Option gamma and stock returns

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September, 2022

Abstract

Stocks with high net gamma exposure robustly underperform stocks with low high net gamma exposure by 10% per year. This effect is distinct from multiple previously documented return predictors, and survives many robustness checks. We show that stocks with low net gamma exposure negatively predicts future realized volatility. We argue that investors command a risk premium to hold low net gamma exposure stocks, which are riskier. Lastly, we show that the volatility predictability stems from a non-informational channel, and not from private information.

JEL Classification: G11, G12, G14

Keywords: Cross-section of stock returns, option demand, gamma hedging, return predictability

A. Soebhag: soebhag@ese.eur.nl. Financial support by Tinbergen Institute and Erasmus Research Institute of Management is gratefully acknowledged. The views expressed in this paper are not necessarily shared by Robeco Institutional Asset Management. We welcome comments, including references to related papers we have inadvertently overlooked.

1 Introduction

Since the introduction of exchange-based option trading in 1973, the trading activity of derivatives experienced large growth. Especially in recent years, single stock options have seen exceptional growth. For example, total options volumes were 160% of total share volumes in February 2021, and single stock call volumes are up +400% relative to 2018[1]. A key question is whether option trading is able to affect the price dynamics of underlying assets. Recent anecdotal stock-level evidence indeed suggests so: the rising share prices, and volatility, of GameStop in the beginning of 2021 was partially attributed to retail investors that bought large amount of call options [2]. Option market makers need to purchase shares on the market to hedge themselves to remain delta-neutral. Such hedging behaviour can have a large impact on asset prices.

How aggressively option market makers need to trade stocks in order to remain delta-neutral depends on the gamma of the option. Gamma measures how much the price of an option accelerates when the price of the underlying security changes. When market makers have short gamma exposure, they have to buy stocks when they are rising, and short them when they are falling, thereby amplifying initial price movements and amplifying volatility. On the other hand, when market makers have long gamma exposures, the opposite effect occurs: market makers buy stocks when they are falling, and sell when they are rising, thereby acting as a volatility dampener.

Given the growing activity seen in option markets, a natural question is whether this gamma-related flow is a systematic driver of asset returns. In this paper, we aim to answer this question by studying the cross-sectional implications of the net gamma exposure on future

[1]See Goldman Sachs Global Macro Research (february, 2021).

[2]See the Financial Times (2021)

equity returns. Following Barbon and Buraschi (2020), we directly proxy the net gamma exposure (Γ) of a stock as the gamma-weighted sum of open interest across the options written on that stock. We sort individual stocks into decile portfolios by their net gamma exposure during the previous month and examine the next month return on the resulting portfolios. Stocks in the lowest Γ decile generate about 10.44% higher annual returns compared to stocks in the highest Γ decile. After controlling for several benchmark models (such as the 5-factor model of Fama-French), we still find that the difference between the risk-adjusted returns on the portfolios with the lowest and highest Γ remains negative and highly significant.

Our results are consistent with the hypothesis that risk-averse investors demand additional compensation in the form of higher expected returns to hold stocks with negative net gamma exposure. When the gamma exposure is negative (positive), delta decreases (increases) when the price of the underlying asset increases. Hence market makers that engage in delta-hedging strategies are required to buy (sell) the underlying more aggressively after an increase in the underlying's price. This results into additional positive (negative) market pressure, which increases (decreases) the magnitude of the initial price movement. Thus, the initial price movement is dampened (reinforced) when the net gamma exposure is positive (negative). Hence, the relation between net gamma exposure and volatility is expected to be negative. This relationship also implies that risk-averse investors tend to be averse towards negative net gamma exposure, and demand a compensation to hold such stocks. On the other hand, stocks with positive net gamma exposure are considered as safer assets. In that case, investors are willing to pay higher prices, and accept lower expected returns. We confirm that stocks with a lower net gamma exposure tend to have higher realized volatility in the next month.

To ensure that the differences in returns are driven by the net gamma exposure rather than other stock characteristics, we conduct bi-variate portfolio sorts and re-examine the alpha differences. After controlling for almost 20 different well-known stock return predictors, we find that the negative relationship between net gamma exposure and future stock returns remains negative and statistically significant. Furthermore, we also examine the cross-sectional relationship at the individual stock-level using Fama and MacBeth (1973) cross-sectional and panel regressions. Controlling for all predictors jointly, these regressions provide strong evidence for an economically and statistically significant negative relation between the net gamma exposure and future stock returns. We also provide evidence of significant variation in the net gamma exposure premium over time.

We investigate the robustness of our findings. First, we construct a gamma factor and conduct spanning regressions. We show that the gamma factor is not spanned by well-known factor models. Second, we proxy the net gamma exposure using slightly different alternative definitions, and show that the documented negative relationship remains highly significant. Third, we find that the net gamma exposure premium is highly significant in the cross-sections of the 1000 largest and the 1000 most liquid stocks in the Center for Research in Security Prices (CRSP) universe. Fourth, our results are robust to changes in data filters. Fifth, we show that the predictive power stems mainly from ATM and OTM options, and options with a maturity beyond one month. Sixth, we show that the negative relationship between the net gamma exposure and next month return remains robust after the controlling of a wide range of option-based predictors.

Our study is related to several streams of the literature. First, there is a growing literature that shows evidence that options play a role in the price discovery process. Hu (2014) shows 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. Ni, Pearson, and Poteshman (2005) show that on expiration dates the closing prices of stocks with listed options cluster at option strike prices, driven by hedge rebalancing of option market makers. Hendershott and Seasholes (2007) study explicitly the link between non-informational order imbalances (buy minus sell volume) to predict daily stock returns at the market level. Second, a few studies investigate the relationship between gamma imbalances and asset prices. Ni et al. (2021) shows that the net gamma exposure predicts the next day absolute return, and provides a non-informational channel argument. Similar, our studies find that the net gamma exposure negatively predicts the realized volatility in the next month, and that this is driven by hedge rebalancing, rather than option trading on private information. Baltussen et al. (2021) studies intraday momentum on the index level and finds that this is driven by gamma hedging demand from market participants. Both Barbon and Buraschi (2020) and Barbon et al. (2021) document a link between gamma imbalances and intraday momentum and reversal for individual stocks.

The remainder of this paper is structured as follows. We describe the data and variable construction in section 2. The empirical results are presented in 3. We run a series of robustness tests in section 4. In section 5 we examine how net gamma exposure affects stock volatility and trading volume. Section 6 concludes.

2 Data and variable definitions

We use data of U.S.-listed options that are written on individual stocks trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotation (NASDAQ). From OptionMetrics we obtain daily implied volatility, trading volume, open interest and Greeks for each option contract.

The option data runs from Jan. 1, 1996 (the first date in the OptionMetrics database) until Dec. 31, 2021. We match the option data to stock return data obtained from CRSP. We only use stocks where the share code equals 10 or 11, and exchange code 1, 2, or 3. Furthermore, we eliminate stocks with a price per share less than 5 dollar and/or stocks with a market capitalization below the 20th NYSE percentile in order to exclude micro-caps from our sample. Accounting variables are obtained from Compustat and matched to our sample.

2.1 Net gamma exposure:

Let S_t be the value of the underlying asset at time t, K the strike price of an option and C_t the price of an option. The delta (Δ_t) of an option C_t is defined as the first derivative of the option price w.r.t the underlying price: $\Delta_t = \frac{\delta C_t}{\delta S_t}$. Option market makers aim to neutralize their exposure to movements in S_t in their option portfolio by engaging in delta-hedging. At time t, delta-hedging of an option portfolio requires buying or selling an amount of the underlying equal to $-\Delta_t$. However, Δ_t is a function of S_t. Thus, changes in S_t also changes the value of Δ_t. Hence, delta-hedging requires a dynamic adjustment of the position on the underlying. The extent in which Δ_t changes when S_t changes is the gamma, Γ_t, which is the second-order derivative of the option price w.r.t the price of the underlying, i.e. $\Gamma_t = \frac{\delta^2 C_t}{\delta S^2}$. A high absolute value of Γ_t implies that Δ_t is very sensitive to changes to S_t, and that the delta-hedger must trade more of the underlying to achieve delta-neutrality.

To estimate the net gamma exposure (Γ) on a individual-stock level, we follow Baltussen et al. (2021) and Barbon and Buraschi (2020). For a call option (C) on the underlying stock i on day t with strike price $s \in S_t^c$ and maturity $m \in M_t^c$, the $\Gamma_{i,t}$ is computed as:

$$\Gamma_{i,t}^c = \Gamma_{i,s,m,t}^c \times OI_{i,s,m,t}^c \times 100 \times S_t$$

Where $\Gamma_{i,s,m,t}^C$ denotes the option's gamma, $OI_{i,s,m,t}^c$ is the option's open interest, 100 is the adjustment from option contracts to shares and S_t is the price of the underlying. For a put option (P) on the underlying stock i on day t with strike price $s \in S_t^p$ and maturity $m \in M_t^p$, the $\Gamma_{i,t}$ is computed as:

$$\Gamma_{i,t}^p = \Gamma_{i,s,m,t}^p \times OI_{i,s,m,t}^p \times (-100) \times S_t$$

Here we multiply by (-100) as this represents short gamma for option market makers. To compute the aggregated net gamma exposure for stock i at day t, we sum over all Γ^c's and Γ^p's at every strike price and every maturity:

$$\Gamma_{i,t} = \left(\sum_{s \in S^c} \sum_{m \in M^c} \Gamma_{i,s,m,t}^c + \sum_{s \in S^p} \sum_{m \in M^p} \Gamma_{i,s,m,t}^p \right) \times \left(\frac{S_t}{100 \times VOL_{i,t-1}} \right) \tag{1}$$

The first term between brackets denotes the amount (in dollars) that option market makers need to trade for a one-dollar change in S_t. We facilitate cross-sectional comparison by multiplying this term by the second term: Multiplying by S_t and dividing by 100, and scale by the average dollar trading volume over the last 21 business days. This changes the interpretation to the amount that needs to be hedged for a 1% change in the underlying stock.

Figure 1 provides an overview of the coverage of our sample relative to the CRSP universe. Data from OptionMetrics is only available from January 1996 on. At the start of 1996, only 45% of number of stocks have valid net gamma exposures available. In terms of total market capitalization, we cover 61% of the CRSP universe in terms of market capitalization in January 1996. Over time, the number of stocks being covered grows, where we obtain over 95% coverage in terms of the number of stocks in 2021, and over 99% in terms of market capitalization.

Figure 2 presents the distribution of the net gamma exposure across stocks for each month in our sample. First, we document significant cross-sectional differences in the net gamma exposure across stocks. On average, the net gamma exposure equals 1.23 for the 75th percentile, whereas it equals 0.05 for the 25th percentile. Second, we also document variation in the net gamma exposure over time. During periods of financial uncertainty and high volatility (such as the Great Financial Crisis or the Dot-com Bubble), the net gamma exposure is lower. Third, we find that most of the stocks have a positive net gamma exposure. In our sample, 21.8% of the stock-month observations have a negative net gamma exposure.

2.2 Other predictors:

To control for other cross-sectional effects, we construct a wide-range of predictors. The following factor loadings and firm characteristics, that are known to forecast the cross-section of stock returns, are constructed: the size (ME) is defined as the firm size and is measured as the natural logarithm of the market value of equity (which equals the stock price multiplied by the number of shares outstanding in millions of dollars) at the end of month t for each stock j.

We compute the following accounting variables: the book-to-market ratio (BM) is computed as the book value of stockholder equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock at the end of the last fiscal year, t1, scaled by the market value of equity at the end of December of year t1. Depending on data availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of preferred stock (Fama & French, 1992). In addition, we compute a monthly version of the B/M ratio, following Asness and Frazzini (2013). Following Hou, Xue, and Zhang (2015), we compute the annual growth rate of total assets, denoted IA, as the change in book assets (Compustat item AT) divided by the lagged AT. The quarterly operating profitability, denoted ROE, is measured by income before extraordinary items (item IBQ) divided by one-quarter-lagged book equity. We compute 1-year net-share issuance (NSI) as the firm's 1-year growth in market equity minus the 1-year equity return (in logs), following Pontiff and Woodgate (2008). The NSI measure excludes cash dividends. The 5-year composite share issuance (CSI) measure is defined as the firm's 5-year growth in market equity, minus the 5-year equity return, in logs, following Daniel and Titman (2006). We compute operating profitability (OP) as revenues minus cost of goods sold, minus selling, general, and administrative expenses minus interest expense all divided by book equity (Fama & French, 2015). We compute cash profitability (CP), following Ball et al. (2016), by defining accruals as the change in accounts receivable from $t-2$ to $t-1$, plus the change in prepaid expenses, minus the change in accounts payable, inventory, deferred revenue, and accrued expenses.

The following trade/price-based variables are constructed: We estimate market beta (MKT) as the market beta of individual stocks using daily returns over the prior year. Likewise, we define total return volatility (VOL) as the volatility of daily returns over the prior year. We define realized volatility (RV) as the volatility of daily returns during month t. Momentum (MOM), for each stock in month t, is defined as the cumulative return on the stock over the previous 11 months starting two months ago to avoid the short-term reversal effect, that is, momentum is the cumulative return from month t–12 to month t–2 (Jegadeesh & Titman, 1993). Following Jegadeesh (1990), we define short-term reversal (SREV) for each stock in month t as the return on the stock over the previous month. Following Amihud (2002), for each stock in month t, we define illiquidity to be the ratio of the absolute monthly stock return to its dollar trading volume, $ILLIQ_{i,t} = |R_{i,t}|/VOLD_{i,t}$, where $R_{i,t}$ is the return on stock i in month t, and $VOLD_{i,t}$ is the monthly trading volume of stock i in dollars. Idiosyncratic volatility ($IVOL$) is calculated as the standard deviation of the daily abnormal return, based on CAPM model, over the past 90 trading days. Following Bali et al. (2011), we measure demand for lottery-like stocks using MAX, which is calculated as the average of the five highest daily returns of the stock during the given month t. We require a minimum of 15 daily return observations within the given month to calculate MAX.

Lastly, we construct option-based predictors. First of all, we measure implied volatility (IV) as the open interest weighted implied volatility for all options traded on that day, following Ge et al. (2016). Furthermore, we compute the total call volume relative to the total option volume in month t (CVOL). Lastly, we compute the total outstanding call option open interest relative to the total option open interest (COI).

3 Empirical Results

In this section, we conduct a wide range of tests to assess the predictive power of the net gamma exposure over future stock returns. First, we conduct univariate portfolio-level analyses. Second, we analyse the persistency of the net gamma exposure on the portfolio-level. Third, we show the average stock - and portfolio characteristics to provide an overview of the composition of net gamma exposure portfolios. Fourth, we conduct bi-variate portfolio sorting and stock-level regressions to control for other characteristics. Fifth, we control for multiple control variables in a multivariate setting. Sixth, we show that the net gamma exposure also negatively predicts extreme returns in the next month. Lastly, we provide evidence that the net gamma exposure premium is significantly time varying.

