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Option gamma and stock returns

Amar Soebhag *

Erasmus School of Economics, Burgemeester Oudlaan 50, Rotterdam, 3062PA, The Netherlands
Robeco Asset Management, Weena 850, Rotterdam, 3014 DA, The Netherlands

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Stocks with high net gamma exposure systematically underperform stocks with low net gamma exposure. This effect is distinct from other well-known return predictors, and survives many robustness checks. We show that stocks with low net gamma exposure negatively predict future realized volatility, and 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.

1. Introduction

Since the introduction of exchange-based option trading in 1973, the trading activity of derivatives has experienced significant 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 that this is the case: 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 trade shares on the market to hedge themselves to remain delta-neutral. Such hedging behaviour can potentially 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 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.

As the activity in option markets continues to grow, an important question arises: does gamma-related flow play a systematic role in driving asset returns? This paper aims to answer this question by examining the cross-sectional implications of net gamma exposure on future 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 at the end of 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

* Correspondence to: Erasmus School of Economics, Burgemeester Oudlaan 50, Rotterdam, 3062PA, The Netherlands.
E-mail address: soebhag@ese.eur.nl.

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

[2] See the Financial Times (2021).

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for several benchmark factor models, 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 findings support the hypothesis that risk-averse investors require higher expected returns as compensation for holding 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) price 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 solely driven by net gamma exposure, rather than other stock characteristics, we conduct bivariate portfolio sorts. 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 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 net gamma exposure and future stock returns. We also provide evidence of significant variation in the net gamma exposure premium over time.

Next, we investigate the robustness of our findings. First, we construct a 2-by-3 gamma factor, à la Fama and French (1993), to conduct spanning regressions. We show that the gamma factor is not spanned by well-known factor models. Second, we use alternative definitions to proxy the net gamma exposure and show that the documented negative relationship remains highly significant. Third, the net gamma exposure has predictive power on daily and weekly frequencies. Fourth, we find that the net gamma exposure premium is highly significant in the cross-sections of the 1000 largest and 1000 most liquid stocks in the Center for Research in Security Prices (CRSP) universe. Fifth, our results are robust to changes in data filters. Sixth, we show that the predictive power mainly stems from ATM and OTM options, as well as options with a maturity beyond one month. Lastly, we demonstrate that the negative relationship between the net gamma exposure and next month's return remains robust even after controlling for a wide range of option-based predictors.

Our study is related to several streams of the literature. First, there is a growing body of evidence that shows that options play a role in the price discovery process. Hu (2014) show that option market makers delta hedge trades causes the information reflected in option trading to be impounded into underlying equity prices. Ni et al. (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 the link between non-informational order imbalances to predict daily stock returns at the market level.

Second, several studies have explored the relationship between gamma imbalances and asset prices. Ni et al. (2021) show that net gamma exposure predicts the next day's absolute return, and provides a non-informational trading argument. Similar, our study finds that net gamma exposure negatively predicts realized volatility in the next month, driven by hedge rebalancing, rather than option trading on private information. The main difference between our study and Ni et al. (2021) is our focus on predicting future equity returns and documenting a risk premium for stocks with negative net gamma exposures. Baltussen et al. (2021) find, at the market-level, that returns between the previous close and 15:30 pm positively predict the return between 15:30 pm and market close, driven by hedging demand as measured by net gamma exposure. Barbon and Buraschi (2020) and Barbon et al. (2021) find that end-of-the-day predictability interacts with the net gamma exposure. These three studies all focus on intraday returns, whereas we focus on lower frequency returns. Furthermore, these studies do not show the direct effect of the net gamma exposure on returns in the following trading day(s). However, we find that net gamma exposure predicts next-day, next-week, and next-month returns, and hence is not temporary, nor reverting.

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). We collect daily implied volatility, trading volume, open interest and Greeks for each option contract from OptionMetrics. The option data runs from Jan. 1, 1996 (the first date in the OptionMetrics database) until Dec. 31, 2021. We match this data to stock return data obtained from CRSP. We only use stocks where the share code equals 10 or 11, and exchange code equals 1, 2, or 3. Furthermore, we eliminate stocks with a price per share less than 5 dollar and 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.

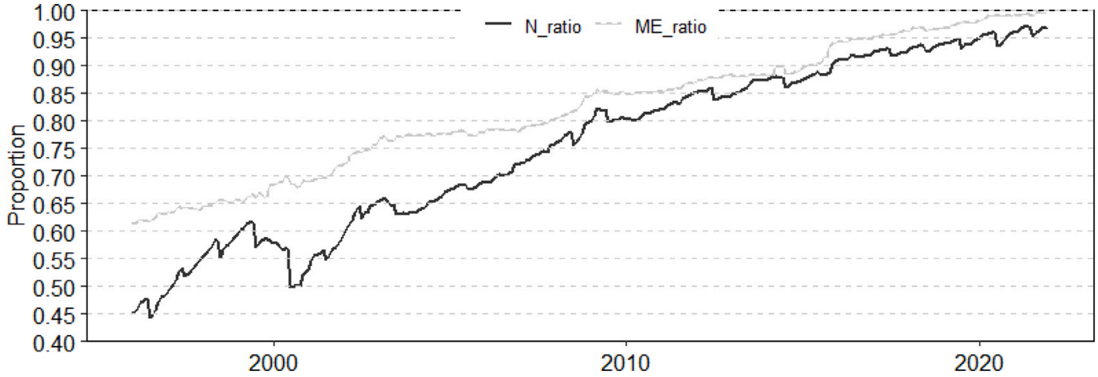

Fig. 1. Net gamma exposure coverage.
This figure shows the coverage of the net gamma exposure data relative to the CRSP sample. The solid black line ('N_ratio') represents the fraction of stocks with non-missing Γ data relative to the number of stocks in the CRSP sample. The solid grey line ('ME_ratio') 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.

2.1. Net gamma exposure

Let S_t be the value of the underlying asset at time t, K is the option's strike price and C_t is the option's price. 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 $-\Delta_t$. Since Δ_t is a function of S_t, changes in S_t affect 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 $m \in M_t^c$, $\Gamma_{i,t}$ 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 $m \in M_t^p$, $\Gamma_{i,t}$ is computed as:

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

We multiply by (−100) as this represents short gamma for option market makers. To compute the aggregated Γ 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 total dollar amount 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. To limit the impact of outliers, we trim Γ at the 1% and 99% each month.

