Option Liquidity and Gamma Imbalances

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Abstract

We study the relationship between the market makers' inventory and liquidity for S&P 500 options. Option spreads are higher when the aggregate gamma inventory is negative, i.e., when market makers act as momentum traders to keep their portfolio delta neutral. Aggregate gamma inventory can explain up to 1/3 of the daily variation in spreads. We show that market makers have balanced gamma inventory whenever markets are illiquid, volatile, and financial intermediaries are constraint. Our results indicate that market makers actively adjust option expensiveness to balance their inventory in the desired direction. Standard option valuation models and market microstructure theories contradict our findings.

Keywords: Liquidity Risk, Option Markets, Option Liquidity, Liquidity Spirals, Hedge Demand, Gamma Risk

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I. Introduction

Options are a central cornerstone for financial markets because of their diverse functionality. Market makers usually take the opposite side of a trade and thereby provide liquidity. By quoting requirements and market-making obligations, they have to absorb buying and selling pressure and build up inventories, which might deviate from the market makers' optimal inventory. The inventory requires hedging, which is costly and risky due to market imperfections such as discrete trading or jumps in the underlying (Figlewski, 1989). Deviations from the optimal inventory, associated risks, and hedging costs should be reflected in an option's liquidity and the market makers' compensation for liquidity provision, i.e., the option's spread.

We investigate this conjecture in the market for S&P 500 options and ask: What is the relation between hedging needs and option liquidity? When do market makers require more compensation for providing liquidity? Which positions are associated with higher liquidity costs? To answer those questions, we compute the daily inventory of market makers and determine the magnitude of their hedging activities by the aggregated gamma inventory. Gamma measures changes in an option's delta and therefore measures to which extent market makers have to rebalance their inventory. The aggregate gamma exposure approximates the hedging cost of market makers (Gârleanu, Pedersen and Poteshman, 2009).

We start by comparing the aggregate gamma inventory (AGI) to liquidity measures constructed from intraday option trades. The options market's liquidity decreases with the aggregate gamma inventory. A negative AGI is associated with wider option spreads, i.e., higher compensation for the market maker, while a positive AGI is associated with narrower spreads. This indicates that market makers do not like negative gamma exposure and require higher compensation to provide liquidity. Further, we show that market makers manage their AGI proactively in turbulent times. When markets are volatile, illiquid, and intermediaries are constraint, the rebalancing activities of option market makers reduce to a minimum, i.e., the aggregate gamma inventory is around zero. As a result, market makers are less willing to transact an option, translating to increasing option expensiveness (VRP) and increasing liquidity risk premiums.

We compute volume-weighted effective relative spreads for each option series and

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categorize them into five moneyness buckets. Regressions of the effective spread buckets on AGI show that the aggregate gamma inventory explains a significant fraction of the realized spread. All coefficients are negative and economically meaningful. For example, a one-standard-deviation decrease in AGI translates into an 1.5% higher relative spread for out-of-the-money options. Hence, the market makers' compensation for providing liquidity increases significantly. Additionally, the analysis reveals that up to one-third of the variation in relative spreads is explained by AGI. The effect is especially strong for near the money options, which have large gamma exposure and thus larger rebalancing costs. Our results are unchanged when we include the current volatility level (VIX) as a control variable. We also control for the previous-day relative effective spread but find that our main conclusion is still valid. Panel regressions confirm the strong negative relationship between AGI and options market liquidity. Using spreads determined from high-frequency option quotes and high-frequency implied volatility effective spreads does not change our conclusion.

What can explain these results? Previous literature documents that an option's gamma and the associated rehedging costs are an essential determinant for the bid-ask spread (Engle and Neri, 2010; Jameson and Wilhelm, 1992) and the interplay between option demand and option prices (Gârleanu et al., 2009). Moreover, the theoretical and empirical work of Stoikov and Sağlam (2009), and Wu, Liu, Lee and Fok (2014) underline the importance of proactive management of an option inventory when facing unheadgeable risk. In particular, the systematic management of the gamma exposure of the aggregated inventory seems to be a crucial component in the risk management framework of option market makers. However, these studies suggest that the magnitude of gamma is relevant, not the directional exposure of market makers. A high positive gamma should have the same effect as a high negative gamma.

The findings of Baltussen, Da, Lammers and Martens (2021), Barbon, Beckmeyer, Buraschi and Moerke (2022) and Ni, Pearson, Poteshman and White (2021) indicate that the gamma imbalance plays a crucial role in the systematic rebalancing of hedges. When market makers have negative aggregate gamma inventory, their hedge-demand goes in the same direction as the underlying moves (momentum traders). Accordingly, a potential mechanism that rationalizes our findings are illiquidity spi-

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rals from the underlying. For instance, when markets are short (long) gamma on aggregate and the S&P 500 decreases, the market maker has to sell (buy) the underlying to keep the inventory delta-neutral. Hence, market makers trade in the same direction as most of the market when aggregate gamma is negative. Therefore, it may be harder to find a counterparty to execute the trade, or the conditions may be less favorable because market makers demand liquidity.

We test this hypothesis by comparing AGI to two illiquidity measures. The first is the Amihud (2002) measure that proxies illiquidity in the stock market. The second is the funding illiquidity measure from Hu, Pan and Wang (2013). We show that markets are indeed more illiquid when AGI is negative, as suggested by higher levels of illiquidity. Nevertheless, controlling for funding and market illiquidity does not change the strong negative relationship between AGI and option market liquidity. Therefore, we conclude that liquidity spirals cannot rationalize our results.

However, the analysis reveals that market makers' aggregate gamma inventory is extremely balanced (close to 0) whenever market or funding illiquidity is high. This suggests that market makers manage their inventory such that their hedge-demand is relatively low in illiquid times. We investigate this finding and show that market illiquidity, realized volatility, and intermediary health explains balanced AGI levels. Therefore, whenever markets are illiquid, volatile, and financial intermediaries are constrained, option market makers balance their inventory exceptionally well. Especially intermediary constraints seem to explain days with balanced AGI. These findings are in line with the implications of Chen, Joslin and Ni (2019) and Farago, Khapko and Ornthanalai (2021), who show that during market turmoil, the liquidity provision by SPX options market makers deteriorates as they reduce their supply and even become net buyers.

How do market makers have such a balanced gamma inventory in turbulent times? First, of course, they strategically adjust their quotes such that market participants buy more when inventory is negative and sell more when inventory is positive (Ho and Macris, 1984). Second, our analysis also indicates that market makers adjust overall option expensiveness to either receive a higher compensation or balance their gamma inventory in the desired direction, as suggested by extremely positive and negative levels of the variance risk premium. We reinforce this conjecture and show that states in which AGI is balanced predict higher reversal returns, a proxy for

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overall liquidity compensation (Nagel, 2012).

The remainder of this work is structured as follows: Section II. reviews literature, section III. details the data, section IV. explains the construction of our aggregated gamma inventory measure, section V. presents our main results that negative aggregated gamma inventory is associated with higher spreads, section VI. presents results for the comovement of balanced gamma inventory and illiquidity, whereas the last section VII. concludes.

II. Literature

Intermediary asset pricing. Our paper contributes to the rapidly expanding literature on the role of financial intermediaries for prices across financial markets. The risk absorption capacity of financial intermediaries is closely related to their compensation for providing liquidity and the formation of asset prices (Adrian, Etula and Muir, 2014; He, Kelly and Manela, 2017). Our analysis shows that during market turmoil, index options market makers proactively reduce their absolute aggregated gamma inventory (AGI) and are less willing to supply liquidity, which leads to elevated option expensiveness and increased liquidity risk premia.

Market microstructure. In general, market makers across financial markets are compensated for providing liquidity by adjusting the quoted bid-ask spread (Glosten, 1987; Glosten and Harris, 1988; Huang and Stoll, 1997; Madhavan, Richardson and Roomans, 1997). However, in derivatives markets, market makers are assumed to hedge their position in the underlying by establishing an initial hedging position and continuously rebalancing the hedge throughout time (Cho and Engle, 1999; Engle and Neri, 2010; Kaul, Nimalendran and Zhang, 2004; Petrella, 2006). Many studies have examined the determinants of bid–ask spreads in the options market (Fahlenbrach and Sandas, 2003; George and Longstaff, 1993; Ho and Macris, 1984; Jameson and Wilhelm, 1992). However, previous empirical studies mainly focus on single option characteristics and their relation to the formation of the bid-ask spread, rather than considering the aggregated inventory of the market maker. Engle and Neri (2010) find that hedge rebalancing costs are an essential component of the bid-ask spread in the options market. The theoretical work of Stoikov and Sağlam (2009) underlines the importance of strategic management of the absorbed inventory when

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facing unhedgeable risk by systematically adjusting the related bid-ask spreads. Accordingly, the empirical work of Wu et al. (2014) confirms that rebalancing costs are more important than initial hedging costs for determining option bid-ask spreads in the Taiwanese option market. Our findings confirm the notion above that the aggregated gamma inventory is proactively management by index option market makers. However, our main contribution is that we show that the sign of their gamma imbalances are from first-order importance.