3.1 Univariate portfolio-level analysis

In this section, we conduct univariate portfolio-level analysis, where we construct deciles every month by sorting stocks on their net gamma exposure (Γ). Subsequently, we compute the one month ahead value-weighted returns for each decile to test whether the zero-cost portfolio generates a significant return. The zero-cost portfolio takes a long position in stocks with the lowest net gamma exposure, and a short portfolio in stocks with the highest net gamma exposure during the previous.

Table 2 presents the time-series averages of one-month-ahead excess (risk-adjusted) returns for each decile. Panel A and B uses breakpoints derived from the full CRSP sample and NYSE universe, respectively, to construct decile portfolios. The first column of each panel reports the average net gamma exposure for each decile. Moving from decile L to decile H, the Γ increases significantly from -0.01 to 0.04. The zero-cost portfolio has an average net gamma exposure of 0.05 with a t-statistic of 17.04. The second column of each panel reports the average excess returns. We find that the average excess return decreases monotonically from 1.45% to 0.58% (panel A) when moving from the lowest Γ decile to the highest Γ decile. The average return difference between decile H and L equals -0.87% per month with a t-statistic of -5.29. This suggests that stocks in the lowest Γ decile generate, on average, 10.44% higher annual returns compared to stocks in the highest Γ decile.

Subsequently, we report the magnitude and statistical significance of risk-adjusted returns estimated from five different factor models: α_{3FM} is the intercept obtained from regressing the excess portfolio returns on the Fama-French 3-factor model augmented with the momentum factor (i); α_{5F} is the alpha relative to the Fama-French 5-factor model (ii); α_{5FM} is the intercept relative to the Fama-French 5-factor model augmented with the momentum factor (iii); α_{Q5} is the alpha relative to the extended Q-factor model of XHZ (iv); α_{Q5M} is the alpha relative to the extended Q-factor model of XHZ augmented by the momentum factor. As shown in the third column of both panels, the α_{3FM} decreases from 66 basis points to -13 basis points per month when moving from decile L to decile H. The alpha spread equals 79 basis points per month (or 9.48% per annum) with a t-statistic of -4.87. We find similar alpha results from alternative factor models with alpha spreads ranging between 79 and 94 basis points per month. After controlling for well-known factor models, the return difference between low Γ and high Γ stocks remains negative and statistically significant.

The results are in line with the hypothesis that stocks with negative hedging pressure can exacerbate stock volatility, whereas hedging pressure from positive gamma exposure may act as a volatility dampener. Risk-averse investors would demand extra compensation in the form of higher expected returns to hold stocks with a negative Γ. Stocks with high positive Γ, on the other hand, are perceived as relatively safer assets, hence investors are willing to pay higher prices for these stocks and accept lower expected returns.

3.2 Gamma persistency

The significant and negative alpha spreads documented in table 2 are obtained by sorting stocks by their previous' month net gamma exposure, and not by their contemporaneous gamma. Investors will only pay high prices for stocks with positive gamma hedging pressure in the past with the expectation that such pressure is persistent over time. In this section, we present results regarding the persistence of net gamma exposure.

Table 3 shows the persistence by examining the average 1-month and 12-month-ahead portfolio transition matrix for our sample. We show the average probability that a stock in decile i (defined by the rows) in one month will be in decile j (defined by the columns) in the subsequent month 12 months. If there is no persistency in the net gamma exposure, we would expect that 10% of the stocks in decile i remains in the same decile 12 months later.

However, the results suggest the contrary. 42% of the stocks in the lowest net gamma exposure decile in a certain month continues to be in the same month one month later. Likewise, over half of the highest gamma decile remains in the same decile 1-month later. On a 12-month basis, the persistency becomes weaker. Only 17% of the lowest decile gamma stocks remains in the same decile after one year, whereas 29% of the highest decile gamma stocks remains in the same decile. Theoretically, investors would pay higher (lower) prices for stocks with positive (negative) net gamma exposure in the past given that this exposure will persist in the future. Our results indeed suggest that gamma is a persistent characteristic, especially on a short-term basis.

3.3 Average portfolio characteristics

We examine the average characteristics of stocks with high vs. low gamma stocks based on Fama and MacBeth (1973) regressions. We report the time-series averages of the slope coefficients from the regressions of the gamma exposure on the stock-level characteristics. For each month t, we estimate the following specification and nested versions:

$$\Gamma_{i,t} = \gamma_{0,t} + \gamma_t X_{i,t} + \epsilon_{i,t} \tag{2}$$

Where $\Gamma_{i,t}$ is the net gamma exposure of stock i in month t and $X_{i,t}$ is a collection of stock-specific variables observable at time t for stock i. The cross-sectional regressions are run at a monthly frequency from January 1996 to December 2021. The results are shown in Table 4. Column (1) shows that the average slope coefficient on the lagged net gamma exposure is positive and significant, implying that stocks with high (low) net gamma exposure in month $t-1$ tend to have a high (low) net gamma exposure in month t as well, consistent with table 3.

Column (2) indicates that stocks with higher net gamma exposure tend to be stocks with lower market beta. Column (3) reports that the average slope coefficient on the 1-month realized volatility significantly negative. Hence, high gamma stocks tend to be less volatile during the month relative to low gamma stocks. Likewise, in column (5) we find that high gamma stocks also exhibit a lower implied volatility than low gamma stocks. Intuitively, this is also what we would expect: positive gamma exposure tends to dampen volatility, whereas negative gamma exposure increases volatility. We find no significant relation between illiquidity, book-to-market and return on equity in columns (4), (6), and (7), respectively. Furthermore, we find that stocks with high operating profitability tend to be stocks with lower net gamma exposure (column 8). Lastly, we find that stocks with high $t-12$ till $t-2$ returns tend to be stocks with a positive gamma exposure.

The last column in table 4 shows that when we include all variables jointly, the cross-sectional relations tend to be weaker or insignificant. We find that market beta, realized volatility, implied volatility, and operating profitability remains statistically significant after controlling for all other variables. In the appendix, table A.2, we also report average characteristics on the portfolio level. The results are consistent with the stock-level characteristics.

3.4 Bivariate portfolio-level analysis

The negative relation between net gamma exposure and equity returns in the univariate portfolios in Table 2 is possibly due to a firm-specific characteristic that is correlated with net gamma exposure and has a significant impact on expected stock returns. This section examines the relation between the net gamma exposure and future stock returns after controlling for a wide set of return predictors.

To this end, we perform conditional bivariate portfolio sorts on the net gamma exposure controlling for: market beta (MKT), the log market capitalization (ME), the book-to-market ratio (BM), operating profitability (OP), cash profitability (CP), investment (IA), net share issuance (NSI), composite share issuance (CSI), return on equity (ROE), momentum (MOM), short-term reversal (REV), 1-year return volatility (VOL), idiosyncratic volatility ($IVOL$), 1-month realized volatility ($RVOL$), illiquidity (ILQ), lottery demand (MAX), implied volatility (IV), call volume ($CVOL$), and call open interest (COI).

We control for a cross-sectional predictor by first forming value-weighted decile portfolios based on the cross-sectional predictor. Then, within each decile, we sort stocks into decile portfolios based on the net gamma exposure, i.e. we use a dependent (conditional) sorting methodology. Subsequently, we average the portfolio returns across the ten deciles of the controlling variable to produce decile portfolios with dispersion in net gamma exposure, but with similar levels of the controlling variable.

The results are shown in 5, where we report the alpha for each decile relative to the Fama-French 5-factor model augmented with the momentum factor. In the last row, we report the high-low spread portfolio. In total, we control for 20 stock characteristics. We find that alpha differences of the high-low portfolio are between 80 and 107 basis points per month, and remains highly significant (all t-values are smaller than -4). These findings suggest that a wide-range of well-known cross-sectional effects are not able to explain the net gamma exposure premium.

3.5 Stock-level regressions

Up till this point, we tested whether the net gamma exposure is a determinant of the cross-section of future equity returns at the portfolio level. Such analysis has the advantage of being non-parametric. On the other side, the sorting methodology aggregates and loses information. Furthermore, the sorting methodology does not allow for a setting in which we can control for other variables simultaneously.

Hence, we now examine the relationship between the net gamma exposure and expected returns at the stock level using Fama and MacBeth (1973) and panel regressions in table 6. Panel A presents the time-series averages of the slope coefficients from the Fama-Macbeth regressions of one-month ahead stock returns on the net gamma exposure with and without control variables. The slope coefficients allows to determine which variables have non-zero premia. We weight observations by their previous month's market capitalization. This corresponds to using WLS instead of OLS. In Panel B we equally-weight observations. Panel C and D shows the results from panel regressions, with and without market-cap weighting, respectively.

Column (1) in panel A reports the univariate regression results, and indicates a negative and statistically significant relation between net gamma exposure and the cross-section of future equity returns. The average net gamma exposure coefficient equals -18.65 with a Newey-West t-statistic of -3.80. To give this slope coefficient an economic significance, we can use the average values of the net gamma exposure in the decile portfolios from table 2. The average difference in $\Gamma_{i,t}$ between stocks in decile H and L is equal to 0.0479. Hence, a stock that moves from decile H to decile L decreases its net gamma exposure by 0.0479, which increases its expected return by 18.65*0.0479=0.89 basis points per month.

The second column in panel A of table 6 controls for implied volatility, call volume (in %), call open interest (in %), and a range of price-based variables. The average slope on Γ remains economically and statistically significant. The third column of Panel A adds accounting variables as control variables. In this specification, the estimated slope coefficient on Γ remains negative and statistically significant. The findings in panel A are robust to changes in estimation techniques. In panel B-D, we find that the estimated coefficient is in all cases negative and statistically significant. The most conservative estimate occurs in panel D column (3), where we equally-weight observations in a panel regression, and is statistically significant. A stock that moves from decile H to decile L increases its expected return by 8.18*0.0479=0.39 basis points per month, which is economically large. Our results suggest that the net gamma exposure premium is not subsumed after jointly controlling for multiple variables.

3.6 Large stock price movements

Stocks with negative gamma exposure require that delta-hedgers buy (sell) additional stocks after an initial increase (decrease). As such, the stock price will increase (decrease) even further and the initial movement may be amplified. When stocks have a positive gamma exposure, the reverse effect occurs: stock price movements are dampened. Hence, one implication of this mechanism is that future extreme returns are more likely to occur when the net gamma exposure is negative.

We examine to what extent extreme returns can be predicted by the net gamma exposure of option market makers. We define $I[r_{t+1} \geq X\%]$ as an indicator variable that takes value one when the next month return is larger than X%. We set X to 25%, 50%, and 75%, respectively. We regress each indicator variable on the net gamma exposure using a panel logit model. We use a panel logit model with fixed effects when regressing the indicator variables on the net gamma exposures (and a set of control variables). The results are shown in table 7.

In panel A, we predict the probability that the next month's return is larger than 25%. In column (1) we show the univariate estimate of the net gamma exposure. The slope on Γ is negative and statistically significant, implying that higher net gamma exposures are associated with a lower probability of 25% or higher return in the next month. In column (2) we control for momentum, short-term reversal, call volume, and call open interest. We find that our estimate remains statistically significant and negative. Our findings are robust to the inclusion of various accounting control variables, as shown in column (3).

In panel B and C, we predict the probability that the next month's return exceeds 50% and 75%, respectively. We find that net gamma exposures also negatively predicts the probability of exceeding 50% and 75% returns in the next month. Our findings are in line with the hypothesis that higher net gamma exposure dampens volatility, and hence negatively predicts future extreme returns.

3.7 Time-varying Gamma premium

The previous analysis provides a static estimate of the gamma premium. In this section, we test if the relation between the net gamma exposure and future stock returns is varying over time or state-dependent by plotting the monthly estimates of the net gamma premium over time. Figure 3 plots the six-month moving average of the monthly estimated slope coefficient of the net gamma exposure on the next month return. The grey-shaded area in the plot indicates the NBER recession dates. The net gamma exposure premium is negative on average, but varies over time. We find that premium tends to decrease during periods of financial crises, such as 2008-2009.

In table 8 we regress the premium on a set of macroeconomic indicator variables that take value 1 when the variable is above its median, else 0. In column (1) we regress the premium on the CFNAI indicator variable. We find that the premium is significantly lower when the CFNAI index is below its median value, indicating that the net gamma premium is more negative during periods of decreasing economic activity. Risk-averse investors would demand a higher premium for stocks with a negative net gamma exposure since such stocks are riskier, especially in an economic downturn. In column (2) we regress the gamma premium against the VIX index, but find no relationship between the above-median VIX and the premium. In column (3), we regress the premium on the sentiment index of Baker and Wurgler (2006). We find that below-median sentiment significantly predicts a more negative gamma premium. In column (4), we regress the premium on the financial uncertainty index (FUNC) of Jurado, Ludvigson, and Ng (2015). We find that above-median financial uncertainty predicts a more negative gamma premium. When uncertainty in financial conditions increase, risk-averse investors will require a higher premium on the relatively riskier negative net gamma stocks. In column (5) we regress the gamma premium on the CFNAI, VIX, sentiment, and FUNC indicator simultaneously. We find that CFNAI and sentiment positively predicts the premium, whereas FUNC predicts the premium negatively.

4 Robustness

We provide multiple robustness tests in this section to corroborate our earlier results. First, we conduct spanning regressions using well-known factor models. Second, we show that our results are robust to slightly different definitions of the net gamma exposure. Third, we examine three different sub-samples. Lastly, we show that our results are robust when we include microcaps and low-priced stocks in our sample.

4.1 Spanning regressions:

Having shown the role of the net gamma exposure in predicting the cross-sectional variation in individual stock returns, we subsequently construct a factor that captures the returns associated with the net gamma exposure and examine to what extent well-known factor models explain this gamma factor. We form a gamma factor using the 2×3 portfolio sorting method of Fama and French (1993). At the end of each month, we sort all stocks into two groups based on the market capitalization, with the breakpoint dividing the two groups being the median market capitalization of stocks traded on the NYSE. Next, we independently sort all stocks into three groups based on the net gamma exposure using the 30th and

70th NYSE percentile values of the net gamma exposure. Taking the intersections of the two classifications results in six portfolios. The gamma factor return is the average return on the two value-weighted low gamma portfolios minus the average of the two high gamma portfolios. In a similar manner, we construct the all Fama-French factors, the momentum factor, and the factors of Hou et al. (2015). We exclude microcaps and stocks with a price below 5$ to mitigate the influence of small, and illiquid stocks.

Panel A of table 9 shows the estimates from spanning regressions using long-minus-short factors. We find that the estimated annualized alphas, relative to several well-known factor models, range between 3.11 and 4.64% on an annual basis. The estimated alphas are statistically significant, with t-statistics between 2.26 and 3.21. As such the gamma factor is not spanned by Fama-French factor models and the Q-factor model (augmented by the momentum factor). In Panel B we conduct the spanning regressions using the long leg of the factor. We find that the low gamma leg is not spanned by the long legs of the other factor returns. Estimated alphas of the long gamma leg ranges between 2.18% and 3.31% on an annual basis, with t-statistics ranging between 2.51 and 3.78. In Panel C, we find that the short gamma leg is spanned by the other short legs, yielding insignificant alphas. These results indicate that the gamma factor is not explained by the well-known factors, driven by its long leg.