Fig. 1 provides an overview of the coverage of our sample relative to the CRSP universe. 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.

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

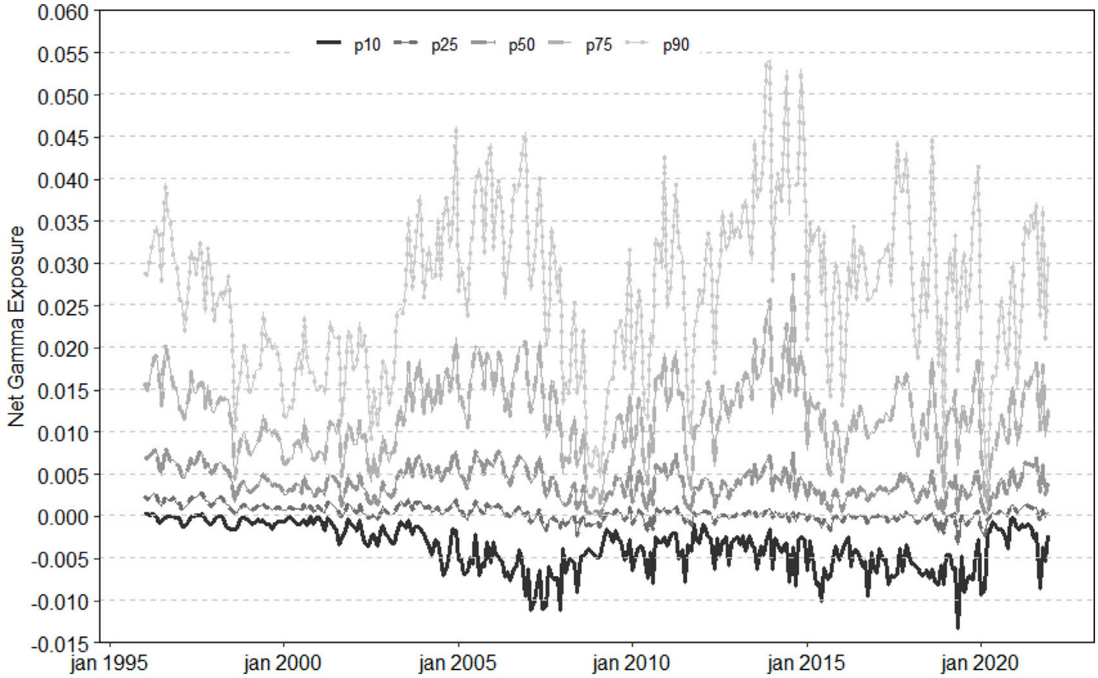

Fig. 2. Cross-sectional distribution of net gamma exposure over time.
This figure shows the distribution of the net gamma exposure over time. The 10th, 25th, 50th (median), 75th, and 90th percentiles of the net gamma exposure are shown over time. The sample runs from January 1996 till December 2021.

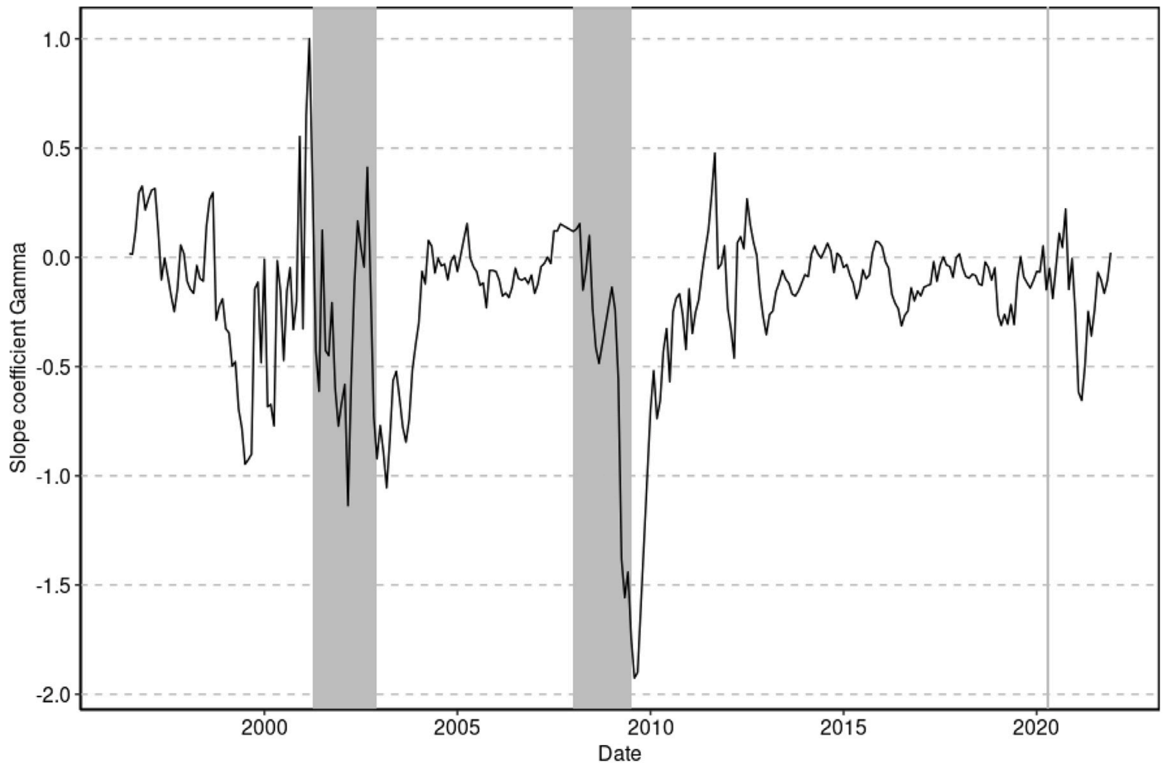

Fig. 3. Gamma premium over time.
This figure shows the gamma premium over time. The solid line depicts the six-month moving average of the monthly slope coefficient of the net gamma exposure (Table 6 column 1). The grey-shaded area indicate periods in which the NBER recession indicator equals 1 (i.e.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

Table 1
Descriptive statistics.

Variable	Panel A: Cross-sectional summary statistics									
	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	–

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 and prices below \$5 at the end of month t. 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.