Intermediary constraints in option markets. Moreover, by supplying liquidity, derivative market makers face unhedgeable parts of risks, for which they are in turn compensated for. Thereby, as market makers are characterized as net-seller in options markets (Gârleanu et al., 2009), incomplete markets expose them to large amounts of market variance risk (Bates, 2003; Cheng, 2019). Johnson, Liang and Liu (2018) state that SPX options are mainly traded in order to transfer unspanned crash risk. Gârleanu et al. (2009) and Bollen and Whaley (2004) document that rising demand for options results a in higher implied volatility. Related work of Fournier and Jacobs (2020) links the amount of inventory risk and wealth of an index options market maker to the variance risk premium. Boyer and Vorkink (2014) findings suggest that high ask prices for lottery-like options are to compensate market makers for bearing unhedgeable risks. Moreover, Jacobs, Mai and Pederzoli (2021) and Farago et al. (2021) find that demand and supply shocks in SPX options are positively correlated in good times and negatively correlated during a crisis. Subsequently, rising demand for index options during a crisis coincides with market makers' reduced supply of liquidity. Similar observations are made by Chen et al. (2019) who link the reduced liquidity provision of financial intermediaries for tail risk insurance to the tightening of intermediary financial constraints during a crisis. The reduced liquidity supply leads to increased option expensiveness and elevated risk premia. Moreover, these findings are in line with Gârleanu and Pedersen (2007) who theoretically link tightening risk management to a reduced liquidity supply. Our results corroborate the preceding relationship between risk-bearing capacity, liquidity supply, and option expensiveness. When markets are illiquid, volatile, and financial intermediaries are constrained, market makers reduce their gamma exposure and adjust the overall option expensiveness as indicated by elevated levels of the VIX.

Liquidity premium. Our paper further incorporates the influence of market liquid-

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ity on financial markets (Acharya and Pedersen, 2005; Amihud, 2002; Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chordia, Sarkar and Subrahmanyam, 2005; Easley, Kiefer, O'Hara and Paperman, 1996; Pástor and Stambaugh, 2003) and the literature that incorporates short-term reversals as proxy for the liquidity premium earned by market makers for equities (Drechsler, Moreira and Savov, 2021; Lehmann, 1990; Lo and MacKinlay, 1990; Nagel, 2012). Nagel (2012) presents evidence that the returns from liquidity provision can be predicted with the VIX. Drechsler et al. (2021) further shows that the provision of liquidity and volatility exposure are tightly linked as they share the same risks. Our results suggest that increases in the liquidity risk premium coincide with balanced gamma inventory of option market makers.

Options and underlying. Another body of literature relates the inventory and related Delta-hedging and rehedging of a representative market maker to the underling's volatility (Baltussen et al., 2021; Barbon and Buraschi, 2020; Golez and Jackwerth, 2012; Hu, 2014; Ni, Pearson and Poteshman, 2005). Ni et al. (2021) show a negative relationship between the market makers' net gamma and a stock's realized volatility. However, Chordia, Kurov, Muravyev and Subrahmanyam (2021) find that SPX options order flow cannot predict index returns. SqueezeMetrics (2020) illustrate the impact of option greeks on hedge demand. We build on the existing literature by investigating the effects of the sign of the aggregated gamma inventory of the index option market makers. Our findings suggest that market makers increase the bid-ask spreads and, in turn, demand a higher liquidity premium when the AGI is negative as they are forced to trade in the direction of the underlying.

III. Data

Our main focus lies on S&P 500 options, for which we merge several databases.

CBOE Open-Close database: We focus on S&P 500 index (SPX) options which trade exclusively on the Chicago Board Options Exchange (CBOE). In order to construct the aggregated inventory of SPX options market makers, we rely on the C1 CBOE Open-Close database. The data distinguishes between buying (long) and selling (short) trades and whether the trade was to open a new position or close an existing one. Volumes are aggregated by origin (customers, professional customers,

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broker dealers, and MMs). Broker-dealers and market makers are denoted as "firms." Customers and professional customers are further broken down into trade size buckets (fewer than 100 contracts, $100-199$ contracts, greater than 199 contracts). The data is available from January 1, 1996 until December 30, 2020. Overall, the data consist of approx. 6.2 million data points. Generally, we do not restrict our data set to specific moneyness or maturity buckets as we wish to measure the full market maker inventory. Therefore, we do not apply any filters to the C1 data. We sum up options that have different option symbols but are of same type, strike, and expiry.

OptionMetrics: We rely on end-of-day option quotes from OptionMetrics Ivy DB and define the options contracts price as the bid-ask-midquote. We adjust options expiry from Saturdays to Fridays and clean the data from duplicated data points. We estimate the risk-free rate from zero coupon Treasury Yields using the piecewise cubic hermite interpolating polynomial, obtained from OptionMetrics. The dividend yield is also obtained from OptionMetrics. If no IV or delta is available, we calculate Black and Scholes (1973) implied volatilities or, if not possible, interpolate missing IVs across moneyness using OTM options. The data is available from January 1, 1996 until December 30, 2020.

CBOE intraday Option Trades: To construct effective relative spreads, we rely on high-frequency trade data for SPX options obtained from the CBOE. The data includes all trades tracked on an intraday basis. The filters we apply rely on Andersen, Archakov, Grund, Hautsch, Li, Nasekin, Nolte, Pham, Taylor and Todorov (2021). We filter out trades with Trade Condition ID of 40 to 44, and focus on normal trades according to the "cancelled trade condition ID." We filter trades where the bid is higher than the ask and trades for which the bid or ask price is zero. We filter out trades with non-existing implied volatility, trade price, or trade volume. Furthermore, we exclude entries for which a transaction price is either lower than the current bid price minus the current spread, or higher than the current offer price plus the current spread, and options with quoted bid-ask spread above 50% of the mid-quote. Lastly, we exclude penny options which have a midprice smaller than $0.1. The data is available from January 1, 2004 until December 30, 2020.

CRSP: For the construction of reversal-strategies returns as a proxy for liquidity provision (Nagel, 2012), we rely on stock return data from the CRSP daily return file. Reversal strategy returns based on daily returns are calculated from daily returns,

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adjusted for stock splits and dividends. We restrict our data to exchange codes 1, 2, and 3 (NYSE, NYSE MKT/AMEX, NASDAQ) and ordinary common shares in the US. If a price is not available, we use the bid-ask midpoint as the share price. We kick out penny stocks with a share price smaller than $1 on the last trading day of the previous calendar month.

We use these **four** different datasets for the construction of the aggregated market maker gamma exposure and the calculation of proxies for liquidity provision, such as effective relative spreads and reversal-strategy returns. These measures are then used in the empirical analysis that follows. Because intraday option trade data is only available from 2004 onwards, we restrict our sample period to January 1, 2004 until December 30, 2020. However, we note that the market maker inventory we use at the beginning of 2004 has been build up over the previous years. That is, we use the preceding years as a 'burn-in period'

IV. Aggregated Gamma Inventory

A. Construction

This section describes the construction of the aggregated market maker gamma exposure for the S&P500.

Market maker inventory: To construct SPX options market maker net inventory for each day, we merge the CBOE Open-Close database data with the quote data from OptionMetrics. Based on the merged data we construct a daily measure of net market maker inventory. For each day t, we keep the option positions from $t-1$ with time to maturity larger than zero. When an option chain expires, the option is assumed to stay in the inventory for the whole day.

We follow Ni et al. (2021) in calculating the market maker inventory. We define net

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open interest as

$$
\begin{aligned}
OI_{j,t}^{\text{buy},y} &= OI_{j,t-1}^{\text{buy},y} + Volume_{j,t}^{\text{Open buy},y} - Volume_{j,t}^{\text{Close sell},y} \\
OI_{j,t}^{\text{sell},y} &= OI_{j,t-1}^{\text{sell},y} + Volume_{j,t}^{\text{Open sell},y} - Volume_{j,t}^{\text{Close buy},y} \\
netOI_{j,t} &= -1 \cdot \left[OI_{j,t}^{buy,cust} - OI_{j,t}^{sell,cust} + OI_{j,t}^{buy,firm} - OI_{j,t}^{sell,firm} \right], \qquad (1)
\end{aligned}
$$

where $OI_{j,t}^{x,y}$ is the open interest of type x (buy or sell) by investor class y (firms and customers) in option j at the close of trade t. $Volume_{j,t}^{\text{Open buy},y}$ are new long positions and $Volume_{j,t}^{\text{Open sell},y}$ are new short positions. $Volume_{j,t}^{\text{Close buy},y}$ are buys that close existing short positions and $Volume_{j,t}^{\text{Close sell},y}$ are sells that close existing long positions, i.e., both type of trades close a previously established position. Hence, they decrease the open interest in the respective option. Because market makers are the opposite side of the trade, we multiply the residual by -1.

Market maker gamma exposure: For each day, we calculate the aggregate gamma exposure of the market maker by gamma weighting the inventory positions for each day and summing over all contracts j, that is,

$$
net\Gamma_t = S_t^2 \cdot \sum_{j=1}^{N} \left(netOI_{j,t} \cdot \Gamma_j \left(S_t, K, \tau, IV, r, d \right) \right), \qquad (2)
$$

where $\Gamma_j(t, S_t)$ is the Black and Scholes (1973) gamma for option j at time t, S_t the current level of the S&P500, K the strike price, τ the time-to-maturity, IV the Black-Scholes implied volatility, r the risk-free rate, and d the dividend yield.

We assume that market makers hedge their inventory at the end of trading day t. On option expiry days, we assume that market maker rehedge at noon, i.e., assign the option a time-to-maturity of half a trading day.[1] If τ is zero, we match the prior day's quotes to get an IV for each option chain.

To account for the time-trend in option markets, we normalize the aggregate gamma inventory (AGI) by the 30-day moving average of total contracts in the market

[1] We think that this assumption is reasonable because the gap risk sometimes amounts to tens of million dollars. Assuming that market makers do not hedge such risks seems more unrealistic. Results are unchanged if we do not account for gap risk.

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makers inventory, that is

$$AGI_t = \frac{net\Gamma_t}{\frac{1}{M}\sum_{i=0}^{n-1} \text{Total Contracts}_{M-i}}, \tag{3}$$

where M equals 30. Therefore, AGI is the dollar gamma exposure per unit of contract.