4.2 Alternative definitions

The main results are based on the net gamma exposure as of the end of the month, which we use to predict the next month return in the cross-section. We construct two alternative measures. First, we impose a one-day implementation lag in the net gamma exposure. Second, instead of using the end-of-month net gamma exposure, we take the average net gamma exposure in the sorting month.

The results are shown in table 10. Panel A shows the results using a 1-day implementation lag. The return spread using end-of-month Γ equals -87 bps (t-stat = -5.29), whereas it is -72 bps (t-stat = -3.91). Risk-adjusted returns vary between -62 and -81 bps per month with an implementation lag, with t-statistics between -4.31 and -2.98. Panel B shows the results using the average monthly net gamma exposure. The return spread equals -53 bps per month, with a t-statistic of -3.01. Risk-adjusted returns vary between -63 and -40 bps per month, with t-statistics between -3.26 and -2.20. In both cases, we document a significant negative relationship between the net gamma exposure and the next month stock return. In the appendix, table A.1, we sort on the end of the month gamma exposure, whereby we scale by market capitalization instead of trading volume, following Baltussen et al. (2021). We find that our results remain robust after scaling by market capitalization. Hence, our findings are robust to slightly different definitions of the net gamma exposure.

4.3 Sub-sample

We document a negative relation between the net gamma exposure and future stock return using equity returns from the CRSP sample where we excluded microcaps, defined as stocks with a market cap below the 20th NYSE market capitalization percentile. Barbon and Buraschi (2020) argue that the effect should be stronger in small and illiquid stocks. In this section, we consider the predictive power of the net gamma exposure on stock returns for large and highly liquid stocks. We show the results in table 11.

We consider the top 1000 largest stock in terms of their market capitalization, in panel A, and regress the excess return on the net gamma exposure. In the univariate regression (column 1), we find that gamma negatively predicts the next month equity returns (t-stat = -4.94). This estimate is also economically significant. A two standard deviation decrease in the net gamma exposure predicts a 38 basis point increase in the next month excess return. Specification (2)-(4) show that the estimate is robust to the inclusion of control variables. In panel B we consider the top 1000 most liquid stocks in terms of the Amihud (2002) measure, whereas we consider the top 1000 stocks with the highest option trading volume. In both panels we also find that the net gamma exposure negatively and significantly predict the next month return. Our results suggest that the net gamma exposure effect is not only present in small and illiquid firms, but also large and liquid firms.

4.4 Data filters

In all analysis presented before, we excluded microcaps and imposed a 5% price filter. We show that our results are qualitatively affected by these restrictions. Table 12 shows the stock-level regression results where we include microcaps and impose no price filter. Panel A presents the time-series averages of the slope coefficients from the Fama-Macbeth regressions of one-month ahead stock returns on the net gamma exposure with and without control variables. In Panel B we equally-weight observations. Panel C and D shows the results from panel regressions, with and without market-cap weighting, respectively.

Column (1) in panel A reports the univariate regression results, and indicates a negative and statistically significant relation between net gamma exposure and the cross-section of future equity returns. The average net gamma exposure coefficient equals -17.41 with a Newey-West t-statistic of -3.52. The second column in panel A of table 6 controls for implied volatility, call volume (in %), call open interest (in %), and a range of price-based variables. The average slope on Γ remains economically and statistically significant. The third column of Panel A adds accounting variables as control variables. In this specification, the estimated slope coefficient on Γ remains negative and statistically significant. The findings in panel A are robust to changes in estimation techniques. In panel B-D, we find that the estimated coefficient is in all cases negative and statistically significant. Our results suggest that the net gamma exposure premium does not rely on the inclusion or exclusion of low-priced stocks and/or microcaps.

4.5 Option moneyness and time to expiration:

We decompose the net gamma exposure in terms of moneyness and in terms of time to expiration. Option gammas are highest when the option is near-the-money. On the other hand, deep in-the-money or deep out-of-money options tend to have low gammas. We classify an option as "near-the-money" whenever the absolute values of the natural log of the ratio of the stock price to the exercise price less than 0.1, following Bali and Hovakimian (2009). When the value exceeds 0.1, a call (put) option is "in-the-money" ("out-the-money"). Vice verse, when this value is below -0.1, a call (put) option is out-the-money (in-the-money). Hence, the net gamma exposure can be decomposed as:

$$\Gamma_{i,t} = \Gamma_{i,t}^{OTM} + \Gamma_{i,t}^{ATM} + \Gamma_{i,t}^{ITM} \tag{3}$$

Furthermore, an option is considered as "fast" when it expires during the next month, else it is classified as "slow":

$$\Gamma_{i,t} = \Gamma^{slow} + \Gamma^{fast} \tag{4}$$

We report the results in table 13. Column (1) shows the results when we regress the next month excess return on the net gamma exposure, indicating that net gamma exposure negatively predicts future stock returns. In column (2), we decompose the net gamma exposure into the ATM, OTM, ITM components and regress the next month excess return on these components. We find that net gamma exposures from ATM and OTM contract negatively predicts future returns, whereas the predictive power for ITM contracts is weaker. In column

(3), we decompose the net gamma exposure into the fast and slow component and regress the next month returns on these components. We find that the slow gamma negatively predicts the next month stock return, whereas the fast gamma component has no predictive power.

4.6 Controlling for other option-based predictors

In table 6 we control for only three option-based predictors. In this section, we extend our set of option-based control variables to ensure that the net gamma exposure is distinct for other well-known option-based variables. We construct the implied volatility skew, proposed by Xing, Zhang, and Zhao (2010), as the difference between the average of implied volatilities extracted from out-of-the-money put options and the average of implied volatilities extracted from at-the-money call options. The IV skew reflects the investor's concern about future downward movements in underlying asset prices. A higher IVSKEW indicates a higher probability of large negative jumps in underlying asset prices. Second, we construct the call-put implied volatility spread (CPIV) of Bali and Hovakimian (2009), which is defined as the difference between the average IV from ATM call options and ATM put options. A high call-put implied volatility spread implies that the call option prices exceed the levels implied by the put option prices and the put-call parity. Third, we add the difference between the historical realized volatility and at-the-money implied volatility (Goyal & Saretto, 2009). Fourth, we compute the volatility-of-volatility variable (VoV) of Baltussen et al. (2018), which measures uncertainty about risk by the volatility of implied volatility (vol-of-vol). Fifth, we compute the net dollar open interest as in equation 1 with gamma being replaced by one. This allows us to control for variation in the net gamma exposure due to open interest and the price of the underlying. Lastly, we compute the net delta exposure, as in equation 1 with gamma being replaced by the delta.

We show the cross-sectional regression results in table 14. In column (1), we present the univariate regression estimate of the net gamma exposure coefficient. This estimate is negative and statistically significant, as we have seen before. In the remaining columns, we subsequently add an option-based predictor as a control variable. In all specifications, we find a negative and statistically significant relationship between the net gamma exposure and future returns. In particular, in column (12), we control for all predictors simultaneously. We find that the negative relationship between the net gamma exposure and the next month return remains statistically significant at the 1%. Furthermore, we find that IV_{skew} and CPIV positively and statistically significantly predict the next month return, where volatility-of-volatility negatively predict future returns. Thus, our results indicate that the net gamma exposure negatively predicts future equity returns even after the inclusion of multiple other option-based predictors.

5 Why is the relationship negative?

Our results suggest that stocks with a negative (positive) net gamma exposure earn a positive (negative) alpha, on average. Why is that? When the gamma exposure is negative (positive), delta decreases (increases) when the price of the underlying asset increases. Hence market makers that engage in delta-hedging strategies are required to buy (sell) the underlying more aggressively after an increase in the underlying's price. This results into additional positive (negative) market pressure, which increases (decreases) the magnitude of the initial price movement. Thus the initial price movement is dampened (reinforced) when the net gamma exposure is positive (negative). Hence, the relation between net gamma exposure and volatility is expected to be negative. This relationship also implies that risk-averse investors also tend to be averse towards negative net gamma exposure, and hence demand additional compensation in the form of higher expected returns to hold such stocks. On the other hand, stocks with positive net gamma exposure are considered safer assets. In that case, investors are willing to pay higher prices, and accept lower expected returns.

To test this relationship, we regress next month's realized volatility on the net gamma exposure. The estimates are shown in table 15. Column (1) in panel A reports the univariate regression results, and indicates a negative and statistically significant relation between net gamma exposure and next month's realized volatility. The average net gamma exposure coefficient equals -12.92 with a Newey-West t-statistic of -3.58. To give this slope coefficient an economic significance, we can use the average values of the net gamma exposure in the decile portfolios from table 2. The average difference in $\Gamma_{i,t}$ between stocks in decile H and L is equal to 0.0479. Hence, a stock that moves from decile H to decile L decreases its net gamma exposure by 0.0479, which increases its monthly realized volatility by 0.62%. The second column in panel A of table 6 controls for implied volatility, call volume (in %), call open interest (in %), and a range of price-based variables. The average slope on Γ remains economically and statistically significant. The third column of Panel A adds accounting variables as control variables. In this specification, the estimated slope coefficient on Γ remains negative and statistically significant. The findings in panel A are robust to changes in estimation techniques (as shown in panel B-D). Consistent with our hypothesis, the relationship between net gamma exposure and future stock return volatility is negative.

5.1 Hedging versus private information

We have shown that the net gamma exposure negatively predicts the realized volatility in the next month. We argue that this is due to option market makers that aim to remain delta-neutral, and hence hedge their exposure away, thereby creating additional price pressure. One alternative explanation is option trading based on private information: if investors possess private information and trade on this in the option market, then they would buy (sell) options when they expect stock volatility to increase (decrease). To distinguish between the two different channels, we decompose the net gamma exposure by following Ni et al. (2021): one component of the net gamma exposure is due to positions that already existed τ days ago and one component that is created between day $t-\tau$ and day t[3]:

$$\Gamma(i,t) = \underbrace{\Gamma(i,t-\tau,S_t)}_{\text{"Old positional Gamma"}} + \underbrace{[\Gamma_{i,t} - \Gamma(i,t-\tau,S_t)]}_{\text{"Information Gamma"}} \tag{5}$$

$\Gamma_{i,t-j,S_t}$ denotes the net gamma exposure created using the open interest at time $t-\tau$. The second component, called the "information gamma", indicates the change of the net gamma exposure due to changes in open interest. This specification allows us to distinguish hedge re-balancing from private volatility information. Option positions that existed at period $t-\tau$ are not driven by private information that is obtained after period $t-\tau$. Hence, the first component allows to measure the effect of hedge rebalancing on future volatility. This specification is sufficient when we assume that information is short-lived. When this is not the case, we can further decompose the net gamma exposure by noting that the net gamma exposure of the old positions at $t-\tau$ can also be written as:

$$\Gamma(i,t-\tau,S_t) = \underbrace{\Gamma(i,t-\tau,S_{t-\tau})}_{\text{"Old Gamma"}} + \underbrace{[\Gamma(i,t-\tau,S_t) - \Gamma(i,t-\tau,S_{t-\tau})]}_{\text{"Hedging Gamma"}} \tag{6}$$

The first component indicates the net gamma exposure using positions established at time $t-\tau$, using the stock price at $t-\tau$. The first component equals the change in the net gamma exposure due to changes in the stock price from $S_{t-\tau}$ to S_t, which can not come from volatility information acquired by traders between $t-\tau$ and t. We use this decomposition to identify whether the effect of the net gamma exposure on volatility is driven by private information or due to hedge re-balancing.

[3]We set $\tau = 5$ following Ni et al. (2021)

We again regress the next month's realized volatility on the net gamma exposure, and its components. Table 17 shows the estimates. In column (1) of panel A, we show the effect of net gamma exposure on realized volatility, as we have shown before in table 15. In column (2), we regress the realized volatility on the old positional gamma and the information gamma. We find that the coefficient of the old positional gamma is negative and statistically significant (t-stat is -4.57), whereas the coefficient on the information gamma is positive and not statistically significant. In column (3) of panel A, we decompose the net gamma exposure even further. The information gamma coefficient remains statistically insignificant. We find that the old gamma negatively predicts future realized volatility. More important, the coefficient on the hedging gamma is negative and statistically significant (t-value is -2.60). Our results are qualitatively similar in panels B-D, where we use other estimation methods. The findings suggest that the negative relationship between the gamma exposure and realized volatility is not driven by private information, but rather by hedge re-balancing. Thus there is a non-informational channel through which the option markets have a pervasive influence on underlying stock prices.

5.2 Future trading volume

Option market makers need to hedge their exposure in order to remain delta-neutral. When gamma becomes larger in absolute value, the option market maker needs to trade more aggressively to achieve delta-neutrality. Hence, one implication of gamma-hedging is that stocks with a high absolute gamma exposure predicts future trading volume positively since the dollar amount that needs to be hedged will increase. We regress the percentage change in stock trading volume on the absolute net gamma exposure. The results are shown in table 16. In panel A of table 16 we show the estimates from Fama-Macbeth (1973) regressions using value-weighted observations. Column (1) shows the univariate regression results. We find that larger (absolute) net gamma exposures positively predicts higher trading volumes in the next month. This estimate is statistically significant, with a t-statistics of 5.69. In column (2) and (3) we include multiple control variables in our estimation. We find that our estimate of the effect of the absolute gamma exposure on trading volume remains robust to the inclusion of control variables. In the remaining panels, we use different estimation methodology. We find that all estimates of the effect of absolute gamma on future trading volume remains positive and statistically significant, consistent with our hypothesis.

6 Conclusion

In this study, we examine the relation between the net gamma exposure and the cross-section of expected returns over the sample period of January 1996 to December 2021. We document a significant negative relationship between the net gamma exposure in the equity option market and future stock returns. These results are consistent with the hypothesis that stocks with negative hedging pressure can exacerbate stock volatility, whereas positive hedging pressure acts as a volatility dampener. Risk-averse investors would demand extra compensation in the form of higher expected returns to hold stocks with a negative net gamma exposure. Stocks with high positive net gamma exposure, on the other hand, are perceived as relatively safer assets, hence investors are willing to pay higher prices for these stocks and accept lower expected returns.

Our estimates are economically significant. Stocks in the lowest net gamma exposure decile generate, on average, 10.44% higher annual returns compared to stocks in the highest decile. After controlling for well-known factor models, the risk-adjusted return difference remains negative and statistically significant. Furthermore, in bi-variate conditional sorts, we find that a wide-range of well-known cross-sectional effects are not able to explain the gamma exposure premium. The results remain robust in a multivariate setting, using stock-level regressions. We also add several other option-based predictors as control variables, and find that the net gamma exposure is distinct from these predictors.

