FE5214: Introduction to Quantitative Investing

Project on Gamma Exposure Quantitative Research

Instructor: Prof. Chen Kan, Dr. Ding Li

Name	Student ID
Hui Yangyifan	A0294960R
Huang Anna	A0296296J
Lim Wei Xuan	A0297957Y
Shu Ning	A0230610B
Zhang Huizi	A0297812U
Zhang Jinkun	A0294711A

Contents

Overview

In this project, we explore the predictive capability and strategic applications of Gamma Exposure (GEX) in forecasting asset returns, with S&P500 options serving as the primary research vehicle. As a second-order Greek, GEX reflects the aggregate hedging flows that market makers generate. By quantifying GEX, we dive into short-term return behavior and volatility regimes.

In the first part, we establish the theoretical foundation for GEX, detailing the mechanics of dynamic hedging, the asymmetry introduced by skewed option demand, and the market implications of the so-called “gamma flip”.

Then, we present a rigorous computation framework using SPY option data from OptionMetrics and benchmark it against SqueezeMetrics estimates. We perform a preliminary statistical analysis of GEX. Statistical analysis confirms the presence of non-Gaussian features in the GEX distribution, including right skewness, fat tails, and temporal clustering, suggesting potential for predictive modeling.

Building on these insights, we design and backtest two simple trading strategies. The first is a mean-reversion model that exploits extreme GEX deviations, conditioned on momentum signals via the Relative Strength Index (RSI). The second is a volatility-targeted straddle strategy, guided by a dual-signal regime combining GEX and the Volatility Risk Premium (VRP). Both strategies exhibit favorable performance, particularly during periods of market stress.

1 Fundamental Mechanism of Gamma Exposure Impacts

1.1 Delta, Gamma and Dynamic Hedging

In the context of financial derivatives pricing and risk management, Delta and Gamma are key “Greeks” used to measure the sensitivity of an option’s value to changes in the underlying asset. Delta represents the rate of change of the option price with respect to changes in the underlying asset price, effectively capturing the directional exposure of a position. Gamma, on the other hand, measures the rate of change of Delta itself, indicating how stable or unstable the Delta is as the underlying price fluctuates. Understanding and managing Delta and Gamma is essential for constructing effective hedging strategies and controlling risk exposure in derivatives portfolios.

The predictive power of GEX is essentially driven by the necessity of option dealers’ (market makers’) re-hedging activities. In order to limit risk and realize profit, an option market-maker must limit his exposure to delta. As the underlying moves, so does the delta-hedging requirement. Market makers are forced to trade the underlying simply due to the price of that asset changing and not for any other fundamental or economic reasons. If, e.g., a market-maker sells a single, 20-delta put contract to an investor, he must then short-sell approximately 20 shares of the underlying stock in order to (temporarily) neutralize the convexity effect of the option’s gains and losses. Since the convexity itself cannot be hedged away, the market maker must commit to re-hedging the option to its new delta whenever the underlying price changes enough to justify action. If in one case the price of the underlying falls and the put delta rises from 20 to 50, the market-maker will be compelled to short-sell an additional 30 shares of the underlying to stay delta-neutral. If instead the underlying rises and the put delta falls to 0, the market-maker would buy back the previously shorted shares. Thus, a market-maker is essentially committed to a predictable and quantifiable regimen of buying and selling stock.

1.2 Effects of Dealers’ Dynamic Hedging

When the option market makers are longing gamma, their delta-hedging activity forces them to “buy low, sell high”. They are sellers when the market rallies and buyers when it drops, conveniently adding liquidity and reducing volatility. When they are shorting gamma, the opposite happens. Dealers’ books are short options, and they “buy high, sell low”. This exacerbates market moves and removes liquidity (frequently, when it’s needed the most). The table below illustrates the impact of dynamic hedging on the price of the underlying asset, where S denotes the underlying security.

Option Dealers' Opening Interest				
Option	Long Put	Short Put	Long Call	Short Call
Underlying	Long S	Short S	Short S	Long S
Price Movements —Dynamic Hedging				
S Up	Short S	Long S	Short S	Long S
S Down	Long S	Short S	Long S	Short S
Impact of Dynamic Hedging				
Impact to S movements	Curb	Promote	Curb	Promote

Table 1: Effects of Dealers' Dynamic Hedging

On an index level, it is generally believed that investors predominantly buy puts for protection and sell calls as part of overwriting strategies. This is evident in the SPX skew, which shows higher implied volatility for puts than calls.

This chart illustrates the volatility skew for SPY options, where implied volatility (IV) is plotted against moneyness. It clearly shows that out-of-the-money (OTM) put options—on the left side of the chart with moneyness below 100%—exhibit significantly higher implied volatilities, reaching levels above 60%. In contrast, OTM call options—on the right side with moneyness above 100%—have much lower IVs, often below 20%. This asymmetry demonstrates that put options carry higher implied volatilities than call options, reflecting the market's greater demand for downside protection and its sensitivity to potential negative tail risks.

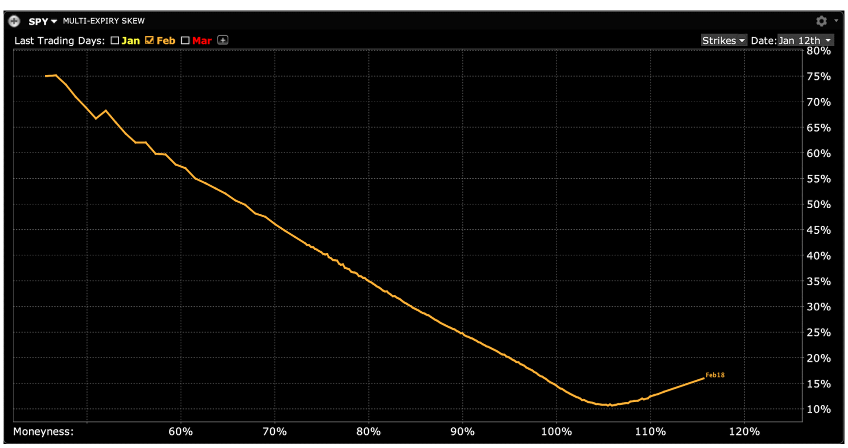

Figure 1: SPX IV Skew, 12 January 2022, Source: Perfiliev

Under this assumption, for dealers, puts carry negative gamma, and calls carry positive gamma.

