Tilburg University

School of Economics and Management

The Effect of Option Demand on Future Stock Volatility: A Sectoral Comparison

Master Thesis Finance

Author	Tom Keersemaker
SNR	2077217
ANR	939474

Supervisor: T. Grünthaler
Second reader: S. Casella

Date: 06-08-2025

1. Introduction

Classical finance theory considers derivative markets as secondary to the underlying asset, primarily serving to transfer risk or hedge without directly influencing the price of the underlying asset. However, empirical evidence contradicts this view. Equity options have become increasingly intertwined with the behavior of the underlying stock. For instance, the GameStop gamma squeeze and AMC Entertainment saw speculative trading activity lead to significant short-term price surges. While these are extreme cases, empirical research has shown that option trading activity has a significant short-term influence on the underlying stock. In other words, options not only reflect expectations of future price movements, but can influence them. One such mechanism through which this occurs is dynamic delta hedging by market makers. Market makers generally avoid directional bets, so they aim to stay neutral to price moves in the underlying asset. They achieve this by frequently adjusting their stock positions in response to changes in gamma, which measures how much an option's sensitivity to price movement changes as the underlying asset moves. This can create feedback loops, as seen in the aforementioned cases, where market makers had to trade in the direction of the price, thereby increasing underlying stock volatility.

While recent empirical research has demonstrated that net gamma exposure can influence short-term price dynamics in equities and indices, much of this work adopts a market-wide perspective. However, this approach may overlook important cross-sector differences, such as variation in liquidity, institutional behavior, and volatility, which could shape how options activity affects the underlying stocks. This thesis addresses this gap by examining whether the effect of option market makers net gamma on next-day volatility differs by sector and what role institutional participation and volatility have in moderating this relationship.

The main research question is: Does the impact of option trading activity on underlying stock volatility vary across sectors? To answer this question, I use net gamma exposure (NGE) as the proxy for the hedge rebalancing activity of market makers in the option market. NGE is the aggregated gamma of all option series for a stock. When NGE is positive, market makers will trade against stock price movements, which results in lower future stock volatility. Conversely, when NGE is negative, market makers are likely to trade with price movements, which generally results in a higher future volatility for the underlying stock. Thus, NGE is a mechanism through which option trading activity can influence the future volatility of the underlying stock.

I will answer the main research question as follows: First, I will test if the expectation that higher NGE results in lower future stock volatility holds for all sectors. Thereafter I consider 2 sub questions. Does a higher institutional ownership in the underlying stock strengthen the negative effect of NGE on future stock volatility? Institutional investors differ from retail traders in behavior, motives, and information access, which may meaningfully influence the effect of NGE. Institutional trading is generally considered to be more motivated by fundamentals. Consequently, it is expected that it amplifies the stabilizing effect of NGE on future stock volatility. However, their trading may be more momentum driven in certain sectors, so that makes it interesting to explore differences between sectors. In addition to institutional ownership, another factor that may impact the relationship between NGE and future stock volatility is the volatility of the underlying stock. Greater price fluctuations in the underlying stock are expected to lead to more frequent and aggressive rebalancing by market makers, which amplifies the effect of NGE. This leads to the second sub question: Does higher stock volatility amplify the effect of NGE on future stock volatility?

To answer the main research question and the two sub-questions, I compiled a dataset using three widely recognized and reliable sources: CRSP (Center for Research in Security Prices), LSEG (London Stock Exchange Group), and OptionMetrics (IvyDB US). These databases provide high-quality financial data and are commonly used in empirical finance research. The dataset spans the period from 2013 to August 2023 and includes daily data on stock returns, option open interest, and gamma values, as well as quarterly data on institutional ownership percentages. The sample consists of 300 U.S.-listed stocks, with 60 stocks selected from each of the following sectors: technology, healthcare, financials, consumer discretionary, and energy. Each stock included in the sample has at least 500 trading days with option data, ensuring sufficient variation.

In the 3 different tests I used the absolute next day return as dependent variable, since this is often utilized as a proxy for stock volatility. To compute NGE I made a necessary assumption that market makers buy calls and puts of equity options and calculated the sum of net gamma of all option series for each firm per day, multiplied by open interest. Then I normalized it by underlying stock price and the amount of shares outstanding, which made the units of gamma comparable across different stocks. Additionally, I used control variables to account for volatility clustering and to allow positive and negative returns to have different impacts on conditional volatility, following Ni et al. (2020). For the second sub question I used realized volatility with a 10-day rolling window, which incorporates the most recent market dynamics and avoids excessive noise.

To address the 3 research questions I made use of panel regressions, because it is a widely used method that can control for common shocks and time-invariant firm characteristics, which should make the results more robust. Additionally, I ran stock-by-stock regressions and summarized the results for each sector. This does not allow for valid statistical inferences for each sector, but it reveals within-sector variation that panel regressions may mask due to assuming common coefficients.

The stock-by-stock regressions provide initial evidence that the relationship between NGE and future stock volatility is generally negative across sectors and aligns with prior literature. However, significance at the individual stock level is limited. The energy sector has the highest amount of significant results at a 5% level (23 out of 60 stocks), alongside the most negative average coefficient (-0.0000802). In contrast, the healthcare sector has a positive average beta. This suggests there are some differences between the sectors.

However, the panel regression results are at odds with my expectation. Contrary to the individual regressions, the coefficients are generally positive, which suggests a positive relationship between NGE. The financial sector is the only sector with a statistically significant result (0.00000075). The results for energy and technology do align with expectations, but they are insignificant.

The results of the panel regressions for the sub questions are more promising. In healthcare, the interaction between NGE and institutional ownership percentage was significant (-0.000057), suggesting that institutional ownership weakens the positive relationship between net gamma and future volatility. In consumer discretionary, the interaction coefficient was also significant, but positive (0.000018). This indicates that higher institutional ownership increases the positive effect of net gamma on future volatility and may potentially be due to more procyclical trading behavior in this sector. In financials and consumer discretionary, the interaction term between past volatility and NGE was -0.0003 and was statistically significant for both of these sectors. This was in line with my expectations that the effect of net gamma becomes more negative as past volatility was high.