The negative relation between net gamma exposure and future stock also exists in samples with liquid and large stocks. Furthermore, the gamma premium is found to be significantly more negative during economic downturns and periods of high financial uncertainty, compared to non-recessionary periods, indicating the time-varying nature of the gamma premium. Net gamma exposures also negatively predict extreme returns, consistent with the idea that positive gamma hedging acts as a volatility dampener.

Lastly, we examine the mechanism behind the negative predictability. We show that net gamma exposure negatively predicts future volatility. Stocks with negative gamma exposure are riskier. Hence risk-averse investors require a premium to be compensated for this risk, which explains why we find a negative return-gamma relationship. Furthermore, we find that hedge re-balancing, not trading on private information, is explaining why net gamma exposure is negatively related to future volatility. Hence, the predictability stems from a non-informational channel via which stock options affect stock returns.

7 Tables and Figures

Table 1: **Descriptive statistics:** This table reports the descriptive statistics of our main variables. The sample consists of stocks listed on NYSE/AMEX/NASDAQ with share code 10 or 11. We exclude stocks with a market capitalization below the 20th NYSE percentile (micro-caps) and prices below $5 as of the portfolio formation. Panel A reports the time-series average of the cross-sectional mean, standard deviation, and quantiles of each variable. Panel B reports the time series average of the cross-sectional correlations of these variables. The sample runs from February 1996 till December 2021.

Panel A: Cross-sectional summary statistics

Variable	Mean	Std	P1	P25	Median	P75	P99
Γ	0.92	2.98	-2.81	0.05	0.41	1.23	8.84
IV	0.47	0.19	0.19	0.33	0.43	0.56	1.08
Call Vol.	0.64	0.20	0.08	0.52	0.65	0.78	1.00
Call OI	0.61	0.17	0.16	0.51	0.62	0.73	0.97
Log(Size)	7.95	1.34	5.86	6.94	7.71	8.75	11.76
RVOL	2.44	1.31	0.72	1.58	2.14	2.97	6.80
VOL	8.86	10.11	1.36	3.76	6.24	11.27	37.48
Mom	18.65	51.49	-55.47	-8.22	10.88	33.96	194.06
MAX	3.07	1.68	0.79	1.96	2.69	3.77	8.68
BM	0.48	0.45	-0.15	0.22	0.39	0.65	1.82
ILQ	0.36	0.88	0.00	0.04	0.13	0.37	3.14

Panel B: Cross-sectional correlations

	Γ	IV	Call Vol.	Call OI	Log(Size)	RVOL	VOL	MOM	MAX	BM	ILQ
Γ	-	-0.11	0.23	0.27	0.15	-0.10	-0.03	0.05	-0.06	-0.02	-0.07
IV	-0.11	-	0.00	-0.03	-0.19	0.62	0.64	0.00	0.57	-0.07	0.25
Call Vol.	0.23	0.00	-	0.54	-0.03	0.02	0.04	0.03	0.07	0.03	0.06
Call OI	0.27	-0.03	0.54	-	-0.07	0.02	0.02	0.01	0.02	0.03	0.09
log(Size)	0.15	-0.19	-0.03	-0.07	-	-0.14	-0.14	0.02	-0.13	-0.06	-0.16
RVOL	-0.10	0.62	0.02	0.02	-0.14	-	0.60	0.00	0.87	-0.07	0.17
VOL	-0.03	0.64	0.04	0.02	-0.14	0.60	-	0.10	0.57	-0.09	0.14
MOM	0.05	0.00	0.03	0.01	0.02	0.00	0.10	-	0.00	-0.04	-0.12
MAX	-0.06	0.57	0.07	0.02	-0.13	0.87	0.57	0.00	-	-0.07	0.16
BM	-0.02	-0.07	0.03	0.03	-0.06	-0.07	-0.09	-0.04	-0.07	-	0.06
ILQ	-0.07	0.25	0.06	0.09	-0.16	0.17	0.14	-0.12	0.16	0.06	-

Figure 1: **Net gamma exposure coverage:** This figure shows the coverage of the OptionMetrics Γ data relative to the CRSP sample. The solid black line represents the fraction of stocks with non-missing Γ data relative to the number of stocks in the CRSP sample. The solid grey shows the market capitalization of firms with non-missing Γ data relative to the market capitalization of the CRSP universe. The sample runs from January 1996 till December 2021.

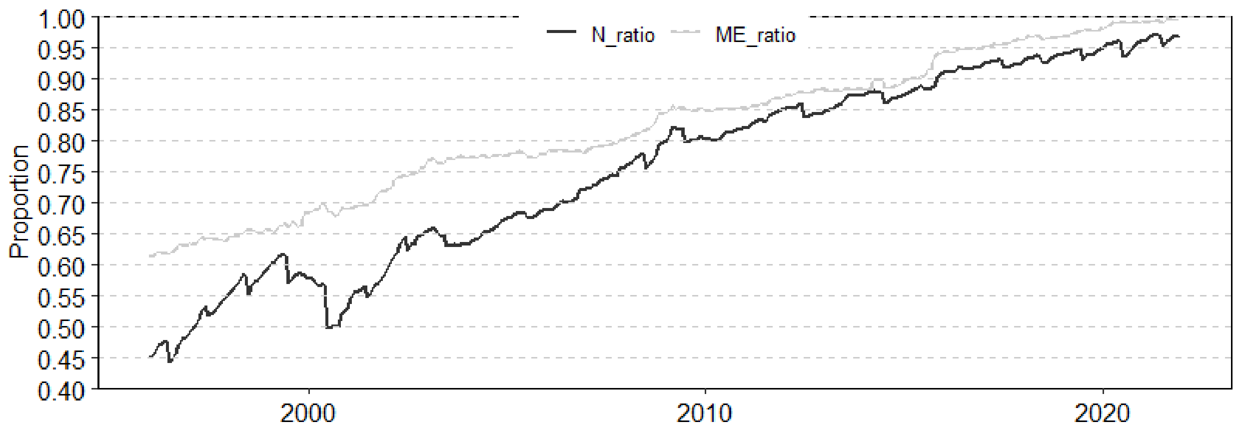

Figure 2: **Net gamma exposure cross-sectional distribution over time:** This figure shows the distribution of the net gamma exposure over time. The 10th, 25th, 50th (median), 75th, and 90th percentiles of the net gamma exposure are shown over time. The sample runs from January 1996 till December 2021.

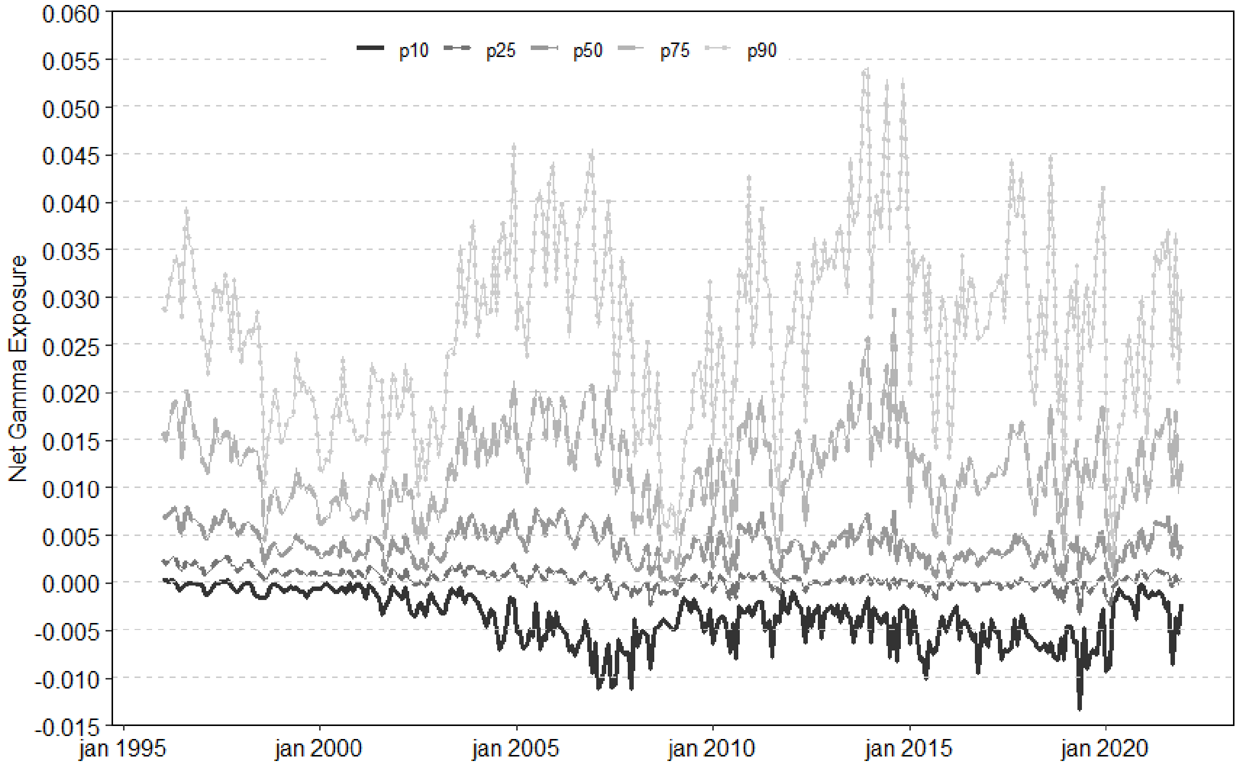

Table 2: **Performance of decile portfolios sorted on the net gamma exposure:** This table reports the performance of decile portfolios formed on the basis of the net gamma exposure (Γ), which measures the total outstanding gamma divided by the average daily dollar trading volume. At the end of month t we sort stocks into ten portfolios based on their Γ, and hold this portfolio during month $t+1$. Panel A (B) presents the results for value-weighted portfolios whereby the breakpoints are based on the full sample (NYSE universe). Stocks with prices above \$5 and microcaps as of the portfolio formation are excluded. We report the average Γ, the return ("R") in percentages, the Fama-French-Carhart four-factor alpha ("α_{3FM}"), the Fama-French-Carhart five-factor alpha ("α_{5F}"), the Fama-French-Carhart six-factor alpha ("α_{5FM}"), Hou, Xue, and Zhang's extended q-factor model alpha ("α_{5Q}"), and augmented with momentum ("α_{5QM}") for each portfolio. The row labeled "L-H" is the self-financing high-minus-low portfolio, which reports the difference in between portfolio H and portfolio L. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1996 and December 2021 with share code 10 or 11. Newey-West t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	Panel A: Full sample breakpoints							**Panel B: NYSE-breakpoints**						
	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q5}	α_{Q5M}	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q5}	α_{Q5M}
L	-0.01***	1.45***	0.66***	0.56***	0.66***	0.58***	0.58***	-0.01***	1.47***	0.68***	0.58***	0.68***	0.60***	0.60***
	(-11.53)	(5.64)	(4.47)	(4.13)	(4.79)	(3.24)	(3.93)	(-11.46)	(5.76)	(4.61)	(4.27)	(4.88)	(3.29)	(3.94)
2	-0.00***	1.25***	0.36***	0.27**	0.35***	0.38***	0.38***	-0.00***	1.25***	0.36***	0.26*	0.35***	0.39***	0.39***
	(-6.32)	(4.74)	(3.42)	(2.14)	(3.39)	(3.16)	(3.59)	(-5.78)	(4.62)	(3.26)	(1.88)	(3.18)	(3.00)	(3.56)
3	0.00***	1.09***	0.22**	0.26*	0.34***	0.34**	0.34**	0.00***	1.10***	0.20**	0.24**	0.30***	0.33***	0.33***
	(4.30)	(3.85)	(2.03)	(1.93)	(2.79)	(2.27)	(2.58)	(4.31)	(3.70)	(1.99)	(2.13)	(2.95)	(3.03)	(3.25)
4	0.00***	1.06***	0.11	0.13	0.17	0.27	0.27	0.00***	0.98***	0.07	0.08	0.13	0.17	0.17
	(11.70)	(3.46)	(0.71)	(0.97)	(1.19)	(2.10)	(2.05)	(10.05)	(3.82)	(0.53)	(0.59)	(0.93)	(1.23)	(1.28)
5	0.00***	1.03***	0.10	0.18	0.21	0.20	0.20	0.00***	1.05***	0.10	0.20	0.21	0.15	0.15
	(16.30)	(3.50)	(0.86)	(1.17)	(1.47)	(1.41)	(1.47)	(13.60)	(3.14)	(0.70)	(1.23)	(1.31)	(1.09)	(1.10)
6	0.01***	0.98***	0.06	0.09	0.12	0.16	0.16	0.01***	0.99***	0.08	0.04	0.07	0.07	0.07
	(19.42)	(3.67)	(0.47)	(0.81)	(1.03)	(1.35)	(1.33)	(16.38)	(3.72)	(0.77)	(0.43)	(0.70)	(0.59)	(0.59)
7	0.01***	0.97***	0.06	0.09	0.09	0.08	0.08	0.01***	1.02***	0.13	0.14	0.15	0.19*	0.19*
	(20.91)	(3.15)	(0.57)	(0.73)	(0.78)	(0.72)	(0.72)	(18.41)	(3.70)	(1.28)	(1.34)	(1.46)	(1.73)	(1.73)
8	0.01***	0.94***	0.09	0.10	0.11	0.16	0.16	0.01***	0.86***	-0.00	0.01	0.00	-0.03	-0.03
	(20.91)	(3.58)	(0.94)	(1.05)	(1.07)	(1.63)	(1.64)	(19.45)	(3.21)	(-0.01)	(0.10)	(0.01)	(-0.23)	(-0.23)
9	0.02***	0.73***	-0.13	-0.06	-0.11	-0.13	-0.13	0.02***	0.77***	-0.08	-0.07	-0.12	-0.17	-0.17
	(20.31)	(2.77)	(-1.51)	(-0.64)	(-1.17)	(-1.11)	(-1.21)	(19.47)	(3.09)	(-0.90)	(-0.69)	(-1.31)	(-1.41)	(-1.49)
H	0.04***	0.58***	-0.13	-0.23***	-0.27***	-0.34***	-0.34***	0.04***	0.58***	-0.12	-0.22***	-0.25***	-0.31***	-0.31***
	(18.88)	(2.73)	(-1.61)	(-2.99)	(-3.65)	(-3.67)	(-3.71)	(18.89)	(2.72)	(-1.23)	(-2.42)	(-2.79)	(-3.01)	(-3.03)
H-L	0.05***	-0.87***	-0.79***	-0.79***	-0.93***	-0.92***	-0.92***	0.05***	-0.88***	-0.80***	-0.80***	-0.94***	-0.91***	-0.91***
	(17.04)	(-5.29)	(-4.87)	(-4.42)	(-5.40)	(-3.62)	(-4.33)	(17.54)	(-5.25)	(-4.64)	(-4.31)	(-5.13)	(-3.50)	(-4.13)

Table 3: **Persistence of the net gamma exposure:** This table presents transition probabilities for net gamma exposure. At each month t, all stocks are sorted into deciles based on an ascending ordering of net gamma exposure. The procedure is repeated in month $t+1$ and $t+12$. Portfolio L (H) is the portfolio of stocks with the lowest (highest) net gamma exposure. For each decile in month t, the percentage of stocks that also fall into each of the month $t+1$ (panel A) or $t+12$ (panel B) decile is calculated. Table presents the time-series averages of the estimated transition probabilities. Each row corresponds to a different month t portfolio and each column corresponds to a different month $t+1$ or $t+12$ portfolio. The sample runs from February 1996 till December 2021.