B. Descriptive Statistics

Figure 1 depicts the time series of the market maker gamma exposure in USD for the whole inventory, for long positions only, and for short positions only. We note that market makers' gamma inventory has increases significantly over the last decade. Before 2011, average net gamma amounted to approx. one billion USD (in absolute terms) and was almost always negative. From 2011 until 2021, the absolute average net gamma was approximately five billion USD and more often positive. The lowest net gamma is observed around the financial crisis, where it dropped to less than −10 billion USD. The largest net gamma inventory was accumulated in 2018, which might be due to sharp increase in volatility in February 2018 ("Volmageddon"). As is evident from long and short net gamma, SPX market makers almost always have a relatively balanced inventory. Both time series have a very similar trend, just in the opposite direction. Figure 2 displays the 30-day moving average of the absolute number of contracts in the market maker's inventory. The plot shows that the number has increased from approx. 1 million contracts in 2004 to 5 million contracts in 2011. Ever since the number has been relatively constant. Therefore, the larger net gammas in more recent years are not merely attributable to more contracts being traded at the CBOE. Lastly, we show AGI, the aggregated gamma inventory per unit of contract, in Figure 3. The figure shows that the absolute dollar gamma per unit of a contract before the financial crisis is comparable to the level in more recent years. Interestingly, after the financial crisis (2009-2012), AGI was very often around zero, indicating that market makers were not willing to build up gamma inventories in either direction.

Table I presents summary statistics for the aggregated net gamma (long & short) and our aggregated gamma inventory measure. The table shows that AGI is, on

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average, relatively centered around 0. The standard deviation equals 500 USD per unit of contract. The skewness equals 0.10 and indicates that the distribution is close to normal. The daily autocorrelation is relatively high because inventories do not build up abruptly.

V. Liquidity and Gamma Inventory

A. Option Markets

Effective relative spread: Using intraday trade data, we obtain the effective relative spread as the direct costs that market makers charge for transacting in options markets. The spread reflects the costs and risks liquidity providers in option markets face, such as hedging needs, rebalancing costs, and model risk (Green and Figlewski, 1999). Therefore, it is a conventional measure of liquidity. An increase in the effective spread signifies a deterioration of liquidity. We follow Christoffersen, Goyenko, Jacobs and Karoui (2018) and compute the effective relative spread for the k^{th} trade from intraday trade data as

$$ES_{k,j} = \frac{2|O^P_{k,j} - O^M_{k,j}|}{O^M_{k,j}}, \tag{4}$$

where $O^P_{k,j}$ is the trade price of the k^{th} trade for option chain j and $O^M_{k,j}$ is the midpoint of the best bid and ask at the time of the k^{th} trade. We take the volume-weighted average of all $ES_{k,j}$ to obtain the daily effective relative spread for each option chain j as

$$ES_j = \frac{\sum_k Vol_k ES_{k,j}}{\sum_k Vol_k}. \tag{5}$$

Next, we categorize options by their moneyness $m = \frac{K}{S}$ and divide them into ten buckets. Deep-out-of-the-money (DOTM) ranges from $m > 1.1$ for calls and $m < 0.9$ for puts, out-of-the-money (OTM) from $1.025 < m \leq 1.1$ for calls and $0.975 \leq m < 0.9$ for puts, at-the-money (ATM) from $0.975 \leq m \leq 1.025$ for both calls and puts, in-the-money (ITM) from $0.9 \leq m < 0.975$ for calls and $1.025 < m \leq 1.1$ for puts, and deep-in-the-money (DITM) for $m < 0.9$ for calls and $m > 1.1$ for puts. Within

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each bucket, we take the median effective spread of each option series.

Quoted spread: The effective spread measures the actual costs paid by investors whenever an option is traded. Quoted prices also express the general willingness of market makers to trade an option. Quoted prices represent the intersection between demand and supply and are a crucial determinant of the traded price. Therefore, we also determine the quoted spread as a measure of liquidity from high-frequency trade data.[2] We calculate the quoted spread QS_j for each option chain j as

$$QS_j = \frac{\text{Ask}_j - \text{Bid}_j}{O_j^M}, \tag{6}$$

where $O_j^M = (\text{Ask}_j + \text{Bid}_j)/2$ is the mid-price, and Bid_j and Ask_j are the respective bid and offer prices. As above, we categorize options into ten moneyness buckets and use the median within each bucket.

Implied volatility effective spread: Chaudhury (2015) points out that conventional measures of option liquidity, such as relative spreads and dollar spreads, are sometimes poorly suited to measure the liquidity of an option. These measures tend to be biased toward lower-priced options. In particular, relative spreads seem to classify lower-priced options as relatively illiquid when they are often the most liquid in terms of speed and ease of trade execution. To make option spreads comparable across moneyness, we also calculate the implied volatility effective spread ($IVES$). We compute the $IVES$ for each trade k as

$$IVES_{k,j} = \frac{2 \cdot |IV_{k,j}^P - IV_{k,j}^M|}{IV_{k,j}^M}, \tag{7}$$

where $IV_{k,j}^P$ is the Black and Scholes (1973) implied volatility for the trade price of the k^{th} trade of option chain j. $IV_{k,j}^M$ is the the implied volatility of the mid-price. As above, we take the volume-weighted average of all $IVES_{k,j}$ and use the same moneyness buckets.

OLS Regressions: We start by regressing the relative effective spread ES_t^B for each

[2] Furthermore, we calculate end-of-day quoted spreads. We use all available option quotes from OptionMetrics but remove quotes that could mechanically drive our results. We remove options with a negative bid-ask spread or a bid-ask spread that is larger than 50% of the mid-price. Finally, we remove options that do not have open interest because they often have stale quotes.

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moneyness bucket B on our measure of aggregated market maker gamma inventory AGI_t, that is,

$$ES_t^B = \alpha + \beta_1 AGI_t + \text{Controls} + e_t. \tag{8}$$

Controls include the option-implied volatility index VIX_t and the previous-day effective spread ES_{t-1}^B. We standardize all explanatory variables to ensure comparability. We use HAC-robust standard errors with a lag of 10.

In Panel A of Table II, we show results regressing the call option's effective spreads on AGI. The coefficient for AGI is negative and statistically highly significant throughout all buckets. A negative gamma inventory is associated with higher spreads, and a positive gamma is associated with lower spreads. A one standard deviation decrease in AGI is associated with a 1.53% higher relative spread for OTM calls and 0.29% for ITM calls. As the absolute spread increases with moneyness, it is natural to expect a higher impact for OTM options. The explained variation is large, especially for options that are not DOTM or DITM. The largest R^2 is obtained for ATM calls and amounts to 34%. The explained variation is highest for options with the highest gamma (ATM calls). This indicates that the gamma inventory is extremely relevant in explaining call options' liquidity that exposes the market maker to the highest gamma risk. Market makers more actively set the spreads for those options following their aggregate gamma inventory.

Panel B of Table II uses the VIX as an additional explanatory variable. As is evident, the inclusion of the VIX does not affect the importance of AGI. All coefficients across all moneyness buckets are virtually unchanged. In terms of R^2, the VIX adds explanatory power only for the ITM and DITM buckets. Panel C controls for the effective spread of the previous day. Again, we find that AGI is a significant explanatory variable for liquidity of call options. The economic magnitude decreases after the inclusion of ES_{t-1}^B but is still sizable. A one standard deviation decrease in AGI is associated with approx. 0.4% higher relative spreads for DOTM and OTM calls, 0.15% for ATM and ITM calls, and 0.05% for DITM calls. The explained variation increases significantly, and ranges between 22% for DOTM calls and 75% for ATM calls, with a large fraction attributable to AGI.

Table III shows similar results for effective relative spreads of put options. The mag-

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nitude of the coefficients, significance level, and explained variation are comparable to the results for call options. For instance, a one standard deviation decrease in AGI is associated with an 1.5% increase in OTM put spreads. The results are also robust to the inclusion of the VIX and ES^B_{t-1}. Thus, the aggregate gamma exposure of market makers affects the liquidity of all option types.

Panel Regressions: We also perform panel regressions to control for the heterogeneity of the data. The model we apply uses fixed effects for each bucket B and reads as

$$ES^B_t = \alpha^B + \beta_1 AGI^B_t + \beta_2 VIX^B_t + \beta_3 ES^B_{t-1} + e^B_t. \tag{9}$$

As additional robustness, we repeat the analysis but replace the effective spread with the quoted spread (QS) from high-frequency trade data and implied-volatility effecitve spreads. Table IV reports the results.[3] Our measure of aggregate gamma inventory shows a significant negative impact on effective relative spreads for all specifications. A one standard deviation decrease in AGI_t implies a 0.7% increase in effective relative spreads without considering the previous day's effective spread and a 0.2% increase with its inclusion. The level of volatility as measured by the VIX_t is not able to explain the effective spreads and does not add any explanatory power. The within R^2 equals 10% for AGI and increases to 34% when we include the previous-day spread. Turning to quoted option spreads, we observe similar results. A decrease in AGI is associated with increased quoted spreads. The coefficient is comparable in magnitude and significance. The within R^2 decreases to 6%.

For the implied volatility effective spreads ($IVES$), results are similar in terms of coefficient magnitude and explained variation. The economic significance of AGI increases when we use a spread measure that is more appropriate in comparing a panel of options. The absolute coefficient of 0.038 is half the coefficient of the previous day implied volatility spread (0.075). The difference is larger when we use ES or QS. Additionally, the contribution of AGI to the explained variation increases using $IVES$. For all regressions we calculate entity fixed effects for each moneyness

[3] We do not include time fixed effects because the effective spreads themselves exhibit a time trend that would be perfectly correlated with a time fixed effects. Further robustness checks for $IVES$ show that our results are robust to using further lags of the spread measure as well as monthly time fixed effects in addition to entity fixed effects. The results are depicted in Table XI.

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bucket and calculate clustered standard errors for each bucket (entity) and each month (time).

AGI is also able to predict future spreads in panel regressions with remarkably high R^2, as shown in Table V. The economic and statistical significance is comparable.