1.3 Gamma Flip

A gamma flip is a term used to mark the stock price at which dealers are estimated to switch from a net positive gamma position to a net negative gamma position, or vice versa. If we're above the gamma flip, the volatility tends to be low, as the market has to swim against the current of the options flow. But should the market drop into negative gamma territory, expect fireworks. In this scenario, delta-hedging flows move in the same direction as the market, potentially amplifying the price action. As volatility rises, systematic and managed volatility funds tend to cut exposure, further adding to the selling pressure and provoking more negative gamma flows.

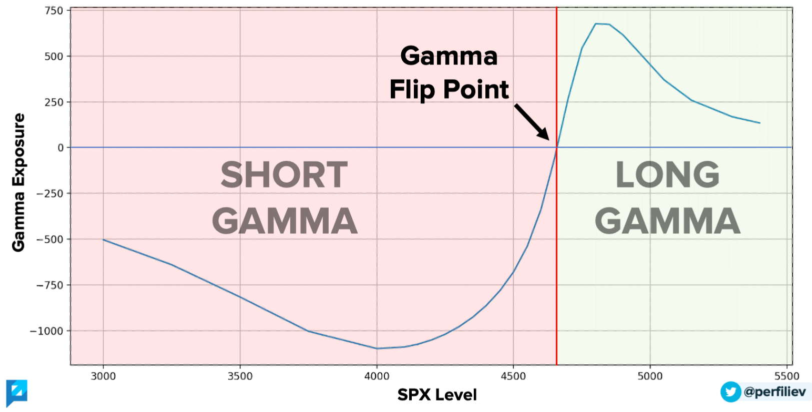

Figure 2: SPX Gamma Exposure, 12 January 2022, Source: Perfiliev

1.4 When is Gamma Effect the Strongest?

For any single option, gamma is a bell-shaped curve centered around the strike. And it's the highest for short-dated, at-the-money (ATM) options.

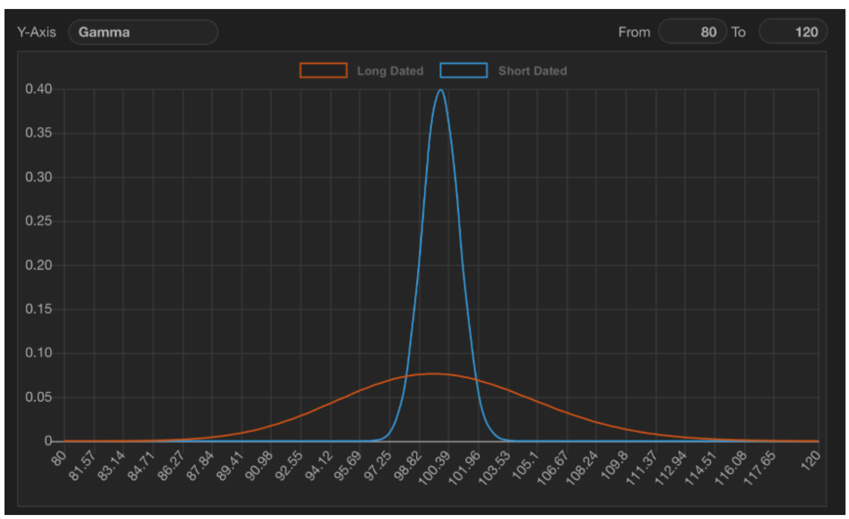

Figure 3: The Shape of Gamma with respect to Strike, Source: Perfiliev

The most open interest is frequently concentrated around nice, round strikes.

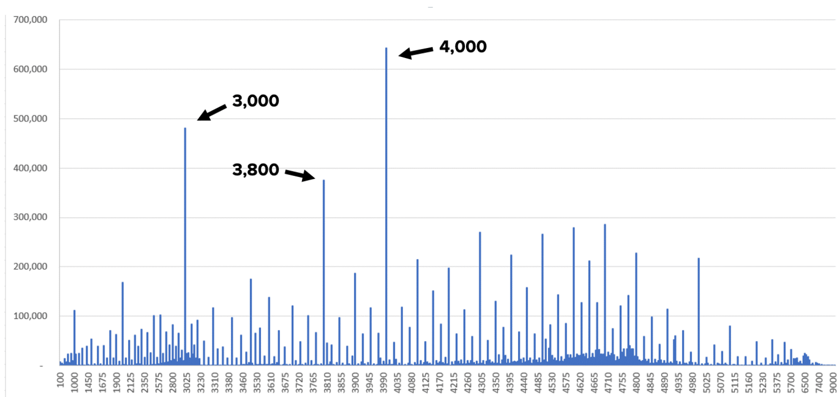

Figure 4: Total SPX Open Interest, Source: Perfiliev

Large expiries play an important role. There is an SPX options expiration every Monday, Wednesday, and Friday, and traditional monthly options expire every third Friday of the month. However, longer maturities tend to be listed on a quarterly (Mar/Jun/Sep/Dec). Since these maturities have been around for longer, they accumulate considerable open interest. Quarterly third Friday options also have the added benefit of SPX futures expiring on the same date. Delta-hedging and unwinding these positions can increase market activity around the expiration time.

It also depends on the available liquidity at the time. The higher the liquidity, the more likely the market will simply absorb any delta-hedging flows without even noticing it. However, at times of low liquidity, gamma flows can be responsible for significant price action around options expirations.

Gamma tends to lose its power in a high volatility environment, as delta becomes less sensitive to underlying moves.

2 Exploration of Gamma Exposure

2.1 Assumptions

The size and liquidity of the equity option market is what makes it possible to glean predictive information from the impact of hedging activity, but it also introduces some challenges. With a few assumptions, we attempt to overcome those challenges.

1. All traded options are facilitated by delta-hedgers. This is to say that every option contract is either bought by, or sold by, a market participant whose business is to profitably manage a book of options.

