. Investors trading through Merrill Lynch or E-trade are examples of public customers while an option trader at Goldman Sachs who trades for the bank's own account is an example of a firm proprietary trader. Because public customers and firm proprietary traders comprise all non-market maker option market participants, for each option series, the net market maker position can be computed as the

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[5] These data are used by Ni, Pearson, and Poteshman (2005).

negative of the sum of the public customer and firm proprietary trader open interest in that option series.

The CBOE and ISE Open/Close data used for the 2002-2012 period contain eight categories of volume for each option series at the close of every trade day: open buy, open sell, close buy and close sell by public investors and firm proprietary traders. The categorization of investors as public customers or firm proprietary traders follows the OCC classification. For each option series, we cumulate the buy and sell trades of the public customers and firm proprietary traders to develop estimates of the long and short open interests of the two groups of customers, and then estimate the net market maker position as the negative of the sum of the public customer and firm proprietary trader open interests. This procedure introduces some errors into the estimates of option market maker positions because some trading volume occurs on option exchanges other than the CBOE and ISE and also because we do not capture changes in open interest due to option exercises. Results in the Internet Appendix show that these errors are unlikely to introduce important biases into the main results.

Daily stock returns, closing prices, and number of shares outstanding are obtained from the Center for Research in Securities Prices (CRSP). For some analyses we use estimates of option gammas taken from the Ivy DB database produced by OptionMetrics LLC and signed volume from TAQ.

4. Regression specifications and results

4.1. Net gamma of likely delta-hedgers

The number of purchased and written positions in each option series is identical. At any point in time for any underlying stock, the net gamma of the option positions in each option series (and, hence, in the options on any underlying stock) of *all* investors is zero.

We denote by *net*Γ_t the net gamma of the likely delta-hedgers' option positions on a stock at the close of trade date *t*. The likely delta hedgers are either options market makers or market makers plus firm proprietary traders, who together constitute all non-public customer traders. We use the fact that the sum of the market maker, public customer, and firm proprietary trader open interest on any option series at any point of time must be zero to construct *net*Γ_t as follows.

For each stock, we measure the likely delta hedgers' net open interest at the close of trade date *t* in the *j*th option series as the negative of the net open interest of the other investor classes. The delta hedger net open interest in option series *j* at the close of trade date *t* is

$$netOpenInterest_{j,t} = -\big[1_{\{MM\}}\big(OpenInterest_{j,t}^{Buy,Firm} - OpenInterest_{j,t}^{Sell,Firm}\big) \qquad (1)$$

$$+OpenInterest_{j,t}^{Buy,Public} - OpenInterest_{j,t}^{Sell,Public}\big],$$

where $netOpenInterest_{j,t}$ is the net open interest (in units of option contracts) of the likely delta hedgers in option series *j* and $OpenInterest_{j,t}^{x,y}$ is the open interest of type *x* (i.e., buy or sell) by investor class *y* (i.e., Firm Proprietary or Public Customer) in option series *j* at the close of trade date *t*. The indicator function $1_{\{\bullet\}}$ takes the value one if the set of likely delta hedgers is assumed to consist only of market makers (*MM*), and zero if the set of likely delta hedgers is assumed to include both market makers and firm proprietary traders.

For the period of 1990 to 2001, we obtain $OpenInterest_{j,t}^{x,y}$ from the CBOE. For the period of 2002 to 2012, for each option series we estimate the buy and sell open interest by cumulating the CBOE and ISE open buy, close sell, open sell and close buy volumes as follows:

$$OpenInterest_{j,t}^{Buy,y} = OpenInterest_{j,t-1}^{Buy,y} + Volume_{j,t}^{OpenBuy,y} - Volume_{j,t}^{CloseSell,y}, \qquad (2)$$

$$OpenInterest_{j,t}^{Sell,y} = OpenInterest_{j,t-1}^{Sell,y} + Volume_{j,t}^{OpenSell,y} - Volume_{j,t}^{CloseBuy,y}, \qquad (3)$$

where $Volume_{j,t}^{OpenBuy,y}$ and $Volume_{j,t}^{OpenSell,y}$ are volumes from investor class y to establish new purchased and written positions, and $Volume_{j,t}^{CloseBuy,y}$ and $Volume_{j,t}^{CloseSell,y}$ are volumes to close existing written and purchased positions, respectively.

The delta hedger net gamma due to option series j is just the product of the delta hedger net open interest in that series and the gamma of series j for time t and stock price S_t, denoted $\Gamma_j(t, S_t)$, multiplied by 100 to account for the fact that option gammas conventionally are expressed on a per-share basis and each option contract is for 100 shares of the underlying stock. Summing over the different option series, the normalized delta hedger net gamma on an underlying stock at the close of trade date t is

$$net_t\Gamma = 100\left(\frac{S_t}{M_t}\right) \times \sum_{j=1}^{N_t} netOpenInterest_{j,t}\Gamma_j(t, S_t), \tag{4}$$

where N_t, S_t, and M_t are respectively the number of option series available for trading, the underlying stock price, and the number of shares outstanding, all as of the close of trading on date t. As discussed in Appendix A, the normalization by S_t/M_t is either required or suggested by the theoretical models. When computing $\Gamma_j(t, S_t)$ all quantities (i.e., the stock price, the time to expiration of the jth option, the risk-free, and the volatility and dividend rates of the underlying stock) are at their time t values.

In the empirical work below, we use Black-Scholes gammas as proxies for $\Gamma_j(t, S_t)$. When computing the Black-Scholes gammas, the risk-free rate is set to day t's continuously compounded, annualized 30 day LIBOR rate, the volatility of the underlying asset is set to the annualized sample volatility estimated from daily log returns over the 60 trading days leading up to t, and the dividend rate is set equal to the continuously compounded, annualized rate that produces a present value of dividends over the interval from t to the option expiration equal to the present value of the actual dividends paid over the interval. The assumptions of the Black-Scholes model are violated in a few ways (e.g., the volatilities of the underlying stocks are not constant, there may well be jumps in the underlying stock return process, and the options are American rather than European.) We believe the Black-Scholes model provides adequate approximations to gamma for our purposes. The OptionMetrics gammas are computed using the implied volatility to incorporate the possibility of early exercise and volatility skew. As a robustness check we present results using option gammas taken from the OptionMetrics database to verify that our findings are not affected in any important way by our use of the Black-Scholes model.

4.2. Relation between market maker net gamma and stock return volatility

Panels A and B of Figure 1 are bar charts that depict average absolute stock return on day $t + 1$ as a function of market maker net option gamma on the underlying stock at the close of day t for the 1990-2001 and 2002-2012 periods, respectively. We report the results separately for the two periods in this figure, and in the several tables below, because the open interest data cover all positions of non-market maker traders in the first period, and around two-thirds of the positions in the later period.

We construct the two panels of Figure 1 in the following way. First, for each underlying stock for which there are data available for at least 500 trade days, we use equations (1) to (3) to obtain at the end of each trade date the market maker net gamma. Recall that this market maker net gamma is normalized by multiplying the trade day's closing stock price and dividing by the number of shares outstanding. Next, we sort the stock's normalized market maker net gamma into ten equally sized bins and compute for each bin the stock's average next day absolute return. The height of each bin in the figure is the average of this quantity across underlying stocks.

Figure 1 suggests that there is a negative relations between market maker net option gamma and the variability of stock absolute returns. The negative relations is monotonic and economically meaningful: the average daily absolute return of the low net market maker gamma group is 100 basis points greater than the average absolute return for the high net market maker gamma group during the first sample period, and 50 basis points greater during the second period.[6] The difference between the two periods probably is due to the facts that during the later period the dispersion (standard deviation) of volatility is lower and we use noisier measures of open interest and thus the gammas of the market maker positions.

The negative relation between net gamma and future volatility is reliable statistically. We do not, however, report the results of statistical tests, because there is a possible alternative explanation for the negative relation. If investors trade on private information in the option market, then we would expect them to buy (sell) options when they have information that the variability of underlying stocks is going to increase (decrease). The evidence in Pan and Poteshman (2006) and Ni, Pan and Poteshman (2008) showing that directional and volatility information trading is detectable from option demand leads us to develop a specification that recognizes the informed trading in the option market. Our specification also addresses the possibility that investors might trade options based on past public information that is correlated with future stock return volatility.

4.3. Impact of options on underlying stock volatility

The key to develop a specification that recognizes the possibility of trading in the option market based on private information is the identification of changes in the net option gamma of likely delta hedgers that do not result from investors buying or selling options on the basis of

[6] The figures are similar if the market maker net gamma is not normalized or if market maker plus firm proprietary net gamma is used in place of market maker net gamma.

private information. We isolate such changes by recognizing that part of the change in the delta hedgers' net gamma from time $t-\tau$ to time t comes from changes in the gammas of the "old" option positions held by the delta hedgers at $t-\tau$ and argue below that this component of the change in the net gamma is likely to be uncorrelated with trading based on private information. While the discussion is cast in terms of private information, the identification strategy also applies to public information that is not accounted for by the control variables included in the regression model that we develop.

We begin by decomposing the delta hedgers' net gamma at time t into the part that is due to positions that existed τ dates earlier at time $t-\tau$ and the part that is due to new positions that were established between $t-\tau$ and t. To decompose the net gamma, first define $N_{t-\tau}^{t}$ to be the number of different contracts on an underlying stock that were available for trading at time $t-\tau$ and expire after t, and then define

$$net\Gamma_t(t-\tau, S_t) = 100\left(\frac{S_t}{M_t}\right) \times \sum_{j=1}^{N_{t-\tau}^{t}} netOpenInterest_{j,t-\tau}\Gamma_j(t, S_t) \qquad (5)$$

to be the net gamma at time t of the likely delta hedger option positions that existed at date $t-\tau$. This definition uses the net open interest from time $t-\tau$, $netOpenInterest_{j,t-\tau}$, but sums only over the option series that expire after time t and uses for each series the gamma as of time t. In other words, this is the net gamma, at time t, of the "old" positions that existed τ days earlier (and that expire after t). In terms of this more general notation, the net gamma variable defined earlier in equation (3) is $net\Gamma_t = net\Gamma_t(t, S_t)$.