	L	2	3	4	5	6	7	8	9	H
Panel A: 1-month transition matrix										
L	42.17	16.02	7.13	5.77	5.55	5.45	5.37	4.71	4.38	3.85
2	15.74	27.57	16.90	10.87	7.87	6.03	5.01	3.98	3.06	2.18
3	7.29	18.53	26.95	17.44	10.75	6.64	4.67	3.39	2.26	1.40
4	5.98	11.20	19.29	21.58	15.48	10.48	6.91	4.47	2.85	1.53
5	5.94	7.80	11.50	17.84	18.43	14.97	10.27	6.84	4.20	2.24
6	5.55	5.97	7.25	11.05	16.84	17.77	15.11	10.60	6.61	3.27
7	4.95	4.75	4.64	7.16	11.80	16.79	18.57	15.70	10.66	5.16
8	4.86	3.83	3.14	4.52	7.36	12.10	17.54	20.44	16.99	9.43
9	4.28	2.76	2.07	2.56	4.16	6.97	11.60	19.91	26.20	19.83
H	3.25	1.56	1.12	1.21	1.77	2.80	4.95	9.94	22.79	51.11
Panel B: 12-month transition matrix										
L	16.91	11.44	8.48	8.17	9.16	9.37	9.52	9.62	9.85	9.88
2	10.88	13.57	13.59	11.84	10.68	9.53	8.66	7.36	6.50	5.39
3	8.29	13.68	17.26	14.31	11.27	9.34	7.46	6.18	4.53	3.66
4	8.28	11.68	14.99	14.71	12.42	10.59	8.40	6.99	5.42	3.78
5	8.50	10.83	11.72	12.95	12.52	11.26	10.26	8.73	6.57	5.08
6	8.70	9.61	10.02	10.94	11.58	11.55	11.56	10.28	8.72	6.58
7	9.38	8.68	7.99	9.23	10.53	11.70	12.17	11.94	10.87	8.40
8	9.22	7.85	6.84	7.59	9.04	10.62	12.19	13.40	13.45	11.26
9	10.03	6.91	5.26	5.92	7.35	9.37	11.13	13.46	16.25	16.98
H	9.82	5.77	3.83	4.33	5.44	6.66	8.65	12.05	17.84	28.99

Table 4: **Average stock characteristics:** This table reports the estimated slope coefficients from the regressions of the net gamma exposure (Γ) on stock-level characteristics and risk factors. Panel regressions are run for the following econometric specification and nested versions thereof: $\Gamma_{i,t} = \gamma_{0,t} + \gamma_{1,t}X_{i,t} + \epsilon_{i,t}$. With $\Gamma_{i,t}$ being the net gamma exposure of stock i in month t and $X_{i,t}$ is a collection of stock-specific variables observable at time t stock i: The market beta (MKT), 1-month realized volatility (RVOL), Amihud's illiquidity (ILQ), Implied volatility (IV), the book-to-market ratio (BM), return on equity (ROE), operating profitability (OP), cash profitability (CP), investments over assets (IA), and 1-year momentum (MOM). Both stock - and time fixed effects are included in the panel regressions. The sample spans the period February 1996 to December 2021. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Γ_{t-1}	0.415***											0.407***
	(18.94)											(18.17)
MKT		-0.007***										-0.003***
		(-7.22)										(-3.28)
RVOL			-0.317***									-0.270***
			(-9.11)									(-9.03)
ILQ				0.032								0.027
				(1.49)								(1.17)
IV					-0.010***							0.009***
					(-3.66)							(3.55)
BM						-0.002						-0.001
						(-1.25)						(-0.93)
ROE							-0.000					-0.000
							(-0.24)					(-0.73)
OP								-0.000***				-0.000***
								(-5.08)				(-4.13)
CP									0.000*			0.000
									(1.89)			(1.43)
IA										0.000		0.000
										(0.23)		(1.35)
MOM											0.002**	-0.000
											(2.58)	(-0.29)

Table 5: **Bivariate portfolio analysis with conditional sorts:** This table shows the Fama-French, augmented with momentum, 6-factor alpha obtained from conditional bivariate sorts. Stocks are first sorted into deciles based on one control variable, and then stocks within each control variable decile are further sorted into value-weighted deciles based on Γ. The control variables are defined in Section 2.2. The last row presents the differences in 6-factor alpha between Decile 10 (High) and Decile 1 (Low). Newey-West adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	MKT	ME	BM	BM_m	OP	CP	IA	NSI	CSI	ROE	MOM	SREV	VOL	IVOL	RV	ILQ	MAX	IV	CVOL	COI
L	0.71***	0.63***	0.66***	0.70***	0.58***	0.65***	0.72***	0.67***	0.70***	0.64***	0.68***	0.56***	0.69***	0.73***	0.68***	0.67***	0.70***	0.72***	0.71***	0.58***
	(4.52)	(3.95)	(4.00)	(3.90)	(3.50)	(4.12)	(4.14)	(4.17)	(3.49)	(4.40)	(3.82)	(3.60)	(4.37)	(4.32)	(3.81)	(3.92)	(3.49)	(4.49)	(4.06)	(3.62)
2	0.36***	0.37***	0.35**	0.40***	0.50***	0.48***	0.39***	0.38***	0.29**	0.32***	0.37***	0.34***	0.52***	0.37***	0.31**	0.33***	0.29**	0.35***	0.26**	0.48***
	(2.94)	(2.71)	(2.63)	(2.90)	(3.61)	(3.22)	(2.60)	(3.35)	(2.29)	(3.32)	(3.24)	(2.81)	(3.55)	(2.75)	(2.50)	(2.68)	(2.29)	(2.77)	(2.41)	(3.20)
3	0.28**	0.20	0.27**	0.22**	0.27**	0.14	0.06	0.26*	0.50***	0.31**	0.27**	0.45***	0.25**	0.23**	0.30**	0.25**	0.50***	0.23*	0.41***	0.22**
	(2.26)	(1.48)	(2.42)	(2.46)	(2.43)	(1.40)	(0.52)	(1.91)	(3.38)	(2.42)	(2.24)	(3.18)	(2.19)	(2.38)	(2.65)	(2.02)	(3.38)	(1.76)	(3.13)	(2.35)
4	0.28**	0.34**	0.32*	0.17	0.17	0.38**	0.13	0.18	0.05	0.17	0.27	0.08	0.16	0.03	0.19	0.25**	0.05	0.15	0.35**	0.36**
	(2.10)	(2.47)	(1.81)	(1.09)	(1.12)	(1.97)	(0.93)	(1.18)	(0.30)	(1.21)	(1.43)	(0.98)	(1.58)	(0.18)	(1.42)	(2.18)	(0.30)	(1.23)	(2.46)	(2.72)
5	0.09	0.05	0.22	0.15	0.19*	0.16	0.22	0.13	0.29**	0.25	0.10	0.01	0.30**	0.41**	-0.01	0.21*	0.29**	0.25**	0.30**	0.43**
	(0.74)	(0.53)	(1.56)	(1.11)	(1.78)	(1.30)	(1.37)	(0.80)	(2.11)	(1.57)	(0.97)	(0.07)	(2.24)	(2.56)	(-0.09)	(1.85)	(2.11)	(2.05)	(2.08)	(2.52)
6	0.09	0.08	0.22***	0.10	0.12	0.07	0.12	0.19**	0.19	0.06	0.17*	0.17	0.12	0.13	0.31***	-0.01	0.19	0.02	0.06	-0.01
	(0.93)	(0.70)	(2.76)	(0.89)	(1.21)	(0.87)	(1.58)	(2.04)	(1.56)	(0.71)	(1.67)	(1.48)	(1.09)	(0.84)	(3.90)	(-0.07)	(1.56)	(0.24)	(0.53)	(-0.12)
7	0.18**	-0.10	0.03	0.16*	0.04	0.10	0.10	0.13	0.11	0.19	0.11	0.18**	0.20**	-0.04	0.18**	-0.02	0.11	0.20**	0.08	0.12
	(2.01)	(-1.11)	(0.24)	(1.69)	(0.31)	(0.82)	(0.80)	(1.37)	(1.18)	(1.26)	(0.91)	(2.26)	(2.05)	(-0.37)	(2.40)	(-0.25)	(1.18)	(2.28)	(0.79)	(0.98)
8	0.10	-0.21**	-0.05	0.00	0.07	0.01	0.06	0.08	0.01	0.08	0.09	-0.01	-0.05	-0.01	-0.10	-0.24**	0.01	0.02	0.07	0.01
	(1.53)	(-1.79)	(-0.74)	(0.05)	(0.98)	(0.07)	(0.64)	(1.12)	(0.14)	(1.03)	(0.83)	(-0.08)	(-0.44)	(-0.16)	(-0.87)	(-2.14)	(0.14)	(0.23)	(0.84)	(0.06)
9	-0.23**	-0.04	-0.20**	-0.22**	-0.25**	-0.15*	-0.13	-0.23***	-0.12	-0.20	-0.20**	-0.05	-0.17*	-0.08	-0.18*	-0.05	-0.12	-0.16**	-0.22**	-0.09
	(-2.37)	(-0.25)	(-2.05)	(-2.52)	(-2.05)	(-1.65)	(-1.20)	(-2.56)	(-1.46)	(-1.68)	(-2.25)	(-0.52)	(-1.88)	(-0.75)	(-2.24)	(-0.37)	(-1.46)	(-2.02)	(-2.04)	(-0.83)
H	-0.28***	-0.36***	-0.21**	-0.22**	-0.18**	-0.25***	-0.31***	-0.24***	-0.25**	-0.23**	-0.22***	-0.24***	-0.29***	-0.34***	-0.31***	-0.39***	-0.25**	-0.31***	-0.27***	-0.28***
	(-2.89)	(-3.10)	(-2.35)	(-2.57)	(-2.25)	(-2.94)	(-4.03)	(-2.83)	(-2.35)	(-2.64)	(-2.73)	(-3.87)	(-2.95)	(-3.50)	(-3.71)	(-3.74)	(-2.35)	(-3.85)	(-3.52)	(-3.48)
H-L	-1.00***	-0.99***	-0.87***	-0.92***	-0.76***	-0.90***	-1.03***	-0.92***	-0.95***	-0.87***	-0.90***	-0.80***	-0.98***	-1.07***	-1.00***	-1.06***	-0.95***	-1.03***	-0.97***	-0.86***
	(-4.90)	(-4.20)	(-4.53)	(-4.38)	(-3.86)	(-4.72)	(-5.15)	(-4.59)	(-4.28)	(-4.63)	(-4.59)	(-4.58)	(-4.85)	(-4.95)	(-4.33)	(-4.43)	(-4.28)	(-5.23)	(-4.48)	(-4.12)

Table 6: **Stock-level regressions:** This table reports estimates from regressing the next month's excess returns on the Γ and a set of predictive variables using Fama and MacBeth (1973) regressions and panel regressions. Observations are both vale-weighted (panel A and C) and equally-weighted (panel B and D). Regression specification (1) has no control variables. Regression specification (2) adds implied volatility (IV), Call Volume / Total option volume (Call Vol.), Call open interest / Total option open interest (Call OI), and a range of price-based control variables: market beta, total return volatility, idiosyncratic volatility, realized volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Specification (3) subsequently adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. All coefficients are multiplied by 100. The constant is omitted for brevity. Both time - and firm fixed effects are included in the panel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Value-weighted FMB			**B: Equal-weighted FMB**			**C: Value-weighted Panel**			**D: Equal-weighted Panel**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Γ	-18.65***	-18.08***	-16.78***	-17.97***	-12.08***	-12.37***	-11.33***	-10.58***	-9.58***	-12.53***	-8.93***	-8.18***
	(-3.80)	(-3.21)	(-3.48)	(-3.15)	(-3.02)	(-3.21)	(-4.90)	(-3.60)	(-3.24)	(-5.64)	(-3.72)	(-3.49)
IV		0.33***	0.56***		0.79***	0.90***		2.43***	2.49***		2.24***	2.59***
		(4.42)	(3.31)		(6.59)	(6.03)		(3.47)	(3.01)		(8.68)	(7.96)
Call Vol.		-0.08	-0.12		0.41**	0.45**		0.07	0.05		0.75***	0.73***
		(-0.34)	(-0.46)		(2.15)	(2.45)		(0.24)	(0.15)		(5.25)	(5.22)
Call OI		0.15	0.14		0.35**	0.28		0.69	0.42		1.01***	0.79***
		(0.28)	(0.29)		(2.03)	(1.62)		(1.59)	(0.94)		(5.19)	(4.02)
Obs.	406K	391K	363K	406K	391K	363K	406K	391K	363K	406K	391K	363K
R^2	1.78%	16.35%	19.17%	0.43%	10.01%	11.49%	0.10%	0.46%	0.61%	0.02%	0.97%	1.15%
Price Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Acc. Controls	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Table 7: **Predicting extreme returns:** This table reports estimates from regressing the next month's 'extreme return' indicator on the Γ and a set of predictive variables using panel logit regressions. In panels A, B and C, the indicator variable takes value one when the next month's absolute return is larger than 25%, 50%, and 75%, else zero, respectively. Regression specification (1) has no control variables. Regression specification (2) adds call volume / total option volume (Call Vol.) and call open interest / total option open interest (Call OI), and a range of price-based control variables: 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Specification (3) subsequently adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. Time fixed effects are included. One-way cluster (by date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: $I[R_{t+1} > 25\%]$			**B:** $I[R_{t+1} > 50\%]$			**C:** $I[R_{t+1} > 75\%]$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Gamma	-4.21***	-11.55***	-11.55***	-4.03***	-13.36***	-13.14***	-2.85**	-11.53***	-12.63***
	(-14.76)	(-15.72)	(-14.43)	(-5.51)	(-5.54)	(-4.91)	(-2.10)	(-2.32)	(-2.26)
MOM		0.12***	0.11***		0.12***	0.11***		0.08***	0.04
		(14.26)	(10.68)		(8.68)	(6.54)		(2.94)	(0.98)
SREV		-0.95***	-0.97***		-1.97***	-1.99***		-2.89***	-2.66***
		(-16.88)	(-15.64)		(-13.60)	(-11.85)		(-9.90)	(-7.78)
Call. Vol		0.33***	0.32***		0.65***	0.70***		1.03***	1.29***
		(7.30)	(6.53)		(5.06)	(4.87)		(3.77)	(4.14)
Call OI		0.12**	0.07		0.01	-0.06		0.11	-0.11
		(2.25)	(1.11)		(0.03)	(-0.36)		(0.34)	(-0.30)
Obs.	406K	391K	363K	406K	391K	363K	406K	391K	363K
Acc. Controls	NO	NO	YES	NO	NO	YES	NO	NO	YES

Figure 3: **Gamma premium over time:** This figure shows the gamma premium over time. The solid line depicts the six-month moving average of the monthly slope coefficient of the net gamma exposure (Table 6 column 1). The grey-shaded area indicate periods in which the NBER recession indicator equals 1 (i.e. the economy is in a recession). The sample runs from February 1996 till December 2021.