2. Call options are sold by investors and bought by market-makers. It is difficult to determine the "direction" of a trade in an ultra-liquid market, as in the case of SPX options. A vast majority will trade at the midpoint of the bid and ask. It is apparent from an analysis of skew, open interest at strike, and (circularly) the effects of GEX, however, that the practice of call overwriting (and stock collaring) drives the market for calls.

3. Put options are bought by investors and sold by market-makers. As with calls, puts are primarily used by investors who are already exposed to the underlying market, and who are looking to modify the return profile of their portfolio by using options. The "protective put" commands a premium for this reason, thus influencing the apparent vertical skew of index options.

4. Market-makers hedge precisely to the option delta. If market-makers hedged their deltas every time an option's delta changed, they would be trading incessantly. In reality, market-makers utilize "hedging bands" to balance the twin challenges of hedging costs and delta risk. Since it is not feasible to gauge the breadth of every market-maker's hedging band, we simply use the delta of the option. With these assumptions, we can compute GEX.

2.2 Calculation of Gamma Exposure

The formula for gamma contribution from each option is

$$\text{Gamma Exposure} = \text{Option's Gamma} \times \text{Contract Size} \times \text{Open Interest} \times S.$$

where S is the spot price of the underlying asset.

This gives the total option's change in delta per one point move in the index. But in real trading, we care more about how much delta changes if the index changes by 1 percent. Hence, the final formula is

$$\text{Gamma Exposure} = \text{Option's Gamma} \times \text{Contract Size} \times \text{Open Interest} \times S^2 \times 0.01.$$

Based on the assumption, we treat the gamma exposure of the Call option as positive and the gamma exposure of the put option as negative. Summing gamma contributions across the option contracts gives us the total gamma exposure (GEX), i.e.,

$$\text{GEX} = \text{Call Gamma Exposure} - \text{Put Gamma Exposure}.$$

We also define a similar factor to compare their significance

$$\text{GEX Skew} = \frac{\text{Call Gamma Exposure} - \text{Put Gamma Exposure}}{\text{Call Gamma Exposure} + \text{Put Gamma Exposure}}.$$

2.3 Data Description

In this project, we select SPY as the subject of our study. SPY is an ETF that tracks the performance of the S&P 500 Index. SPY and its options are particularly suitable for gamma exposure research due to their exceptionally high liquidity, tight bid-ask spreads, and large open interest across a wide range of strike prices and maturities. These characteristics not only ensure data reliability and robustness of empirical analysis, but also reflect the significant role SPY options play in institutional hedging and market-making activities, making them an ideal proxy for studying dealer positioning and gamma-related market dynamics.

The data we used to compute GEX are downloaded from OptionMetrics, which provides data on U.S. options and their underlying securities. We use daily data from 2016 to 2022 to calculate GEX.

Another data source used in this study is SqueezeMetrics, a widely recognized platform that provides gamma exposure estimates for the S&P 500 Index. By incorporating both SPX and SPY option data and applying proprietary adjustments, its GEX estimates are considered more robust than those derived solely from SPY options.

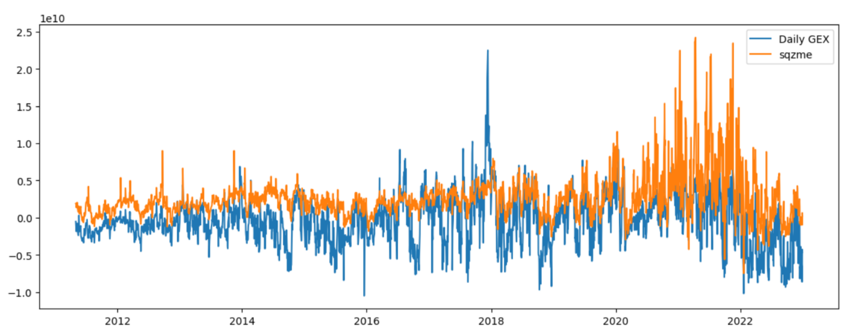

Figure 5: GEX Calculated from OptionMetrics vs SqueezeMetrics

In the subsequent statistical analysis and strategy evaluation, we rely on the GEX estimates provided by SqueezeMetrics.

2.4 Statistical Properties of GEX

Figure 6 illustrates the GEX of S&P500 from 2011 to early 2025. During the early years, GEX remained relatively stable with moderate fluctuations above the zero level, reflecting a balanced market environment. Beginning in late 2019 and intensifying throughout 2020, GEX increased significantly in both magnitude and volatility, coinciding with the COVID-19 pandemic and heightened market activity. In 2021, the S&P 500 index experienced a steady upward trend with low volatility; thus we observe that GEX values were frequently positive. After peaking in early 2022, GEX gradually declined but remained elevated compared to the pre-2020 period, suggesting structural changes in market dynamics.

Throughout the sample, GEX frequently takes on positive values, particularly during stable or bullish periods, implying that dealers were often gamma long, which generally contributes to market stabilization.

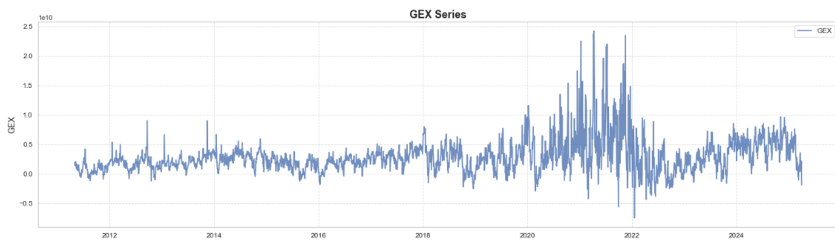

Figure 6: GEX Series

This histogram of GEX shows a right-skewed distribution. The long right tail indicates the presence of extreme positive GEX values, suggesting heavy-tailed behavior and potential market stress during high GEX periods. The QQ plot confirms the same pattern observed in the histogram.