Given the definition in equation (5), we can decompose the net gamma at time t into the part due to the old positions that existed at date $t-\tau$ and the part due to the new positions established between $t-\tau$ and t, that is

$$net\Gamma_t = net\Gamma_t(t-\tau, S_t) + [net\Gamma_t - net\Gamma_t(t-\tau, S_t)]. \tag{6}$$

This decomposition is useful because the option positions that existed at $t-\tau$ cannot have been established based on private volatility information acquired subsequent to the close of trading at day $t-\tau$. If volatility information were short-lived, and in particular if volatility information obtained prior to $t-\tau$ were not useful in predicting volatility after t, then this decomposition would be sufficient. Specifically, we could include the variables $net\Gamma_t(t-\tau, S_t)$ and $net\Gamma_t - net\Gamma_t(t-\tau, S_t)$ separately in the regression specification and the coefficient on $net\Gamma_t(t-\tau, S_t)$ would reflect only the effect of hedge rebalancing on volatility.

Volatility information, however, may not be short-lived, and we address this possibility by further decomposing the net gamma of the delta hedgers' old positions that existed at $t-\tau$ as

$$net\Gamma_t(t-\tau, S_t) = [net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})] + net\Gamma_t(t-\tau, S_{t-\tau}), \tag{7}$$

where $net\Gamma_t(t-\tau, S_{t-\tau})$ is defined by substituting $S_{t-\tau}$ for S_t in equation (5). The second component on the right hand side of equation (5), $net\Gamma_t(t-\tau, S_{t-\tau})$, is the gamma of the delta hedgers' positions held at $t-\tau$, computed using the time $t-\tau$ stock price, while the first component $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ represents the change in the net gamma of the delta hedgers' positions at $t-\tau$ that is due to changes in the stock price from $S_{t-\tau}$ to S_t and changes in time to maturity. Variation in this latter variable comes from the fact that the gamma of an option is greatest (or smallest, for a written option) when the stock price is close to the option strike price, and close to zero when the stock price is distant from the strike. We use this variation to identify the effect of hedge rebalancing on volatility because the change in the delta hedgers' net gamma due to the changes in the gammas of options existing at date $t-\tau$ cannot result from volatility information acquired by traders between $t-\tau$ and t.

For any part of the correlation between the variable $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ and the absolute return $|r_{t+1}|$ to be due to private volatility information about $|r_{t+1}|$ acquired on or prior to $t-\tau$, two conditions must both be met. First, some part of the volatility information must be realized prior to date t (and thus contribute to the stock price change from $t-\tau$ to t and thereby the change in gamma $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ and some part of the information must be realized after t in the return $|r_{t+1}|$. Second, any dependence between the stock price change from $t-\tau$ to t and $|r_{t+1}|$ must not be captured by the lagged absolute return control variables that we will include in our regression specification.

Since these conditions cannot be entirely ruled out *a priori*, it is worth noting that even if they are satisfied, it is more likely that the correlation between volatility information and $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ will be positive than negative. A positive correlation will increase the estimated coefficient on the $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ variable and hence bias against any finding that hedge rebalancing affects stock return volatility. To see why any correlation is likely to be positive, suppose that just prior to $t-\tau$ some public customer (e.g., a hedge fund) obtains private information that volatility will increase and buys a large number of near-the-money options in order to profit from the information. Market makers will write these options, and the gamma of the corresponding market maker position will be negative. As the underlying stock price changes from $S_{t-\tau}$ to S_t, the near-the-money options will move away from the money which will cause the gammas of the options to decrease and the market maker gamma to increase (since they have written the options). As a result, the change in gamma $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ will be positively related to the customers' private information about $|r_{t+1}|$.

In light of these considerations, the main variable in our specification is $net_t\Gamma(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$, that is the change in the net gamma between $t-\tau$ and t of option positions held by the likely delta hedgers at time $t-\tau$ that results from the change in the underlying stock price from $S_{t-\tau}$ to S_t. In addition, we also include the other two components $net\Gamma_t(t-\tau,S_{t-\tau})$ and $net\Gamma_t-net\Gamma_t(t-\tau,S_t)$ separately as independent variables in our regression specifications. The three variables sum to the delta hedger net gamma at time t, $net\Gamma_t$.

Our specification must also control for other variables that predict volatility and are correlated with the gamma measures. The leading candidates for such control variables are functions of past returns, as the existence of volatility clustering in returns (i.e., GARCH effects) has been documented. We control for volatility clustering in a computationally tractable fashion by including lagged absolute returns in the regression specification. This approach to model volatility clustering was proposed by Schwert and Seguin (1990) and used by Barclay, Hendershott, and Jones (2006). Because we estimate the regressions firm-by-firm, we do not need to control explicitly for firm characteristics that affect volatility, as these will be subsumed in the constant terms. Also, to allow positive and negative returns having different impacts on conditional volatility, we follow Glosten, Jagannathan and Runkle (1994) and interact each of the past absolute returns with an indicator variable that takes the value one if the return is positive.

Our specification has one time-series equation for each underlying stock, and the main variable $net\Gamma(t-\tau,S_t)-net\Gamma(t-\tau,S_{t-\tau})$ is the first one on the right-hand side of the following equation:

$$|r_{t+1}| = a + b[net\Gamma(t-\tau,S_t) - net\Gamma(t-\tau,S_{t-\tau})] + c \times net\Gamma_t(t-\tau,S_{t-\tau}) \quad (8)$$
$$+d[net\Gamma_t - net\Gamma_t(t-\tau,S_t)] + \sum_{i=0}^{9} e_i|r_{t-i}| + \sum_{j=0}^{9} f_j\left|r_{t-j}\right| \times I^{r_{t-j}>0} + \varepsilon_t$$

where $I^{r_{t-i}>0}$ is one if r_{t-i} is larger than zero. We will estimate model (8) for each underlying stock with τ set equal to 3, 5, and 10 trade dates. Our primary prediction is that the b coefficients are negative.

For each underlying stock, the second independent variable measures the likely delta hedgers' net gamma τ trade dates in the past. The delta-hedging effect also predicts that this variable's coefficient will be negative. However, a negative estimate for c will not provide unambiguous evidence that delta-hedging impacts underlying stock variability, because new options positions based on volatility information will also tend to make this coefficient negative. Of course, insofar as any increase or decrease in volatility associated with volatility information trading appears and disappears in fewer than τ days, a negative c coefficient does, in fact, indicate that delta-hedging affects stock price variability. The third independent variable $net\Gamma_t - net\Gamma_t(t-\tau, S_t)$ measures the change in net gamma from $t-\tau$ to t that results from the change in the delta hedgers' option position from $t-\tau$ to t. Since both the delta re-hedging and volatility information stories predict a negative coefficient for this variable, a negative coefficient estimate does not provide straightforward evidence for either. These second and third independent variables also serve to control for volatility trading based on private information. The current and nine past daily lags of absolute returns control for volatility clustering. Their interactions with the signs of returns capture the asymmetric effect of returns on volatility.

For the first period 1990-2001we estimate 2,112 equations (one for each underlying stock) simultaneously in a stacked regression, allowing the coefficients in each equation to differ. We do the same for the 3,620 stocks during the second period 2002-2012. As indicated above, we analyze the two periods separately because the open interest data cover all non-market maker investors in the first period, but our open interest estimates reflect only about two-thirds of trading volume during the second period. We exclude stocks for which there are fewer than 500 trade days. Market-wide shocks will induce correlation between firms at a moment in time, and firm-specific shocks will induce auto-correlation across time. Furthermore, persistent common shocks such as business cycles can induce correlations between different firms in different periods. Due to these factors we compute standard errors adjusted for firm and time clustering and common shocks based on the method detailed in Thompson (2011) using a lag of ten days, computing the residuals from the average (across stocks) coefficient estimates.

Table 1 contains descriptive statistics on the absolute return variables $|r_{t+1}|$ and the net position gamma ($net\Gamma$) and its first component $[net\Gamma(t-\tau, S_t) - net\Gamma(t-\tau, S_{t-\tau})]$ for the two groups of likely delta hedgers, market makers (Market Maker) and market makers plus firm proprietary traders (Market Maker + Firm). The statistics are first calculated for each underlying stock and then the averages across the underlying stocks are reported. The average mean and median absolute returns are 0.030 or 3.0% and 0.022 or 2.2% for the first and second periods, respectively. For market makers, the average mean value of the normalized net position gamma is 0.003 (–0.004), and the average standard deviation is 0.008 (0.016) for the first (second) period. The negative mean of the net gamma variable in the second period indicates that public investors (non-market makers) held more purchased options in the second period than during the first. For market makers plus firm proprietary traders, the average mean and standard deviation are slightly larger. When we consider market makers as the delta hedgers, the mean and standard deviation of the component of net gamma due to changes in stock prices, i.e., the key gamma variable $net\Gamma(t-\tau, S_t) - net\Gamma(t-\tau, S_{t-\tau})$, are 0.000 and 0.005, respectively, for the first period, and 0.000 and 0.009 for the second period. Similar values can be observed for market makers plus firm proprietary traders.

Table 2 reports the results of estimating model (8) for the case $\tau = 5$ trade days. Below we show that the findings are insensitive to the choice of τ. The table reports averages across underlying stocks of point estimates and t-statistics for the averages.

The average of the coefficient estimates on the key right-hand side gamma variable $net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$ is equal to –0.576 (t-statistic –7.46) for the first period in Panel A, and –0.329 (t-statistic –7.35) for the second period in Panel B when market makers are the potential delta hedgers. This result indicates that there is a negative relation between market maker net gamma and the variability of the underlying stock return that is not rooted in volatility information trading. Hence, the main prediction from above is confirmed, and there is evidence that option market activity has a pervasive influence on underlying stock prices. Furthermore, the effect appears to be economically meaningful. From Table 1 the average daily absolute return of the stocks in our first (second) sample period is 303 (220) basis points, and the standard deviation of the key right hand side variable is 0.005 (0.009) for the first (second) period. Thus, a one standard deviation shock to the market maker key gamma variable is associated with a 0.576×0.005 = 28.8 (0.329×0.009 = 29.6) basis point change in absolute return for the first (second) period. Consequently, we estimate that on the order of 9.5% (= 28.8/303) of the daily absolute return of optioned stocks in the first sample period, and 13.4% (= 29.6/220) in the second period can be accounted for by option market participants re-balancing the hedges of their option positions.