Ni et al. (2020) provide direct empirical evidence that option market activity can influence the volatility of the underlying stock through non-informational channels. Their core finding is a significant negative relationship between net gamma and future stock volatility, which indicates market maker hedging behavior tends to stabilize prices by trading against price movements when they are net long gamma. They show that this effect holds for a wide range of stocks, including liquid and illiquid, and small and large firms. This study forms the foundation for my thesis, which examines whether this effect varies across sectors.

Compared to Ni et al. (2020) I use a more simplified approach with only net gamma as the main variable, while they decompose net gamma into 3 different components: A hedge component, a lagged net gamma and an information component. This is to isolate the effect of hedge rebalancing from baseline from old positions and informed trading. Additionally, they utilize signed trading volume and don't have to make general assumptions on market maker behavior. My results from the individual stock regressions show some alignment: The average regression coefficient is negative for all sectors except healthcare and a notable portion of stocks show significant effects. However, my panel regressions contradict their findings: For the financial sector, the coefficient was positive. The difference in results is likely because of different modelling choices, and the inability to directly observe the trades of delta-hedging market participants.

In conclusion, this thesis finds limited evidence that the effect of NGE on future underlying stock volatility varies across sectors, since most results were insignificant. Furthermore, the effect of NGE on future stock volatility was not as expected: A higher NGE was associated with a higher future stock volatility. However, the role of institutional ownership in moderating the relationship between NGE and future stock volatility does differ between the consumer discretionary and the healthcare sector. The mixed and insignificant results highlight challenges of using general assumptions for all firms and sectors. Overall, my thesis lays the groundwork for a deeper exploration of the effect of option trading activity on underlying stock volatility.

The rest of the thesis is organized as follows: Section 2 provides a literature review of the topic. Section 3 outlines the hypothesis development and describes the empirical models used to test them. Section 4 discusses the data sources, sample selection and filtering criteria used to ensure a reliable dataset. Descriptive statistics and the empirical findings are presented in section 5. Finally, section 6 will provide the conclusion and discuss some limitations and suggestions for future research and the appendix contains the result of a robustness test.

2. Literature Review

The potential for option market trading to influence the underlying asset has long been a topic of debate in financial economics. Since option trading activity has grown dramatically over the last decade, through algorithmic trading and a high increase in retail participation, this topic has become increasingly relevant. The possibility of option trading influencing the underlying asset is at odds with classical option pricing models like the Black-Scholes model, which assumes perfect markets: No transaction costs, no bid-ask spreads, continuous trading and perfect hedging. In this framework, option trading does not affect the underlying stock price since the option price is a function of the underlying stock price, volatility, time to maturity etc. and market makers can continuously and perfectly hedge their option exposure. In reality hedging is costly, delayed and can impact price especially when gamma exposure is high, meaning option positions become more sensitive to movement in the underlying stock and require more frequent hedge adjustments. These frictions open the door for potential influence of option trading on the underlying stock. Accordingly, a growing body of empirical research has documented how option trading activity can affect the underlying stock in several ways.

2.1 Effect of demand pressure on option pricing

Bollen and Whaley (2004) investigate the relationship between net-buying pressure (difference between the number of buyer-motivated contracts traded and the number of seller-motivated contracts traded) and the shape of the implied volatility function (IVF) for individual stock and index options. They find that call option demand drives the transitory changes in IVF for stock options and put option demand drives the permanently downward sloping shape for the S&P 500 index option. This difference can be explained by the fact that institutional investors seek some portfolio insurance. Since there is a higher demand for OTM puts, market makers will increase the price to compensate for the risk they take on by writing these puts. They have to take this approach, because they cannot perfectly hedge large positions in these puts without incurring significant costs. The changes for calls are transitory, since market makers will rebalance and because calls in stock options are typically driven by speculation, which will subside eventually. Although the focus of their paper is on the effect of demand pressure on option prices via shifts in implied volatility rather than the underlying stock, it shows how hedging constraints influence prices. Market makers can absorb some of the impact of demand pressure by adjusting option prices, but this doesn’t eliminate the risk they already hold. To manage their positions, they must actively hedge, which can result in this pressure potentially spilling over into the underlying stock itself.

Garleanu et al. (2009) complement Bollen and Whaley (2004) by developing a theoretical model and by exploring the relationship between the level of option demand and the level of option prices. In their model the intermediaries are risk-averse and competitive and are not able to perfectly hedge. They show that demand for an option increases its price by an amount proportional to the variance of the unhedgeable part of the option (jump risk, stochastic volatility and discrete time trading) and the prices of other options also change depending on how much their risks are correlated. Their empirical findings show that demand pressure has a significant positive effect on the level of the implied volatility curve. Additionally, this relationship is stronger when there is less option trading activity. Moreover, they find that the effect is even more pronounced when market makers previously experienced losses than after gains, providing additional evidence that intermediary constraints influence option prices.

2.2 Transmission of demand to the underlying asset

While the previous papers focus on the effect of demand on option pricing, more recent research shows how these pressures are transmitted to the underlying stock. Ni et al. (2020) provide direct empirical evidence of this mechanism by analyzing how option trading activity influences underlying stock prices through noninformational channels. The authors develop a decomposition framework that links changes in stock return volatility to net gamma exposure derived from option open interest and signed trading volume. In this framework, a large net gamma position held by likely delta-hedgers (such as option market makers and firm proprietary traders) leads to more intense hedge rebalancing, which moves the underlying stock price. Their finding is a significant negative relationship between these net gammas and future stock return volatility, meaning that when delta hedgers like market makers hold large net gamma positions, their hedging activity reduces volatility, because they trade against the price movement of the underlying stock. Moreover, their results are not restricted to the option expiration week and hold for liquid and illiquid stocks and small- and large capitalization stocks alike.