Discussion: Our results show that market makers provide more liquidity when the gamma inventory is positive and less liquidity when the gamma inventory is negative. Put differently, spreads are tighter when gamma inventory is positive and broader when gamma inventory is negative. The effect is most pronounced for at-the-money options that have the highest gamma. Jameson and Wilhelm (1992) and Gârleanu et al. (2009) show that an option's gamma is an essential determinant of its bid-ask spread and expensiveness because of higher variability in the market maker's hedge portfolio. However, both studies suggest that the magnitude is essential, not the direction of gamma. What potential channels could rationalize that a negative gamma exposure is more important than a positive gamma exposure? A negative (positive) gamma exposure indicates that the hedging demand of the market maker will enhance (dampen) the underlying's move. Therefore, negative (positive) gamma exposure is generally associated with increasing (decreasing) volatility (see, among others, the theoretical contribution of Jarrow (1994)). Potentially, the execution of the market maker's delta hedge is significantly more accessible when the gamma exposure is positive. For instance, if the S&P 500 increases over one trading day and assumes a positive gamma exposure, the market maker has to sell the underlying to be delta-neutral. Hence, in a market where demand exceeds supply, the market maker finds a counterparty that buys the market makers S&P 500 position more effortlessly. On the other hand, if the market maker has a negative gamma inventory and the stock price decreases, the market maker has to sell to remain delta-neutral. With aggregate prices falling, aggregate selling in the S&P occurs and it will be harder for the market maker to find a counterpart, taking liquidity from markets. Therefore, our findings might result of liquidity spillovers from the underlying.

B. Market and Funding Liquidity

Less liquidity in the options market might be a byproduct of less market liquidity in the underlying or less funding liquidity (Brunnermeier and Pedersen, 2009). To

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test whether our results can be explained by mere liquidity dry-up that spirals to the options market, we obtain two liquidity measures. The first is the measure of Amihud (2002) that proxies for stock market illiquidity. The second is the measure of Hu et al. (2013) that proxies for funding illiquidity.

We plot the relationship between AGI and market illiquidity in Figure 4. Negative gamma inventories coincide with higher levels of illiquidity. The mean illiquidity level conditional on $AGI < -100$ equals 0.165, while the mean level conditional on $AGI > 100$ is 0.087. Hence, markets are generally more illiquid when AGI is negative. When we regress the illiquidity measure on the absolute conditional AGI, we find a negative relationship between AGI and illiquidity for $AGI > 100$ (adj. R^2 of 7.5%) and a positive relationship for $AGI < -100$ (adj. R^2 of 3.6%). Hence, markets are more liquid when AGI is positive, and liquidity increases with higher levels of AGI. In contrast, markets are more illiquid when AGI is negative and illiquidity increases with decreasing AGI.

Figure 5 plots the relationship between AGI and funding liquidity. We also find a higher level of funding illiquidity for days with negative AGI. The conditional mean amounts to 2.21 for $AGI < -100$ and 1.68 for $AGI > 100$. Regressing funding illiquidity on absolute conditional AGI shows that the relationship is not reversed. The coefficient for $AGI < -100$ equals -0.0012 (-2.99) and for $AGI > 100$ it equals -0.0007 (-2.49). The adj. R^2s are 13.3% for negative AGI, and 4.6% for positive AGI.

Table VI repeats our panel regression including both illiquidity proxies. The results show that including either illiquidity proxy does not change our results. Neither the coefficient of AGI nor its statistical significance changes, even if we include both illiquidity proxies. The within-R^2 is also unaffected. The same conclusion holds using the quoted spread as the dependent variable. The economic significance of the coefficient of AGI doubles when using implied volatility effective spreads, providing even more robustness to our results. Hence, we conclude that our finding is not merely a phenomenon of illiquidity spillovers. Options markets are more illiquid (higher spreads) when aggregate gamma inventory is negative. AGI_t is also able to predict future spreads when using the illiquidity measures as controls, as shown in Table VII. The economic and statistical significance is comparable.

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VI. Balanced Gamma Inventory

Interestingly, Figure 4 and Figure 5 both reveal that states with extreme illiquidity almost always coincide with a very balanced gamma inventory of market makers. Moreover, both figures show that illiquidity peaks when $AGI \approx 0$. This suggests that market makers actively manage their option inventory such that the hedge-portfolio changes little.

A. Illiquidity, Volatility, and Intermediary Health

We elaborate on this finding and run a probit model. The independent variable is a dummy that expresses balanced AGI. The dummy equals one when absolute AGI_t is lower than the 20^{th} percentile and zero otherwise. As suggested by Figure 4, we hypothesize that it is more likely to see a dummy of one if market-wide illiquidity is high. Additionally, we test whether AGI is balanced when the market is more volatile. Lastly, we include the intermediary health factor from He et al. (2017) that proxies for intermediary constraints. Low levels suggest that intermediaries are constrained. All measures react to turbulent market episodes, and we argue that the market actively reduces its rebalancing needs in such states by obtaining a gamma-neutral inventory.

We interpret our dependent variable as a probability. The higher the prediction of the model, the more likely it is for the dummy to take a value of one, or put differently, to obtain a low AGI_t (below the 20^{th} percentile) state. Table VIII presents the results. All coefficients show the expected sign and are highly significant for all specifications. The R^2 is especially strong for HKM_t in columns (3) and (5).

Note that we can only interpret the sign and the significance level. In order to interpret the economic significance, we need to calculate the marginal effects and plug the predicted value into the probability density function. For example, if we take the full model (7) and assume that RV_t and the Amihud$_t$ measure are elevated (80^{th} percentile: $= 0.16$ for RV_t and 0.2 for Amihud), whereas the HKM_t measure is low (20^{th} percentile: 0.05). If the Amihud$_t$ illiquidity measure increases by one unit, the probability to end up in a low AGI_t state increases by 0.5726 ($= \phi(0.88 + 1.48 \cdot 0.20 + 1.42 \cdot 0.16 - 36.8 \cdot 0.05) \cdot 1.48$). If RV_t increases by one unit, the probability

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that the "low AGI_t" is one would increase by 0.5493. The effect is economically largest for the HKM_t measure. If HKM_t were reduced by one unit, the probability of ending in a low AGI_t state would increase by 1400.23%.[4] All marginal effects are significant at the 1% level.

In contrast, we can look at world states where liquidity is high, and markets are calm. We calculate marginal effects for a low RV_t and Amihud illiquidity (20^{th} percentile: 0.0714 for Amihud and 0.0949 for RV_t) measure, and a high level of HKM_t (80^{th} percentile: 0.0673 for HKM_t). Increasing the Amihud measure by one unit, increases the probability of being in a low AGI_t state by only 0.0325 ($= \phi(0.88 + 1.48 \cdot 0.07 + 1.42 \cdot 0.06 - 36.8 \cdot 0.09) \cdot 1.48$). Furthermore, if we would increase RV_t by one unit, the probability of ending up in a low AGI_t state would increase by 0.0311, way smaller than above. Lastly, decreasing HKM_t by one unit would increase the probability by 0.8069, again, way smaller than above. All marginal effects are highly statistically significant.

B. Option Expensiveness

States of balanced AGI_t are well explained by measures of market illiquidity, volatility, and intermediary constraints. Intermediary constraints seem to be the most crucial determinant in explaining low AGI_t, which is in line with Chen et al. (2019). The authors show that constraints require financial intermediaries to aggressively hedge their risk exposure during turbulent market episodes such that they no longer provide liquidity to the options market. Those episodes are also related to option expensiveness.

Increasing option expensiveness has two effects on the market maker. First, compensation for providing liquidity increases. When market makers take the short side of the trade, they receive a higher option premium. This, in turn, increases the willingness of other market participants to take the short side of the trade such that they receive the higher premium. Market makers are more likely to balance their inventory when other market participants are also willing to provide liquidity.

Therefore, we test whether states with balanced gamma inventory are related to

[4] It is of course not realistic to reduce a limited ratio by one unit. Therefore we are left with such extreme numbers.

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option expensiveness. As in Chen et al. (2019), we use the variance risk premium (VRP) as a measure of option expensiveness. Figure 6 plots the relationship between AGI and the VRP. We observe that high levels of the variance risk premium almost always occur when AGI is relatively balanced. Interestingly, negative levels of the variance risk premium also coincide with balanced AGI. This indicates that market makers actively adjust the variance risk premium to control their AGI during turbulent times. As a result, they either receive higher compensation or increase the willingness of other participants to provide liquidity to the options market.

We, therefore, expect a strong relationship between balanced AGI and the variance risk premium. Table IX reports results in which we use the balanced AGI dummy as an explanatory variable. The analysis shows that balanced AGI states are significantly related to increasing option expensiveness. The dummy is positive and significant in contemporaneous regressions and predictive regressions. The R^2 is approx. 16%. Even after we control for today's option expensiveness, the dummy significantly predicts tomorrow's option expensiveness. Similar results are obtained when using the aggregate level of implied volatility (VIX) as the dependent variable.

C. Liquidity Risk Premium

Nagel (2012) finds that the VIX is highly correlated with returns from liquidity provision. The argument is that the VIX_t proxies for underlying state variables driving market makers' willingness to provide liquidity. For example, an underlying state variable could be AGI_t since the market seems to be very illiquid when AGI_t approaches zero. Market makers do not want to leave their "sweet spot" of a balanced inventory ($AGI_t \approx 0$) because low absolute gamma means less hedge rebalancing activity for market makers. Therefore, liquidity risk premiums should increase when AGI is balanced.

We test the relationship between AGI and liquidity risk premium. As in Nagel (2012), we use reversal-strategy returns as a proxy for the liquidity premium.[5] The original sample of Nagel (2012) spans the period January 1998 to December 2010. To make results comparable, we analyze the full sample (2004-2020), the Nagel (2012) sample (2004-2010), and the more recent sample (2011-2020). We use the

[5] Appendix A details the exact calculation.