2.2. Other predictors

To control for other cross-sectional effects, we construct a wide-range of firm characteristics that are know to forecast the cross-section of equity returns, including:

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 times the number of shares outstanding) at the end of month t for each stock j. 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, $t-1$, scaled by the market value of equity at the end of December of year $t-1$. Depending on data availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of preferred stock (Fama and French, 1992). In addition, we compute a monthly version of the B/M ratio, following Asness and Frazzini (2013). Following Hou et al. (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 and French, 2015). We also 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.

Furthermore, we create multiple price-based variables. We estimate market beta (MKT) as the market beta of individual stocks using daily returns over the past 251 trading days. Likewise, we define total return volatility (VOL) as the volatility of daily returns over the past 251 trading days. We define realized volatility (RV) as the volatility of daily returns during month t. Idiosyncratic volatility ($IVOL$) is calculated as the standard deviation of the daily abnormal return, based on CAPM model, over the past 90 trading days. 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 and 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. Following Bali et al. (2011),

Table 2
Performance of decile portfolios sorted on net gamma exposure.

	Panel A: Full sample breakpoints							Panel B: NYSE-breakpoints						
	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q4}	α_{Q4M}	Γ	R	α_{3FM}	α_{5F}	α_{5FM}	α_{Q4}	α_{Q4M}
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)

This table reports the performance of decile portfolios formed on the basis of net gamma exposure (Γ). We compute the net gamma exposure of a stock as in Eq. (1). 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). 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 q-factor model alpha ("α_{4Q}"), and augmented with momentum ("α_{4QM}") for each portfolio. The row labelled "H-L" 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. Stocks with prices below $5 and microcaps as of the portfolio formation are excluded. 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.

Table 3
Persistence of net gamma exposure.

	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

This table presents transition probabilities for net gamma exposure. At month t, all stocks are sorted into deciles based on net gamma exposure. The procedure is repeated in month $t+1$ and $t+12$. The transition probability is the average percentage of stocks that move from decile i at month t to decile j at month $t+j$. Panel A considers the one-month transition (j = 1). Panel B considers the one-year transition (j = 12). The sample runs from February 1996 till December 2021.

Table 4
Average stock characteristics.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Γ_{t-1}	41.46***											40.69***
	(18.94)											(18.18)
β_{mkt}		−0.69***										−0.27***
		(−7.23)										(−3.33)
RVOL			−31.72***									−27.03***
			(−9.11)									(−9.03)
ILQ				3.20								2.72
				(1.49)								(1.17)
IV					−1.00***							0.87***
					(−3.66)							(3.55)
BM						−0.15						−0.07
						(−1.25)						(−0.86)
ROE							−0.00					−0.01
							(−0.24)					(−0.72)
OP								−0.00***				−0.00
								(−5.08)				(−0.57)
CP									−0.00***			0.00
									(−5.49)			(0.51)
IA										0.00		0.02
										(0.23)		(1.37)
MOM											0.15**	−0.01
											(2.58)	(−0.26)

This table reports the estimated slope coefficients from the regression of the net gamma exposure (Γ) on stock-level characteristics. 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. $X_{i,t}$ is a collection of stock-specific variables observable at time t stock i: market beta (MKT), 1-month realized volatility (RVOL), the illiquidity (ILQ) measure of Amihud (2002), 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. All coefficients are multiplied by 100. Observations are weighted by their previous month's market capitalization. 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.

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. 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 (Call Vol). Lastly, we compute the total outstanding call option open interest relative to the total option open interest (Call OI).

We present the summary statistics and the correlation matrix of our set of variables in Table 1. In Panel A, the mean, standard deviation, percentiles, and the maximum are first computed cross-sectionally on each day and then averaged over time. The results indicate that the distribution of Γ is skewed to the right, with a mean of 0.92 and median of 0.05, in line with Fig. 2. Panel B shows the average cross-sectional correlations among the variables. We find that Γ moderately correlated with other variables in our sample.

3. Empirical results

In this section, we carry out a comprehensive set of tests to evaluate the predictive power of Γ on future stock returns. First, we conduct univariate portfolio-level analyses. Second, we analyse the persistence of Γ at the portfolio-level. Third, we show average stock characteristics to show how net gamma exposure loads on other return predictors. Fourth, we conduct bivariate portfolio sorting and stock-level regressions to control for other characteristics. Fifth, we show that Γ negatively predicts extreme returns in the next month. Lastly, we provide evidence that the Γ-premium is time-varying.

3.1. Univariate portfolio-level analysis

In this section, we conduct univariate portfolio-level analysis. We construct decile portfolios every month by sorting stocks on their Γ. Subsequently, we compute the one month ahead value-weighted return for each portfolio to test whether the zero-cost portfolio generates a significant return. The zero-cost portfolio takes a long position in lowest decile portfolio, and a short position in the highest decile portfolio.

Table 2 displays time-series averages of one month ahead excess (risk-adjusted) returns for each decile. Panel A and B use breakpoints derived from the full CRSP sample and NYSE universe, respectively, to construct decile portfolios. The first column of each panel reports the average Γ for each decile. Moving from decile L to decile H, Γ increases significantly from −0.01 to 0.04. The zero-cost portfolio has an average Γ of 0.05 with a t-statistic of 17.04. The second column of each panel reports average excess returns. We find that the average excess return decreases monotonically from 1.45% to 0.58% (panel A) when moving from the

Table 5
Bivariate portfolio analysis with conditional sorts.

	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)

This table shows the Fama–French, augmented with momentum, 6-factor alpha obtained from conditional bivariate sorts. Stocks are sorted into deciles based on one control variable, and subsequently 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 H and Decile 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. Stocks with prices below $5 and microcaps as of the portfolio formation are excluded. 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.

Table 6
Stock-level regressions.

	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

This table reports estimates from regressing next month's excess returns on Γ and a set of predictive variables using Fama and MacBeth (1973) and panel regressions. Observations are both value-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 for panel regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

Table 7
Predicting extreme returns.

	A: $I[abs(R_{t+1}) > 25\%]$			**B:** $I[abs(R_{t+1}) > 50\%]$			**C:** $I[abs(R_{t+1}) > 75\%]$		
	(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
Price controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
Acc. controls	NO	NO	YES	NO	NO	YES	NO	NO	YES

This table reports estimates from regressing the next month's 'extreme return' indicator on 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.

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_{Q4} is the alpha relative to the Q-factor model of Hou et al. (2015) (iv); α_{Q4M} is the alpha relative to the Q-factor model augmented by the momentum factor.