While Ni et al. (2020) focus on identifying and quantifying the hedging effects associated with market makers' net gamma exposure at the individual stock level, my thesis extends their framework to the sector level to examine whether the strength of this effect is consistent across sectors or exhibits systematic variation. There are several reasons why the results may not be uniform. For instance, sectors that generally have higher volatility may have a larger need for hedge rebalancing due to higher gamma sensitivity, caused by faster and greater movement in delta. Another example is institutional presence in which sectors with generally a higher institutional presence may be associated with more balanced option flows that are less likely to require more aggressive hedging compared to sectors that are less institutionally dominated in which option trading is likely to be more motivated by sentiment and momentum rather than fundamentals.

Baltussen et al. (2020) provide further evidence for the notion that option trading has an influence on the underlying asset through hedging activity. Focusing on the S&P 500 index, they investigate intraday return mechanics, specifically intra-day momentum (the continuation of price direction). They compute the net gamma exposure of option market makers and find that intraday momentum is more pronounced when the net gamma exposure of option market makers is negative, because they delta hedge in the same direction as the market. Conversely, when their net gamma exposure was positive, market intraday momentum was no longer present, because then the hedging flows dampen price movement. Their results show further evidence of positioning of option market activity impacting the price of the underlying asset, although their focus is on index options and intraday movements.

3. Hypothesis Development

3.1 Impact of net gamma exposure on stock returns

Market makers exposed to large net gamma positions must rebalance frequently to keep their position delta neutral. This frequent rebalancing can move the underlying stock price. The effect is strongest when gamma is high, as positions become extremely sensitive to price changes. In the framework of Ni et al. (2020) large positive net gamma exposure predicts lower volatility in stock returns as, delta-hedgers trade against the underlying stock. I will first test whether this basic hedging-induced price pressure mechanism holds for my own sample of stocks.

H1: Higher net gamma exposure of delta hedging option market participants leads to lower volatility in future underlying stock returns.

Unfortunately I lack access to signed trading volume and investor classification, which indicates whether a trade is buyer- or seller-initiated and if trades are from end-users like retail or institutions or from market makers or firm proprietary traders. As a result, I cannot precisely determine market maker positioning. This limitation means my proxy for gamma exposure is based on assumptions about trade direction and counterparty roles instead of observed behavior in the option market. The assumptions I make to proceed are as follows:

- Market makers take the opposite side of end-user demand. This means that when open interest increases in a given option series, I assume the trade is initiated by an end user and absorbed by the market maker. Although this is a simplistic and strong assumption it is reasonable since the core role of market makers is providing liquidity for which they earn the bid-ask spread in exchange and they generally do not try to make directional profits. Goyenko and Zhang (2019) show that there is a negative net order flow across both calls and puts for equity options and on average positive delta inventory positions. This is consistent with a generally negative end-user demand for equity options as shown by Garleanu et al. (2009). Therefore, I will make the assumption for my sample that market makers are long gamma, since they buy calls and puts of equity options.
- Market makers hedge precisely their option deltas.

For a call/put option on day t on stock i with strike price s ∈ S C t and maturity m ∈ MC t the NGE is computed as follows:

$$NGE^{C}_{i,s,m,t} = \Gamma^{C}_{i,s,m,t,i} \cdot OI^{C}_{i,s,m,t} \cdot 100 \tag{1}$$

$$NGE^{P}_{i,s,m,t} = \Gamma^{P}_{i,s,m,t} \cdot OI^{P}_{i,s,m,t} \cdot 100 \tag{2}$$

The total net gamma exposure will then be calculated as follows:

$$NGE_{i,t} = \left(\sum_{s\in S^C}\sum_{m\in M^C} NGE^{C}_{s,m} + \sum_{s\in S^P}\sum_{m\in M^P} NGE^{P}_{s,m}\right) \cdot \frac{S_{i,t}}{M_{i,t}} \tag{3}$$

Where Γ is the gamma of an option, OI is the open interest, $S_{i,t}$ is the price of the underlying stock i at time t and $M_{i,t}$ is the amount of shares outstanding. I included the normalization factor $\frac{S_{i,t}}{M_{i,t}}$ following Ni et al. (2020) to make the units of gamma the same across firms.

To test the hypothesis that greater net gamma exposure of delta hedging option market participants leads to lower volatility in stock returns. I will run the following regression for each individual stock:

$$|r_{t+1}| = \alpha + \beta_1 \cdot NGE_t + \sum_{k=0}^{9} \gamma_k |r_{t-k}| + \sum_{j=0}^{9} \theta_j \left|r_{t-j}\right| \cdot I^{r_{t-j}>0} + \varepsilon_t \tag{4}$$

Then I will run the following panel regression for each sector:

$$\left|r_{i,t+1}\right| = \alpha_i + \delta_t + \beta_1 \cdot NGE_{i,t} + \sum_{k=0}^{9} \gamma_k \left|r_{i,t-k}\right| + \sum_{j=0}^{9} \theta_j \left|r_{i,t-j}\right| \cdot I^{r_{i,t-j}>0} + \varepsilon_{i,t} \tag{5}$$

Where the dependent variable $|r_{t+1}|$ is the absolute next-day return of the stock, which serves as a proxy for realized volatility, NGE_{t-5} is the net gamma exposure, $\sum_{k=0}^{9} \gamma_k |r_{t-k}|$ are lags of absolute returns to account for volatility clustering and $\sum_{j=0}^{9} \delta_j \left|r_{t-j}\right| \cdot I^{r_{t-j}>0}$ are the interactions between lagged absolute returns and a return dummy where $I^{r_{t-j}>0}$ is 1 if r_{t-j} is greater than 0, and ε_t is the error term. These control variables are chosen following Ni et al. (2020). α_i and δ_t are firm- and time fixed effects.