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dummy variable that takes the value of one when the variable AGI_t is below the 20^{th} percentile and perform predictive regressions from t to $t+1$. Results are reported in Table X.

The balanced AGI dummy is positive and highly significant for the full sample. If AGI_t is below the 20^{th} percentile, the costs for supplying liquidity, measured by reversal-returns, increase by 0.5539 in $t+1$. The effect doubles for the period until 2010 and is insignificant for the subsample starting in 2011. The adjusted R^2 is 1.51% and especially high with 11.73% for the 2004-2010 subsample. In Panel B, we use the VIX_t as an explanatory variable to compare our results to the findings of Nagel (2012). For the full sample, the coefficient is positive with a value of 0.4972 and highly statistically significant. The economic and statistical significance of the coefficient increases for the subsample from 2004-2010. The R^2 is 16.86%. For the subsample from 2011 onwards, the coefficient is also insignificant. This period is characterized by calm markets and low liquidity risk premiums. Following Nagel (2012), the correlation appears to be high during periods of market turbulence but not necessarily during quiet times, which explains the insignificance of the second subsample.

Panel C includes both the dummy for low AGI_t states and the VIX_t. The coefficient for the dummy is sizeable, and it is statistically significant. In a low AGI_t state, the liquidity supply compensation in $t+1$ is 0.2822 higher and increases with a higher VIX_t. The same effect is observable for the subsample, including the financial crisis. R^2 reaches levels of 17.79%, and the coefficients increase statistically and economically compared to the full sample analysis. For the second subsample, the effect is not observable.

In Panel D, we also include the interaction between the dummy variable and the VIX_t. In a low AGI_t state, the slope of the VIX coefficient increases by 0.1678, i.e., future liquidity provision cost increase more with increasing VIX_t than in a high AGI_t state. Furthermore, the intercept increases from 0.2430 to 0.5086 (0.2430 + 0.2656), meaning that liquidity provision costs are generally higher in a low AGI_t state. For the subsample, including the financial crisis, the R^2 increases to 17.50%, which is very sizeable for predictive regressions. The explanatory power is entirely driven by our "low AGI_t" dummy, supporting our hypothesis that a low AGI_t captures states of high liquidity costs as compensation for market makers'

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deviation from their desired inventory levels.

We find that low AGI_t states (below the 20^{th} percentile) coincide with higher future costs of liquidity provision for the entire sample. A subsample analysis reveals that the effect is mainly driven by the period, including the financial crisis. The period from 2011 onwards is accompanied primarily by calm financial markets and low costs for raising liquidity in financial markets. Figure 3 shows that AGI_t was particularly low during the financial crisis, explaining why the dummy responds more strongly in the subsample analysis from 2004-2010.

VII. Conclusion

Our paper presents evidence on illiquidity premia for the SPX index option market. We construct a measure of the aggregated gamma inventory of SPX option market makers and find large markups in effective realized spreads for states with negative aggregated gamma inventory. Hence, options markets are more illiquid when aggregate gamma inventory is negative. Our results are robust to several control variables, for quoted spreads and implied volatility effective spreads, and in panel analysis. We rule out illiquidity spirals from the underlying as the economic force that drives our results.

Additionally, we show that the aggregate gamma inventory of option market makers is balanced during turbulent times, as indicated by higher illiquidity, volatility, and financial constraints. We show that such episodes coincide with extremely positive and negative observations of the variance risk premium, which measures overall option expensiveness. This suggests that market makers actively adjust the expensiveness of option prices to either increase their compensation or to balance gamma inventory in the desired direction. We solidify this finding by showing that the liquidity risk premium can, in part, be predicted by balanced gamma inventory.

Our findings indicate that option market makers do not desire negative gamma balances, thereby representing sharp deviations from the market makers' optimal inventory. In contrast, options markets are liquid when aggregate gamma inventory is positive. This contradicts theoretical studies that show that the magnitude of gamma, not the direction, plays a vital role for option liquidity.

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Appendix

A Calculation of reversal-strategy returns

The weight w_{it}^R and the strategy's payoff L_t^R for the reversal-strategy return for each stock i is defined as

$$
\begin{aligned}
w_{it}^R &= -\left(\frac{1}{2}\sum_{i=1}^{N}\left|R_{it-1}-R_{mt-1}\right|\right)^{-1}\left(R_{it-1}-R_{mt-1}\right) \\
L_t^R &= -\left(\frac{1}{2}\sum_{i=1}^{N}\left|R_{it-1}-R_{mt-1}\right|\right)^{-1}\sum_{i=1}^{N}\left(R_{it-1}-R_{mt-1}\right)R_{it},
\end{aligned}
\tag{10}
$$

where $R_{mt-1} = 1/N\sum_i^N R_{it-1}$ is the equal weighted market index return. The calculation follows Lehmann (1990). Dividing by the first term in equation (10) ensures that the strategy is either \$1 short or \$1 long. Calculating the returns for five different lags $j = 1,\ldots,5$ controls for long lived positive autocorrelation from private information (Llorente, Michaely, Saar and Wang, 2002; Wang, 1994). We average over the returns for all five lags and obtain the raw return. Subsequently, we beta-adjust the returns by regressing the raw return on the CRSP value-weighted market return f_t and its interaction with the lagged sign of the market return $f_t \cdot \text{sign}\left(f_{t-1}\right)$ (equation (11))

$$
L_t^R = \beta_0 + \beta_1 f_t + \beta_2\left(f_t\cdot\text{sign}\left(f_{t-1}\right)\right) + e_t \tag{11}
$$

$$
\beta_{t-1} = \hat{\beta}_1 + \hat{\beta}_2\cdot\text{sign}(f_{t-1}) \tag{12}
$$

$$
\text{hedged return}_t = L_t^R - \beta_{t-1}f_t. \tag{13}
$$

We calculate time-varying betas according to equation (12) and the beta adjusted hedged return according to equation (13).

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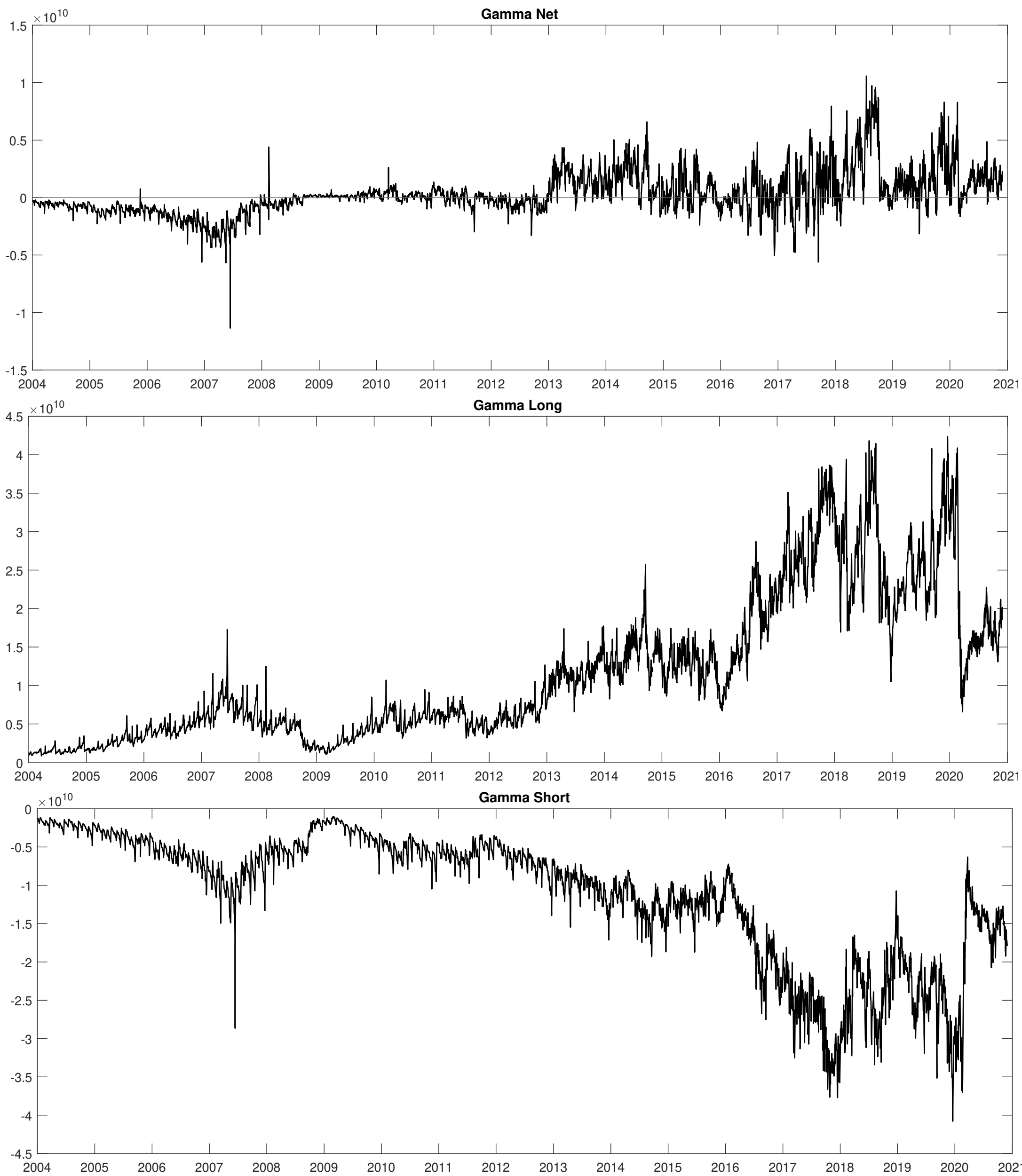
B Figures

Figure 1. Time-Series of $net\Gamma_t$



Note. The figure depicts the aggregated, long, and short SPX option market maker gamma weighted inventory scaled by the squared level of the SPX from Equation (2). The time series covers the period from 2004 to 2020.