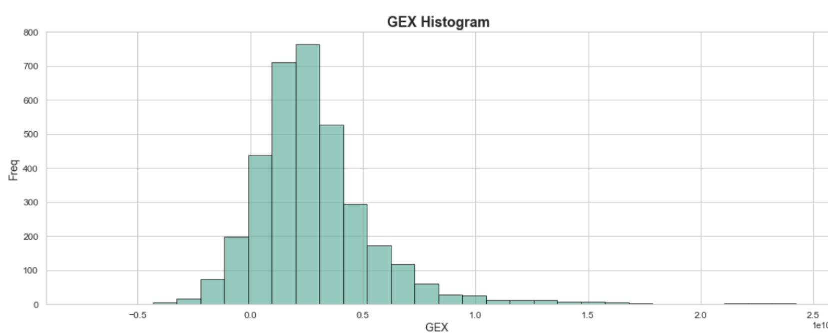

Figure 7: GEX Histogram

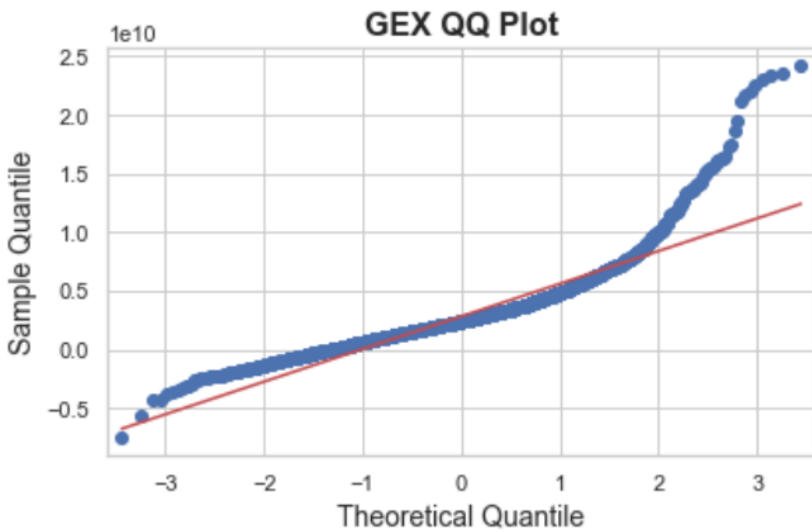

Figure 8: GEX QQ Plot

2.5 Market Impact of GEX

Using the above computations, a GEX figure that is positive implies that option market-makers will hedge their positions in a fashion that strikes volatility (buying into lows, selling into highs). A GEX figure that is negative implies the opposite (selling into lows, buying into highs), thus magnifying market volatility. A corollary is that a GEX figure approaching zero will allow the market to move naturally and without any particular interference from market-makers' re-hedging activities. The figure below, plotting SPY returns against SPY options' prior day Gamma Exposure, bears this out.

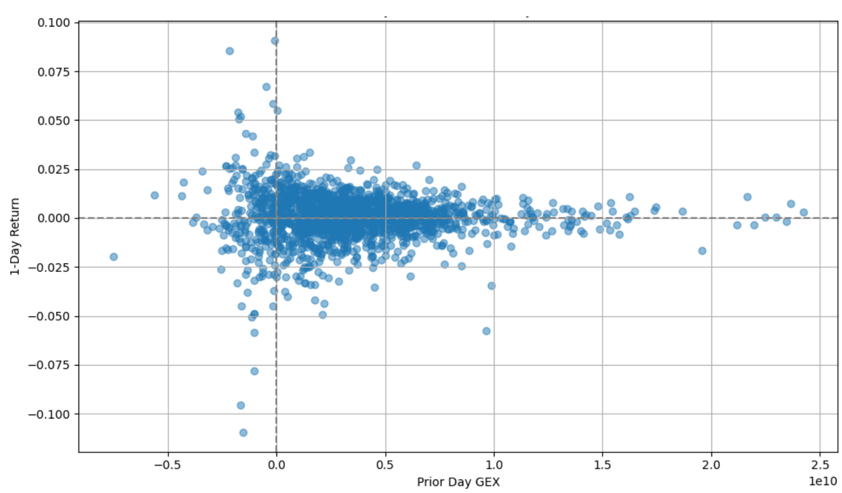

Figure 9: 1-Day Return vs Prior Day

3 GEX-Based Strategy Trials

In this section, we experiment with two quantitative strategies based on our findings in GEX, using simple logics and backtesting for demonstration.

3.1 Mean Reversion Strategy

The mean-reverting strategy leverages Gamma Exposure (GEX) to identify contrarian trading opportunities. Empirical evidence corroborates that extreme GEX conditions often precede sharp reversals. For example, during the March 2020 COVID-19 crisis, JPMorgan estimated that over $100 billion in equity was sold in two days due to extreme short gamma hedging, which subsequently led to a pronounced rebound. In essence, the GEX factor acts as a proxy for dealer hedging pressure; when that pressure becomes extreme, the market is primed to revert toward equilibrium. This insight underpins our strategy, which is designed from a market dealer perspective with the aim of maximizing risk-adjusted profits.

3.1.1 Statistical Diagnostics of GEX

To motivate a GEX-based strategy, we examine the statistical characteristics of daily GEX for the S&P 500 (May 2011–April 2025). Its distribution is highly non-normal, with a pronounced positive skew (≈ 2.04) and extreme kurtosis (≈ 9.14), suggesting rare but significant volatility shocks or one-sided option positioning could lead to outlier large positive observations far beyond the mean.

Figure 8 confirms such non-normality as sample quantiles deviate more frequently than a Gaussian assumption would predict. This fat-tail property is crucial for strategy design: extreme GEX readings might signal unusual market conditions and potential mean reversion opportunities.

To motivate a GEX-based strategy, we examine the statistical characteristics of daily GEX for the S&P 500 (May 2011–April 2025). The distribution of GEX is highly non-normal, with a pronounced right skew (skewness ≈ 2.04) and extreme kurtosis (≈ 9.14). Such values indicate a long right tail and fat-tailed behavior, meaning that while GEX is usually moderate, it occasionally attains very large positive values far beyond the mean. These moments suggest that rare but significant market events (e.g. volatility shocks or one-sided option positioning) lead to outlier GEX observations.