The stock-by-stock regressions allow the coefficients to vary across firms and expose heterogeneity in the net gamma-future volatility relationship. The panel regression can control for time-invariant firm characteristics and common market-wide shocks, and allows for valid statistical inference at the sector level, which the individual stock regressions cannot provide. A limitation is that large differences across firms in the net gamma – future volatility relationship could be obscured by the sector-level panel estimates.

I expect $\beta_1 < 0$, meaning that higher net gamma exposure predicts lower future volatility.

3.2 Sectoral differences in the impact of net gamma exposure

3.2.1 The moderating role of institutions in the net gamma – future volatility relationship

The baseline hypothesis examines the general relationship between net gamma exposure and stock return volatility. However, it is unlikely that this effect is uniform across sectors. Sector-specific characteristics can either strengthen or weaken this relationship. One such characteristic is the degree of institutional ownership.

Institutional investors differ systematically from retail investors in terms of their trading motives, access to information, and execution strategies. While retail trading can be influenced by sentiment or speculative behavior, institutional trading is more likely to be guided by fundamentals or quantitative models. Additionally, institutions often rely on algorithmic execution techniques, which reduce the price impact of trades by distributing orders over time. This results in more stable and predictable order flow, especially given the high volumes institutions typically manage.

Furthermore, institutional demand is generally less concentrated in a single direction compared to retail demand. For instance, institutions are more likely to use complex option strategies such as spreads or covered calls, rather than purchasing out-of-the-money calls for speculative purposes. This can reduce the extent to which market makers must engage in aggressive hedging activity. As a result, the likelihood of hedging-induced volatility events, such as gamma squeezes triggered by abrupt and concentrated buying pressure, may be lower in environments with higher institutional participation. These considerations lead to the following hypothesis:

H2: A higher percentage of institutional ownership strengthens the negative relationship between net gamma and future stock volatility.

To test this, I use institutional ownership, defined as the percentage of shares held by institutions as a moderating variable. This variable is updated quarterly, so it changes only at a quarterly frequency. However, NGE varies daily and thus the interaction term will have enough variation.

To test this hypothesis I will run the following panel regression:

$$|r_{i,t+1}| = \alpha_i + \delta_t + \beta_1 \cdot NGE_{i,t} + \beta_2 \cdot \mathrm{IO}_{i,q(t)} + \beta_3\left(NGE_{i,t} \cdot \mathrm{IO}_{i,q(t)}\right) + \gamma' X_{i,t} + \varepsilon_{i,t} \quad (6)$$

Where $\mathrm{IO}_{i,q(t)}$ is the firm institutional ownership percentage corresponding to stock i and the quarter of day t, $NGE_{i,t} \cdot \mathrm{IO}_{i,q(t)}$ is the interaction term between the net gamma exposure of stock i and its institutional ownership percentage in the corresponding quarter and $\gamma' X_{i,t}$ are all the controls that were utilized for the regression in 3.1. I expect $\beta_3 < 0$, meaning that institutional ownership strengthens the negative impact of net gamma exposure on future stock volatility.

3.2.2 Volatility as enhancer of the net gamma – future stock volatility relationship

Volatility is another factor that may shape the impact of net gamma on future stock volatility. Intuitively, the greater the volatility of the underlying stock, the more likely it is that the price moves significantly, thereby causing changes in delta. Hypothetically, if there are 2 stocks with roughly equal net gamma exposure, but one of these 2 stocks has a higher volatility, the stock with the higher volatility requires more frequent and more aggressive rebalancing. Gamma exposure implies sensitivity to the second derivative of price and a higher volatility makes these price movements more pronounced and more frequent. Therefore, volatility amplifies hedging pressure induced by net gamma exposure and therefore increasing its effect on the underlying stock return. Furthermore, this can create a feedback loop, often referred to as a gamma squeeze: prices move more due to volatility, which causes market makers to hedge more aggressively, which generates further pressure on price.

Lastly, investors and speculators tend to trade more options on stocks with higher volatility according to Lakonishok et al. (2007). This increased trading activity—both buying and writing of options—raises overall option market volume and open interest. While market makers take the opposite side of these trades, the heightened option activity leads to more frequent and larger adjustments in market makers' hedging positions. These adjustments amplify the sensitivity of market makers' net gamma exposure and its impact on the underlying stock's price dynamics. This leads to the following hypothesis:

H3: The effect of net gamma exposure on underlying stock volatility is stronger when underlying stock volatility is higher.

To test this empirically, it is important to use the right measure of volatility. The volatility needs to be ex-ante, as market makers adjust for expected—not realized—price swings. For this test, I will use past realized volatility over a rolling window of 10 trading days. This window captures recent market dynamics while avoiding excessive day-to-day noise. While implied volatility is also an ex-ante measure, it is not a pure statistical estimate, as it incorporates demand for options and embedded risk premia. Moreover, the same investor flows that influence gamma exposure can also inflate implied volatility, making it a potentially biased proxy for volatility expectations. By contrast, realized volatility may understate future volatility ahead of known events such as earnings, which have not occurred yet. However, this is a limited concern, since such events are short-lived. To test H3 I will run the following panel regression:

$$\left|r_{i,t+1}\right| = \alpha_i + \delta_t + \beta_1 \cdot NGE_{i,t} + \beta_2 \cdot \sigma_{i,t} + \beta_3 \cdot \left(NGE_{i,t} \cdot \sigma_{i,t}\right) + \gamma' X_{i,t} + \varepsilon_{i,t} \qquad (7)$$

Where $\sigma_{i,t}$ is the 10-day rolling volatility of stock i and $NGE_{i,t} \cdot \sigma_{i,t}$ is the interaction between that volatility and the NGE of stock i.

I expect $\beta_3 < 0$ meaning that when volatility is high, the stabilizing effect of gamma exposure on future stock volatility becomes stronger.