The average coefficients on the variables $net\Gamma_t(t-\tau,S_{t-\tau})$ and $net\Gamma_t - net\Gamma_t(t-\tau,S_t)$ on the second and third columns are also negative and significant. In both cases, the negative estimates may come from the market makers delta hedging their option positions, volatility information trading by non-market makers, or some combination of the two. The current and lagged absolute stock return variables all have positive and significant coefficient estimates, which is consistent with the well-known phenomenon of volatility clustering in stock returns. Their interactions with the dummies for positive returns all have negative and significant coefficient estimates, which is consistent with the asymmetric effect of returns on volatility. The lagged absolute returns also control for the overall level of volatility. To save space, we only report the coefficient estimates on the variables related to the lagged absolute returns from day $t-4$ to $t-1$; those for days $t-9$ to $t-5$ are omitted.

The fourth and fifth columns of Table 2 (the columns headed "Market Maker plus Firm Proprietary Positions") are based on the alternative assumption that both market makers and firm proprietary traders delta-hedge their option positions. Thus, the three gamma variables in this specification are computed using the combined option positions of the market makers and firm proprietary traders.

These results are very similar to those using the market maker gamma variables, with the principal difference being that the magnitudes of the average coefficient estimates on the three gamma variables are slightly smaller. For example, the average coefficient on the variable $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ is –0.510 (with t-statistic –7.53) rather than –0.576 for the 1990-2001 sample period, and is –0.127 (with t-statistic –6.42) rather than –0.329 for the 2002-2012 period. There are similar small differences in the average coefficient estimates on the other two gamma variables, while the average coefficient estimates on the lagged absolute return variables and their interactions are almost unchanged. The small decreases in the magnitudes of the coefficient estimates on the gamma variables are consistent with the hypothesis that not all of the firm proprietary traders delta hedge and thus including their positions in the computation of the gamma variables dampens the effect. Nevertheless, these results also indicate that there is a negative relation between gamma and volatility that is not due to volatility information trading. We also estimate specifications in which we replace the absolute return with its daily change and report the results in Table 8 in the Internet Appendix. The coefficient estimates on the first and third components of net position gamma remain negative and statistically significant.

The extent to which re-balancing by delta-hedgers impacts the frequency of large stock price moves is also of interest. We assess the impact on large stock price movements by re-estimating equation (8) with the dependent variable $|r_{t+1}|$ replaced by one of two indicator variables: the first takes the value one when $|r_{t+1}|$ is greater than 3% and otherwise is zero, and the second takes the value one when $|r_{t+1}|$ is greater than 5% and otherwise is zero. The estimation is carried out in the same way as before, and the results are reported in Table 3. The results indicate that the average coefficient on the $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ variable is negative and significant for both the 3% and the 5% dependent indicator variables for both periods. Consequently, there is evidence that the re-balancing of delta hedges of option positions impacts the probability of large absolute stock returns on underlying stocks. In our sample the unconditional probability that a daily absolute return will be greater than 3% is 0.282 during the first period, and 0.213 during the second period. A one standard deviation movement in our key net gamma variable is 0.005 (0.009) in the first (second) period. As a result, a one standard deviation increase to this variable reduces the probability that the daily absolute return on the underlying stock is greater than or equal to 3% by 0.015 (= –3.079 × 0.005) and 0.028 (= –3.147×0.009) in the first and second periods, respectively. This change in probability corresponds to a 5.3% reduction from 0.282 to 0.267 in the first period, and a 13.3% reduction from 0.213 to 0.185 in the second period. A similar argument indicates that for daily absolute returns greater than 5%, the probability is reduced by 14% from 0.136 to 0.116 in the first period, and by 40% from 0.088 to 0.053 in the second period.

Hence, delta hedge rebalancing by market makers appears to have an important impact on large stock price movements. Although it is unclear how microstructure effects such as bid-ask bounce could bias toward our findings in the first place, the fact that the main effect is present for large absolute returns suggests that microstructure phenomena are unlikely to provide an alternative explanation for our results.

4.4 Effect of option expiration and subsample tests

Ni, Pearson, and Poteshman (2005) present evidence that stock trading to rebalance option market makers' delta hedges of their option positions contributes to stock price clustering on the option expiration Friday and the preceding Thursday, but find no evidence of any effect prior to the expiration week. This raises the possibility that the negative relation between volatility and gamma documented above is not pervasive but rather is driven by the observations from option expiration dates or the immediately preceding trading days. This concern is exacerbated by the fact that the gammas of options that are very close-to-the-money become large as the remaining time to expiration shrinks to zero, implying that delta hedgers with positions in such options may need to engage in considerable stock trading just prior to expiration to maintain their hedges.

Table 4 addresses this issue by presenting results for specifications in which we also include interactions between an expiration week dummy variable and the net gamma variables in model (8). The coefficient estimates on the gamma variables in Table 4 are similar to those in Table 2. For example, when market makers are the delta hedgers, the coefficient estimate on the first component of net gamma changes from −0.576 to −0.610 for the first period, and from −0.329 to −0.311 for the second period. These results indicate that the negative relation between the gamma of delta hedgers' options positions and stock return volatility is not limited to option expiration weeks. The point estimate on the interaction term between the expiration week dummy and the key net gamma variable is negative in both sample periods, but insignificant. The coefficients on the other interaction terms, which are of less interest, are of both signs, with some being significant. Overall, there is no convincing evidence that the relation between delta-hedger gamma and volatility is different in expiration weeks. As above, to same space we do not report the coefficient estimates on the lagged returns.

Table 5 presents the results of estimating model (8) for sub-samples of illiquid and liquid stocks and sub-sample of large and not-large firms. An illiquid stock is defined to be one with an average relative bid-ask spread less than the median, while an illiquid stock is one with an average bid-ask spread greater than the median. Large firms are defined to be the 200 optionable stocks with the greatest average stock market capitalization during the sample period; the not-large firms are all others. Again, to save space, we omit the coefficients on the lagged absolute return variables. For illiquid firms, the average coefficient estimate on the key gamma variable is −0.780 (t-statistic −6.26) for the first period and −0.373 (t-statistic −6.42) for the second period; for liquid firms the corresponding estimates are −0.373 (t-statistic −3.01) for the first period and −0.272 (t-statistic −5.49) for the second period. Thus, the effect of hedge rebalancing on stock volatility is greater for less liquid stocks, which is unsurprising.

Turning to the results for different size firms, for the not-large firms the coefficient estimate on the key gamma variable is −0.632 (t-statistic −6.57) for the first period 1990-2001, and −0.337 (t-statistic −5.63) for the second period 2002-2012. For the large firms, the average coefficient estimates on the gamma variables are all negative and significant but of smaller magnitudes. Thus, the effect of hedge rebalancing on stock volatility is found in both large and not-large firms, but is smaller in magnitude for large firms.

Section 4.5 Robustness to choice of lag length τ and use of Black-Scholes gammas

The primary results in Table 2 are based on a choice of $\tau = 5$ days in constructing the prior option positions. Such a choice is inherently somewhat arbitrary. Those results are also based on option gammas from the Black-Scholes model. This subsection presents evidence that the results are robust to different choices.

Table 6 reports the results of re-estimating the regressions from Table 2, but now defining the prior option positions to be those that existed $\tau=10$ days previously. To save space, we do not report the coefficient estimates on the lagged return variables. Comparing the average coefficient estimates for the gamma variables shown in Table 6 to the corresponding averages in Table 2, one can see that the results are similar. For example, in the second columns of Panel A, the average coefficient on the key variable $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ decreases from –0.576 (*t*-statistic = –7.46) to –0.607 (*t*-statistic = –8.66), while in the fourth column the average coefficient on this variable changes from –0.510 (*t*-statistic = –7.53) to –0.463 (*t*-statistic = –7.26). In Panel B for the second sample period, the average coefficients on the key gamma variable also decrease slightly, from –0.329 to –0.350, and from –0.127 to –0.182 in the second and forth columns, respectively. Unreported results based on a lag length of $\tau = 3$ days are also similar to those for the lag length of $\tau = 5$ days reported in Table 2.

As mentioned above, the option position gammas that underlie the results in Tables 2–6 were computed using Black-Scholes gammas for the options that constitute the positions. Table 7 addresses the issue of whether the results are robust to using different estimates of gammas in computing the position gammas. The regressions for which results are reported in Table 7 use position gammas that are computed using option gammas taken from the OptionMetrics Ivy DB database when they are available, and Black-Scholes gammas when OptionMetrics gammas are not available. OptionMetrics computes gammas using standard industry practices: it uses the binomial model to capture the possibility of early exercise of American options, the actual implied volatility of the option for which the gamma is being computed, the term structure of interest rates, and estimates of the dividend yield on the underlying stock and the future ex-dividend dates (OptionMetrics LLC 2011, pp. 29–30). A limitation of the OptionMetrics gammas is that they are not always available. First, options that are well in-the-money frequently have quoted prices that violate elementary arbitrage bounds. In such cases (specifically, when the bid-ask average violates elementary arbitrage bounds) OptionMetrics is unable to compute the implied volatility, and thus is unable to compute the option gamma. For our purposes this problem is not important, because the gammas of in-the-money options tend to be small regardless of the option-pricing model used to compute them, and we can safely use Black-Scholes gammas in such cases. Second, the OptionMetrics data begin only in 1996, and thus are not available during 1990–1995. Another limitation of OptionMetrics gammas is that they may introduce endogeneity between net gamma and absolute returns as gamma is a function of implied volatility, which is related to the subsequent absolute returns.

Table 7 presents the average coefficient estimates for the stock time-series regressions and the corresponding t-statistics, where we use OptionMetrics gammas during 1996–2012, the period for which the OptionMetrics gammas are available. To make the comparison, we also include the results based on Black-Sholes options gamma for the 1996-2001 period in Panel A1 and for the 2002-2012 period in Panel B1. Comparing the average coefficient estimates using OptionMetrices gammas to the corresponding averages using Black-Scholes gammas, one can see that the results are similar. For example, the average coefficient estimates on the key gamma variable $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ on the second column change from −0.504 to −0.509 and from −0.329 (in Panel B Table 2) to −0.321 for the first and second sample periods, respectively. The fourth and fifth columns of Table 7 present results for Market Makers plus Firm Proprietary traders, which are also consistent with previous results. These results suggest that our use of the Black-Scholes model to compute the option gammas does not introduce any important errors in the regression results.