To formally test stationarity, we apply the Augmented Dickey-Fuller (ADF) and KPSS tests. The ADF test strongly rejects the unit-root null (ADF statistic ≈ -6.395, $p < 0.001$), indicating the GEX series is likely mean-reverting. However, the KPSS test rejects the null of stationarity (≈ 2.067, $p = 0.01$). This apparent contradiction can be reconciled by noting the possibility of structural breaks or regime shifts in 2011–2025. For instance, the extraordinary volatility during the March 2020 crash caused unprecedented negative GEX, shifting the short-term mean. Such events violate the constant-mean assumption of KPSS, even though the series mean-reverts within regimes. In practice, we interpret these results as evidence that GEX has inherent mean reversion (no permanent unit root), but its base level can change after major market upheavals. This reinforces the motivation for a short-horizon mean-reverting strategy: we can exploit transient deviations of GEX and price from equilibrium, while being mindful that extreme events (e.g. 2020, 2025) may introduce new regimes.

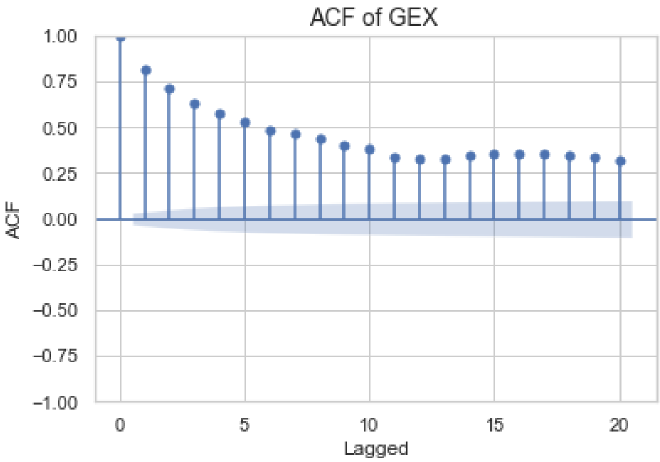

Figure 10: ACF of GEX

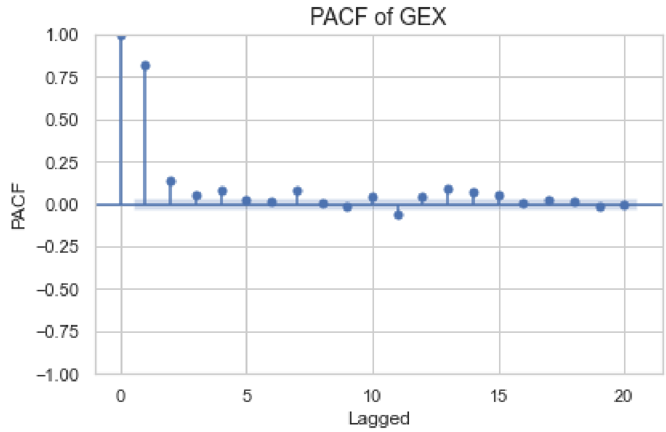

Figure 11: PACF of GEX

Autocorrelation analysis shows that the GEX series exhibits an AR(1) structure. Significant positive autocorrelation persists up to 10 lags before the 95% confidence bounds are reached. This "long memory" hints that GEX shocks are not fleeting one-day events but can influence the market for several days.

The PACF is large at lag 1 and near zero thereafter, consistent with an AR(1) process. This suggests daily GEX can be modeled as a mean-reverting process with a strong immediate dependence on the previous day and quickly diminishing higher-lag effects.

3.1.2 Signal Construction

Given the observed structural breaks, a 120-day rolling window is employed to compute the local mean and standard deviation for the GEX series. This normalization adjusts the baseline to account for regime shifts and allows us to identify days when GEX is unusually high or low relative to its local history.

Trading signals are generated based on extreme Z-scores

$$Z_t = \frac{GEX_t - \mu_{120,t}}{\sigma_{120,t}}.$$

Long Signal: Triggered when GEX < 0 and $Z_t < -1$, implying excessive short gamma exposure. Such conditions typically occur during market sell-offs, illustrated by the deep GEX decline in March 2020.

Short Signal: Triggered when GEX > 0 and $Z_t > +1$, indicating excessive long gamma exposure, which has been observed preceding corrections (as in June 2021).

No Position: If neither condition is met.

However, not every extreme GEX guarantees an immediate price reversion –the market can stay overbought or oversold longer than anticipated. To enhance robustness, we incorporate a momentum filter using the Relative Strength Index (RSI). The 10-day RSI gauges recent price momentum on a 0–100 scale (low values = oversold, high = overbought). We require the RSI to confirm the contrarian entry to avoid fighting strong trends. Specifically, a preliminary buy signal (from negative GEX) is only confirmed if RSI < 30 (signaling the index is deeply oversold). Similarly, a sell signal (from positive GEX) is confirmed only if RSI > 80 (overbought). If the RSI condition is not met, we ignore the GEX signal (treat it as 0). This filter aligns with the intuition that, for example, even if GEX is extremely negative, one should only buy if there are signs the market is technically oversold (in the absence of such signs, a negative GEX could just reflect a continuing bearish trend). This dual-layer filtering ensures the strategy only trades when both fundamental (dealer hedging) and technical (momentum) indicators align.

3.1.3 Backtesting and Analysis

The backtesting framework applies the confirmed signal to SPY daily returns. For each trading day t, the signal generated is executed with a one-day lag to avoid lookahead biases.

$$r_{t+1}^{(\text{strategy})} = \text{Final\_Signal}_t \times r_{t+1}^{(\text{SPY})}.$$

Above setup leads to a low frequency of trades only when both GEX and Z-score conditions align. Indeed, over 2011–2025, the strategy took 141 trades (93 long and 48 short days) out of 3500 trading days, remaining in cash about 96% of the time. Such selective engagement is by design, aiming to capture only the most statistically anomalous setups where mean reversion is strongest.

We observe clusters of black dots during volatility spikes, for instance, a flurry in late 2018 and March 2020 when GEX became strongly negative. Black squares mark points where the RSI filter confirmed the GEX signal - these are the days the strategy actually took a position.The cumulative return of the strategy (black line labeled "Strategy PnL") demonstrates a total return of +77.24% and a decent Sharpe ratio of 0.7 as of 11th April 2025, because the strategy is mostly in cash and only occasionally takes directional risk. Importantly, the growth is achieved with relatively small drawdowns compared with SPY −the curve ratchets upwards in a stepwise fashion with only mild interim dips. This reflects the strategy's capital preservation during non-signaled periods and its positive expectancy when trades occur.