4. Data Description

4.1 Data Sources

I combine stock and option level data from the following sources:

- CRSP (Center for Research in Security Prices): This database provides daily-stock level data including returns, closing prices and shares outstanding
- Optionmetrics (IvyDB US): Provides end-of-day data for American equity options. This include gamma and and open interest
- LSEG: institutional ownership data

These databases are widely used as sources in the financial literature.

4.2 Sample selection

The time period I choose for my thesis is 2013 until end of August 2023. This time period provides sufficient observations to get reliable results from my analysis and covers different business cycles, ending in August 2023 due to data availability constraints in Optionmetrics. To ensure a clean sample and reliable results I only include firms that have at least 500 trading days with option data and at least an average stock price of $5 to avoid including penny stocks. My sample consists of in total 300 stocks (60 for each sector) across information technology and communication services, healthcare, financials, energy, consumer discretionary. These stocks were drawn from a random sample, with more weight applied to highly liquid stocks.

4.3 Data filters

I start with a stock list that includes only stocks from the five sectors I focus on, and require each to have at least 1,000 trading days. This helps ensure that the stocks are more likely to have enough option-trading data. Then, I compute the average price of each stock over its trading period and filter out those with an average price below $5 to avoid penny stocks, which are typically less liquid, more volatile, and less likely to have actively traded options. First, I filter out option observations with volume below 10, open interest below 100, best bid and best offer below 10 cents, and contracts with an excessive spread between these ($3), as these are more likely to be stale, inactive, or irrelevant from a hedging perspective. Next, I remove stocks with fewer than 500 option trading days to ensure a statistically meaningful sample and to avoid including stocks that only have meaningful option activity during short speculative periods. After these steps, I draw the random sample described in the paragraph above. This results in a total of 555,847 stock-date observations.

5. Results

5.1 Descriptive statistics

Table 1

Descriptive statistics

Sector	*variable*	*mean*	*SD*	*Min.*	*0.25*	*0.5*	*0.75*	*Max.*
Tech	$\lvert r_t \rvert$	0.0229	0.0263	0.0000	0.0073	0.0162	0.0301	0.3832
	NGE_t	51.5448	41.8477	2.4034	23.5915	42.3426	66.3198	371.6540
Healthcare	$\lvert r_t \rvert$	0.0262	0.0330	0.0000	0.0084	0.0185	0.0338	0.5562
	NGE_t	20.4289	22.6173	0.3564	6.8947	13.5688	25.8005	204.5525
Financials	$\lvert r_t \rvert$	0.0167	0.0198	0.0000	0.0052	0.0116	0.0216	0.2787
	NGE_t	21.7280	21.6999	0.7672	8.7662	15.1594	27.1253	232.0340
Energy	$\lvert r_t \rvert$	0.0257	0.0296	0.0000	0.0082	0.0181	0.0340	0.4773
	NGE_t	24.3852	22.8122	0.4763	9.0782	16.9745	32.2721	190.2349
Consumer discretionary	$\lvert r_t \rvert$	0.0232	0.0273	0.0000	0.0072	0.0161	0.0301	0.3854
	NGE_t	68.1062	55.0286	2.8108	31.2689	52.1488	88.6477	447.2995

This table reports means, standard deviations, extrema and quantiles for the normalized net gamma variable and the daily absolute return. The descriptive statistics are first calculated for each underlying stock, and then the averages across the underlying stocks in each sector are reported.

Table 1 presents some descriptive statistics of the key variables used in the main regression. Absolute daily returns are generally the highest in the healthcare and energy sectors and show the greatest variability in these sectors. On the other hand, the financials sector shows a modest 1.67% as average absolute daily return and a 1.98% standard deviation, indicating more stable price behavior. The relatively higher average and dispersion of daily returns in the healthcare and energy sectors may reflect a greater sensitivity to sector-specific shocks. In the energy sector this could be linked to commodity price fluctuations or geopolitical events and in the healthcare sector to drug approvals for example.

Normalized net gamma also has substantial variation across the different sectors. Consumer discretionary and Technology & Communications show the highest average and maximum net gamma values, which may suggest elevated option trading activity and/or hedging demand compared to other sectors. Financials, healthcare and energy have considerably lower means, which implies less hedging-related positioning in these sectors. The quantiles for the net gamma variable show a wide spread, which suggests there is considerable heterogeneity within each sector as well as between each sector.

Interestingly, the mean absolute daily returns and the mean net gamma exposure do not have a clear inverse relationship. For example, the financials sector has one of the lowest mean net gamma exposure, but also the lowest mean absolute return. Consumer Discretionary and Tech have a very high mean net gamma, but also relatively high average absolute returns. The stocks in these sectors generally trade at higher multiples and may attract more speculative flows, which can inflate net gamma but also increase realized volatility since they are more vulnerable to news and shifts in sentiment. The healthcare and energy sector behave as expected: a low net gamma exposure and higher average absolute returns.