As shown in the third column of panel A, 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 93 basis points per month. In addition, the results do not significantly differ when we use NYSE-breakpoints (panel B). After controlling for well-known factor models, the return difference between low and Γ stocks remains negative and statistically significant.

Table 8
Time-varying gamma premium.

	(1)	(2)	(3)	(4)	(5)
CFNAI	0.12**				0.091***
	(3.32)				(6.51)
VIX		−0.05			0.19*
		(−0.83)			(1.80)
Sentiment			0.12**		0.14***
			(2.02)		(3.26)
FUNC				−0.15**	−0.29**
				(−2.64)	(−2.46)
Obs.	302	302	302	302	302
R^2	1.3%	0.2%	1.2%	2.0%	5.5%

This table presents the estimates from regressing the estimated gamma premium (from Table 6 column 1) on a set of macroeconomic indicators. CFNAI denotes the Chicago Fed National Activity Index. VIX is CBOE's Volatility Index on the S&P 500. Sentiment denotes the sentiment measure of Baker and Wurgler (2006). FUNC is the financial uncertainty index of Jurado et al. (2015). All regressors are standardized by their full-sample mean and standard deviation. 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.

Table 9
Spanning regressions.

A: Long-Short	$\hat{\alpha}$	Mkt	SMB	HML	RMW	CMA	UMD	IA	ROE	$t(a)$	R^2	$s(e)$	Sh^2_f	$\hat{\alpha}^2/s^2(e)$
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^2_f	$\hat{\alpha}^2/s^2(e)$
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^2_f	$\hat{\alpha}^2/s^2(e)$
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

The table shows the estimated intercepts α (annualized in percentages), slopes, t-statistics of 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 the Q-factor model of 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.

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 additional 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. Transition probabilities

The significant and negative alpha spreads documented in Table 2 are obtained by sorting stocks by their previous' month net gamma exposure, 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 will persist over time. In this section, we present results regarding the persistence of Γ.

Table 3 shows the persistence by examining the portfolio transition matrix. 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 period. If there is no persistency in Γ, we would expect that 10% of the stocks in decile i remains in the same future decile.

However, the results suggest the contrary. 42% of the stocks in the lowest Γ decile in a certain month continues to be in the same decile 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,

Table 10
Daily and weekly stock-level regressions.

	Panel A: Daily horizon						Panel B: Weekly horizon					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Γ	−3.13***	−3.06***	−2.23***	−2.59***	−3.31***	−2.91***	−6.04***	−5.62***	−4.95***	−5.25***	−6.75***	−6.39***
	(−3.02)	(−2.97)	(−5.91)	(−7.58)	(−7.79)	(−7.78)	(−3.11)	(−2.97)	(−3.62)	(−4.67)	(−5.13)	(−5.53)
R_{t-1}		−0.45**	−0.75***	−1.46***	−1.50***	−2.00***		−3.11***	−3.59***	−4.31***	−4.27***	−4.34***
		(−2.38)	(−3.80)	(−7.63)	(−7.80)	(−10.76)		(−6.85)	(−7.80)	(−9.79)	(−9.70)	(−10.12)
$R_{t-1} \times \Gamma$			1.51	13.51	10.40	13.75*			9.87	23.69	15.07	22.59
			(0.16)	(1.62)	(1.31)	(1.81)			(0.47)	(1.28)	(0.95)	(1.51)
IV				−0.10*	−0.10**	−0.42***				0.05	0.06	−0.10
				(−1.97)	(−1.85)	(−5.23)				(0.23)	(0.24)	(−0.60)
Call Vol.					0.07***	0.07***					0.08***	0.08***
					(10.28)	(10.26)					(3.72)	(3.80)
Call OI.					0.13***	0.08***					0.29***	0.27***
					(5.54)	(4.12)					(2.82)	(3.23)
Obs.	10.65M	10.64M	10.64M	10.57M	8.70M	8.39M	10,63M	10,63M	10,63M	10.56M	8.69M	8.38M
R^2	1.61%	3.78%	4.40%	8.57%	9.59%	16.39%	1.69%	3.70%	4.25%	8.62%	9.70%	16.74%
Price controls	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO	YES	YES
Acc. controls	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	NO	YES

This table reports estimates from regressing future excess returns on Γ and a set of predictive variables using Fama and MacBeth (1973) regressions, whereby observations are value-weighted. We regress the next day and next week excess return on the net gamma exposure in panel (A) and (B), respectively. Regression specifications 5 and 11 add a range of price-based control variables: market beta, total return volatility, idiosyncratic volatility, 1-year momentum, 1-month reversal, and the illiquidity measure of Amihud (2002). Column 6 and 12 subsequently add 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.

Table 11
Decomposing the net gamma exposure.

	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)
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%

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 value-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 results into Γ_{fast} and Γ_{slow} respectively. In all specifications, we control for implied volatility, call volume, call open interest, and all price-based and accounting-based control variables mentioned in Section 2.2. 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 for panel regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

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) Γ in the past given that this exposure will persist in the future. Our results 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 panel regressions. We report the slope coefficients from the regressions of the gamma exposure on stock-level characteristics. We estimate the following specification