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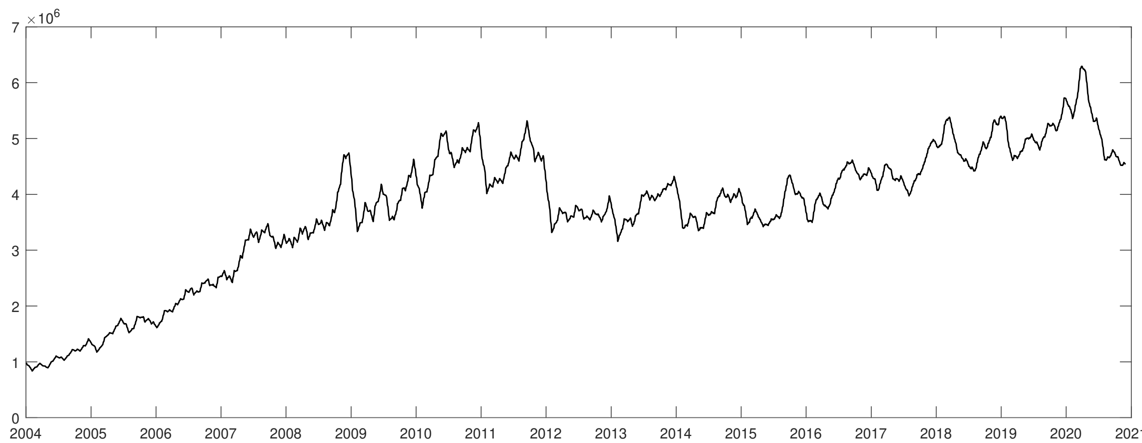
Figure 2. Time-Series of Absolute Number of Contracts



Note. The figure depicts the 30-day moving-average of the absolute number of contracts in the market maker inventory. The time series covers the period from 2004 to 2020.

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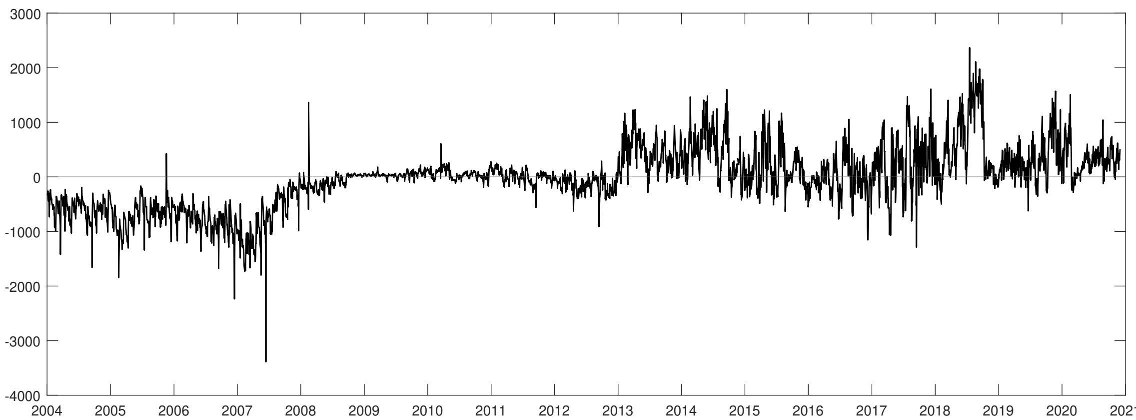
Figure 3. Time-Series of Normalized Aggregated Gamma Inventory (AGI)



Note. The figure depicts the net gamma inventory normalized by the 30-day moving-average of the absolute number of contract from Equation (3). The time series covers the period from 2004 to 2020.

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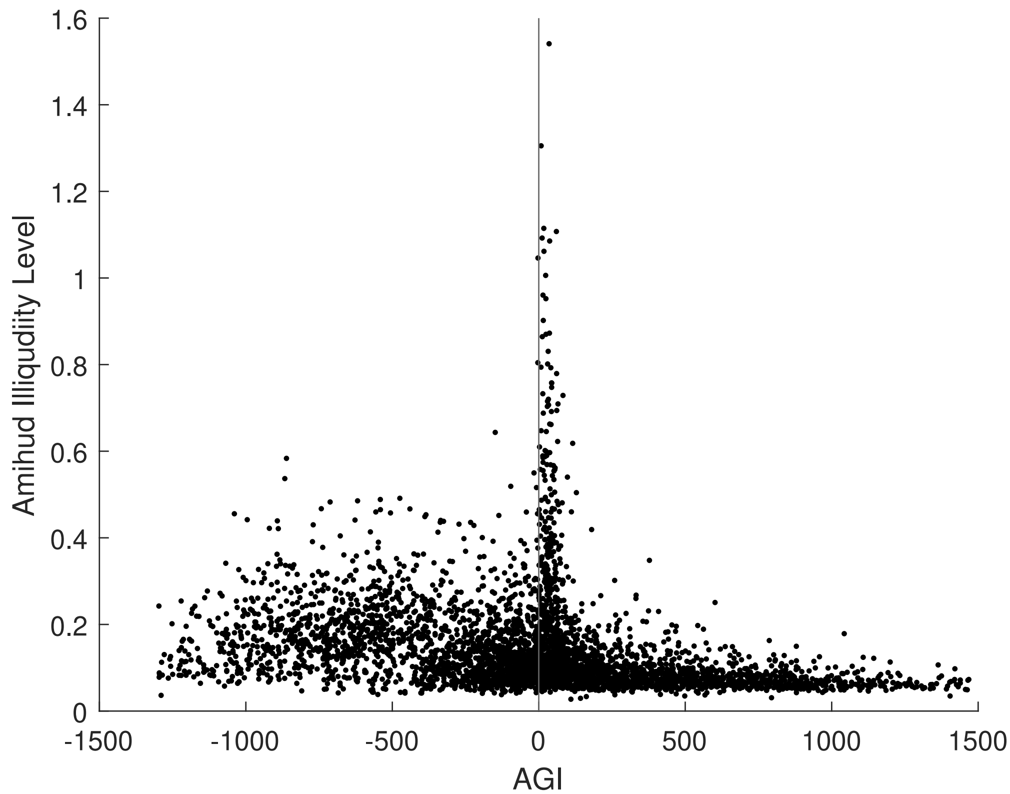
Figure 4. AGI and Market Illiquidity



Note. The figure illustrates the relationship between aggregated Gamma inventory (AGI) and the illiquidity measure of Amihud (2002). For visual purposes, we remove the top and bottom 1% of AGI. The time series covers the period from 2004 to 2020.

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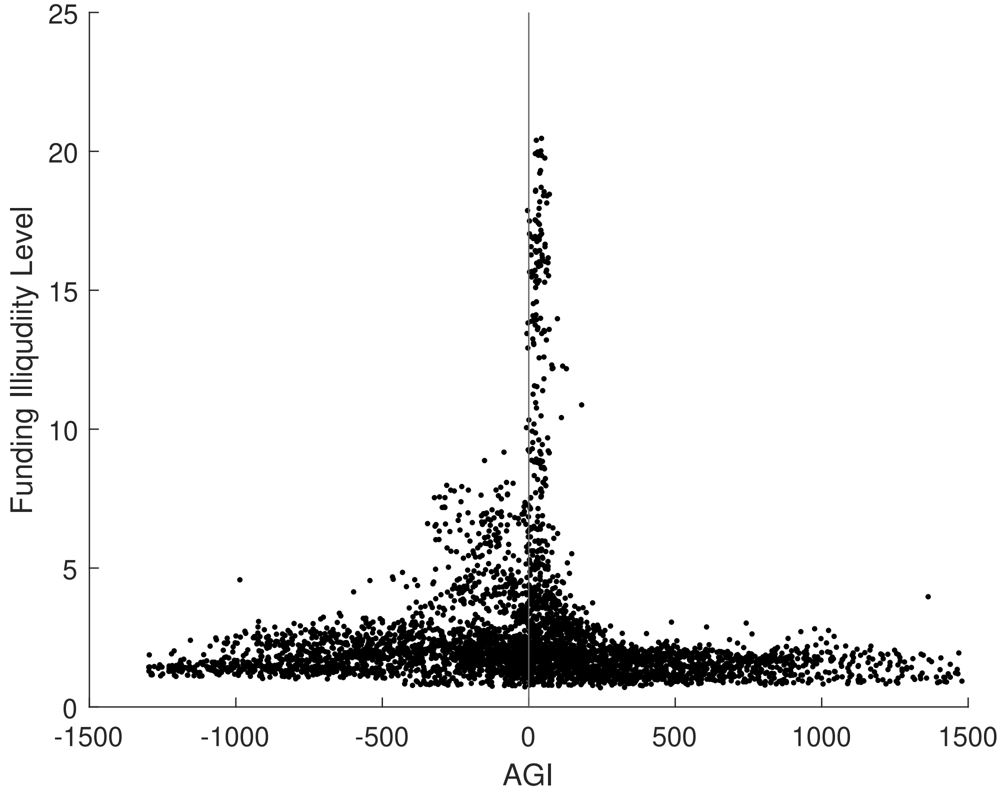
Figure 5. AGI and Funding Illiquidity



Note. The figure illustrates the relationship between aggregated Gamma inventory (AGI) and the funding illiquidity measure of Hu et al. (2013). For visual purposes, we remove the top and bottom 1% of AGI. The time series covers the period from 2004 to 2020.