4.6 Cross-sectional average gamma and S&P500 index absolute returns

The summary statistics in Table 1 indicate that market maker net gamma was on average positive and negative over the 1990-2001 and 2002-2012 sample periods, respectively. If there is correlation across stocks in the market makers' net gammas so that gammas are generally negative or positive at certain times, hedge rebalancing might increase (reduce) the volatility of the aggregate stock market. To test this hypothesis, we use the cross-sectional average gammas of all optionable stocks to examine whether they help explain S&P 500 index absolute daily returns. The results are reported in Table 8. The coefficient estimates on the cross-sectional average of the first component of gamma, $avg[net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})]$, are negative and significant, with the estimates being –0.808 (t-statistic –2.16) and –0.476 (t-statistic –2.42) for the first and second periods, respectively. These results are consistent with the hypothesis that options market maker delta hedging rebalancing also affects the subsequent volatility of the S&P 500 index. The economic magnitude of the effect is comparable to albeit smaller than that for the individual stocks. The average daily absolute return of the S&P 500 index in the first (second) sample period is 70 (89) basis points, and the standard deviation of the average of the first component of gamma is 0.0004 (0.0013) for the first (second) period. Thus, a one standard deviation shock to the average gamma variable related to hedging rebalancing has a 4.6% (= 0.808 × 0.0004 /0.007) impact on the daily absolute return of the S&P 500 index in the first sample period and a 7.0% (= 0.476 × 0.0013 /0.0089) impact in the second period. For individual stocks, the previously discussed corresponding impacts based on the results in Table 2 are 9.5% and 13.4% of the daily absolute returns of optionable stocks in the two sample periods. Table 8 also shows that the third component of the market maker position gamma is negatively and significantly related to the subsequent index volatility, which indicates that investors options' position changes are also negatively relate to subsequent market realized volatility.

4.7 Alternative hypothesis: Do investors buy more options when volatility is high?

A possible alternative explanation for our findings is that investors might buy more options when stock return volatility is high. If investors tend to purchase more options when volatility is high, then options market makers will tend to write more options and their positions will tend to have negative gamma when volatility is high. This alternative hypothesis suggests that the negative relation between market maker net gamma and contemporaneous and past volatility might be due to volatility causing option trading rather than to option hedge rebalancing impacting volatility.

Investors do buy more options when volatility is high (Lakonishok, Lee, Pearson, and Poteshman 2007, Table 5). But they also write more options when volatility is high, and the estimated coefficients on volatility in the regression results reported in Lakonishok, Lee, Pearson, and Poteshman (2007) Table 5 indicate that the impact of volatility on investors' option writing is slightly greater than the impact of volatility on their option buying.[7] This makes it unlikely that the alternative hypothesis explains our findings.

[7] Specifically, the estimated coefficients on volatility in the Tobit regressions explaining call and put buying in Lakonishok, Lee, Pearson, and Poteshman (2007) Table 5 are 2.028 and 0.149, respectively, with a sum of 2.028 + 0.149 = 2.177. The estimated coefficients on call and put writing are 1.666 and 0.580, respectively, with a sum of 1.666 + 0.580 = 2.246.

To further investigate the possible alternative explanation, we regress each of the components of gamma on contemporaneous and lagged absolute returns and lagged values of gamma as follows:

$$\Gamma_t = a + \sum_{i=0}^{9} b_i \times |r_{t-\mathrm{i}}| + \sum_{j=1}^{5} c_j \times \Gamma_{t-j} + \varepsilon_t,$$

where Γ_t is one of three components of the net position gamma and the $|r_{t-i}|$ for i = 0, 1, …, 9 are the contemporaneous and lagged absolute returns. If investors buy (sell) options when volatility is high (low), then the coefficients b_i will be negative.

We report the results in Table 9. Many of the point estimates of the coefficients on the various lagged absolute returns in the regressions explaining the first component of the net position gamma, $net\Gamma_t(t-5, S_t) - net\Gamma_t(t-5, S_{t-\tau})$, are negative, but all of the negative point estimates are insignificant. In the top panel (1990-2001) the one significant estimate (which is also the largest estimate) of a coefficient on a contemporaneous or lagged absolute return is positive. In the bottom panel (2002-2012) only one coefficient on an absolute return variable is even marginally significant (at the 10% level), and the point estimate is positive. In each panel the sum of the point estimates on the contemporaneous and lagged absolute return variables is positive. These results do not provide any support for the alternative hypothesis that the relation between the first component of the net position gamma $net\Gamma_t(t-5, S_t) - net\Gamma_t(t-5, S_{t-\tau})$ and the subsequent absolute return $|r_{t+1}|$ is found because the first component of the net position gamma is caused by current or past volatility.

When the dependent variable is the market maker net position gamma from five days in the past, $net\Gamma_t(t-5, S_{t-5})$, the coefficient estimates on $|r_{t-4}|$ through $|r_t|$ are negative and generally significant in both sample periods. This is to be expected, because these returns are from dates after t – 5 when the variable $net\Gamma_t(t-5, S_{t-5})$ is observed—the significant coefficients on these returns are not evidence that volatility causes market maker gamma but rather are consistent with the hypothesis that the net gamma from t – 5 contains information about volatility on dates t – 4 through t. In contrast, the coefficient estimates on $|r_{t-9}|$ to $|r_{t-5}|$ are generally positive, consistent with the hypothesis that non-market maker investors sell rather than buy options after high past volatility.

The third component of the net position gamma is $net\Gamma_t - net\Gamma_t(t-5, S_t)$, the change in gamma due to changes in options market maker positions. For this component the coefficients on the $|r_{t-i}|$ are both positive and negative and generally not statistically significant, with the only significant coefficient (t-statistic of 2.18) being positive. Thus, none of the results in Table 9 provide support for the hypothesis that investors buy more options when volatility is high.

4.8 The effect on stock signed volume

If hedge rebalancing explains the relation between options market maker net position gamma and subsequent stock returns, then it should also be the case that the net position gamma is related to stock order imbalances. Specifically, we hypothesize that the interaction between the net position gamma on day t and the sign of the stock return on day t + 1 negatively relates to the stock order imbalance on day t +1. The reasoning is that when market makers have negative gamma positions, increases (decreases) in stock prices cause their option position delta to decrease (increase). They then buy (sell) stock to maintain the delta of their options positions. In this case, as summarized in Table 10 Panel A, the interaction of gamma at t with the sign of the stock return on date t+1 ($I^{signR_{t+1}}$) will be negatively related to the stock order imbalance on t +1. Similarly, if delta hedgers' positions have positive gamma, increases (decreases) in stock prices will causes their options position deltas to increase (decrease). They then sell (buy) stock to maintain the deltas of their positions. In this case, the interaction of gamma at t and $I^{signR_{t+1}}$ is also negatively related to the signed volume on date $t+1$.

We use the TAQ data to estimate the daily signed volume of the optionable stocks during the period 2003-2012, which is the period for which we have both TAQ and option Open/Close data. Panel B of Table 10 shows that the interaction of day t gamma with $I^{signR_{t+1}}$ is negatively related to the subsequent stock net buy volume, controlling for $I^{signR_{t+1}}$ and lagged net buy volumes. The magnitude of effect is economically meaningful. The coefficient estimate on the interaction of the first component of market maker position gamma with $I^{signR_{t+1}}$ is −18.846. A one standard deviation decrease in this interaction variable is associated with a 0.0339 increase in net buy volume, equivalent to 9.2% of the standard deviation of daily stock net buy volume.[8] This economic magnitude is comparable to that of the effect of the position gamma on stock return volatility.

4.9 Return reversals

When delta hedgers rebalance delta hedges of negative gamma positions, they need to buy (sell) the underlying stock after the stock price increases (decreases). Their buying (selling) pressure may cause stock prices to exceed their fundamental values, leading to subsequent reversals. On the other hand, when delta hedgers rebalance hedge of positive gamma positions they need to sell stock after stock price increases, and buy after stock price decreases. In this case, the stock prices are less likely to reverse.

We find this is the case and report the results in Table 11. We first sort the pooled observations of stock-dates into terciles using the key gamma variable $(net\Gamma_t(t-\tau, S_t) -$

[8] The standard deviation of this interaction variable is 0.0018, and 0.0339 = 0.0018 × 18.846. The standard deviation of net buy stock volume is 0.3674, so 0.0339 is 0.0339/0.3674=9.2% of the standard deviation of net buy volume.

$net\Gamma_t(t-\tau, S_{t-\tau})$, that is the change in the position gamma due to stock price movement. Then for each tercile we compute correlation between r_{t+1} and r_{t+2}. The results in Table 11 reveal that in both sample periods the low gamma tercile has the smallest return autocorrelation, as expected. The differences in the correlations between the low and high terciles are −0.008 (t-statistic −4.26) and −0.009 (t-statistic −6.01) for the first and the second sample periods, respectively. However, the highest hedging gamma tercile does not have the highest autocorrelation, possibly because rebalancing of the hedges of positive gamma positions tends to make the day $t + 1$ return close to zero. Recognizing that the correlation is a cross-product of demeaned returns (and with daily data the demeaning is not important), the fact that the hedge rebalancing tends to limit stock price movements on date $t + 1$ creates a tendency to make the measured correlations closer to zero, which can offset the tendency to create positive autocorrelations.

Table 11 also shows the correlations for terciles of observations sorted on the component of gamma most likely to be related to information ($net\Gamma_t - net\Gamma_t(t-\tau, S_t)$), i.e., the change of position gamma due to change of option open interest. The differences in the correlations of the low and high terciles are still negative, −0.003 (−0.004) for the first (second) sample period, but the magnitudes are much smaller with no or marginal statistical significance.

5. Conclusion

We have documented that there is a significant negative relation between stock return volatility and the net gammas of the option positions of the option market participants likely to delta hedge their option positions. This relation is consistent with the hypothesis that rebalancing of option hedges affects stock return volatility. The estimated magnitudes are economically significant. We estimate that approximately 9.5% (13.4%) of the daily absolute return of optioned stocks during the 1990-2001 (2002-2012) sample period can be attributed to option market participants re-balancing the stock hedges of their options positions. Furthermore, the hedge re-balancing is estimated to alter the probability of daily absolute stock returns greater than 300 (500) basis points by 5% (14%) during the 1990-2001 sample period, and by 13% (40%) during the 2002-2012 period. Delta hedge rebalancing also helps explain stock order imbalances.