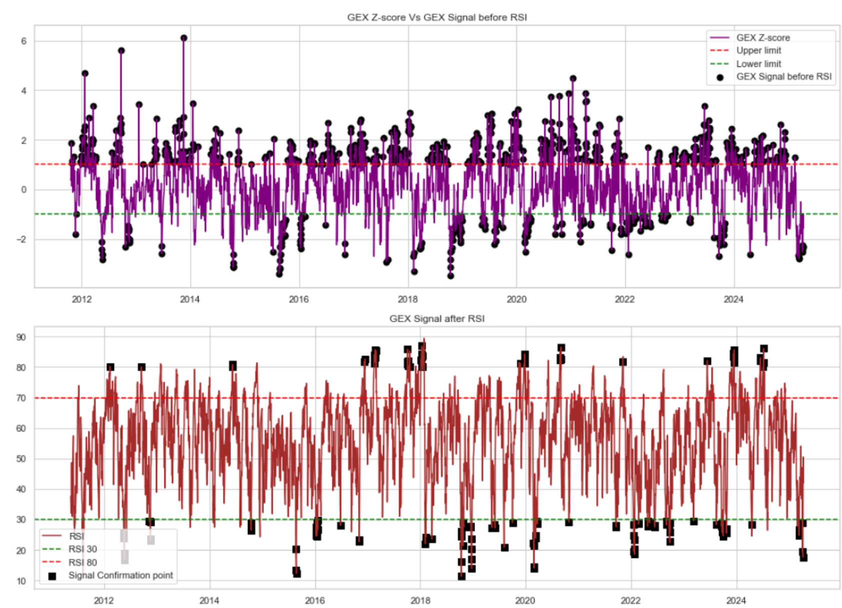

Figure 12: GEX Signal before and after RSI

Figure 13: MR Strategy vs SPY

The backtest confirms the theoretical basis of the strategy. When GEX is extremely positive, it indicates that market-makers are long gamma and tend to hedge by selling into rallies and buying dips, which compresses further upward movement and results in only modest corrections. In contrast, when GEX is extremely negative, market-makers are short gamma, leading to aggravated price declines as they sell into lows and buy into further drops. Our strategy exploits these extremes: extreme negative GEX, when confirmed by oversold RSI conditions, marks an opportune moment for a long entry, as seen during the March 2020 crash. This combination of GEX extremes and technical confirmation reflects academic principles that integrate fundamental market flow signals with momentum indicators to time turning points.

The strategy's performance during periods of exceptional stress—such as the 2020 crash and tariff-induced global sell-off in April 2025—demonstrates its robustness with a significantly lower drawdown compared to S&P 500 (see scaled illustration below, supported by the sharp rebound observed on April 9, 2025). While many strategies falter during extreme volatility, our approach leverages the heavy-tailed, non-Gaussian distribution of GEX to generate profitable, risk-managed trades, essentially turning a statistical challenge into a competitive edge.

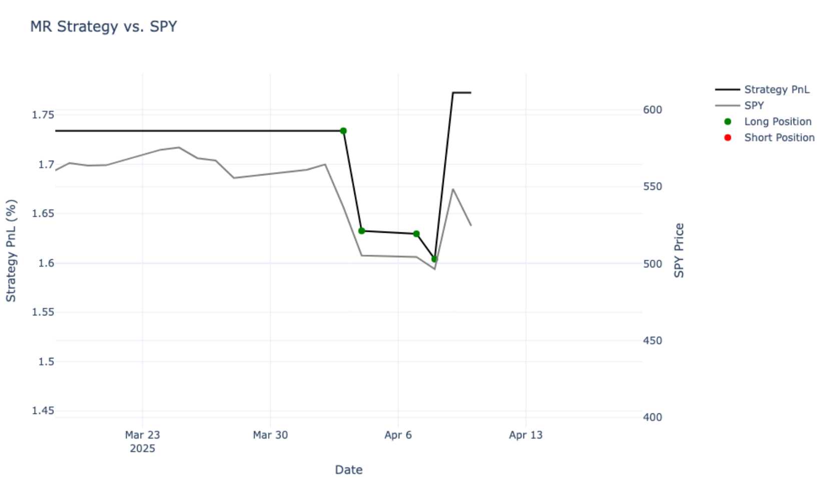

Figure 14: MR Strategy vs SPY

However, during prolonged bull markets, the model's infrequent signals meant that cumulative gains were more modest compared to straightforward long positions. Nonetheless, the strategy provided uncorrelated alpha by earning profits during major drawdowns, thereby offering a diversified risk profile. In essence, this strategy harvests the volatility mean-reversion risk premium by capitalizing on transient dislocations in dealer hedging, thereby linking options market microstructure directly to index returns.

Comments

Overall, the strategy exhibits a mean-reverting character: it profits from market snap-backs after extreme conditions, and stays out (or exits quickly) during persistent trends. The strategy's two-factor signal—melding the GEX Z-score with RSI confirmation—ensures that trades occur only when both fundamental and technical conditions suggest a reversal. This methodology is particularly appealing from a dealer perspective, where capturing transient reversals during periods of market dislocation can potentially reduce downside risk and improve risk-adjusted returns.

Most recently, Trump's tariff chaos caused a significant spike in GEX and overbought conditions in SPY, triggering short signals that successfully captured the ensuing pullback on 9th April 2025. These case studies demonstrate the strategy's ability to navigate different market regimes: it stayed cautious in low-vol environment, and aggressively contrarian in high-vol mean-reverting scenarios.

On the other hand, the Sharpe ratio of 0.7 reflects the inherent challenges of low-frequency signals, signal timing, and execution delays. Future refinements may involve adopting dynamic thresholding via regime-switching models to adjust signal criteria in response to evolving market conditions. This approach would allow threshold values—such as the ± 1 Z-score and RSI criteria—to automatically adapt to different volatility regimes. Moreover, incorporating additional filters such as the VIX or the Dark Index could further validate our signals by providing complementary measures of market sentiment and liquidity, helping to distinguish genuine reversal conditions from transient noise. Enhanced risk management is also crucial; the integration of stop-loss mechanisms and volatility-targeted position sizing could significantly mitigate adverse moves during rapid market transitions, ensuring that losses are contained and that the strategy's risk profile is more tightly controlled.