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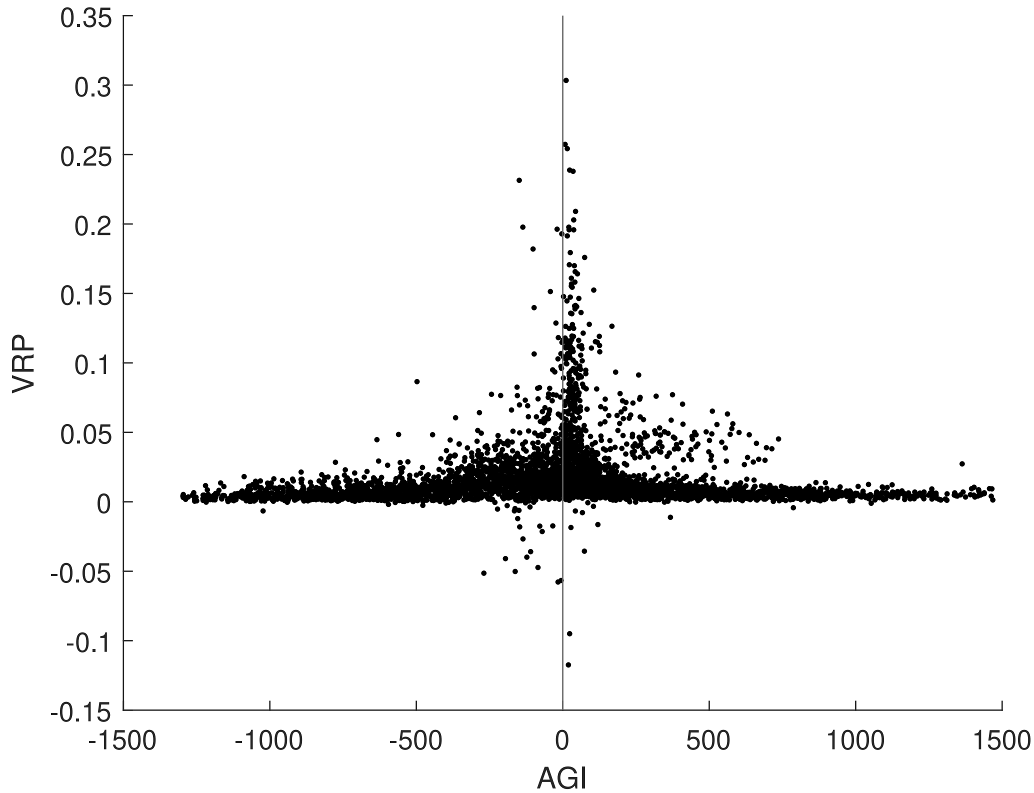

Figure 6. AGI and the Variance Risk Premium

Note. The figure illustrates the relationship between aggregated Gamma inventory (AGI) and the variance risk premium of Bekaert and Hoerova (2014). For visual purposes, we remove the top and bottom 1% of AGI. The time series covers the period from 2004 to 2020.

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C Tables

Table I. Summary Statistics

	Mean	Median	Min.	Max.	Std.	Skew.	ρ
Net gamma	0.0294	0.0021	-1.1358	1.0571	0.1894	1.0897	0.8896
Net gamma long	1.1462	0.7636	0.0839	4.2356	0.9353	1.0737	0.9892
Net gamma short	-1.1169	-0.8527	-4.0788	-0.1001	0.8313	-1.0232	0.9870
AGI_t	-0.0268	0.0056	-3.3875	2.3681	0.5481	0.1001	0.9192

Note. The table depicts summary statistics of the aggregated net gamma inventory of market makers. We decompose the net gamma position into long and short positions and report our measure for aggregated gamma inventory (AGI_t) according to equation (3). Net gamma, net gamma long, and net gamma short is reported in units of 10 billion. AGI_t is reported in units of thousands. ρ denotes the daily autocorrelation. The time series covers the period from 2004 to 2020.

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Table II. Call Effective Spread

	DOTM	OTM	ATM	ITM	DITM
α	0.0733	0.0541	0.0226	0.0074	0.0030
	(50.11)	(57.73)	(49.76)	(37.29)	(38.02)
AGI_t	-0.0068	-0.0153	-0.0080	-0.0029	-0.0010
	(-5.53)	(-18.83)	(-21.84)	(-23.69)	(-19.45)
adj. R^2	0.0230	0.2940	0.3387	0.2187	0.1328
Panel B: Controlling for VIX_t					
α	0.0678	0.0627	0.0200	0.0034	0.0015
	(19.59)	(28.58)	(13.98)	(4.64)	(5.72)
AGI_t	-0.0068	-0.0153	-0.0080	-0.0029	-0.0010
	(-5.62)	(-20.02)	(-21.01)	(-21.88)	(-17.89)
VIX_t	0.0027	-0.0042	0.0013	0.0020	0.0007
	(1.63)	(-3.97)	(1.77)	(4.97)	(5.26)
adj. R^2	0.0264	0.3158	0.3474	0.3226	0.2012
Panel C: Controlling for VIX_t and ESO_{t-1}					
α	0.0375	0.0180	0.0043	0.0016	0.0010
	(14.23)	(13.26)	(9.84)	(5.28)	(5.48)
AGI_t	-0.0039	-0.0044	-0.0017	-0.0013	-0.0007
	(-5.40)	(-12.06)	(-10.54)	(-9.84)	(-13.16)
VIX_t	0.0015	-0.0013	0.0002	0.0009	0.0005
	(1.61)	(-4.05)	(1.32)	(3.57)	(4.80)
ES_{t-1}	0.0198	0.0202	0.0109	0.0033	0.0009
	(16.94)	(41.11)	(55.84)	(12.84)	(9.71)
adj. R^2	0.2194	0.6679	0.7528	0.5215	0.2784

Note. The table depicts regressions of effective relative spreads of call options for different moneyness buckets on our measure of aggregated gamma inventory (AGI_t) and several control variables. The time series covers the period from 2004 to 2020. T-statistics are given in parenthesis below and are calculated using HAC-robust standard errors with lag length 10.

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Table III. Put Effective Spread

Panel A: Baseline regression					
	DOTM	OTM	ATM	ITM	DITM
α	0.0743	0.0378	0.0225	0.0090	0.0043
	(46.13)	(49.62)	(47.56)	(41.25)	(40.79)
AGI_t	-0.0095	-0.0149	-0.0088	-0.0032	-0.0010
	(-6.70)	(-20.80)	(-22.63)	(-22.64)	(-14.32)
adj. R^2	0.0623	0.3867	0.3678	0.2240	0.0550
Panel B: Controlling for VIX_t					
α	0.0858	0.0438	0.0209	0.0060	0.0040
	(22.36)	(21.84)	(14.62)	(7.42)	(15.61)
AGI_t	-0.0095	-0.0148	-0.0088	-0.0033	-0.0011
	(-6.80)	(-22.45)	(-22.04)	(-20.75)	(-14.30)
VIX_t	-0.0057	-0.0029	0.0008	0.0015	0.0001
	(-3.43)	(-3.09)	(1.08)	(3.52)	(1.10)
adj. R^2	0.0842	0.4015	0.3706	0.2721	0.0557
Panel C: Controlling for VIX_t and ESO_{t-1}					
α	0.0179	0.0086	0.0039	0.0025	0.0031
	(11.95)	(5.82)	(9.23)	(6.50)	(10.25)
AGI_t	-0.0019	-0.0028	-0.0017	-0.0014	-0.0008
	(-5.07)	(-5.67)	(-10.40)	(-13.18)	(-10.24)
VIX_t	-0.0013	-0.0006	0.0001	0.0007	0.0001
	(-3.60)	(-2.96)	(0.95)	(3.43)	(1.29)
ES^B_{t-1}	0.0302	0.0193	0.0117	0.0039	0.0008
	(58.23)	(25.96)	(61.67)	(23.49)	(3.85)
adj. R^2	0.6626	0.7919	0.7871	0.5073	0.0907

Note. The table depicts regressions of effective relative spreads of put options for different moneyness buckets on our measure of aggregated gamma inventory (AGI_t) and several control variables. The time series covers the period from 2004 to 2020. T-statistics are given in parenthesis below and are calculated using HAC-robust standard errors with lag length 10.

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Table IV. Panel Regressions with VIX_t and ES_{t-1}

	ES_t			QS_t			$IVES_t$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AGI_t	-0.0073 (-4.31)	-0.0073 (-4.32)	-0.0017 (-2.52)	-0.0098 (-3.40)	-0.0098 (-3.41)	-0.0025 (-2.92)	-0.0073 (-6.71)	-0.0073 (-6.72)	-0.0038 (-3.48)
VIX_t		-0.0004 (-0.33)	-0.0012 (-1.98)		-0.0001 (-0.05)	-0.0026 (-2.34)		0.0002 (0.19)	-0.0002 (-0.46)
ES^B_{t-1}			0.0128 (3.92)						
QS^B_{t-1}						0.0260 (4.17)			
$IVES^B_{t-1}$									0.0075 (8.73)
within R^2	0.0976	0.0979	0.3400	0.0614	0.0614	0.4520	0.1120	0.1120	0.2220
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table depicts panel regressions of effective spreads (ES), quoted spreads (QS), and implied volatility effective spreads ($IVES$) for different moneyness buckets (entities i) on our measure of aggregated gamma inventory (AGI_t) and several control variables. All independent variables are standardized. T-statistics are calculated with standard errors clustered for ten buckets (five moneyness buckets and separation for puts and calls) and months. All regressions include entity fixed effects. The time series covers the period from 2004 to 2020.