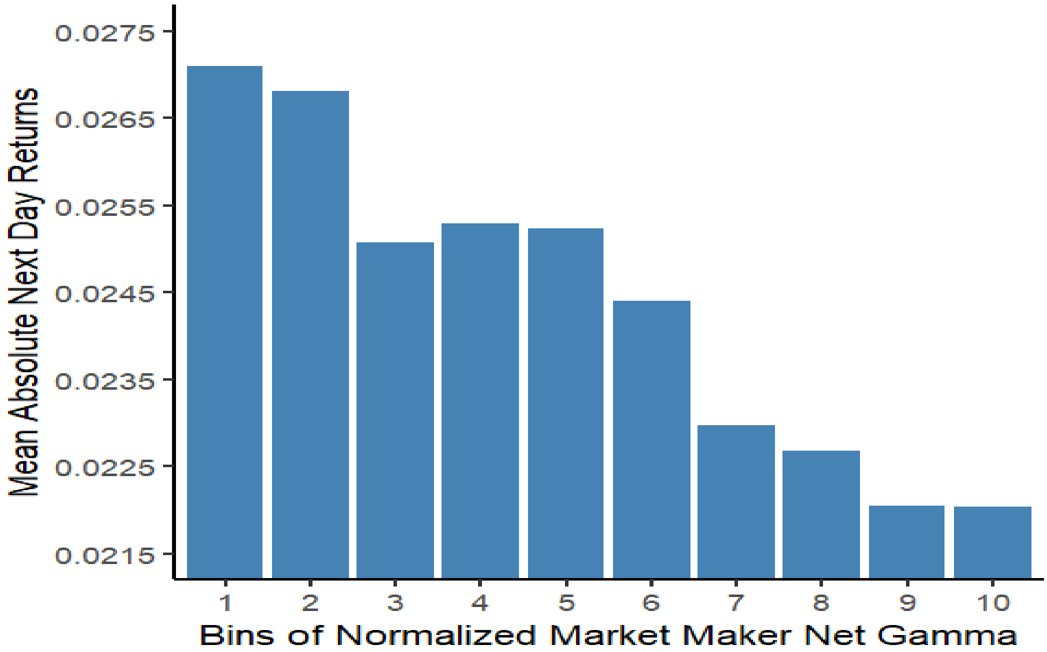

Figure 1
Relation between absolute stock return and market maker net gamma
The normalized market maker net gamma is computed every day for all stocks in my sample over the time period of 2013-2023. The net gamma for each underlying stock is then sorted into 10 bins of equal size and the average next day stock absolute return is computed for every bin. The panel depicts the result for each bin of averaging this quantity across underlying stocks. Bin 1 is the lowest and bin 10 is the highest.

Figure 1 suggests a negative relation between net gamma and the variability of next day absolute stock returns. The negative relation is economically significant and is almost monotonic, except for the small jump for bins 4 and 5 compared to bin 3. This small spike could perhaps be caused by mid gamma stocks in more volatile sectors. The average daily absolute return of the low net gamma group is approximately 50 basis points greater than the average daily absolute return for the highest net gamma group.

5.2 Impact of net gamma exposure on future stock volatility

Table 2

Stock-by-stock regression descriptives

Sector	Mean β	median β	SD β	Mean SE	Significant N
Tech	-0.0000043	-0.0000085	0.0000809	0.000038	19
Healthcare	0.0000337	-0.0000015	0.0002863	0.000091	11
Financials	-0.0000051	-0.0000073	0.0001037	0.000082	10
Energy	-0.0000802	-0.0000462	0.0001361	0.000055	23
Consumer discretionary	-0.0000165	-0.0000035	0.0001329	0.000023	15

This table reports some descriptive statistics of the main-stock-by-stock regression. It shows the mean, median and standard deviation of the beta of NGE, average standard error and the amount of stocks with results that are at least significant at a 5% level. Newey-West standard errors were used for this regression to account for autocorrelation and heteroskedasticity.

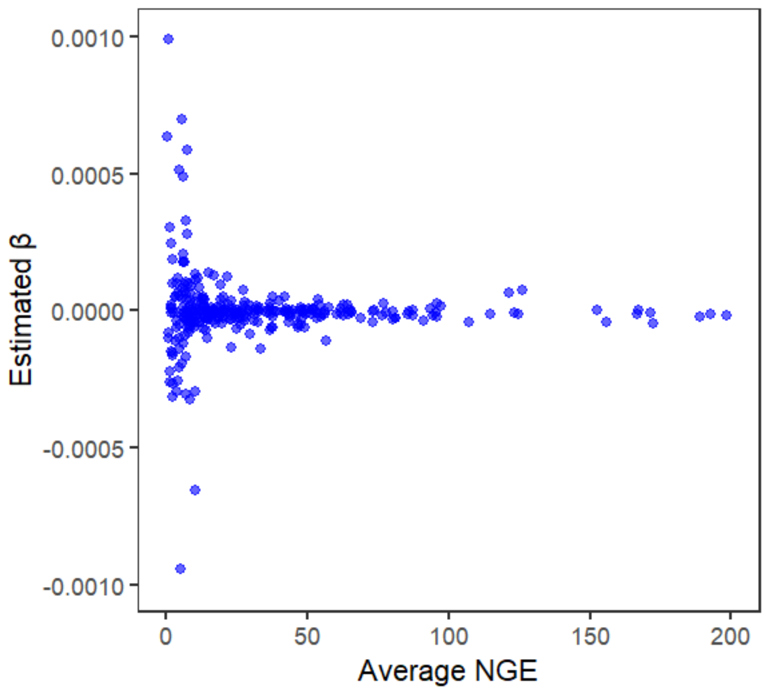

Figure 2
Relationship between average NGE and its beta
Scatterplot of stock-level average NGE vs. estimated coefficient from stock-by-stock regression. Each dot represents a single stock, with the x-axis showing its average NGE over the sample period and the y-axis showing its corresponding beta. Some extreme values were removed to improve readability.

Table 2 shows that except for the healthcare sector, the average and median beta are negative, which is in line with the hypothesis that higher net gamma predicts lower future volatility. However, most companies in the individual stock regression did not get significant results. The descriptives show that the energy sector had the most companies where the effect of net gamma was significant for at least the 5% level (23 out of 60) and it had the most negative average beta (-0.0000802). The high standard deviations, especially for healthcare, reflects high heterogeneity within each sector.

Figure 2 illustrates the relationship between the average NGE of a stock and the corresponding regression coefficient from the individual stock regressions. The dense clustering of points near zero suggests that NGE has little to no statistically significant effect on future volatility for most stocks and there is no visible linear relationship. Overall it suggests NGE may be a noisy measure.

Table 3

Main panel regressions results

Sector	β	Standard error
Tech	-0.0000003	0.0000058
Healthcare	0.0000104	0.0000083
Financials	0.0000075***	0.0000020
Energy	-0.0000027	0.0000066
Consumer discretionary	0.0000019	0.0000033

This table reports the results of the main panel regressions. It shows the regression coefficient of the NGE of each panel regression and the corresponding standard error. *** denotes significance at a 1% level. The model includes firm and time fixed effects. Standard errors are clustered by firm and time.