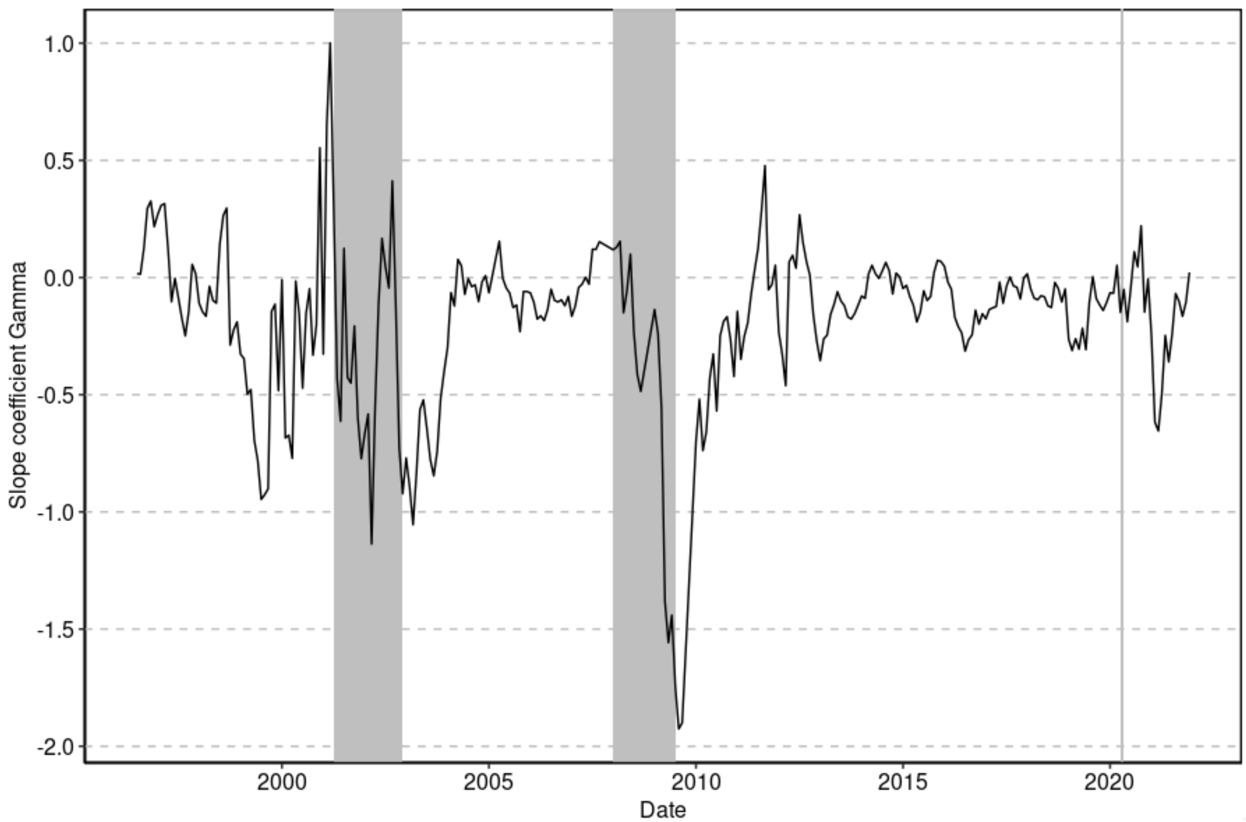

Table 8: **Time-varying gamma premium:** this table presents the estimates from regressing the estimated gamma premium (from table 6 column 1) on a set of macroeconomic indicators: CFNAI takes value 1 if the Chicago Fed National Activity Index is above its median, else 0. The VIX takes value 1 if the VIX is above its median, else 0. Sentiment takes value 1 if the Sentiment index of Baker and Wurgler (2006) is above its median, else 0. FUNC takes value 1 if the financial uncertainty index of Jurado et al. (2015) is above its median, else 0. Newey-West t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	(1)	(2)	(3)	(4)	(5)
CFNAI	0.096**				0.072***
	(3.32)				(6.51)
VIX		−0.006			0.026*
		(-0.83)			(1.80)
Sentiment			0.176**		0.212***
			(2.02)		(3.26)
FUNC				−0.820**	−1.617**
				(-2.64)	(-2.46)
Obs.	302	302	302	302	302
R^2	1.3%	0.2%	1.2%	2.0%	5.5%

Table 9: **Spanning regressions:** The table shows the estimated intercepts α (annualized in percentages), slopes, t-statistics for the intercepts $t(a)$, R^2, and residual standard errors $s(e)$ from spanning regressions of each of the factors of a model on the 2-by-3 gamma factor. The factor models are the three-factor model of Fama and French (1993), the five-factor model of Fama and French (2015), the cash-based five-factor model of Fama and French (2018), and Hou et al. (2015), all augmented with the momentum factor. The table also shows the maximum squared Sharpe ratio ($Sh^2(f)$) and the marginal contribution of the gamma factor to a model's $Sh^2(f)$, that is, $a^2/s^2(e)$. Panel A uses long-minus-short factors. Panel B (C) uses the long (short) legs in spanning regressions. The data runs from February 1996 till December 2021.

A: Long-Short	$\hat{\alpha}$	Mkt	SMB	HML	RMW	CMA	UMD	IA	ROE	$t(a)$	R^2	$s(e)$	Sh_f^2	$\hat{\alpha}^2/s^2(e)$
FF3	3.11	0.066	0.164	-0.183			-0.262			2.260	0.414	0.018	0.073	0.021
FF5	4.06	0.039	0.093	-0.069	-0.196	-0.109	-0.255			3.122	0.449	0.018	0.124	0.037
FF5$_c$	4.09	0.032	0.102	-0.098	-0.203	-0.094	-0.252			3.096	0.444	0.018	0.131	0.037
Q	4.64	0.036	0.124				-0.222	-0.130	-0.216	3.209	0.416	0.018	0.238	0.046
B: Long	$\hat{\alpha}$	Mkt	SMB	HML	RMW	CMA	UMD	IA	ROE	$t(a)$	R^2	$s(e)$	Sh_f^2	$\hat{\alpha}^2/s^2(e)$
FF3	2.18	0.787	0.781	-0.157			-0.351			2.506	0.956	0.011	0.079	0.026
FF5	2.84	1.009	0.910	-0.027	-0.253	-0.241	-0.360			3.596	0.960	0.011	0.129	0.047
FF5$_c$	2.83	0.984	0.893	-0.031	-0.220	-0.226	-0.359			3.532	0.959	0.011	0.135	0.046
Q	3.31	0.987	0.899				-0.342	-0.204	-0.297	3.776	0.958	0.011	0.286	0.061
C: Short	$\hat{\alpha}$	Mkt	SMB	HML	RMW	CMA	UMD	IA	ROE	$t(a)$	R^2	$s(e)$	Sh_f^2	$\hat{\alpha}^2/s^2(e)$
FF3	0.20	-1.069	1.609	0.456			-0.031			0.208	0.921	0.013	0.040	0.000
FF5	0.61	-0.979	1.438	0.068	0.146	0.337	-0.074			0.695	0.929	0.012	0.053	0.002
FF5$_c$	0.67	-0.791	1.228	0.056	0.252	0.273	-0.090			0.777	0.932	0.012	0.050	0.002
Q	1.00	-0.877	1.357				0.431	0.103	-0.085	1.144	0.927	0.012	0.111	0.005

Table 10: **Sorting on alternative gamma definitions:** This table reports the performance of decile portfolios formed on the basis of Γ. In panel A: Γ is measured with a 1-day implementation lag. In panel B: Γ is measured as the average net gamma exposure within month t. At the end of month t we sort stocks into ten portfolios based on their Γ, and hold this portfolio during month $t+1$. The results are shown for value-weighted portfolios whereby the breakpoints are based on the NYSE universe. Stocks with prices above \$5 and classified as microcaps as of the portfolio formation are excluded. We report the time-series average of the net gamma exposure (Γ), the return ("R") in percentages, the Fama-French-Carhart four-factor alpha ("α_{3FM}"), the Fama-French-Carhart five-factor alpha ("α_{5F}"), the Fama-French-Carhart six-factor alpha ("α_{5FM}"), Hou, Xue, and Zhang's extended q-factor model alpha ("α_{5Q}"), and augmented with momentum ("α_{5QM}") for each portfolio. The row labeled "L-H" is the self-financing high-minus-low portfolio, which reports the difference in between portfolio H and portfolio L. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between February 1996 and December 2021 with share code 10 or 11. Newey-West t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	Panel A: 1-day implementation lag:							**Panel B: Average monthly gamma:**						
	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q5}	α_{Q5M}	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q5}	α_{Q5M}
L	-0.01***	1.36***	0.53***	0.48***	0.57***	0.51**	0.51***	-0.01***	1.23***	0.40***	0.24*	0.34**	0.38**	0.38**
	(-11.79)	(5.24)	(3.37)	(3.11)	(3.72)	(2.47)	(2.94)	(-9.86)	(4.64)	(2.89)	(1.73)	(2.48)	(2.09)	(2.59)
2	-0.00***	1.06***	0.19*	0.13	0.21**	0.28**	0.28**	-0.00***	1.02***	0.14	0.15	0.22*	0.29**	0.29**
	(-5.75)	(3.71)	(1.84)	(1.10)	(2.07)	(2.22)	(2.40)	(-4.59)	(3.61)	(1.22)	(1.10)	(1.91)	(2.19)	(2.43)
3	0.00***	1.06***	0.14	0.10	0.18	0.23*	0.23*	0.00***	0.98***	0.07	0.08	0.15	0.19	0.19
	(4.51)	(3.55)	(1.16)	(0.74)	(1.50)	(1.85)	(1.97)	(5.22)	(3.22)	(0.65)	(0.61)	(1.47)	(1.46)	(1.65)
4	0.00***	1.19***	0.30**	0.32***	0.37***	0.43***	0.43***	0.00***	1.04***	0.18	0.22*	0.29**	0.35***	0.35***
	(10.18)	(4.93)	(2.45)	(2.66)	(3.01)	(2.74)	(2.90)	(11.55)	(3.26)	(1.30)	(1.87)	(2.64)	(2.94)	(3.07)
5	0.00***	0.98***	0.03	0.11	0.13	0.13	0.13	0.00***	1.12***	0.23*	0.35**	0.38***	0.33***	0.34**
	(13.67)	(3.22)	(0.27)	(0.93)	(1.06)	(1.09)	(1.07)	(15.88)	(3.51)	(1.70)	(2.48)	(2.67)	(2.69)	(2.63)
6	0.01***	0.95***	0.00	0.02	0.03	-0.02	-0.02	0.01***	1.09***	0.10	0.13	0.12	0.05	0.05
	(16.47)	(3.38)	(0.03)	(0.30)	(0.34)	(-0.17)	(-0.17)	(18.85)	(4.20)	(0.82)	(1.08)	(1.09)	(0.49)	(0.50)
7	0.01***	1.04***	0.17	0.14	0.16	0.15	0.15	0.01***	0.91***	0.01	0.05	0.06	0.12	0.12
	(18.46)	(3.77)	(1.49)	(1.39)	(1.56)	(1.49)	(1.48)	(20.03)	(3.08)	(0.06)	(0.43)	(0.53)	(1.01)	(1.03)
8	0.01***	0.85***	-0.03	0.05	0.02	-0.01	-0.01	0.01***	0.87***	0.00	-0.01	-0.00	0.05	0.05
	(19.46)	(3.04)	(-0.27)	(0.49)	(0.21)	(-0.08)	(-0.09)	(19.89)	(3.18)	(0.03)	(-0.11)	(-0.02)	(0.56)	(0.55)
9	0.02***	0.76***	-0.06	-0.08	-0.12	-0.13	-0.13	0.02***	0.85***	0.05	0.09	0.06	-0.01	-0.01
	(19.52)	(3.15)	(-0.66)	(-1.00)	(-1.33)	(-1.14)	(-1.15)	(19.29)	(3.77)	(0.76)	(1.28)	(0.81)	(-0.12)	(-0.12)
H	0.04***	0.63***	-0.09	-0.22**	-0.25***	-0.30***	-0.30***	0.04***	0.70***	-0.05	-0.16**	-0.20***	-0.25***	-0.25***
	(18.75)	(2.99)	(-1.04)	(-2.61)	(-3.19)	(-2.99)	(-2.99)	(17.80)	(3.37)	(-0.69)	(-2.16)	(-2.80)	(-2.92)	(-2.98)
H-L	0.05***	-0.72***	-0.62***	-0.69***	-0.82***	-0.81***	-0.81***	0.05***	-0.53***	-0.46***	-0.40**	-0.54***	-0.63***	-0.63***
	(17.49)	(-3.91)	(-3.65)	(-3.42)	(-4.31)	(-2.98)	(-3.39)	(16.42)	(-3.01)	(-3.11)	(-2.20)	(-3.22)	(-2.71)	(-3.26)

Table 11: **Various sub-samples:** This table reports estimates from regressing monthly excess returns on the Γ and a set of predictive variables using panel regressions, whereby observations are weighted by their 1-month lagged market capitalization. Panel A uses the sample consisting of the largest 1000 firms in terms of market capitalization. Panel B uses the sample consisting of the 1000 most liquid firms according to the illiquidity measure of Amihud (2002). Panel C considers the sample of the top 1000 firms with most option trading volume in a month. Regression specification (1) has no control variables. Regression specification (2) adds market beta, total return volatility, idiosyncratic volatility, realized volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002) as control variable. Regression specification (3) subsequently adds implied volatility (IV), Call Volume / Total option volume (Call Vol.), Call open interest / Total option open interest (Call OI). Specification (4) adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. All coefficients are multiplied by 100. The constant is omitted for brevity. Both time - and firm fixed effects are included in panel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Top 1000 largest:				**B: Top 1000 most liquid:**				**C: Top 1000 most option trading:**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Gamma	-11.36***	-9.89***	-10.84***	-9.78***	-11.41***	-10.01***	-10.91***	-9.90***	-11.54***	-9.82***	-11.14***	-10.12***
	(-4.94)	(-3.68)	(-3.67)	(-3.28)	(-4.97)	(-3.73)	(-3.69)	(-3.32)	(-4.92)	(-3.58)	(-3.60)	(-3.26)
IV			3.78***	3.49**			3.88***	3.56**			4.56***	4.19***
			(2.89)	(2.56)			(2.93)	(2.58)			(3.18)	(2.78)
Call Vol.			0.02	-0.00			0.01	-0.01			-0.03	-0.02
			(0.06)	(-0.01)			(0.03)	(-0.02)			(-0.06)	(-0.04)
Call OI			0.66	0.38			0.64	0.37			0.99	0.64
			(1.39)	(0.78)			(1.32)	(0.75)			(1.63)	(1.03)
Obs.	301K	297K	296K	277K	301K	301K	300k	281K	302K	294K	294K	272K
R^2	0.11%	0.34%	0.42%	0.57%	0.11%	0.40%	0.49%	0.63%	0.11%	0.37%	0.48%	0.62%
Price Controls	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES
Acc. Controls	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES

Table 12: **Stock-level regressions with microcaps and without price filters:** This table reports estimates from regressing the next month's excess returns on the net gamma exposure and a set of predictive variables using Fama and MacBeth (1973) regressions and panel regressions. Observations are both vale-weighted (panel A and C) and equally-weighted (panel B and D). Regression specification (1) has no control variables. Regression specification (2) adds implied volatility (IV), Call Volume / Total option volume (Call Vol.), Call open interest / Total option open interest (Call OI), and a range of price-based control variables: market beta, total return volatility, idiosyncratic volatility, realized volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Specification (3) subsequently adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. All coefficients are multiplied by 100. The constant is omitted for brevity. Both time - and firm fixed effects are included in panel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Value-weighted FMB			**B: Equal-weighted FMB**			**C: Value-weighted Panel**			**D: Equal-weighted Panel**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Gamma	-17.41***	-19.75***	-18.46***	-18.79***	-18.92***	-19.17***	-10.23***	-9.27***	-8.16***	-15.72***	-15.29***	-13.75***
	(-3.52)	(-3.01)	(-3.19)	(-3.10)	(-3.90)	(-3.75)	(-4.63)	(-3.24)	(-2.84)	(-6.14)	(-5.13)	(-4.86)
IV		1.27***	1.12***		0.89***	0.97***		4.00***	3.66***		5.03***	4.55***
		(3.46)	(3.09)		(3.30)	(3.78)		(3.63)	(3.21)		(7.78)	(7.29)
Call Vol.		0.01	-0.03		0.80***	0.78***		0.27	0.24		1.26***	1.26***
		(0.04)	(-0.13)		(5.54)	(5.98)		(0.92)	(0.79)		(8.23)	(8.26)
Call OI		0.05	0.09		0.29**	0.28*		0.50	0.22		1.33***	1.07***
		(0.09)	(0.18)		(2.23)	(1.97)		(1.11)	(0.47)		(6.14)	(5.19)
Obs.	564K	530K	485K	564K	530K	485K	564K	530K	485K	564K	530K	485K
R^2	1.71%	15.23%	17.93%	0.32%	8.16%	9.29%	0.07%	0.44%	0.57%	0.02%	0.88%	0.93%
Price Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Acc. Controls	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Table 13: **Decomposing the net gamma exposure:** This table reports estimates from regressing monthly excess returns on Γ and a set of predictive variables using Fama and MacBeth (1973) regressions and panel regressions. Observations are both vale-weighted (panel A and C) and equally-weighted (panel B and D). The net gamma exposure is decomposed in two different ways. First, the net gamma exposure can be decomposed into an 'near-the-money' component (Γ_{NTM}), 'out-the-money' component (Γ_{OTM}), and 'in-the-money' component (Γ_{ITM}). An option is classified as "near-the-money" whenever the absolute values of the natural log of the ratio of the stock price to the exercise price less than 0.1. When the value exceeds 0.1, a call (put) option is "in-the-money" ("out-the-money"). Vice verse, when this value is below -0.1, a call (put) option is out-the-money (in-the-money). The second decomposition is in terms of option expiration: an option is considered as "fast" when it expires within the next month, else it is classified as "slow". This leads to Γ_{fast} and Γ_{slow} respectively. All coefficients are multiplied by 100. The constant is omitted for brevity. Both time - and firm fixed effects are included in panel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Value-weighted FMB			**B: Equal-weighted FMB**			**C: Value-weighted Panel**			**D: Equal-weighted Panel**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Γ	-16.78***			-12.37***			-9.58***			-8.18***		
	(-3.48)			(-3.21)			(-3.24)			(-3.49)		
Γ_{NTM}		-13.25***			-11.05***			-11.06***			-9.08***	
		(-4.58)			(-3.88)			(-3.43)			(-3.78)	
Γ_{OTM}		-29.17***			-26.35***			-47.20***			-34.88***	
		(-3.62)			(-4.40)			(-3.67)			(-6.34)	
Γ_{ITM}		-34.83*			-1.59			-33.37*			2.62	
		(-1.91)			(-0.14)			(-1.89)			(0.24)	
Γ_{fast}			18.62			5.64			-4.95			-8.21**
			(0.60)			(0.34)			(-1.04)			(-2.54)
Γ_{slow}			-26.25***			-14.39***			-13.13***			-8.15***
			(-3.40)			(-3.36)			(-3.25)			(-2.82)
IV	1.32***	1.38***	1.13***	1.79***	1.82***	1.81***	3.72***	3.71***	3.70***	5.30***	5.26***	5.30***
	(3.31)	(3.62)	(2.81)	(6.03)	(5.93)	(5.82)	(3.01)	(2.98)	(2.98)	(7.96)	(7.89)	(7.96)
Call Vol.	-0.12	-0.15	-0.18	0.45**	0.47**	0.43**	0.05	0.06	0.01	0.73***	0.75***	0.73***
	(-0.46)	(-0.55)	(-0.64)	(2.45)	(2.65)	(2.45)	(0.15)	(0.19)	(0.04)	(5.22)	(5.32)	(5.21)
Call OI	0.14	0.56	0.31	0.28	0.39**	0.33**	0.42	1.36***	0.52	0.79***	1.04***	0.79***
	(0.29)	(1.17)	(0.61)	(1.62)	(2.19)	(2.07)	(0.94)	(3.12)	(1.16)	(4.02)	(5.43)	(3.99)
Obs.	363K	363K	363K	363K	363K	363K	363K	363K	363K	363K	363K	363K
R^2	19.17%	20.24%	19.58%	11.49%	11.78%	11.56%	0.61%	0.69%	0.62%	1.15%	1.17%	1.15%
Price Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Acc. Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 14: **Controlling for option-based predictors:** This table reports estimates from regressing the next month's excess returns on the Γ and a set of predictive variables using Fama and MacBeth (1973) regressionss, whereby observations are vale-weighted. Regression specification (11) adds a range of price-based control variables: market beta, total return volatility, idiosyncratic volatility, realized volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Specification (12) subsequently adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. All coefficients are multiplied by 100. The constant is omitted for brevity. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Γ	-18.65***	-15.82***	-16.33***	-17.25***	-17.63***	-17.64***	-18.94***	-18.87***	-18.81***	-19.34***	-18.14***	-16.76***
	(-3.80)	(-3.36)	(-3.35)	(-3.62)	(-3.69)	(-2.82)	(-2.98)	(-2.99)	(-2.92)	(-3.18)	(-2.88)	(-3.15)
RV-IV		-1.28*	-0.94	-0.82	-0.63	-0.60	0.19	0.12	0.20	-0.06	0.02	-0.04
		(-1.68)	(-1.12)	(-1.00)	(-0.73)	(-0.72)	(0.19)	(0.12)	(0.19)	(-0.05)	(0.03)	(-0.06)
IV_{skew}			0.58	1.29*	1.65**	1.29**	1.10*	1.05*	1.00*	0.97*	1.11***	0.99**
			(0.90)	(1.90)	(2.32)	(2.04)	(1.95)	(1.86)	(1.85)	(1.77)	(2.78)	(2.50)
VOV				-1.73***	-1.80***	-1.56***	-1.49***	-1.37***	-1.39***	-1.30***	-0.75**	-0.76**
				(-2.87)	(-3.08)	(-2.96)	(-2.84)	(-2.77)	(-2.85)	(-2.75)	(-2.45)	(-2.42)
CPIV					4.05**	4.51**	4.63**	4.78**	4.82**	4.65**	4.39***	4.55***
					(2.33)	(2.54)	(2.56)	(2.55)	(2.62)	(2.42)	(3.08)	(2.98)
DOI						-0.01	0.01	0.03	0.01	-0.03	-0.05	-0.05
						(-0.14)	(0.11)	(0.29)	(0.08)	(-0.26)	(-0.55)	(-0.59)
IV							0.71	0.69	0.71	0.52	1.34**	1.15*
							(0.92)	(0.93)	(0.92)	(0.71)	(2.46)	(1.96)
Call Vol.								-0.16	-0.16	-0.13	-0.07	-0.09
								(-0.71)	(-0.68)	(-0.52)	(-0.32)	(-0.38)
Call OI.									0.12	0.29	0.25	0.26
									(0.25)	(0.99)	(0.94)	(1.09)
Δ										0.06	0.04	0.05
										(0.88)	(0.90)	(1.25)
Obs.	406K	393K	361K	361K	354K	354K	354K	353K	353K	353K	349K	324K
R^2	1.79%	7.45%	7.96%	8.40%	8.82%	10.19%	10.72%	11.12%	11.56%	12.59%	19.55%	22.34%
Price Controls	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES
Acc. Controls	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES

Table 15: **Volatility and net gamma exposure:** This table reports estimates from regressing the next month's realized volatility on Γ and a set of predictive variables using Fama and MacBeth (1973) regressions and panel regressions. Observations are both vale-weighted (panel A and C) and equally-weighted (panel B and D). Regression specification (1) has no control variables. Regression specification (2) adds implied volatility (IV), Call Volume / Total option volume (Call Vol.), Call open interest / Total option open interest (Call OI), and a range of price-based control variables: market beta, total return volatility, idiosyncratic volatility, realized volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Specification (3) subsequently adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. All coefficients are multiplied by 100. The constant is omitted for brevity. Both time - and firm fixed effects are included in panel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Value-weighted FMB			**B: Equal-weighted FMB**			**C: Value-weighted Panel**			**D: Equal-weighted Panel**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Gamma	-12.92***	-3.41***	-3.24***	-12.19***	-3.29***	-3.20***	-1.87***	-1.55***	-1.51***	-4.00***	-2.54***	-2.51***
	(-3.58)	(-4.91)	(-4.60)	(-3.51)	(-3.92)	(-4.09)	(-6.40)	(-7.11)	(-6.53)	(-13.64)	(-12.46)	(-12.33)
IV		7.07***	-4.41		7.69***	1.60		3.26***	3.23***		2.53***	2.44***
		(7.78)	(-1.01)		(11.54)	(0.78)		(22.10)	(21.04)		(34.65)	(32.76)
Call Vol.		3.52***	7.01***		3.06***	7.67***		-0.16***	-0.16***		-0.06***	-0.06***
		(29.62)	(7.65)		(30.98)	(11.27)		(-5.78)	(-5.66)		(-4.51)	(-4.51)
Call OI		-0.07*	-0.05		-0.04*	-0.03		0.54***	0.54***		0.25***	0.24***
		(-1.77)	(-1.64)		(-1.89)	(-1.47)		(15.43)	(14.86)		(13.48)	(13.01)
Obs.	406K	391K	363K	406K	391K	363K	406K	391K	363K	406K	391K	363K
R^2	5.38%	51.41%	52.18%	1.31%	43.11%	43.48%	0.32%	21.21%	21.11%	0.26%	15.39%	15.24%
Price Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Acc. Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES

Table 16: **Predicting future trading volume:** This table reports estimates from regressing the next month's percentage change in trading volume on the absolute Γ and a set of predictive variables using Fama and MacBeth (1973) regressions and panel regressions. Observations are both vale-weighted (panel A and C) and equally-weighted (panel B and D). Regression specification (1) has no control variables. Regression specification (2) adds implied volatility (IV), Call Volume / Total option volume (Call Vol.), Call open interest / Total option open interest (Call OI), and a range of price-based control variables: market beta, total return volatility, idiosyncratic volatility, realized volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Specification (3) subsequently adds accounting control variables: book-to-market ratio, return on equity, investment/assets, operating profitability, and cash profitability. The constant is omitted for brevity. Both time - and firm fixed effects are included in the panel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Value-weighted FMB			**B: Equal-weighted FMB**			**C: Value-weighted Panel**			**D: Equal-weighted Panel**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\|Gamma\|$	1.01***	1.06***	1.04***	3.04***	3.05***	2.99***	1.24***	1.01***	0.94***	3.18***	2.61***	2.51***
	(5.69)	(4.90)	(4.83)	(5.17)	(6.43)	(6.40)	(7.79)	(4.41)	(4.13)	(23.92)	(20.94)	(20.59)
IV		0.72***	0.69***		0.55***	0.53***		0.80***	0.75***		0.53***	0.51***
		(12.80)	(13.13)		(10.41)	(9.79)		(9.52)	(9.97)		(14.59)	(13.45)
Call. Vol.		-0.04***	-0.04***		-0.00	-0.00		-0.07***	-0.06***		-0.00	-0.00
		(-2.78)	(-3.05)		(-0.40)	(-0.13)		(-5.08)	(-5.11)		(-0.32)	(-0.38)
Call OI		0.07***	0.07***		-0.00	-0.01		0.06***	0.06***		0.02**	0.01*
		(4.03)	(4.24)		(-0.17)	(-0.48)		(3.71)	(3.55)		(2.08)	(1.80)
Obs.	406K	391K	363K	406K	391K	363K	406K	391K	363K	406K	391K	363K
R^2	1.11%	12.21%	14.25%	0.54%	10.03%	10.79%	0.33%	5.51%	5.57%	0.40%	4.35%	4.82%
Price Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Acc. Controls	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