Table V. Predictive Panel Regressions with VIX_t and ES_t

	ES_{t+1}			QS_{t+1}			$IVES_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AGI_t	-0.0072 (-4.29)	-0.0072 (-4.30)	-0.0017 (-2.44)	-0.0098 (-3.42)	-0.0098 (-3.43)	-0.0026 (-3.05)	-0.0073 (-6.72)	-0.0073 (-6.72)	-0.0038 (-3.41)
VIX_t		-0.0004 (-0.33)	-0.0012 (-1.98)		-0.0001 (-0.05)	-0.0026 (-2.49)		0.0002 (0.18)	-0.0002 (-0.47)
ES^B_t			0.0128 (3.93)						
QS^B_t						0.0259 (4.18)			
$IVES^B_t$									0.0075 (8.67)
within R^2	0.0962	0.0966	0.3400	0.0619	0.0619	0.4520	0.1120	0.1120	0.2220
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table depicts predictive panel regressions of effective spreads (ES_{t+1}), quoted spreads (QS_{t+1}), and implied volatility effective spreads ($IVES_{t+1}$) at $t+1$ for different moneyness buckets (entities i) on our measure of aggregated gamma inventory (AGI_t) and several control variables at t. All independent variables are standardized. T-statistics are calculated with standard errors clustered for ten buckets (five moneyness buckets and separation for puts and calls) and months. All regressions include entity fixed effects. The time series covers the period from 2004 to 2020.

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Table VI. Panel Regressions with Illiquidity Measures

	ES_t			QS_t			$IVES_t$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AGI_t	-0.0018 (-2.50)	-0.0018 (-2.81)	-0.0018 (-2.67)	-0.0026 (-2.91)	-0.0029 (-3.14)	-0.0029 (-3.39)	-0.0039 (-3.57)	-0.0036 (-3.50)	-0.0036 (-3.58)
ES^B_{t-1}	0.0128 (3.84)	0.0127 (3.80)	0.0128 (3.81)						
QS^B_{t-1}				0.0258 (4.07)	0.0259 (4.07)	0.0259 (4.08)			
$IVES^B_{t-1}$							0.0073 (8.67)	0.0071 (8.40)	0.0071 (8.46)
Market Illiq.	-0.0003 (-0.94)		-0.0003 (-1.30)	-0.0006 (-0.99)		0.0001 (0.19)	0.0007 (3.77)		-0.0000 (-0.06)
Funding Illiq.		-0.0004 (-0.60)	0.0000 (0.03)		-0.0017 (-1.62)	-0.0018 (-1.89)		0.0017 (3.50)	0.0018 (2.61)
within R^2	0.3380	0.3380	0.3380	0.4480	0.4490	0.4490	0.2240	0.2260	0.2260
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table depicts panel regressions of effective spreads (ES), quoted spreads (QS), and implied volatility effective spreads ($IVES$) for different moneyness buckets (entities i) on our measure of aggregated gamma inventory (AGI_t) and several control variables. All independent variables are standardized. T-statistics are calculated with standard errors clustered for ten buckets (five moneyness buckets and separation for puts and calls) and months. All regressions include entity fixed effects. The time series covers the period from 2004 to 2020.

Table VII. Predicitve Panel Regressions with Illiquidity Measures

	ES_{t+1}			QS_{t+1}			$IVES_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AGI_t	-0.0017 (-2.43)	-0.0017 (-2.71)	-0.0016 (-2.54)	-0.0026 (-3.04)	-0.0028 (-3.09)	-0.0027 (-3.19)	-0.0039 (-3.51)	-0.0036 (-3.45)	-0.0035 (-3.53)
ES^B_t	0.0128 (3.85)	0.0127 (3.79)	0.0128 (3.81)						
QS^B_t				0.0258 (4.07)	0.0258 (4.07)	0.0258 (4.08)			
$IVES^B_t$							0.0073 (8.61)	0.0070 (8.32)	0.0071 (8.38)
Market Illiq.	-0.0003 (-0.96)		-0.0005 (-2.25)	-0.0006 (-0.96)		-0.0004 (-0.69)	0.0007 (3.89)		-0.0003 (-0.98)
Funding Illiq.		-0.0001 (-0.13)	0.0005 (0.91)		-0.0010 (-1.11)	-0.0005 (-0.98)		0.0021 (3.50)	0.0024 (2.92)
adj. R^2	0.3370	0.3370	0.3380	0.4480	0.4480	0.4480	0.2230	0.2270	0.2270
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. The table depicts panel regressions of effective spreads (ES_{t+1}), quoted spreads (QS_{t+1}), and implied volatility effective spreads ($IVES_{t+1}$) at $t+1$ for different moneyness buckets (entities i) on our measure of aggregated gamma inventory (AGI_t) and several control variables at t. All independent variables are standardized. T-statistics are calculated with standard errors clustered for ten buckets (five moneyness buckets and separation for puts and calls) and months. All regressions include entity fixed effects. The time series covers the period from 2004 to 2020.

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Table VIII. Probit model: Balanced Aggregate Gamma Inventory

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	-1.2670	-1.5440	1.7640	-1.6200	1.0800	1.0970	0.8820
	(-31.73)	(-27.02)	(16.28)	(-29.89)	(10.40)	(8.05)	(7.37)
Amihud	3.0050			1.0330	2.2020		1.4800
	(15.38)			(4.08)	(7.93)		(4.57)
RV		5.4950		4.8880		2.2030	1.4200
		(13.52)		(10.69)		(7.14)	(4.00)
HKM			-4.5970		-3.8650	-3.9140	-3.6800
			(-21.42)		(-22.74)	(-18.15)	(-20.14)
adj. R^2	0.0608	0.1250	0.2690	0.1290	0.2840	0.2830	0.2880

Note. The table depicts a probit model of a binary dummy variable which takes the value of one if absolute AGI_t is in its 20^{th} percentile. Independent variables include other measures of illiquidity such as the Amihud (2002) illiquidity measure, the intermediary capital ratio from He et al. (2017), and realized volatility (RV_t). The coefficient of HKM is divided by 10 for the sake of comparability. The time series covers the period from 2004 to 2018.

Table IX. Option Expensiveness

	VRP_t	VRP_{t+1}	VRP_{t+1}	VIX_t	VIX_{t+1}	VIX_{t+1}
α	0.0124	0.0125	0.0021	0.1671	0.1672	0.0043
	(11.12)	(11.13)	(4.46)	(30.79)	(30.53)	(4.52)
dummy_t	0.0261	0.0258	0.0038	0.1064	0.1058	0.0021
	(4.27)	(4.27)	(3.38)	(4.51)	(4.49)	(2.39)
VRP_t			0.8384			
			(23.82)			
VIX_t						0.9749
						(159.57)
adj. R^2	0.1657	0.1610	0.7473	0.2119	0.2097	0.9586

Note. The table depicts contemporaneous and predictive regressions of VRP and VIX on a dummy variable which takes the value of one, if the AGI_t variable is lower than the 20^{th} percentile at t. The time series covers the period from 2004 to 2020.

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Table X. Reversal Returns

	Full sample	2004-2010	2011-2020
Panel A: Baseline regression			
α	0.5527	0.5195	0.5739
	(17.80)	(16.08)	(12.37)
dummy_t	0.5539	1.0374	0.0792
	(5.73)	(8.46)	(0.66)
adj. R^2	0.0151	0.1173	-0.0002
Panel B: VIX_t			
α	0.0687	-0.2446	0.5269
	(0.79)	(-2.08)	(4.21)
VIX_t	0.4972	0.7697	0.0546
	(6.55)	(7.46)	(0.50)
adj. R^2	0.0261	0.1686	-0.0003
Panel C: Controlling for VIX_t and $dummy_t$			
α	0.1170	-0.1309	0.5281
	(1.37)	(-1.06)	(4.21)
VIX_t	0.4090	0.6102	0.0430
	(5.21)	(5.20)	(0.39)
dummy_t	0.2822	0.3948	0.0674
	(3.11)	(3.52)	(0.55)
adj. R^2	0.0290	0.1779	-0.0005
Panel D: Controlling for VIX_t and interaction			
α	0.2430	-0.0729	0.5345
	(2.61)	(-0.60)	(4.28)
VIX_t	0.2185	0.2354	0.2047
	(2.39)	(1.68)	(1.77)
dummy_t	0.2656	0.5596	0.0140
	(2.98)	(4.66)	(0.12)
$\text{dummy}_t \cdot VIX_t$	0.1678	0.0927	0.0092
	(2.23)	(1.15)	(0.08)
adj. R^2	0.0324	0.1750	0.0003

Note. The table depicts predictive regressions of reversal strategy returns at $t+1$ (Nagel, 2012) on a dummy variable which takes the value of one, if the AGI_t variable is lower than the 20^{th} percentile at t. Furthermore, we include several control variables at time t. The time series covers the period from 2004 to 2020.

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Table XI. Robustness

	$IVES_t$				
	(1)	(2)	(3)	(4)	(5)
AGI_t	-0.0005	-0.0029	-0.0030	-0.0029	-0.0029
	(-2.09)	(-3.20)	(-3.28)	(-3.23)	(-3.27)
$IVES^B_{t-1}$		0.0049	0.0048	0.0047	0.0047
		(8.90)	(8.67)	(8.49)	(8.50)
$IVES^B_{t-2}$		0.0044	0.0043	0.0042	0.0043
		(9.49)	(9.31)	(9.40)	(9.41)
VIX_t		-0.0003			
		(-0.90)			
Market Illiq.			0.0004		-0.0000
			(3.49)		(-0.16)
Funding Illiq.				0.0012	0.0012
				(3.16)	(2.37)
within R^2	0.0002	0.2570	0.2580	0.2590	0.2590
Entity FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	No	No	No

Note. The table depicts panel regressions of implied volatility effective spreads ($IVES_t$) at t for different moneyness buckets (entities i) on our measure of aggregated gamma inventory (AGI_t) and several control variables. All independent variables are standardized. T-statistics are calculated with standard errors clustered for ten buckets (five moneyness buckets and separation for puts and calls) and months. The time series covers the period from 2004 to 2020.

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