Table 12
Controlling for option-based predictors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Γ	−18.65***	−15.82***	−16.33***	−17.25***	−17.63***	−17.64***	−18.94***	−18.87***	−18.81***	−19.34***	−21.27***	−20.83***	−18.99***
	(−3.80)	(−3.36)	(−3.35)	(−3.62)	(−3.69)	(−2.82)	(−2.98)	(−2.99)	(−2.92)	(−3.18)	(−4.34)	(−3.66)	(−4.14)
RV-IV		−1.28*	−0.94	−0.82	−0.63	−0.60	0.19	0.12	0.20	−0.06	1.30	1.18	1.13**
		(−1.68)	(−1.12)	(−1.00)	(−0.73)	(−0.72)	(0.19)	(0.12)	(0.19)	(−0.05)	(1.13)	(1.49)	(1.96)
IV_{skew}			0.58	1.29*	1.65*	1.29**	1.10*	1.05*	1.00*	0.97*	1.47***	1.33***	1.22***
			(0.90)	(1.90)	(2.32)	(2.04)	(1.95)	(1.86)	(1.85)	(1.77)	(3.12)	(3.52)	(3.14)
VoV				−1.73***	−1.80***	−1.56***	−1.49***	−1.37***	−1.39***	−1.30***	−1.20***	−0.72***	−0.76***
				(−2.87)	(−3.08)	(−2.96)	(−2.84)	(−2.77)	(−2.85)	(−2.75)	(−2.90)	(−2.65)	(−2.68)
CPIV					4.05**	4.51**	4.63**	4.78**	4.82**	4.65**	5.22**	4.95***	5.16***
					(2.33)	(2.54)	(2.56)	(2.55)	(2.62)	(2.42)	(2.57)	(3.19)	(3.11)
DOI						−0.01	0.01	0.03	0.01	−0.03	0.03	0.02	0.01
						(−0.14)	(0.11)	(0.29)	(0.08)	(−0.26)	(0.42)	(0.32)	(0.14)
IV							0.71	0.69	0.71	0.52	0.40	1.33	1.09
							(0.92)	(0.93)	(0.92)	(0.71)	(0.52)	(2.63)	(2.07)
Call Vol.								−0.16	−0.16	−0.13	−0.05	−0.03	−0.06
								(−0.71)	(−0.68)	(−0.52)	(−0.21)	(−0.11)	(−0.26)
Call OI.									0.12	0.29	0.57**	0.49*	0.47*
									(0.25)	(0.99)	(2.19)	(1.82)	(1.84)
Δ										0.06	−0.71***	−0.70***	−0.71***
										(0.88)	(−3.35)	(−3.20)	(−3.16)
O/S											6.52***	6.59***	6.65***
											(3.04)	(3.00)	(2.97)
Obs.	406K	393K	361K	361K	354K	354K	354K	353K	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%	14.05%	20.65%	23.45%
Price controls	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Acc. controls	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES

This table reports estimates from regressing the next month's excess returns on Γ and a set of predictive variables using Fama and MacBeth (1973) regressions, whereby observations are value-weighted. Columns 1 till 11 incrementally adds an option-based predictor to the estimation. Section 4.5 provides a description of each option-based predictor. Regression specification (12) 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 (13) 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.

Table 13
Volatility and net gamma exposure.

	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	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES

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 value-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 for panel regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

Table 14
Information gamma and hedge gamma.

	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)
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%

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 value-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 $\Gamma(t-\tau, S_{t-\tau})$. In all specifications, we control for implied volatility, call volume, call open interest, and all price-based and accounting-based control variables mentioned in Section 2.2. 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 for panel regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

Table 15
Earnings announcement returns and net gamma exposure.

	(1)	(2)	(3)	(4)	(5)
Γ	−3.13***	−2.01***	−2.68***	−1.82***	−2.70***
	(−3.02)	(−5.07)	(−6.92)	(−5.27)	(−6.67)
I[Earnings]		5.22	0.16	3.85	2.58
		(1.05)	(0.96)	(1.02)	(1.04)
Γ × I[Earnings]		−14.24	18.82	−11.19	−7.42
		(−0.97)	(0.40)	(−1.00)	(−1.01)
R_{t-1}			−1.76***		−1.91***
			(−8.56)		(−10.14)
$\Gamma \times R_{t-1}$			19.04**		13.12
			(2.07)		(1.64)
Obs.	10.65M	10.64M	8.39M	10.64M	8.39M
R^2	1.61%	2.74%	17.46%	2.99%	17.63%
Controls	NO	NO	YES	NO	YES

This table reports estimates from regression next day's excess return on Γ, an earnings announcement dummy, the interaction between Γ and the dummy, and a set of predictive control variables using Fama and MacBeth (1973) regressions. In columns 1–3, the earnings announcement dummy takes value 1 (else 0) on day t if there is an earnings announcement. In columns 4–5, the earnings announcement dummy takes value 1 (else 0) on days $[t-1, t+2]$ if there is an earnings announcement on day t. Column 5 includes all control predictors stated in Section 2.2. Observations are value-weighted. All coefficients are multiplied by 100. The constant is omitted for brevity. 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.

and its 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 results are shown in Table 4. Column (1) shows that the slope coefficient on the lagged Γ is positive and significant, implying that stocks with high (low) Γ in month $t-1$ tend to have a high (low) Γ in month t as well, consistent with Table 3. Column (2) indicates that stocks with higher Γ tend to be stocks with lower market beta. This could be driven by the fact that stocks with net high gamma are relatively low-volatility stocks, which typically tend to be low-beta stocks as well. Column (3) shows a negative slope coefficient on the 1-month realized volatility. 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 exhibit lower implied volatility than low gamma stocks. Intuitively, this is not surprising: positive Γ tends to dampen volatility, whereas negative Γ increases volatility. We find no significant relation between illiquidity and Γ. This might be due to the fact that Γ is standardized by stock dollar volume and implicitly accounts for differences in liquidity. Furthermore, we find that book-to-market and return on equity (columns 6 and 7) are not related to Γ. We also find that stocks with higher profitability tend to be stocks with lower Γ (column 8 and 9). This is

Table 16
Predicting future trading volume.

	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

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 value-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 for panel regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

Table 17
Dynamic return-volume relationship and gamma exposures.

	(1)	(2)	(3)	(4)	(5)
R_t	3.43***	3.33***	1.20**	1.25***	1.10***
	(7.03)	(6.33)	(2.52)	(2.69)	(2.40)
$V_t \times R_t$	0.89***	1.00***	0.71***	0.75***	0.79***
	(7.84)	(7.82)	(6.06)	(6.74)	(7.19)
$V_t \times R_t \times \|\|Gamma\|\|$		−16.31	−6.95***	−5.93***	−6.55***
		(−1.05)	(−3.78)	(−3.31)	(−3.81)
IV			−0.04	−0.33***	−0.38***
			(−0.76)	(−4.40)	(−4.74)
Call Vol.			0.07***	0.06***	0.06***
			(8.51)	(8.78)	(9.10)
Call OI			0.03	−0.00	−0.02
			(1.30)	(−0.10)	(−1.30)
Obs	10.64M	9.52M	7.82M	7.82M	7.81M
R^2	3.27%	4.25%	9.82%	14.11%	16.85%
Price controls	NO	NO	NO	YES	YES

This table reports estimates from regression the excess return at $t+1$ (r_{t+1}) on r_t, the interaction between r_t and turnover, and the interaction between r_t, turnover and absolute net gamma exposures. In column (4), we control for market beta, total volatility, and idiosyncratic volatility. In column (5), we also control for one-year momentum, one-month return reversal, and the illiquidity measure of Amihud (2002). Observations are value-weighted. All coefficients are multiplied by 100. The constant is omitted for brevity. 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.

in line with the result that firms with high operating profitability tend to earn higher one-month-ahead alpha (Fama and French, 2018). Lastly, we find that stocks with high momentum stocks tend to be stocks with positive Γ.