3.2 ATM Straddle Strategy

In this section, we present a volatility-driven options trading strategy that integrates At-the-Money (ATM) straddles with a dual-signal regime based on Gamma Exposure (GEX) and the Volatility Risk Premium (VRP). The strategy dynamically allocates capital to either long or short straddle positions on SPY options, depending on market positioning (as derived from GEX) and volatility expectations (as indicated by VRP). We assess the performance of this strategy over the period from 2010 to 2022, analyzing cumulative P&L, market conditions, and trade signals.

3.2.1 ATM Straddle Construction

The ATM straddle strategy involves purchasing both a call and a put option with identical strike prices and expiration dates, anticipating elevated volatility in the underlying asset. It profits from significant price movements in either direction. We select the SPY ETF as the underlying asset and use SPY options to construct straddle positions, due to its high liquidity and substantial open interest.

The selection criteria are as follows:

- **Frequency:** We Select ATM call and put options on each trading day.
- **Strike Price Condition:** We Select the ATM option pair (call + put) whose strike prices are closest to the closing price of SPY on that day.

- **Days Till Expiration Condition:** Options with Days till Expiration (DTE) between 2 and 14 days are preferred. If multiple pairs meet this criterion, we choose the pair with the minimum DTE. If none is within the range, we select the pair closest to it.

We select near-term options based on the following reasons: they offer higher gamma, enabling greater sensitivity to short-term price movements; they are more cost-effective due to lower time value; and they exhibit heightened sensitivity to changes in implied volatility, making them particularly suitable for event-driven strategies. These features make near-term options an effective choice for constructing ATM straddles aimed at capturing short-term volatility.

3.2.2 Signal Construction

Gamma Exposure (GEX) measures the aggregate gamma positioning of market makers or dealers, reflecting sensitivity to underlying price movements due to delta-hedging. When GEX is high (positive), dealers are long gamma and tend to stabilize the market by selling into rallies and buying dips, which is suitable for short straddles. When GEX is low or negative, dealers are short gamma and their hedging activities amplify volatility, which is suitable for long straddles.

We compute the 5th and 95th percentiles of GEX using a 21-day rolling window. These thresholds define "extremely low" and "extremely high" GEX levels.

Volatility Risk Premium (VRP) refers to the difference between implied volatility (IV) and realized volatility (RV). It is defined as

$$VRP = \text{VIX} - \text{RV},$$

where

$$\text{VIX} = \frac{\text{VIX close price}}{100},$$

$$\text{RV} = \text{Annualized volatility using EWMA with 21-day (or 10-day) log returns of SPY.}$$

When VRP is positive, it means that the market is expecting higher volatility in the future than what has actually been realized. In this case, option prices tend to be higher because implied volatility is elevated. Option sellers might find options overpriced, while buyers of options might be paying a premium for the potential volatility they believe is coming. So it is often a good environment for selling options (short straddles); when VRP is negative, it means that the market has underestimated the future volatility. In this case, option prices tend to be lower because implied volatility has fallen relative to realized volatility, which is suitable for long straddles.

Trading signals are generated based on GEX and VRP:

- **Long Signal:** Triggered when GEX $<$ its 5th percentile and VRP < 0.
- **Short Signal:** Triggered when GEX $>$ its 95th percentile and VRP > 0.
- **No Position:** If neither condition is met.

3.2.3 Backtesting and Analysis

P&L is computed based on the 1-day holding strategy, by entering the position on one trading day and exiting it on the following day, assuming no transaction costs.

Position	Time	Cash Flow	Explanation
Long Straddle	t	$-(C_{\text{ASK}} + P_{\text{ASK}})$	Pay premium to buy call and put
	$t+1$	$+(C_{\text{BID}} + P_{\text{BID}})$	Sell both options at bid prices
Short Straddle	t	$+(C_{\text{BID}} + P_{\text{BID}})$	Receive premium from selling call and put
	$t+1$	$-(C_{\text{ASK}} + P_{\text{ASK}})$	Buy back options at ask prices

Table 2: PnL of Long and Short Straddles

Then we show the cumulative returns over the backtesting period.

Figure 15: Cumulative Returns of Straddle Strategy

The result shows a low frequency of trades only when both GEX and VRP conditions align. For details, over 2925 trading days, the strategy generates only 9 long signals and 169 short signals. Most days yield no action due to the stringent conditions set by the GEX and VRP thresholds. But when trades are executed, they tend to be profitable, whether long or short. This means we have a high win rate and it indicates that the strategy is generally efficient in capturing favorable market conditions.

An analysis of the top ten profit and loss performances reveals that the maximum drawdown can reach up to 13.54%, while the maximum profit rate is only 3.49%. This highlights that the magnitude of losses significantly exceeds the potential for profits.

Date	Profit	Date	Loss
2011-08-08	3.49%	2020-06-11	-13.54%
2022-08-08	3.13%	2021-06-18	-3.90%
2020-06-12	2.09%	2021-06-21	-2.36%
2021-06-17	2.08%	2022-07-11	-1.51%
2021-03-19	2.04%	2012-06-21	-1.21%
2011-08-04	1.91%	2013-07-11	-1.12%
2011-08-10	1.76%	2019-12-02	-1.08%
2021-04-12	1.66%	2011-08-23	-1.09%
2022-10-26	1.59%	2016-06-10	-1.06%
2022-08-18	1.53%	2019-02-15	-0.97%

Table 3: Top Ten Profit and Loss Performances

Notable drawdowns occurred in June 2020 and June 2021. Possible explanations for these significant declines include:

- **External Shocks:** During these periods, unexpected news or policy changes likely influenced the market, resulting in sharp fluctuations. For example, the economic outlook projections from the Federal Reserve and the ongoing COVID-19 pandemic likely contributed to heightened market volatility.
- **Lag in Signal Adaptation:** The signals from GEX and VRP are computed using a 21-day rolling window. As a result, these historically derived signals may not have been able to capture rapid market changes, particularly in the presence of significant short-term price volatility.