Table 17: **Information Gamma and Hedge Gamma:** This table reports estimates from regressing next month's realized volatility on Γ and a set of predictive variables using Fama and MacBeth (1973) regressions and panel regressions. Observations are both vale-weighted (panel A and C) and equally-weighted (panel B and D). $\Gamma(t-\tau, S_t)$ is the net gamma exposure using the open interest at $t-\tau$. Γ_{info} is the information gamma, defined as the difference between Γ and $\Gamma(t-\tau, S_t)$. $\Gamma(t-\tau, S_{t-\tau})$ is the net gamma exposure at time $t-\tau$. Γ_{hedge} is the hedge gamma, defined as the difference between Γ_{info} and $\Gamma(t-\tau, S_{t-\tau})$. All coefficients are multiplied by 100. The constant is omitted for brevity. Both time - and firm fixed effects are included in [anel regressions. Newey-West t-statistics are reported between parentheses for Fama-Macbeth regressions. Two-way cluster (by stock and date) adjusted t-statistics are given in parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	A: Value-weighted FMB			**B: Equal-weighted FMB**			**C: Value-weighted Panel**			**D: Equal-weighted Panel**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Γ	-3.24***			-3.20***			-1.51***			-2.51***		
	(-4.60)			(-4.09)			(-6.53)			(-12.33)		
$\Gamma(t-\tau, S_t)$		-3.25***			-3.44***			-1.78***			-2.90***	
		(-4.57)			(-3.82)			(-7.00)			(-13.44)	
Γ_{info}		0.45	-0.03		2.18	1.43		0.69	0.94*		-0.05	0.23
		(0.22)	(-0.02)		(1.27)	(1.62)		(1.14)	(1.84)		(-0.14)	(0.64)
$\Gamma(t-\tau, S_{t-\tau})$			-3.00***			-2.93***			-1.61***			-2.59***
			(-5.00)			(-3.80)			(-6.11)			(-11.22)
Γ_{hedge}			-4.13**			-6.81***			-2.38***			-4.93***
			(-2.60)			(-3.05)			(-4.14)			(-10.39)
IV	3.44***	3.79***	3.52***	2.94***	3.34***	3.08***	3.23***	3.34***	3.3***	2.44***	2.63***	2.63***
	(27.53)	(14.99)	(27.03)	(30.43)	(14.09)	(33.36)	(21.04)	(20.90)	(20.90)	(32.76)	(34.63)	(34.62)
Call Vol.	-0.05	-0.06	-0.08**	-0.03	-0.02	-0.04*	-0.16***	-0.18***	-0.18***	-0.06***	-0.06***	-0.06***
	(-1.64)	(-1.57)	(-2.18)	(-1.47)	(-0.69)	(-1.91)	(-5.66)	(-5.78)	(-6.23)	(-4.51)	(-4.64)	(-4.83)
Call OI.	0.51***	0.54***	0.51***	0.26***	0.29***	0.26***	0.54***	0.57***	0.56***	0.24***	0.26***	0.26***
	(15.42)	(12.65)	(14.43)	(12.11)	(9.76)	(9.49)	(14.86)	(15.34)	(14.58)	(13.01)	(13.61)	(13.17)
Obs.	363K	351K	351K	363K	351K	351K	363K	351K	351K	363K	351K	351K
R^2	52.18%	54.36%	54.64%	43.48%	45.76%	45.88%	21.11%	21.60%	21.65%	15.24$	15.94%	15.95%
Price Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Acc. Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

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A Additional tables & figures

Table A.1: **Performance of decile portfolios sorted on the net gamma exposure:** This table reports the performance of decile portfolios formed on the basis of the net gamma exposure (Γ), which measures the total outstanding gamma divided by the market capitalization. At the end of month t we sort stocks into ten portfolios based on their Γ, and hold this portfolio during month $t+1$. Panel A (B) presents the results for value-weighted portfolios whereby the breakpoints are based on the full sample (NYSE universe). Stocks with prices above \$5 and microcaps as of the portfolio formation are excluded. We report the average Γ, the return ("R") in percentages, the Fama-French-Carhart four-factor alpha ("α_{3FM}"), the Fama-French-Carhart five-factor alpha ("α_{5F}"), the Fama-French-Carhart six-factor alpha ("α_{5FM}"), Hou, Xue, and Zhang's extended q-factor model alpha ("α_{5Q}"), and augmented with momentum ("α_{5QM}") for each portfolio. The row labeled "L-H" is the self-financing high-minus-low portfolio, which reports the difference in between portfolio H and portfolio L. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1996 and December 2021 with share code 10 or 11. Newey-West t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	Panel A: Full sample breakpoints							Panel B: NYSE-breakpoints						
	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q5}	α_{Q5M}	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q5}	α_{Q5M}
L	-0.10***	1.45***	0.64***	0.53***	0.65***	0.59***	0.59***	-0.10***	1.44***	0.63***	0.53***	0.65***	0.58***	0.58***
	(-8.63)	(5.11)	(4.18)	(3.80)	(4.63)	(3.27)	(3.89)	(-8.63)	(5.00)	(4.08)	(3.64)	(4.57)	(3.15)	(3.78)
2	-0.01***	1.16***	0.34***	0.16	0.22**	0.23**	0.23**	-0.01***	1.22***	0.41***	0.20*	0.26**	0.27**	0.27***
	(-6.28)	(4.83)	(3.07)	(1.23)	(2.08)	(1.97)	(2.51)	(-6.25)	(5.31)	(3.27)	(1.72)	(2.59)	(2.52)	(3.30)
3	0.00***	1.15***	0.38***	0.25	0.32**	0.32*	0.32**	0.00***	1.12***	0.33**	0.15	0.23*	0.19	0.20
	(2.95)	(4.74)	(2.67)	(1.52)	(2.29)	(1.86)	(2.19)	(2.68)	(4.65)	(2.48)	(0.97)	(1.79)	(1.17)	(1.44)
4	0.01***	0.91***	0.11	-0.03	-0.01	-0.03	-0.03	0.01***	0.96***	0.15*	0.06	0.08	0.05	0.05
	(13.06)	(4.03)	(1.07)	(-0.29)	(-0.08)	(-0.32)	(-0.34)	(13.46)	(4.17)	(1.80)	(0.77)	(1.07)	(0.53)	(0.55)
5	0.02***	0.88***	0.09	0.04	0.07	0.09	0.09	0.02***	1.01***	0.22**	0.11	0.14	0.17	0.17
	(18.17)	(3.51)	(0.87)	(0.37)	(0.72)	(0.87)	(0.88)	(17.40)	(4.43)	(2.05)	(0.83)	(1.12)	(1.26)	(1.33)
6	0.04***	1.03***	0.22*	0.16	0.18	0.24	0.24*	0.04***	0.94***	0.17*	0.09	0.13	0.22*	0.22*
	(20.06)	(4.27)	(1.94)	(1.45)	(1.47)	(1.63)	(1.77)	(17.86)	(3.78)	(1.68)	(0.87)	(1.30)	(1.71)	(1.94)
7	0.06***	0.84***	0.05	0.06	0.07	0.02	0.02	0.06***	0.78***	-0.01	-0.03	-0.02	-0.02	-0.02
	(19.34)	(3.42)	(0.54)	(0.67)	(0.72)	(0.24)	(0.24)	(16.81)	(3.21)	(-0.16)	(-0.31)	(-0.27)	(-0.20)	(-0.20)
8	0.10***	0.70**	-0.13	-0.14	-0.15*	-0.15	-0.15	0.10***	0.87***	0.06	0.02	0.02	0.00	0.00
	(17.73)	(2.60)	(-1.59)	(-1.50)	(-1.68)	(-1.48)	(-1.53)	(15.39)	(3.49)	(0.69)	(0.24)	(0.23)	(0.02)	(0.02)
9	0.17***	0.74**	-0.14	-0.00	-0.07	-0.12	-0.12	0.16***	0.73***	-0.11	-0.05	-0.09	-0.14	-0.14
	(15.88)	(2.74)	(-1.60)	(-0.03)	(-0.84)	(-1.11)	(-1.39)	(13.90)	(2.71)	(-1.13)	(-0.40)	(-0.86)	(-1.19)	(-1.31)
H	0.40***	0.78**	-0.23	0.01	-0.08	-0.17	-0.17	0.38***	0.69**	-0.28**	-0.08	-0.16	-0.21	-0.21*
	(13.24)	(2.17)	(-1.55)	(0.05)	(-0.47)	(-0.97)	(-1.17)	(12.25)	(2.19)	(-2.54)	(-0.63)	(-1.46)	(-1.53)	(-1.87)
H-L	0.49***	-0.67**	-0.88***	-0.52**	-0.73***	-0.76**	-0.76***	0.48***	-0.75***	-0.91***	-0.62***	-0.82***	-0.79***	-0.79***
	(8.64)	(-2.45)	(-3.80)	(-2.00)	(-3.31)	(-2.53)	(-3.22)	(7.92)	(-3.02)	(-4.13)	(-2.72)	(-4.02)	(-2.78)	(-3.53)

Table A.2: **Average portfolio characteristics:** This table reports the average characteristic of decile portfolios formed on the basis of the net gamma exposure, which measures the total outstanding gamma divided by the average daily dollar trading volume. At the end of month t we sort stocks into ten portfolios based on their net gamma exposure, and hold this portfolio during month $t+1$. We compute the value-weighted average of a characteristic for each decile. The row labeled "L-H" is the self-financing high-minus-low portfolio, which reports the difference in the average characteristic value between portfolio H and portfolio L. The sample consists of stocks listed on NYSE/AMEX/NASDAQ for the period between January 1996 and December 2021 with share code 10 or 11. Newey-West t-statistics are reported between parentheses. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

	MKT	ME	BM	BM_m	RMW	CP	IA	NSI	CSI	ROE	MOM	SREV	VOL	IVOL	RV	ILQ	MAX	IV	CVOL	COI
L	1.01***	9.98***	0.38***	0.38***	0.86***	0.80**	0.17***	0.01***	0.39**	0.07***	0.14***	-0.03***	0.00***	0.02***	0.02***	0.00***	0.39***	0.37***	0.48***	0.46***
	(64.11)	(80.17)	(24.48)	(25.94)	(2.68)	(2.50)	(8.44)	(2.64)	(4.34)	(10.39)	(5.18)	(-7.83)	(5.43)	(12.42)	(15.83)	(3.81)	(4.34)	(20.19)	(83.53)	(81.58)
2	1.06***	9.25***	0.43***	0.43***	0.91**	0.85**	0.22***	0.02***	0.42***	0.05***	0.20***	-0.01***	0.00***	0.02***	0.02***	0.0*** 0	0.42***	0.41***	0.53***	0.51***
	(67.32)	(82.59)	(24.01)	(23.30)	(2.06)	(1.98)	(5.24)	(4.08)	(5.25)	(6.44)	(5.03)	(-3.49)	(4.41)	(9.98)	(13.23)	(4.53)	(5.25)	(16.57)	(51.16)	(43.58)
3	1.09***	8.88***	0.47***	0.45***	0.36***	0.34***	0.20***	0.03***	0.45***	0.05***	0.21***	-0.00	0.00***	0.02***	0.02***	0.00***	0.45***	0.41***	0.59***	0.57***
	(54.19)	(95.59)	(21.45)	(19.74)	(7.97)	(12.49)	(5.97)	(5.88)	(5.78)	(10.75)	(5.23)	(-1.13)	(4.93)	(9.65)	(12.62)	(7.26)	(5.78)	(17.09)	(58.78)	(52.32)
4	1.10***	9.05***	0.46***	0.43***	0.33***	0.32***	0.20***	0.02***	0.47***	0.04***	0.22***	0.00	0.00***	0.02***	0.02 ***	0.00***	0.47***	0.41***	0.61***	0.59***
	(53.06)	(114.12)	(23.30)	(20.96)	(38.34)	(27.29)	(6.19)	(5.21)	(5.49)	(13.34)	(4.48)	(0.21)	(4.16)	(9.38)	(12.32)	(7.32)	(5.49)	(15.86)	(69.72)	(60.41)
5	1.09***	9.27***	0.44***	0.41***	0.35***	0.36***	0.20***	0.02***	0.46***	0.06***	0.24***	0.01***	0.00***	0.02***	0.02***	0.00***	0.46***	0.40***	0.63***	0.60***
	(79.94)	(148.52)	(23.75)	(18.55)	(22.63)	(21.05)	(7.39)	(5.56)	(5.37)	(4.04)	(4.95)	(2.71)	(4.30)	(9.87)	(14.12)	(5.09)	(5.37)	(17.14)	(76.55)	(63.16)
6	1.10***	9.57***	0.43***	0.39***	0.41***	0.39***	0.20***	0.02***	0.47***	0.05***	0.24***	0.01***	0.00***	0.02***	0.02***	0.00***	0.47***	0.39***	0.63***	0.60***
	(90.95)	(133.21)	(20.02)	(18.03)	(9.75)	(11.86)	(9.12)	(5.22)	(5.35)	(8.94)	(5.46)	(4.06)	(4.94)	(10.50)	(15.25)	(5.78)	(5.35)	(20.06)	(80.43)	(61.04)
7	1.09***	9.80***	0.41***	0.38***	0.38***	0.36***	0.18***	0.02***	0.48***	0.06***	0.25***	0.02***	0.00***	0.02***	0.02***	0.00***	0.48***	0.38***	0.64***	0.60***
	(99.25)	(157.30)	(18.26)	(17.12)	(27.59)	(15.20)	(10.53)	(4.75)	(4.96)	(11.21)	(5.77)	(6.74)	(5.18)	(11.67)	(14.89)	(5.28)	(4.96)	(21.40)	(81.35)	(59.01)
8	1.06***	10.15***	0.40***	0.36***	0.75**	0.72**	0.17***	0.02***	0.47***	0.06***	0.23***	0.02***	0.00***	0.02***	0.02***	0.00***	0.47***	0.37***	0.64***	0.60***
	(103.73)	(177.55)	(19.41)	(18.19)	(2.71)	(2.55)	(11.82)	(4.12)	(4.69)	(7.30)	(6.68)	(10.18)	(4.47)	(11.14)	(16.45)	(5.09)	(4.69)	(22.11)	(73.99)	(52.17)
9	1.02***	10.62***	0.37***	0.33***	0.54***	0.50***	0.16***	0.01***	0.47***	0.07***	0.23***	0.03***	0.00***	0.02***	0.02***	0.00***	0.47***	0.35***	0.64***	0.59***
	(66.87)	(151.27)	(17.29)	(17.53)	(5.56)	(4.95)	(12.00)	(3.30)	(4.56)	(10.01)	(6.18)	(12.85)	(5.98)	(12.17)	(16.24)	(5.06)	(4.56)	(21.95)	(76.96)	(54.86)
H	0.90***	11.15***	0.35***	0.31***	0.60***	0.57***	0.14***	0.01**	0.41***	0.07***	0.20***	0.04***	0.00***	0.01***	0.02***	0.00***	0.41***	0.32***	0.65***	0.60***
	(30.11)	(81.61)	(18.44)	(18.54)	(4.98)	(4.60)	(16.17)	(2.22)	(4.33)	(14.47)	(8.79)	(17.86)	(4.15)	(8.27)	(16.71)	(3.51)	(4.33)	(23.53)	(72.70)	(51.85)
H-L	-0.10***	1.17***	-0.03**	-0.07***	-0.26	-0.23	-0.03*	-0.00	0.03	-0.00	0.06***	0.06***	-0.00***	-0.00***	-0.00***	-0.00***	0.03	-0.05***	0.1***7	0.14***
	(-3.13)	(15.39)	(-2.25)	(-5.45)	(-1.13)	(-1.00)	(-1.84)	(-0.82)	(1.06)	(-0.29)	(3.77)	(15.18)	(-4.88)	(-10.46)	(-8.97)	(-3.73)	(1.06)	(-7.29)	(26.26)	(18.72)