The negative relation is not restricted to the option expiration week, and is found in liquid and illiquid stocks and the stocks of large and small capitalization firms. We also show that there is a negative relation between the cross-sectional average of the gammas of options market makers' net positions and subsequent S&P 500 index absolute returns. Finally, we find evidence consistent with return reversals when the net options positions of delta hedgers have negative gammas. These results show that there is a non-informational channel through which the option markets have a pervasive influence on underlying stock prices.

Appendix

Frey and Stremme (1997), Sircar and Papanicolaou (1998), and Schönbucher and Wilmott (2000) model the impact on stock prices and return volatility of stock trading that either dynamically hedges or dynamically replicates an options position. The three papers analyze very similar models, with different focuses and emphases. The models are built so that in the special cases of no delta hedgers, the price dynamics of the underlying asset specialize to the usual geometric Brownian motion with constant instantaneous volatility σ. When there are delta hedgers, the instantaneous volatility is

$$\text{volatility} = v(\bullet)\sigma,$$

where σ is a constant and the arguments of the scaling function v include the gamma of the delta hedgers' aggregate option position. When the demand functions and other assumptions are chosen so that the model reduces to geometric Brownian motion and the Black-Scholes-Merton model, the form of the scaling function v in Sircar and Papanicolaou (1998) is[9]

$$v(t,S) = \frac{1+\Delta(t,S)/M}{1+\Delta(t,S)/M+(S/M)\Gamma(t,S)} = 1\Bigg/\left(1+\frac{(S/M)\Gamma(t,S)}{1+\Delta(t,S)/M}\right), \tag{A1}$$

where M is the number of shares of stock outstanding, S is the price per share, $\Delta = \partial V(t, St)/\partial S$ and $\Gamma = \partial^2 V(t, S)/\partial S^2$ are the delta and gamma of the delta-hedgers' aggregate option position, and $V(t, S)$ is the value of the option position of the delta-hedgers.

[9] See equation (24) on p. 55 of Sircar and Papanicolaou (1998), the definition of ρ in terms of ζ on page 51, and the meaning of ζ on p. 50. The signs on Δ and Γ differ from those that appear in Sircar and Papanicolaou (1998) because here the symbols Δ and Γ represent the partial derivatives of the delta hedgers' aggregate option position, while the results in Sircar and Papanicolaou are expressed in terms of the trading strategy in shares. (The hedging strategy involves a position of $-\Delta$ shares.)

Platen and Schweizer (1998) describe a similar model in which the scaling function is[10]

$$v(t,S)=\frac{1}{1+(S/\gamma)\Gamma(t,S)}, \tag{A2}$$

where γ is a parameter that appears in the demand function. In this model it seems natural to assume that the demand parameter is proportional to the number of shares outstanding, i.e. that $\gamma = M/\alpha$, where α is constant. Alternatively, one might let M be a measure of stock trading volume. Making either of these assumptions, the scaling function in (A2) becomes

$$v(t,S)=\frac{1}{1+\alpha(S/M)\Gamma(t,S)}. \tag{A3}$$

Finally, Frey (2000) presents a simple model in which the scaling function is

$$v(t,S)=\frac{1}{1+\rho S\Gamma(t,S)}, \tag{A4}$$

where the parameter ρ measures the sensitivity of the stock price to the trades stemming from hedge rebalancing. In this case, it is reasonable to assume that ρ is inversely proportional to the shares outstanding or trading volume, i.e., that it can be written as $\rho = \lambda/M$. Under this assumption, the scaling function in (A4) becomes

$$v(t,S)=\frac{1}{1+\lambda(S/M)\Gamma(t,S)}. \tag{A5}$$

Recalling that the instantaneous volatility is given by the product $v(t,S)\sigma$, the testable prediction that comes from these analyses is that hedge rebalancing will impact the variability of the returns of the underlying stocks. There will be a negative relation between the net gamma of delta-hedging investors' option positions on an underlying stock and the variability of the stock's

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[10] This is based on equation (2.7) of Platen and Schweizer (1998), where we have used the fact that $\partial\xi/\partial(\log s) = s(\partial\xi/\partial s)$ and also adjusted the equation to reflect the fact that equation (2.7) of Platen and Schweizer (1998) provides the volatility rather than the scaling function v.

return. Notably, in all models $\Gamma(t, S)$ is either the key or (except for the parameters) the only determinant of the scaling function v. Further, scaling by S/M is either part of the model (i.e., equation (1)), or a consequence of auxiliary assumptions that seem natural (equations (A3) and (A5)). Dimensional analysis also suggests scaling $\Gamma(t, S)$ by the ratio S/M. The units of Δ, Γ, S, and M are shares, $(\text{shares})^2/\$$, \$/share, and shares, respectively, implying that the ratio $(S/M)\times\Gamma(t, S)$ is dimensionless. For these reasons, our empirical analysis below focuses on the relation between gamma and stock return volatility using the normalized gamma $(S/M)\,\Gamma(t, S)$.

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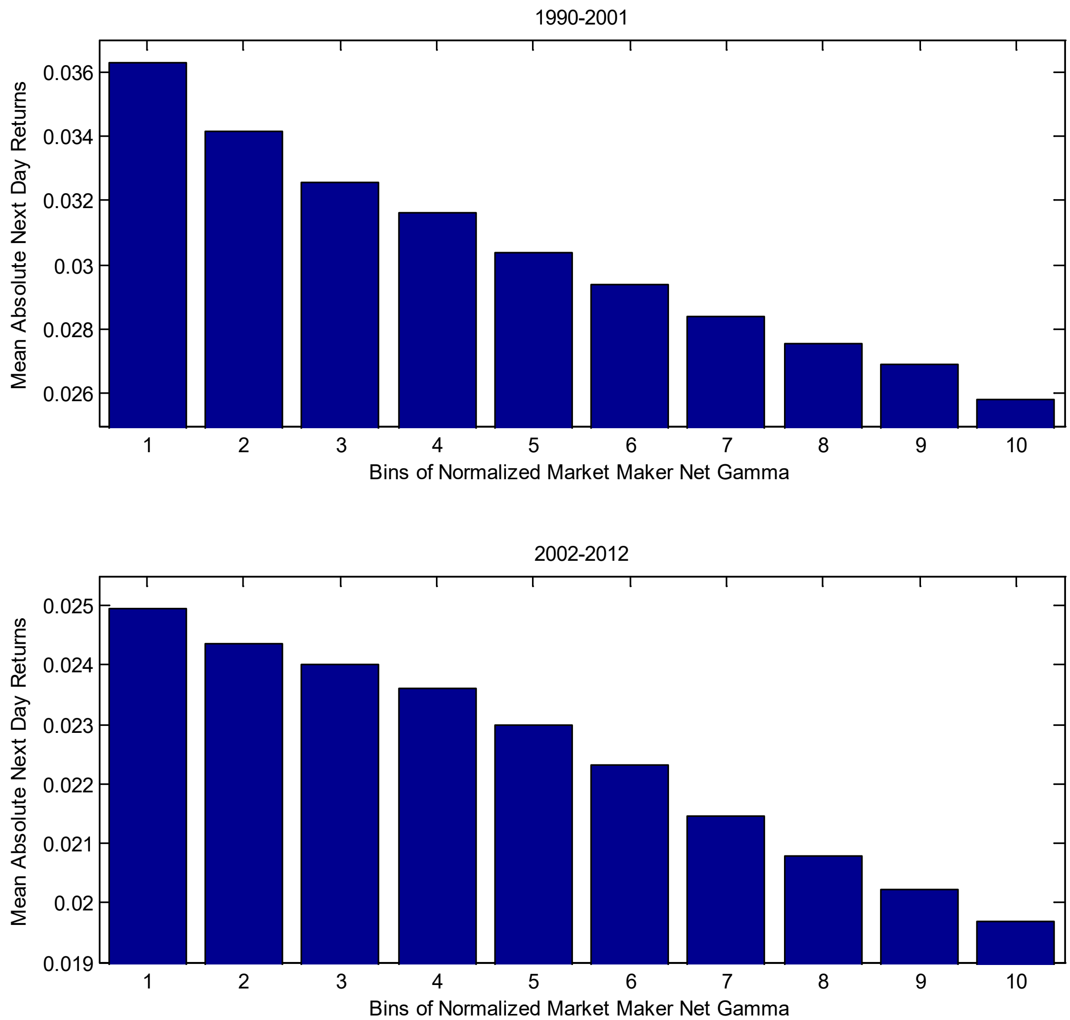

Figure 1. Normalized market maker net gamma is computed every day for every underlying stock that has at least 500 trade days of data over the 1990-2001 and 2002-2012 time periods. The normalized market maker gamma for each underlying stock is then sorted into ten bins of equal size and the average next day stock return is computed for each bin. The two panels depict the results for each bin of averaging this quantity across underlying stocks.

Table 1
Descriptive statistics, τ = 5 days
Means, standard deviations, extrema, and quantiles for the variables used in the regression models. The descriptive statistics are first calculated for each underlying stock, and then the averages across the underlying stocks are reported. MM indicates market makers are delta hedgers, and MM+F indicates market makers and firm proprietary traders are delta hedgers, $|r_t|$ is daily stock absolute return, $net\Gamma_t$ is delta hedgers' net position gamma, S/M is stock price divided by shares outstanding, $net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$ is the component of $net\Gamma_t$ due to past stock price change, $net\Gamma_t(t-\tau, S_{t-\tau})$, is the component of $net\Gamma_t$ due to net position gamma τ days ago, and $net\Gamma_t - net\Gamma_t(t-\tau, S_t)$ is the component of $net\Gamma_t$ due to change of option position.