The last column in Table 4 shows that when we include all variables jointly, the cross-sectional relations tend to be weaker or insignificant. Only market beta, realized volatility, and implied volatility remains statistically significant. In the Appendix, Table A.1 reports average characteristics at the portfolio-level. The results are consistent with the stock-level characteristics.

3.4. Bivariate portfolio-level analysis

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

Table 18
Net gamma exposure and mispricing.

	Panel A: Mispricing											
	Low	2	3	4	5	6	7	8	9	High	High-Low	
MISP	43.73	45.79	46.69	46.52	45.74	44.87	44.21	43.18	41.87	39.81	−3.92***	(−11.72)
	Panel B: Short selling											
Volume	43.35	42.86	43.08	43.00	43.03	42.87	42.79	42.23	41.57	40.80	−2.55***	(−9.79)
Interest	6.26	6.19	6.21	6.12	5.81	5.50	5.03	4.35	3.28	2.44	−3.82***	(−11.44)
	Panel C: Future returns											
Horizon	t + 1	t + 2	t + 3	t + 4	t + 5	t + 6	t + 7	t + 8	t + 9	t + 10	t + 11	t + 12
Cum. Ret.	−0.87***	−1.29***	−1.44***	−1.72***	−1.98***	−2.27***	−2.53***	−2.69***	−2.83***	−2.76***	−2.89***	−3.41***
	(−5.29)	(−4.42)	(−3.46)	(−3.37)	(−3.15)	(−3.02)	(−3.00)	(−3.05)	(−3.18)	(−3.20)	(−3.15)	(−3.17)

At the end of month t we sort stocks into ten portfolios based on Γ, and hold this portfolio during month $t+1$. In panel A, the average mispricing score of Stambaugh et al. (2015) is computed for each decile. A higher mispricing score indicates more overpricing. In panel B, we compute the average short volume and short interest by decile. Short volume ('volume') is obtained from FINRA, and short interest ('interest') is obtained from Markit IHS securities. In panel C, the future portfolio excess (cumulative) return ('Cum. Ret.') during months $t+1 \dots t+12$ is shown of the decile hedge portfolio. Observations are always value-weighted. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

To this end, we perform conditional bivariate portfolio sorts on Γ 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 decile portfolios based on the cross-sectional predictor. Then, within each decile, we sort stocks into decile portfolios based on Γ. Subsequently, we average portfolio returns across the ten deciles of the controlling variable to produce decile portfolios with dispersion in Γ, but with similar levels of the controlling variable.

The results are shown in 5, where we report risk-adjusted value-weighted average returns 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 to this point, we tested whether the net gamma exposure is a determinant of the cross-section of future equity returns at the portfolio level, which has the advantage of being non-parametric. However, 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.

To examine the relationship between Γ and expected returns at the stock level, we employ both (Fama and MacBeth, 1973) regressions and panel regressions, as presented in Table 6. Panel A reports the time-series averages of the slope coefficients obtained from Fama–Macbeth regressions, where we regress 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 Γ 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 economic significance, we can use the average values of Γ in the decile portfolios from Table 2. The average difference in Γ 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 Γ by 0.0479, which increases its expected return by $18.65 \times 0.0479 = 0.89$ 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): 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 remains economically large. Our results suggest that the net gamma exposure premium is not subsumed by other return predictors.

3.6. Large stock price movements

Stocks with negative Γ require that delta-hedgers buy (sell) additional stocks after an initial increase (decrease). This buying or selling further amplifies the stock price movement, leading to an increase or decrease in the stock price. Conversely, when stocks have a positive gamma exposure, this effect is dampened, leading to smaller stock price movements. Therefore, a possible implication of this mechanism is that future extreme (absolute) returns are more likely to occur when Γ is negative.

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

In panel A, we predict the probability that the next month's absolute return is larger than 25%. In column (1), the slope coefficient on Γ is negative and statistically significant. This implies that higher net gamma exposures are associated with a lower probability of 25% or higher absolute 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 absolute 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

In this section, we examine whether the relationship between Γ and future stock returns varies over time or is state-dependent by plotting the monthly estimates of the net gamma premium over time. Fig. 3 plots the six-month moving average of the monthly estimated slope coefficient of Γ 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 significantly 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 variables. In column (1) we regress the gamma premium on the Chicago Fed National Activity Index (CFNAI). We find that decreases in the CFNAI is associated with decreases in the gamma premium. This indicates 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 Γ 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 VIX and the premium. In column (3), we regress the premium on the sentiment index of Baker and Wurgler (2006). We find that lower sentiment decreases the gamma premium. When sentiment turns bearish, risk aversion increases and a higher premium is required on negative net gamma stocks. In column (4), we regress the premium on the financial uncertainty index (FUNC) of Jurado et al. (2015). We find that higher 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 measures simultaneously. We find that CFNAI and sentiment positively predicts the premium, whereas FUNC predicts the premium negatively. Our results are consistent with the idea that the gamma premium is lower (i.e. higher for net negative gamma stocks) during bad states of the economy. During bad states, stocks with positive gamma exposures are considered as safer assets, and hence risk-averse investors command a lower premium for these stocks. Whereas the opposite occurs for stocks with a negative Γ.

4. Robustness

We provide multiple robustness tests in this section to corroborate our earlier results. First, we show that our results are robust to alternative research choices. Second, we conduct spanning regressions using well-known factor models. Third, we assess the predictive power of Γ on higher frequencies. Fourth, we decompose Γ in several components. Lastly, we expand our set of control variables further with a wide range of option-based predictors.

4.1. Alternative research choices

In this section, we show that our results remain qualitatively similar under several alternative methodological choices. First, we restrict our analysis to several sub-samples: the top 1000 largest stock in terms of their market capitalization (A), the top 1000 most liquid stocks in terms of the Amihud (2002) measure (B), and the top 1000 stocks with the highest option trading volume (C). Table A.2 shows panel regression results for each sub-sample. We find that Γ remains a significant and negative predictor in all sub-samples. Second, in all our analysis so far, we have always excluded microcaps and imposed a 5 dollar price filter. In Table A.3, we show similar results when we include microcaps and impose no price filter. As such, our results are not affected by small and illiquid stocks. Third, we show that our results are not driven by the specific construction choices of Γ. In Table A.4, we impose a one-day implementation lag in Γ (panel A), or use the average Γ in the sorting month (panel B). Lastly, panel C, 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). Under all three alternative specifications, we document a significant negative relationship between Γ and the next month stock return. Hence, our findings are robust to slightly different definitions of Γ.