Table 3 shows the results for the panel regression for each sector and interestingly, the financials sector shows a result significant at the 1% level (0.0000075), while in the individual stock regressions it had the least amount of companies with significant results (10 out of 60). Surprisingly, the coefficient is positive which is not in line with my theoretical expectations and the average results from the stock-by-stock regressions in the same sector, which showed a negative mean and median beta. A 1 unit increase in net gamma in the financials sector is associated with a 0.075 basis point increase in next-day absolute returns, holding other factors constant.

The sectors with more significant results for the individual stock regression, weren't significant in the panel regression. These divergences can have several reasons. Firstly, the descriptives for the individual stock regressions gave each stock within a sector equal weight, regardless of size or trading activity. In contrast, the panel regression gives more influence to firms with more variability or more observations in the dependent or independent variables, which can amplify the influence of a few large or volatile stocks. Secondly, firm fixed effects could absorb much of the cross-sectional variation that contributes to significant results for the individual stock regression. The time fixed effects account for systemic shocks. If these shocks also drive volatility and if net gamma is higher during those times, time fixed effects remove some of that variation, explaining the weaker effects in the panel regression.

The general lack of significant results can be explained by me using an assumption that market makers are always long gamma, which was necessary since I could not observe real flows. Theoretically, market makers could generally be short puts in technology for example, while they could generally be long puts in healthcare and I cannot account for this. Another reason could be that the effect of net gamma doesn't necessarily predict the absolute returns next day. Market makers may adjust their hedges over several days, so looking at only the next day could underestimate the effect.

5.3 The moderating role of institutions in the net gamma – future volatility relationship

Table 4

Sector	NGE	IO	NGE • IO
Tech	0.000003	-0.003400	-0.000010
	(0.000010)	(0.002600)	(0.000011)
Healthcare	0.000057***	-0.005900*	-0.000057***
	(0.000014)	(0.003500)	(0.000017)
Financials	0.000006***	-0.000700	-0.000001
	(0.000002)	(0.001300)	(0.000006)
Energy	-0.000009	-0.002200	0.000006
	(0.000020)	(0.002100)	(0.000024)
Consumer Discretionary	-0.000008	-0.007800**	0.000018**
	(0.000005)	(0.003400)	(0.000008)

This table reports the results of the panel regressions. It shows the regression coefficients of each panel regression and the corresponding standard error. ***, **, * denote significance at a 1%, 5% and 10% level respectively. The model includes firm and time fixed effects. IO stands for institutional ownership, which means the percentage of total shares held by institutions. Standard errors are clustered by firm and time.

Table 4 shows the results of the panel regression examining how NGE, institutional ownership and their interaction relate to future volatility. For the tech and energy sectors, there aren't significant results for any of the effects. The interaction term is positive and statistically significant for the consumer discretionary sector, which means that a higher institutional ownership reduces the stabilizing effect of net gamma exposure. In other words, a higher institutional ownership percentage may result in increased volatility when net gamma exposure is high, which is at odds with my hypothesis. The IO variable itself is negative and statistically significant, which means it is associated with lower future stock volatility when net gamma is low. This may suggest that institutions behave more procyclically in this sector and trade in the direction of the trend.

The coefficient for NGE in the healthcare sector is statistically significant and positive, the coefficient for the IO variable is negative although not significant at a 5% level. The coefficient for the interaction term is statistically significant, although it has a small significance in an economic sense. A 1 percentage point increase in institutional ownership reduces the marginal effect of net gamma exposure on next-day absolute returns by 0.0057 basis points. This confirms my hypothesis that institutional ownership strengthens the negative relationship between net gamma exposure and future stock volatility or in this case it reduces the positive effect of net gamma exposure on future stock volatility.

5.4 Volatility as enhancer of the net gamma – future stock volatility relationship

Table 5

Sector	NGE	σ	σ · NGE
Tech	0.0000009	-0.1879***	0.0001
	(0.000003)	(0.0401)	(0.0001)
Healthcare	0.000012	-0.1594***	-0.0001
	(0.000008)	(0.0181)	(0.0002)
Financials	0.000013***	-0.2337***	-0.0003**
	(0.000003)	(0.0479)	(0.0001)
Energy	0.000011	0.0343	-0.0005
	(0.000009)	(0.0990)	(0.0004)
Consumer discretionary	0.000010**	-0.0835	-0.0003**
	(0.000004)	(0.0648)	(0.0001)

This table reports the results of the panel regressions. It shows the regression coefficients of each panel regression and the corresponding standard error. ***, **, * denote significance at a 1%, 5% and 10% level respectively. The model includes firm and time fixed effects. Standard errors are clustered by firm and time.

Table 5 shows the results of the panel regression, examining the relationship between NGE, the 10 day rolling window volatility and their interaction. The coefficient for the 10-day rolling window volatility is statistically significant for tech, healthcare and financials. It has a negative effect on the next-day absolute returns, because the controls accounted for volatility clustering. Since that was already accounted for, this coefficient reflects mean reversion — the tendency for low (or high) volatility to revert to its usual level. This mean reverting tendency is particularly strong for tech, healthcare and the financial sector.

The coefficient of the interaction term is generally negative except for the tech sector and is statistically significant for consumer discretionary and the financial sector. For both of these sectors, a 1 percentage point increase in the rolling-window volatility reduces the marginal effect of net gamma exposure on next-day absolute returns by approximately 0.03 basis points. This suggests that the effect of net gamma exposure on future volatility becomes more negative as past volatility increases, which is in line with my hypothesis. This provides evidence that it has a significant negative effect in high volatility regimes and market maker hedging behavior is most intense in turbulent markets.