	Mean	Std	Min	0.1	0.25	0.5	0.75	0.9	Max
Panel A: 1990-2001									
$|r_t|$	0.030	0.032	0.000	0.003	0.010	0.022	0.041	0.065	0.314
$net\Gamma_t$ **, non-normalized**									
MM	13,515	22,409	-52,341	-6,388	1,563	9,577	21,620	39,465	120,583
MM+F	16,244	28,662	-68,166	-8,220	1,713	11,173	25,744	48,089	160,265
$net\Gamma_t$**, normalized by** ***S/M***									
MM	0.003	0.008	-0.023	-0.003	0.000	0.002	0.006	0.011	0.037
MM+F	0.004	0.009	-0.029	-0.004	-0.001	0.003	0.007	0.013	0.045
$net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$**, normalized by** ***S/M***									
MM	0.000	0.005	-0.029	-0.002	-0.001	0.000	0.001	0.002	0.034
MM+F	0.000	0.005	-0.037	-0.003	-0.001	0.000	0.001	0.003	0.041
$net\Gamma_t(t-\tau, S_{t-\tau})$**, normalized by** ***S/M***									
MM	0.003	0.007	-0.020	-0.003	0.000	0.002	0.006	0.011	0.037
MM+F	0.004	0.008	-0.025	-0.003	0.000	0.003	0.007	0.012	0.045
$net\Gamma_t - net\Gamma_t(t-\tau, S_t)$**, normalized by** ***S/M***									
MM	0.000	0.005	-0.055	-0.003	-0.001	0.000	0.001	0.003	0.0037
MM+F	0.000	0.006	-0.066	-0.003	-0.001	0.000	0.001	0.003	0.0048
Panel B: 2002-2012									
$|r_t|$	0.022	0.025	0.000	0.002	0.007	0.015	0.028	0.048	0.312
$net\Gamma_t$**, non-normalized:**									
MM	-9,122	49,823	-286,396	-57,035	-23,416	-4,157	11,272	31,709	179,336
MM+F	6,787	66,301	-301,300	-48,096	-15,747	3,893	27,320	66,706	345,689
$net\Gamma_t$ **normalized by ×** ***S/M***									
MM	-0.004	0.016	-0.103	-0.018	-0.009	-0.002	0.002	0.008	0.048
MM+F	-0.002	0.019	-0.114	-0.019	-0.008	-0.001	0.004	0.012	0.086
$net\Gamma_t(t-\tau, S_t) - net\Gamma_t(t-\tau, S_{t-\tau})$**, normalized by** ***S/M***									
MM	0.000	0.009	-0.118	-0.003	-0.001	0.000	0.001	0.003	0.086
MM+F	0.000	0.010	-0.140	-0.004	-0.001	0.000	0.001	0.004	0.110
$net\Gamma_t(t-\tau, S_{t-\tau})$**, normalized by** ***S/M***									
MM	-0.001	0.012	-0.050	-0.006	-0.001	0.000	0.003	0.010	0.051
MM+F	-0.002	0.015	-0.077	-0.010	-0.006	-0.001	0.004	0.012	0.062
$net\Gamma_t - net\Gamma_t(t-\tau, S_t)$**, normalized by** ***S/M***									
MM	0.000	0.009	-0.090	-0.004	0.000	0.000	0.000	0.004	0.106
MM+F	0.000	0.014	-0.121	-0.006	-0.001	0.000	0.001	0.005	0.139

Table 2

Regressions of absolute return on components of net position gamma, τ = 5 days

Results of estimating model (8) expressing the absolute return $|r_{t+1}|$ in terms of the components of the normalized net position gammas and lagged returns. $I^{r_t>0}$ is the dummy for positive r_t. The model is estimated for the trader groups Market Makers and Market Makers plus Firm Proprietary traders. Standard errors are constructed from a covariance matrix for the average coefficients, which is formed by clustering observations by date and firm with common shocks, a method detailed in Thompson (2011). The coefficient estimates on the variables related to lagged absolute return from day $t-9$ to $t-5$ are omitted.

	Market Maker		Market Maker +Firm	
Panel A: 1990-2001				
Constant	0.021	(31.27)	0.021	(31.19)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.576	(-7.46)	-0.510	(-7.53)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.605	(-6.99)	-0.508	(-6.84)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.513	(-9.06)	-0.415	(-8.60)
$\lvert r_t\rvert$	0.154	(17.22)	0.155	(17.34)
$\lvert r_t\rvert\times I^{r_t>0}$	-0.043	(-4.70)	-0.043	(-4.71)
$\lvert r_{t-1}\rvert$	0.094	(11.63)	0.094	(11.70)
$\lvert r_{t-1}\rvert\times I^{r_{t-1}>0}$	-0.062	(-7.66)	-0.062	(-7.68)
$\lvert r_{t-2}\rvert$	0.068	(8.94)	0.069	(9.02)
$\lvert r_{t-2}\rvert\times I^{r_{t-2}>0}$	-0.042	(-5.65)	-0.042	(-5.68)
$\lvert r_{t-3}\rvert$	0.053	(7.44)	0.054	(7.52)
$\lvert r_{t-3}\rvert\times I^{r_{t-3}>0}$	-0.031	(-4.21)	-0.031	(-4.23)
$\lvert r_{t-4}\rvert$	0.049	(6.89)	0.050	(6.97)
$\lvert r_{t-4}\rvert\times I^{r_{t-4}>0}$	-0.029	(-3.86)	-0.029	(-3.50)
…	…	…	…	…
Panel B: 2002-2012				
Constant	0.009	(27.59)	0.009	(27.45)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.329	(-7.35)	-0.127	(-6.42)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.190	(-4.24)	-0.103	(-6.03)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.280	(-8.66)	-0.131	(-8.89)
$\lvert r_t\rvert$	0.167	(12.87)	0.167	(12.90)
$\lvert r_t\rvert\times I^{r_t>0}$	-0.079	(-5.64)	-0.079	(-5.65)
$\lvert r_{t-1}\rvert$	0.142	(13.10)	0.143	(13.12)
$\lvert r_{t-1}\rvert\times I^{r_{t-1}>0}$	-0.059	(-5.32)	-0.059	(-5.32)
$\lvert r_{t-2}\rvert$	0.117	(10.91)	0.117	(10.94)
$\lvert r_{t-2}\rvert\times I^{r_{t-2}>0}$	-0.058	(-5.56)	-0.058	(-5.56)
$\lvert r_{t-3}\rvert$	0.110	(10.33)	0.110	(10.34)
$\lvert r_{t-3}\rvert\times I^{r_{t-3}>0}$	-0.045	(-4.52)	-0.045	(-4.52)
$\lvert r_{t-4}\rvert$	0.102	(8.74)	0.102	(8.75)
$\lvert r_{t-4}\rvert\times I^{r_{t-4}>0}$	-0.037	(-3.58)	-0.037	(-3.59
…	…	…	…	…

Table 3
Large return regressions
Results of estimating model (8) with the dependent variable replaced by an indicator for absolute returns in excess of 3%, in the left column, and 5%, in the right column. $I^{r_t>0}$ is the dummy for positive r_t. Gamma variables correspond to market-maker positions. The reported coefficient estimates are the averages of coefficients from OLS regressions for individual stocks. Standard errors are constructed from a covariance matrix for the average coefficients, which is formed by clustering observations by date and firm with common shocks, a method detailed in Thompson (2011). The associated *t*-statistics are reported in parentheses. The coefficient estimates on the variables related to lagged absolute return from dates *t* – 9 to *t* – 5 are omitted.

	$\|r_{t+1}\| > 0.03$		$\|r_{t+1}\| > 0.05$	
Panel A: 1990-2001				
Constant	0.210	(15.72)	0.077	(9.23)
$net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$	-3.079	(-6.52)	-3.934	(-8.10)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-5.477	(-6.54)	-4.843	(-6.88)
$net\Gamma_t - net\Gamma_t(t-\tau,S_t)$	-2.945	(-10.56)	-3.766	(-11.67)
$\|r_t\|$	1.762	(26.95)	1.261	(27.48)
$\|r_t\| \times I^{r_t>0}$	-0.479	(-7.39)	-0.398	(-8.32)
$\|r_{t-1}\|$	1.082	(18.29)	0.770	(18.41)
$\|r_{t-1}\| \times I^{r_{t-1}>0}$	-0.670	(-11.24)	-0.559	(-12.79)
$\|r_{t-2}\|$	0.773	(14.46)	0.528	(13.52)
$\|r_{t-2}\| \times I^{r_{t-2}>0}$	-0.500	(-8.89)	-0.376	(-9.39)
$\|r_{t-3}\|$	0.577	(10.76)	0.403	(10.76)
$\|r_{t-3}\| \times I^{r_{t-3}>0}$	-0.365	(-6.48)	-0.317	(-7.98)
$\|r_{t-4}\|$	0.462	(7.78)	0.451	(7.02)
$\|r_{t-4}\| \times I^{r_{t-4}>0}$	-0.297	(-4.72)	-0.284	(-5.20)
…	…	…	…	…
Panel B: 2002-2012				
Constant	0.047	(9.70)	-0.026	(-8.55)
$net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$	-3.147	(-6.50)	-3.916	(-8.50)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-1.551	(-6.61)	-2.731	(-6.52)
$net\Gamma_t - net\Gamma_t(t-\tau,S_t)$	-2.953	(-4.80)	-4.154	(-8.53)
$\|r_t\|$	1.812	(18.13)	1.231	(13.67)
$\|r_t\| \times I^{r_t>0}$	-1.025	(-9.45)	-0.708	(-7.34)
$\|r_{t-1}\|$	1.578	(18.15)	0.993	(13.15)
$\|r_{t-1}\| \times I^{r_{t-1}>0}$	-0.805	(-8.95)	-0.493	(-6.01)
$\|r_{t-2}\|$	1.303	(15.54)	0.837	(11.40)
$\|r_{t-2}\| \times I^{r_{t-2}>0}$	-0.808	(-8.64)	-0.575	(-6.76)
$\|r_{t-3}\|$	1.131	(13.84)	0.713	(9.95)
$\|r_{t-3}\| \times I^{r_{t-3}>0}$	-0.647	(-7.35)	-0.420	(-5.66)
$\|r_{t-4}\|$	1.271	(14.25)	0.827	(10.03)
$\|r_{t-4}\| \times I^{r_{t-4}>0}$	-0.605	(-7.21)	-0.428	(-5.80)
…	…	…	…	…

Table 4

Regressions of absolute return on components of net position gammas with dummy variables for option expiration weeks, τ = 5 days

Results of estimating model (8) expressing the absolute return $|r_{t+1}|$ in terms of the components of non-normalized net gammas of delta hedgers and lagged absolute returns with expiration day dummy. *ExpD* is a dummy for trade days in expiration week. Standard errors are constructed from a covariance matrix for the average coefficients, which is formed by clustering observations by date and firm with common shocks, a method detailed in Thompson (2011). The associated *t*-statistics are reported in parentheses. The coefficient estimates on variables related to current and lagged absolute returns are omitted.