4.2. Spanning regressions

Having shown the role of Γ in predicting the cross-sectional variation in individual stock returns, we subsequently construct a factor that captures the returns associated with Γ 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 Γ using the 30th and 70th NYSE percentile values of Γ. 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 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.

4.3. Daily and weekly frequencies

Next, we assess the predictive power of Γ on higher frequencies. Table 10 shows the regression estimates using daily returns and weekly returns. Column (1) in panel A reports the univariate regression results, and indicates a negative and statistically significant relation between Γ and the next day's excess return. The average Γ coefficient equals −3.13 with a Newey–West t-statistic of −3.02. This estimate is also economically significant. The daily standard deviation of Γ equals 0.0167. Hence, an one-standard deviation increase in Γ is associated with a 5.5 basis point decrease in the next day's return. The second column (2) controls for the contemporaneous return. The average slope on Γ remains economically and statistically significant at the 1% level. Column 3 till 5 incrementally add an interaction between Γ and return, implied volatility, call volume, and call open interest. In all specifications, we find that the relationship between Γ and next day's return is negative and statistically significant at the 1% level. Our finding is robust to the inclusion of other control variables, as shown in column (6). In panel B, we also regress the next week return on Γ. We, again, document a negative and statistically significant relation. After the inclusion of multiple control variables, this effect remains robust. Thus, our documented effect is also present for higher frequencies.

4.4. Option moneyness and time to expiration

We decompose Γ in terms of moneyness and 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, Γ 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 11. Column (1) shows the results when we regress the next month excess return on Γ, indicating that net gamma exposure negatively predicts future stock returns. In column (2), we decompose Γ into the ATM, OTM, ITM components and regress the next month's excess return on these components. We find that Γ from ATM and OTM options negatively predicts future returns, whereas the predictive power for ITM options is weaker. In column (3), we decompose Γ into the fast and slow component and regress the next month's 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.

4.5. 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 Γ is distinct for other well-known option-based variables. First, we add the difference between the historical realized volatility and at-the-money implied volatility (Goyal and Saretto, 2009). Second, we construct the implied volatility skew, proposed by Xing et al. (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 IV skew indicates a higher probability of large negative jumps in underlying asset prices. Third, we compute the volatility-of-volatility variable (VoV) of Baltussen et al. (2018), which measures uncertainty about risk by considering the volatility of implied volatility. Fourth, 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. Fifth, we compute the net dollar open interest as in Eq. (1) with gamma being replaced by one. This allows us to control for variation in Γ due to open interest and the price of the underlying. Furthermore, we compute the net delta exposure (Δ), as in Eq. (1) with gamma being replaced by the delta. Lastly, we measure trading volume in derivatives relative to the volume in underlying stocks (O/S), following Roll et al. (2010).

We show the cross-sectional regression results in Table 12. In column (1), we present the univariate regression estimate of the Γ 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 tested specifications, we consistently observe a negative and statistically significant relationship between Γ and future returns. In particular, in column (13), we control for all predictors simultaneously. We find that the negative relationship between Γ and the next month return remains statistically significant at the 1%. Furthermore, we find that IV_{skew}, CPIV and O/S positively and significantly predict the next month return, whereas volatility-of-volatility negatively predicts future returns. Thus, our results indicate that Γ 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 negative (positive) Γ 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 Γ is positive (negative). Hence, the relation between Γ and volatility is expected to be negative. This implies that risk-averse investors tend to be averse towards negative Γ and demand compensation in the form of higher expected returns to hold such stocks. On the other hand, stocks with positive Γ 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 Γ. The estimates are shown in Table 13. Column (1) in panel A shows a negative and statistically significant relation between Γ and next month's realized volatility. The average Γ 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 Γ in the decile portfolios from Table 2. The average difference in Γ 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 Γ 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, call open interest 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 Γ and future stock return volatility is negative.

5.1. Hedging versus private information

We have shown that Γ negatively predicts the realized volatility in the next month. We argue that this is driven by option market makers who aim to remain delta-neutral, and hence hedge their exposure away, thereby creating 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 Γ by following Ni et al. (2021): one component of Γ 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 Γ of the old positions at $t-\tau$ can also be written as:

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

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

The first component indicates the net gamma exposure using positions established at time $t-\tau$, using the stock price at $t-\tau$. The second component equals the change in the net gamma exposure due to changes in the stock price from $S_{t-\tau}$ to S_t, which cannot 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.

We regress the next month's realized volatility on Γ, and its components. Table 14 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 13. 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-statistic of −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-statistic of −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. Gamma exposures and earnings announcements

The previous section show that the negative relationship between Γ and stock returns is not driven by private information. In this section, we provide an additional piece of evidence against trading on private information, by focusing on earnings announcements. Suppose that prior to an earnings announcement, some market participant receives private information that stock returns will be positive and buys at-the-money call options in order to profit from this information. As market makers write these options, their position will have a negative net gamma exposure, thereby amplifying returns around earnings announcements.

We test whether the predictive power of Γ on stock returns is stronger on days around earnings announcements. The results are reported in Table 15. The indicator variable $I[Earnings]$ takes value 1 (else 0), in columns 1–3, on days in which there is an earnings announcement (day t). In column 4 and 5, $I[Earnings]$ takes value 1 on days $t-1$ till $t+2$ around the earnings announcement at day t. The interaction between Γ and $I[Earnings]$ measures the additional effect of net gamma exposure on stock returns around earning announcement days. As we have seen before, net gamma exposure predicts at day t predicts day $t+1$ returns negatively and significantly at the 1% level. However, we find that the interaction term $\Gamma \times I[Earnings]$ is insignificant in all specifications. Hence, the effect of the net gamma exposure on stock returns does not differ significantly around earning announcement days.

5.3. 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 Γ. The results are shown in Table 16. In panel A of Table 16 we show the estimates from Fama and MacBeth (1973) regressions using value-weighted observations. In column (1), 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.