5.5 Robustness test

To test the robustness of my main model, I run the same regression but with the assumption that market makers buy calls and sell puts, which can induce situations where they are short gamma. The results of this regression are shown in Table A1 in the appendix. Across both models the sign of the mean and median betas remain mostly stable. However, the number of stocks with significant results in the energy sector drops considerably from 23 to only 9, which means it is very sensitive to how the net gamma variable is constructed. It could mean that market makers have a higher tendency to buy than to sell puts in this sector. The financials sector also has a considerable drop from 10 to 6, but overall the results generally align with the main results.

6. Conclusion

6.1 Summary of findings

This thesis examined how net gamma exposure (NGE) affects future stock volatility for firms in 5 different sectors from 2013 until August 2023, using a stock-by-stock regression and different panel regressions. The NGE variable was constructed based on option market data, with the assumptions that market makers were always on the opposite side of end-user demand and bought both calls and puts, which resulted in them being long gamma. Future stock volatility was proxied by the next-day absolute returns. The aim for my thesis was to test whether the effect of NGE on future stock volatility differed depending on the sector and how this relationship is moderated by institutional ownership of the stock and volatility.

The results provided limited support for the main hypothesis. In the individual stock regressions, the results were in line with my hypothesis, but most of the results were not statistically significant. The panel regressions yielded only a significant result for the financial sector and the regression coefficient was positive, contrary to my expectations that a higher NGE was associated with lower future stock volatility.

For the panel regression that tested the second hypothesis I found mixed results as well. The regression coefficient for the interaction term between NGE and institutional ownership was negative for the healthcare sector, which supported my hypothesis that an increase in institutional ownership strengthens the negative relationship between NGE and future stock volatility or weakens a positive relationship. However, in the consumer discretionary sector the coefficient was positive which did not met my expectation. This meant that there was some divergence between sectors, concerning the role of institutions.

Lastly, my analysis shows that higher past volatility (with a 10-day rolling window) tends to dampen the positive effect of NGE on future stock volatility, which suggest that market maker delta hedging is more impactful during more volatile market phases. However, this moderating effect was only statistically significant for the consumer discretionary and financial sectors.

My main academic contributions are as follows: Firstly, I fill a gap in the literature by examining if the effect of market maker hedge rebalancing on future stock volatility is uniform across different sectors or if there is divergence between the sectors. Secondly, I incorporate interaction effects with past volatility and institutional ownership and show that the impact of net gamma is not uniform across conditions.

6.2 Limitations and recommendations for future research

It is difficult to give practical recommendations, since there were several limitations present in my thesis that diminish the generalizability of my findings. It was not possible to access signed trading volume and investor classification, which indicates whether trades are buyer- or seller-initiated and if trades are from end-users or market makers. Consequently, I had to make a general assumption that may well hold for equity options as a whole, but cannot take differences between sectors and firms into account. It is likely that this introduced measurement errors in my models which may have led to the insignificant results and results that were at odds with my hypothesis. Furthermore, I used next-day absolute returns as a proxy which does not take into account that the effect of market maker hedge rebalancing on future stock volatility may take more time or persists over several days. Lastly, using panel regressions has a limitation. They assume one common coefficient across all firms within each sector, which means that meaningful firm-level variation is diluted.

Future research could address these issues by incorporating real trading data, testing different proxies for realized volatility, testing possible persistence and using more complex statistical methods. Additionally, instead of using a simplified approach one could use a more complex model like Ni et al. (2020) that isolates the effect of hedge rebalancing from informed trading. Another interesting direction for future research would be to use an anomaly like momentum as the dependent variable.

Transparency statement: Use of AI

In the course of this thesis, AI tools were used to support the research process in the following ways:

- Coding assistance: I used AI to generate code for the data cleaning process in R. All code was reviewed, adapted and executed by me.
- Data collecting: AI was used to assist in writing R code for accessing and extracting financial data from WRDS and OptionMetrics. The data retrieved was processed and analyzed by me.
- Language support: AI was used to check grammar and give suggestions to improve clarity of written sections. All final text was edited and approved by me.

Reference list

Baltussen, G., Da, Z., Lammers, S., & Martens, M. (2021). Hedging demand and market intraday momentum. *Journal Of Financial Economics*, *142*(1), 377–403. https://doi.org/10.1016/j.jfineco.2021.04.029

Bollen, N. P. B., & Whaley, R. E. (2004). Does Net Buying Pressure Affect the Shape of Implied Volatility Functions? *The Journal Of Finance*, *59*(2), 711–753. https://doi.org/10.1111/j.1540-6261.2004.00647.x

Gârleanu, N., Pedersen, L. H., & Poteshman, A. M. (2009). Demand-Based option pricing. *Review Of Financial Studies*, *22*(10), 4259–4299. https://doi.org/10.1093/rfs/hhp005

Goyenko, R., & Zhang, C. (2019). Option returns: Closing prices are not what you pay. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3489347

Lakonishok, J., Lee, I., Pearson, N. D., & Poteshman, A. M. (2006). Option Market activity. *Review Of Financial Studies*, *20*(3), 813–857. https://doi.org/10.1093/rfs/hhl025

Ni, S. X., Pearson, N. D., Poteshman, A. M., & White, J. (2020). Does Option Trading Have a Pervasive Impact on Underlying Stock Prices? *Review Of Financial Studies*, *34*(4), 1952–1986. https://doi.org/10.1093/rfs/hhaa082

Appendix

Table A1

Sector	Mean β	median β	SD β	Significant N
Tech	-0.000012	-0.000014	0.000098	19
Healthcare	0.000026	-0.000009	0.000261	12
Financials	-0.000010	-0.000010	0.000127	6
Energy	-0.000039	-0.000014	0.000121	9
Consumer discretionary	-0.000013	-0.000001	0.000149	13

This table reports some descriptive statistics of the robustness stock-by-stock regression. It shows the mean, median and standard deviation of the beta of the net gamma variable and the amount of stocks with results that are at least significant at a 5% level. Newey-West standard errors were used for this regression to account for autocorrelation and heteroskedasticity.