	Market Maker		Market Maker + Firm	
Panel A: 1990-2001				
Constant	0.019	(27.35)	0.019	(27.48)
$net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$	-0.610	(-6.07)	-0.496	(-5.60)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.570	(-6.49)	-0.531	(-5.79)
$net\Gamma_t - net\Gamma_t(t-\tau,S_t)$	-0.533	(-5.94)	-0.482	(-5.10)
$[net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})] \cdot ExpD$	-0.224	(-1.19)	-0.261	(-1.37)
$net\Gamma_t(t-\tau,S_{t-\tau}) \cdot ExpD$	-0.231	(-4.30)	-0.275	(-4.94)
$[net\Gamma_t - net\Gamma_t(t-\tau,S_t)] \cdot ExpD$	0.097	(0.94)	0.106	(0.99)
$ExpD$	-0.002	(-3.40)	-0.002	(-3.54)
…	…	…	…	…
Panel B: 2002-2012				
Constant	0.009	(29.07)	0.009	(29.93)
$net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$	-0.311	(-6.20)	-0.239	(-5.52)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.155	(-4.89)	-0.133	(-5.19)
$net\Gamma_t - net\Gamma_t(t-\tau,S_t)$	-0.377	(-7.99)	-0.533	(-8.73)
$[net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})] \cdot ExpD$	-0.031	(-0.44)	-0.094	(-1.72)
$net\Gamma_t(t-\tau,S_{t-\tau}) \cdot ExpD$	-0.040	(-1.48)	-0.108	(-2.60)
$[net\Gamma_t - net\Gamma_t(t-\tau,S_t)] \cdot ExpD$	0.114	(2.85)	0.119	(2.40)
$ExpD$	-0.001	(-3.98)	-0.001	(-4.12)
…	…	…	…	…

Table 5

Regressions of absolute return on components of net position gammas for subsamples of stocks with different liquidity and size, τ = 5 days

Results of estimating model (8) expressing the absolute return $|r_{t+1}|$ in terms of the components of the normalized net position gammas and lagged returns for the subsamples of low and high liquidity stocks (Panel A a), and large and small firms (Panel B). The model is estimated for the trader group Market Makers. A firm is defined as a high (low) liquidity firm if its average relative stock bid-ask spread is below (above) the median average relative stock bid-ask spread of firms in the sample. A large firm is defined to be a firm that was among the 200 optionable stocks with the greatest average market capitalization during the sample period. Standard errors are constructed from a covariance matrix for the average coefficients, which is formed by clustering observations by date and firm with common shocks, a method detailed in Thompson (2011). The associated *t*-statistics are reported in parentheses. The coefficient estimates on variables related to current and lagged absolute returns are omitted.

Panel A: Low and high liquidity stocks	Low liquidity		High liquidity	
1990-2001				
Constant	0.026	(26.10)	0.012	(24.26)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.780	(-6.26)	-0.373	(-3.01)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.891	(-7.18)	-0.320	(-4.15)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.685	(-6.06)	-0.342	(-3.71)
…	…	…	…	…
2002-2012				
Constant	0.011	(29.35)	0.006	(23.39)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.373	(-6.42)	-0.272	(-5.49)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.229	(-6.46)	-0.157	(-4.27)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.321	(-7.38)	-0.248	(-5.46)
…	…	…	…	…
Panel B: Not large and large firms	**Not Large**		**Large**	
1990-2001				
Constant	0.021	(26.63)	0.016	(23.34)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.632	(-6.57)	-0.519	(-5.60)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.659	(-6.86)	-0.553	(-5.36)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.598	(-7.87)	-0.430	(-4.83)
…	…	…	…	…
2002-2012				
Constant	0.011	(27.81)	0.006	(26.50)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.337	(-5.63)	-0.308	(-5.12)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.197	(-4.58)	-0.160	(-5.30)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.315	(-6.08)	-0.255	(-4.71)
…	…	…	…	…

Table 6

Regressions of absolute return on components of net gamma, τ = 10 days

Results of estimating model (8) expressing the absolute return $|r_{t+1}|$ in terms of the components of the normalized net position gammas and lagged absolute returns, where the prior positions are those that were held τ = 10 days prior to date *t*. Standard errors are constructed from a covariance matrix for the average coefficients, is formed by clustering observations by date and firm with common shocks, a method detailed in Thompson (2011). The coefficient estimates on variables related to current and lagged absolute returns are omitted.

Panel A: Stock 1990-2001	Market Maker		Market Maker +Firm	
constant	0.019	(28.47)	0.019	(27.38)
$net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$	-0.607	(-8.66)	-0.463	(-7.26)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.591	(-5.25)	-0.460	(-5.29)
$net\Gamma_t - net\Gamma_t(t-\tau,S_t)$	-0.496	(-7.12)	-0.382	(-6.08)
…	…	…	…	…
Panel B: Stock 2002-2012				
constant	0.009	(33.91)	0.009	(33.86)
$net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})$	-0.350	(-8.29)	-0.182	(-8.62)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.178	(-4.72)	-0.076	(-3.62)
$net\Gamma_t - net\Gamma_t(t-\tau,S_t)$	-0.269	(-6.87)	-0.126	(-6.83)
…	…	…	…	…

Table 7
Regressions of absolute return on components of net position gamma using gammas provided by OptionsMetrics 1996-2012, τ = 5 days

Results of estimating model (8) expressing $|r_{t+1}|$ in terms of the components of the net position gammas based on option gammas from OptionMetrics and lagged absolute returns. Panel A1 and B1 are the results using Black-Scholes options gamma. Standard errors are constructed from a covariance matrix for the average coefficients, is formed by clustering observations by date and firm with common shocks, a method detailed in Thompson (2011). The coefficient estimates on variables related to current and lagged absolute returns are omitted.

	Market Maker		Market Maker + Firm	
Panel A1: 1996-2001 Black-Scholes Γ				
Constant	0.019	(19.78)	0.019	(19.58)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.504	(-5.97)	-0.411	(-5.96)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.524	(-4.80)	-0.430	(-4.59)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.503	(-9.74)	-0.403	(-8.56)
…	…	…	…	…
Panel A2: 1996-2001 OptionMetrics Γ				
Constant	0.020	(20.94)	0.019	(20.79)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.509	(-6.01)	-0.422	(-6.27)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.518	(-4.76)	-0.430	(-4.68)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.469	(-8.46)	-0.378	(-7.21)
…	…	…	…	…
Panel B1: 2002-2012 Black-Scholes Γ				
Constant	0.009	(27.59)	0.009	(27.45)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.329	(-7.35)	-0.127	(-6.42)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.190	(-4.24)	-0.103	(-6.03)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.280	(-8.66)	-0.131	(-8.89)
…	…	…	…	…
Panel B2: 2002-2012 OptionMetrics Γ				
Constant	0.009	(26.86)	0.009	(26.78)
$net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})$	-0.321	(-6.93)	-0.159	(-6.60)
$net\Gamma_t(t-\tau,S_{t-\tau})$	-0.170	(-3.95)	-0.081	(-4.96)
$net\Gamma_t-net\Gamma_t(t-\tau,S_t)$	-0.275	(-8.02)	-0.148	(-9.34)
…	…	…	…	…

Table 8

Regressions of S&P 500 index absolute returns on cross-sectional averages of components of net position gamma, τ = 5 days

Results of estimating model (8) expressing the absolute return of the S&P 500 index $|r_{t+1}^I|$ in terms of the cross-sectional averages of the components of the normalized net position gammas and lagged returns. $I^{r_t^I>0}$ is the dummy variable that equals one when $r_t^I > 0$. The model is estimated for the trader groups Market Makers and Market Makers plus Firm Proprietary traders. Standard errors are constructed using the Newey-West method with 10 lags. The associated *t*-statistics are in parentheses. The coefficient estimates on the variables related to lagged absolute returns from day *t* – 9 to *t* – 5 are omitted.

	Market Maker		Market Maker + Firm	
Panel A: 1991-2001, S&P 500 Index				
Constant	0.004	(6.84)	0.003	(6.41)
$avg[net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})]$	-0.808	(-2.16)	-0.754	(-2.28)
$avg[net\Gamma_t(t-\tau,S_{t-\tau})]$	-0.276	(-2.74)	-0.150	(-1.74)
$avg[net\Gamma_t-net\Gamma_t(t-\tau,S_t)]$	-0.394	(-3.41)	-0.323	(-2.98)
$\|r_t^I\|$	0.105	(2.58)	0.107	(2.60)
$\|r_t^I\|\times I^{r_t^I>0}$	-0.175	(-4.03)	-0.175	(-4.01)
$\|r_{t-1}^I\|$	0.193	(6.25)	0.194	(6.29)
$\|r_{t-1}^I\|\times I^{r_{t-1}^I>0}$	-0.232	(-7.71)	-0.233	(-7.71)
$\|r_{t-2}^I\|$	0.097	(3.52)	0.099	(3.62)
$\|r_{t-2}^I\|\times I^{r_{t-2}^I>0}$	-0.114	(-4.17)	-0.115	(-4.22)
$\|r_{t-3}^I\|$	0.060	(2.09)	0.062	(2.19)
$\|r_{t-3}^I\|\times I^{r_{t-3}^I>0}$	-0.003	(-0.09)	-0.004	(-0.12)
$\|r_{t-4}^I\|$	0.054	(1.95)	0.057	(2.06)
$\|r_{t-4}^I\|\times I^{r_{t-4}^I>0}$	-0.009	(-0.49)	-0.011	(-0.52)
…	…	…	…	…
Panel B: 2002-2012, S&P 500 Index				
Constant	0.004	(3.32)	0.004	(3.58)
$avg[net\Gamma_t(t-\tau,S_t)-net\Gamma_t(t-\tau,S_{t-\tau})]$	-0.476	(-2.42)	-0.552	(-2.94)
$avg[net\Gamma_t(t-\tau,S_{t-\tau})]$	0.001	(0.04)	0.105	(1.17)
$avg[net\Gamma_t-net\Gamma_t(t-\tau,S_t)]$	-0.281	(-2.30)	-0.208	(-1.91)
$\|r_t^I\|$	0.079	(1.87)	0.075	(1.81)
$\|r_t^I\|\times I^{r_t^I>0}$	-0.039	(-0.85)	-0.038	(-0.84)
$\|r_{t-1}^I\|$	0.078	(2.12)	0.075	(2.04)
$\|r_{t-1}^I\|\times I^{r_{t-1}^I>0}$	-0.029	(-0.58)	-0.029	(-0.60)
$\|r_{t-2}^I\|$	0.022	(0.57)	0.020	(0.51)
$\|r_{t-2}^I\|\times I^{r_{t-2}^I>0}$	-0.002	(-0.04)	-0.003	(-0.07)
$\|r_{t-3}^I\|$	0.010	(0.28)	0.008	(0.23)
$\|r_{t-3}^I\|\times I^{r_{t-3}^I>0}$	0.056	(1.32)	0.054	(1.29)
$\|r_{t-4}^I\|$	-0.035	(-1.29)	-0.037	(-1.33)
$\|r_{t-4}^I\|\times I^{r_{t-4}^I>0}$	0.025	(1.06)	0.023	(1.24)
…	…	…	…	…