Furthermore, we examine how gamma exposures affects the return-volume relationship. Llorente et al. (2002) find that the cross-sectional variation in the relation between volume and return autocorrelation is related to the extent of informed trading in a manner consistent with the theoretical prediction. Specifically, Llorente et al. (2002) estimates the following specification:

$$R_{i,t+1} = C_{0,i} + C_{1,i} R_t + C_{2,i} R_t \times V_t + \epsilon_{t+1} \tag{7}$$

where V_t denotes the turnover. Llorente et al. (2002) argues that stocks that are associated with very significant speculative (hedging) trade have $C_2 > 0$ ($C_2 < 0$). If flows induced by gamma exposures are driven by hedging motivations, we would expect C_2 to be lower for stocks with high absolute gamma exposures. On the other hand, if gamma-related flows are induced by private information, we expect C_2 to be higher for stocks with large absolute gamma exposures. We test whether the return-volume relationship is affected by the absolute gamma exposure in Table 17. In column one, we estimate Eq. (7), and find that C_2 is significantly positive. We extend Eq. (7) by adding an interaction term between turnover, return at t and absolute net gamma exposure, which allows to test whether C_2 differs by absolute net gamma exposure. Column (2) shows a negative coefficient, indicating that high absolute gamma decreases C_2. However, this coefficient is not statistically significant. Once, we control for other variables in columns 3–5, we find that C_2 decreases significantly when absolute net gamma exposure is larger. As such, the return-volume relationship is flatter for stocks with large absolute net gamma exposure, driven by hedging rather than speculative trading.

5.4. Hedging versus mispricing

We argue that net gamma exposure is negatively priced due to risk-averse investors who require compensation to hold stocks with lower, or even negative, net gamma exposure. Alternatively, the predictability can potentially be driven by mispricing and underreaction. Stocks with negative (positive) gamma exposure may be underpriced (overpriced), and hence outperform in month $t+1$. This alternative explanation offers several testable implications.

First, stocks with lower net gamma exposure should have lower exposure to measures of mispricing to explain the negative relationship between Γ and future stock returns, given that mispricing drives our main results. We proxy for mispricing by using the mispricing score of Stambaugh et al. (2015), whereby a higher (lower) mispricing score indicates more (less) overpricing. We construct decile portfolios based on the net gamma exposure, and compute the value-weighted mispricing score by decile. We show the results in panel A of Table 18. Our results indicate that net gamma exposure is negatively associated with mispricing: low net gamma exposure stocks tend to have higher mispricing score than stocks with a higher net gamma exposure. Hence, mispricing cannot drive the negative predictive relationship between net gamma exposure and future stock returns.

Second, if low (high) net gamma exposure stocks are underpriced (overpriced), we would expect less (more) short-selling activity for such stocks. We collect monthly short volume data from FINRA, and monthly short interest data from Markit IHS securities to test this hypothesis. For each decile, based on the net gamma exposure, we compute the value-weighted average short volume and short interest. We show the results in panel B of Table 18. We find that net gamma exposure is negatively associated with both short volume and short interest. This, again, indicates that mispricing is not driving the results.

Lastly, if underreaction drives the predictive relationship between net gamma exposure and future returns, then such mispricing should eventually be corrected by a reversal. We compute the value-weighted cumulative return for the spread portfolio at $t+1$ till $t+12$ to study the return pattern beyond the $t+1$. The results are shown in panel C of Table 18. We find that the cumulative return is negative and statistically significant between $t+1$ and $t+12$, with Newey–West t-statistics ranging between −3.00 and −5.29. We do not observe any reversal effect, which we would expect if mispricing is driven the results. All in all, our results suggest that the negative predictive relationship between net gamma exposure and future returns is not driven by mispricing.

6. Conclusion

In this study, we examine the relation between 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 demand 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 bivariate 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 predictability. We show that net gamma exposure negatively predicts future volatility. Hence, stocks with negative gamma exposure tend to be riskier. As such, 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.

CRediT authorship contribution statement

Amar Soebhag: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization.

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Table A.1
Average portfolio characteristics.

	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***	0.17***	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)

This table reports the average characteristic of decile portfolios formed on the basis of the net gamma exposure. 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 labelled "H-L" 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. Stocks with prices below $5 and microcaps as of the portfolio formation are excluded. 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.

Table A.2
Various sub-samples.

	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

This table reports estimates from regressing monthly excess returns on 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. 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.

Table A.3
Stock-level regressions with microcaps and without price filters.

	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

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 value-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 for panel regressions. Asterisks are used to indicate significance at a 10% (*), 5% (**) or 1% (***) level. The sample runs from February 1996 till December 2021.

Table A.4
Sorting on alternative gamma definitions.

	Panel A: 1-day lag				Panel B: Average monthly gamma				Panel C: Market-scaling			
	Γ	R	α_{5FM}	α_{Q4M}	Γ	R	α_{5FM}	α_{Q4M}	Γ	R	α_{5FM}	α_{Q4M}
L	−0.01***	1.36***	0.57***	0.51***	−0.01***	1.23***	0.34**	0.38**	−0.10***	1.44***	0.65***	0.58***
	(−11.79)	(5.24)	(3.72)	(2.94)	(−9.86)	(4.64)	(2.48)	(2.59)	(−8.63)	(5.00)	(4.57)	(3.78)
H	0.04***	0.63***	−0.25***	−0.30***	0.04***	0.70***	−0.20***	−0.25***	0.38***	0.69**	−0.16	−0.21*
	(18.75)	(2.99)	(−3.19)	(−2.99)	(17.80)	(3.37)	(−2.80)	(−2.98)	(12.25)	(2.19)	(−1.46)	(−1.87)
H-L	0.05***	−0.72***	−0.82***	−0.81***	0.05***	−0.53***	−0.54***	−0.63***	0.48***	−0.75***	−0.82***	−0.79***
	(17.49)	(−3.91)	(−4.31)	(−3.39)	(16.42)	(−3.01)	(−3.22)	(−3.26)	(7.92)	(−3.02)	(−4.02)	(−3.53)

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. In panel C, Γ is computed as in Baltussen et al. (2021) by using the market capitalization as a scaling factor instead of 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 $t+1$. The results are shown for value-weighted portfolios whereby the breakpoints are based on the NYSE universe. We report the time-series average of the net gamma exposure (Γ), the return ("R") in percentages, the Fama–French–Carhart six-factor alpha ("α_{5FM}"), Hou, Xue, and Zhang's q-factor model augmented with momentum ("α_{4QM}") for each portfolio. The row labelled "H-L" 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. Stocks with prices below $5 and microcaps as of the portfolio formation are excluded. 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.

Appendix. Additional tables & figures

See Tables A.1 and A.4.

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