Comments

The current straddle strategy, which leverages Gamma Exposure (GEX) and Volatility Risk Premium (VRP) signals, has demonstrated an ability to capture extremes in market volatility. While this design provides a clear framework for identifying market conditions indicative of tail risk, there is potential to enhance the robustness of the strategy through further refinement of the risk metrics, option selection criteria, and overall trade management.

To improve the strategy's sensitivity to market tail risk, it is advisable to integrate additional measures beyond GEX and VRP. Incorporating skew indicators, such as the 30-day or 10-day skew derived from differences in implied volatility between OTM puts and calls, can provide additional insights into market expectations of downside risk. Moreover, factors like the volatility of volatility (VVIX) and the correlation between SPY spot prices and its implied volatility can further refine the signal generation process, allowing for a more nuanced understanding of market conditions. This enhancement would facilitate a multi-dimensional assessment of tail risk, potentially leading to more accurate trade signals.

In terms of option selection and DTE management, the current practice of choosing the option with the minimal strike distance within a fixed DTE range may benefit from a more dynamic approach. Backtesting different DTE windows—such as 3, 5, 7, 10, and 14 days—could reveal an optimal trade-off between theta decay and the capture of implied volatility. Additionally, dynamically adjusting the target DTE based on the strength of the signal could allow for shorter holding periods during high conviction scenarios and longer durations when the signal is less pronounced. Considering multi-leg configurations or the incorporation of options with slight delta offsets from ATM could further optimize the balance between Vega and Theta exposure.

Beyond signal generation and option selection, improvements in position sizing and exit criteria are key to enhancing overall risk management. Presently, the strategy employs a fixed position size, but a risk-based dynamic sizing approach that adjusts trade allocations based on prevailing market volatility could help mitigate potential drawdowns during turbulent periods. Enhancing the exit strategy by incorporating conditional rules, such as profit or loss thresholds based on changes in the option's Vega, shifts in implied volatility, or specific market events like economic announcements, could further optimize the timing of exits and potentially capture more favorable risk-adjusted returns. Overall, these refinements aim to create a more adaptive trading model that better controls downside risk and improves the consistency of performance across different market regimes.

4 Conclusion

This project investigates the predictive value of Gamma Exposure (GEX) in the context of financial markets and demonstrates its utility in constructing both directional and volatility-based trading strategies.

Empirical analysis reveals that the GEX series exhibits a mean-reverting characteristic but pronounced statistical irregularities, specifically, a right-skewed and heavy-tailed distribution. These properties imply that GEX captures episodes of market dislocation, reflecting the dynamic re-hedging behavior of option market makers, and thereby provides a valuable lens into latent market stress.

Based on this insight, we propose two trading strategies: a mean-reversion strategy that selectively engages based on extreme GEX deviations and technical confirmation (via RSI), and a volatility strategy that employs ATM straddles filtered through joint GEX and Volatility Risk Premium (VRP) signals.

The mean-reversion strategy exhibits robust performance during volatile market regimes with a favorable risk-adjusted return profile and minimal drawdowns, while the straddle strategy effectively captures periods of volatility mispricing, albeit with higher tail risk. Notably, the former maintains high selectivity—executing trades on only 4% of trading days—yet delivers over 77% cumulative return with controlled volatility. The latter strategy, despite fewer long signals, shows high signal accuracy but suffers from asymmetric payoff profiles and exposure to sudden volatility spikes.

Overall, our findings underscore the value of GEX as a mean-reverting, structurally-informed indicator that captures deviations in dealer hedging behavior. Its ability to signal abnormal market conditions makes it a powerful tool for identifying short-term dislocations and timing reversion-based trades within systematic strategies. Moreover, the structural insights provided by GEX link option market positioning to underlying index behavior, bridging microstructure and macro return forecasting.

Future research may explore adaptive thresholding techniques and regime-aware signal filters that account for market volatility structure (e.g., VVIX, implied skew, spot-vol correlation). Enhancing signal responsiveness through shorter rebalancing windows, dynamic DTE selection, and volatility-sensitive position sizing could help mitigate drawdowns. Incorporating conditional exits based on implied volatility shifts or macro events may further refine trade timing and improve performance consistency across regimes.

A References

[1] Barbon, Andrea and Buraschi, Andrea, *Gamma Fragility* (November 5, 2020). University of St.Gallen, School of Finance Research Paper No. 2020/05.

[2] Baltussen, Guido and Da, Zhi and Lammers, Sten and Martens, Martin, *Hedging Demand and Market Intraday Momentum* (January 2, 2021). *Journal of Financial Economics*, Volume 142, Issue 1, October 2021, Pages 377–403.

[3] *Gamma Exposure (GEX): Quantifying hedge rebalancing in SPX options* (2016). SqueezeMetrics.

[4] *Short is Long: Using dark pool short sales as a proxy for buying activity* (2018). SqueezeMetrics.

[5] *The Implied Order Book: Measuring S&P 500 liquidity with SPX options* (2020). SqueezeMetrics.

[6] Perfiliev, S., *How to calculate gamma exposure (GEX) and zero gamma level* (2022, February 3). Perfiliev Financial Blog. https://perfiliev.com/blog/how-to-calculate-gamma-exposure-and-zero-gamma-level/.

[7] 期权情绪指数 - 指数使用 (2020, August 8). RiskMacro. https://riskmacro.com/document/390.html.

B Codes and Data

Our codes are all written in Python. For simplicity, we do not attach our codes in this report. The codes and data used can be found at the GitHub repository: https://github.com/yifandill/Gamma_Exposure_Quant_Research, contributed by Hui Yangyifan, Huang Anna, Lim Wei Xuan. For convenient use of our codes, please check the repository structure below. We only highlight the most important ones.

```
project/
├── README.md
├── data/
│   ├── data_description.txt ........................ Data Description
│   └── data files in different format.
└── src/
    ├── Computation of GEX.ipynb ..................... Experiment on GEX Computation
    ├── Mean-Reverting_Strategy.ipynb ................ Strategy 3.1 Demo
    └── straddle_strategy.ipynb ...................... Strategy 3.2 Demo
```