Table 9
Realized volatility and components of position gamma

The relation between components of market maker position gamma and absolute returns. The dependent variables are three components of net position gamma on day t (Γ_t). Standard errors are constructed from a covariance matrix for the average coefficients, which is formed by clustering observations by date and firm with common shocks. The associated *t*-statistics are reported in parentheses.

1990-2001	$\Gamma_t =$ $net\Gamma_t(t-5,S_t) - net\Gamma_t(t-5,S_{t-\tau})$		$\Gamma_t =$ $net\Gamma_t(t-5,S_{t-5})$		$\Gamma_t =$ $net\Gamma_t - net\Gamma_t(t-5,S_t)$	
Constant	0.003	(1.75)	0.041	(11.38)	-0.013	(-4.44)
$\lvert r_t \rvert$	-0.082	(-1.51)	-0.156	(-2.57)	-0.030	(-0.48)
$\lvert r_{t-1} \rvert$	-0.051	(-0.71)	-0.078	(-1.48)	-0.032	(-0.78)
$\lvert r_{t-2} \rvert$	-0.123	(-1.67)	-0.156	(-3.58)	0.105	(1.85)
$\lvert r_{t-3} \rvert$	-0.048	(-1.23)	-0.140	(-2.89)	0.074	(1.02)
$\lvert r_{t-4} \rvert$	0.140	(2.99)	-0.274	(-3.51)	0.117	(2.18)
$\lvert r_{t-5} \rvert$	0.005	(0.10)	0.038	(0.63)	-0.019	(-0.39)
$\lvert r_{t-6} \rvert$	0.027	(0.80)	-0.004	(-0.09)	0.003	(0.08)
$\lvert r_{t-7} \rvert$	0.030	(0.58)	-0.037	(-0.57)	0.056	(1.20)
$\lvert r_{t-8} \rvert$	0.039	(0.99)	0.007	(0.16)	0.064	(3.11)
$\lvert r_{t-9} \rvert$	0.035	(0.62)	0.006	(0.12)	0.121	(1.53)
Γ_{t-1}	0.456	(35.10)	0.856	(50.33)	0.535	(38.12)
Γ_{t-2}	-0.008	(-0.27)	-0.025	(-1.10)	-0.010	(-2.87)
Γ_{t-3}	0.014	(0.55)	0.008	(2.54)	0.004	(1.77)
Γ_{t-4}	-0.025	(-1.19)	-0.015	(-2.17)	-0.032	(0.53)
Γ_{t-5}	-0.061	(-3.83)	0.016	(2.47)	-0.119	(-5.08)
2002-2012						
Constant	-0.005	(-1.42)	-0.022	(-2.86)	-0.011	(-2.51)
$\lvert r_t \rvert$	-0.112	(-0.44)	-0.274	(-2.00)	0.121	(0.44)
$\lvert r_{t-1} \rvert$	-0.697	(-1.00)	-0.625	(-2.53)	0.981	(0.92)
$\lvert r_{t-2} \rvert$	-0.475	(-0.86)	-0.156	(-0.62)	0.617	(0.79)
$\lvert r_{t-3} \rvert$	1.577	(1.76)	-0.422	(-1.85)	-1.018	(-1.73)
$\lvert r_{t-4} \rvert$	-1.098	(-1.13)	0.302	(0.70)	0.787	(0.82)
$\lvert r_{t-5} \rvert$	1.051	(1.49)	0.460	(1.23)	-0.648	(-0.74)
$\lvert r_{t-6} \rvert$	0.808	(0.93)	0.445	(1.66)	-0.465	(-0.50)
$\lvert r_{t-7} \rvert$	-0.114	(-0.76)	0.609	(1.85)	0.139	(0.55)
$\lvert r_{t-8} \rvert$	-0.766	(-1.14)	0.625	(2.12)	0.532	(1.05)
$\lvert r_{t-9} \rvert$	0.433	(0.95)	-0.257	(-1.35)	0.171	(0.56)
Γ_{t-1}	0.456	(36.47)	0.852	(47.13)	0.530	(38.93)
Γ_{t-2}	-0.004	(-0.31)	-0.013	(-0.73)	-0.008	(-0.37)
Γ_{t-3}	0.009	(0.80)	0.003	(0.19)	0.004	(0.21)
Γ_{t-4}	-0.022	(-1.35)	-0.009	(-0.57)	-0.029	(-1.67)
Γ_{t-5}	-0.063	(-4.79)	0.015	(1.48)	-0.105	(-7.50)

Table 10
Effect of components of net position gamma on net buy volume, τ = 5
The dependent variable is signed stock volume, $netBuyV_{t+1}$, measured as the difference between the buy and sell volumes on date t + 1 scaled by the sum of buy and sell volumes on date t + 1. The indicator variable $I^{signR_{t+1}}$ is one (negative one) if R_{t+1} is positive (negative). t-statistics based on standard errors that reflect serial and cross correlations are reported in parentheses. The sample period is 2003 to 2012. Panel A explains the negative relation between singed stock volume and the interaction of date t gamma with the stock return on date t + 1. Panel B reports the results.

Panel A

MM gamma < 0	if $r_{t+1} > 0$	MMs buy	$\Gamma_t \times r_{t+1} < 0$	$netBuyV_{t+1} > 0$
MM gamma < 0	if $r_{t+1} < 0$	MMs sell	$\Gamma_t \times r_{t+1} > 0$	$netBuyV_{t+1} < 0$
MM gamma > 0	if $r_{t+1} > 0$	MMs sell	$\Gamma_t \times r_{t+1} > 0$	$netBuyV_{t+1} < 0$
MM gamma > 0	if $r_{t+1} < 0$	MMs buy	$\Gamma_t \times r_{t+1} < 0$	$netBuyV_{t+1} > 0$

Panel B: dependent variable: $netBuyV_{t+1}$	Market Maker		Market Maker +Firm	
Constant	0.014	(9.70)	0.014	(9.70)
$[net\Gamma_t(t-\tau,S_t) - net\Gamma_t(t-\tau,S_{t-\tau})\ ] \times I^{signR_{t+1}}$	-18.846	(-3.61)	-12.238	(-3.63)
$[net\Gamma_t(t-\tau,S_{t-\tau})] \times I^{signR_{t+1}}$	-1.080	(-0.27)	-1.342	(-0.48)
$[net\Gamma_t - net\Gamma_t(t-\tau,S_t)] \times I^{signR_{t+1}}$	-14.271	(-3.27)	-6.990	(-3.04)
$I^{signR_{t+1}}$	0.060	(16.11)	0.060	(16.18)
$netBuyV_t$	0.140	(19.52)	0.140	(19.52)
$netBuyV_{t-1}$	0.078	(12.15)	0.078	(12.15)
$netBuyV_{t-2}$	0.060	(9.37)	0.060	(9.37)
$netBuyV_{t-3}$	0.048	(7.62)	0.048	(7.62)
$netBuyV_{t-4}$	0.045	(7.26)	0.045	(7.27)
$netBuyV_{t-5}$	0.038	(6.30)	0.038	(6.30)
$netBuyV_{t-6}$	0.037	(6.23)	0.037	(6.23)
$netBuyV_{t-7}$	0.036	(5.89)	0.036	(5.89)
$netBuyV_{t-8}$	0.037	(6.24)	0.037	(6.24)
$netBuyV_{t-9}$	0.043	(7.22)	0.043	(7.23)

Table 11

Autocorrelations of subsequent returns for stock-dates with low, medium, or high gamma

Observations are pooled into low, medium and high gamma terciles based on the first component of the net position gamma, i.e. $(net\Gamma_t(t-5, S_t) - net\Gamma_t(t-5, S_{t-5}))$, which is the change of market maker position gamma due to past stock price movement ("hedge gamma"), and the third component of position gamma, i.e., $(net\Gamma_t(t, S_t) - net\Gamma_t(t-\tau, S_t))$, which is the change of market maker position gamma due to changes in open interest ("information gamma"). The table reports the average correlation coefficients of date $t + 1$ and $t + 2$ returns for stocks in each gamma tercile. The *t*-statistics are computed from standard errors adjusted for cross-correlations.

	Correlations between subsequent returns r_{t+1} and r_{t+2}	
1990-2001	Observations sorted on hedge gamma $net\Gamma_t(t-5, S_t) - net\Gamma_t(t-5, S_{t-5})$	Observations sorted on information gamma $net\Gamma_t(t, S_t) - net\Gamma_t(t-\tau, S_t)$
Low gamma	0.003	0.011
Medium gamma	0.023	0.011
High gamma	0.011	0.018
Low minus high	-0.008	-0.003
t-statistic	(-4.26)	(-1.42)
2002-2012		
Low gamma	-0.026	-0.029
Medium	-0.020	-0.012
High gamma	-0.017	-0.025
Low minus high	-0.009	-0.004
t-statistic	(-6.01)	(-1.97)