Retail Option Trading and Liquidity: Evidence from High-Frequency Data*

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Abstract

This paper demonstrates that retail trading in the options market impacts the liquidity of underlying stocks. Options contracts have zero net supply, and financial intermediaries engage in delta hedging to manage their net imbalances, unlike retail traders. Consequently, when intermediaries hold a net short (long) option position, their dynamic hedging demands liquidity from (or supplies liquidity to) the underlying stock, leading to market destabilization (or stabilization). Leveraging proprietary option exchange data that categorizes option trading by trader type, we document this effect and show that it is stronger for stocks and periods where liquidity supply is expected to be limited.

Key words: retail trading, derivatives, liquidity, feedback effects
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1 Introduction

Stock liquidity has been related to outcomes of interest for both corporate finance and asset pricing. This justifies the large literature understanding the determinants of liquidity such as exchange design (Anand and Venkataraman, 2016; Hendershott and Moulton, 2011), tick size reductions (Bessembinder, 2003), transparency (Boehmer, Saar, and Yu, 2005), and algorithmic trading (Boehmer, Fong, and Wu, 2021). One overlooked potential determinant of stock liquidity is the trading of stock options. Intermediaries (typically market makers) in the options market absorb the net option demand from end users and hedge out any directional risk through periodic rebalancing. We show that intermediary hedge rebalancing of the aggregate risk exposures arising from aggregate retail option demand has been affecting the liquidity of the market for the underlying stocks.

Depending on the risk exposure of intermediaries, their hedge-rebalance trading can either add to or drain liquidity from the underlying stock market. Options contracts have zero net supply, and financial intermediaries engage in delta hedging to manage their net imbalances, unlike retail traders. Specifically, when intermediaries hedge an aggregate long option position with stock, they need to buy (or sell) more stock as the underlying price falls (or rises) to remain delta-neutral.[1] In this scenario, the delta hedge rebalancing trades of intermediaries act as a stabilizing force in the stock market. In contrast, if intermediaries are net short options, the mechanism reverses. They demand liquidity as the price either rises or falls, acting as a destabilizing force. Thus, the market liquidity of the stock underlying the option is directly affected.

This liquidity effect is latent and predictable: the hedge rebalancing trades of the intermediary are a known function of the realized movements in the underlying stock. However, it is important that not every trader is delta hedging their option position. Suppose the net aggregate demand is also hedged by the counterparty (for example, sophisticated volatility arbitrageurs); in that case, the trading in the stock market of the counterparty and the intermediary will cancel out.[2] Furthermore, the trades of sophisticated investors could

[1]Equity option market makers aggregate risk across options of different maturities, strikes, and types (call or put) on a given stock. If they are long calls, they are short the stock to delta hedge, if they are long puts they are long the stock to delta hedge. However, as the price of the underlying rises, they need to purchase stock regardless of whether the hedge position comes from call options or put options.

[2]For example, market makers hedge their option inventory to remove directional risk, while proprietary traders hedge their option inventory to capture mispricing in option implied volatility.

be informed and relate to liquidity through an information channel. Thus, identifying different groups of traders and their aggregate demand is crucial for empirically identifying this mechanism as a potential determinant of liquidity. We focus on retail traders, a group of option end-users that are both uninformed and unlikely to delta hedge their inventory and can thus cause hedge rebalancing flows from intermediaries that can affect liquidity in the underlying stock.

We use a novel dataset—the Open/Close dataset from the CBOE C1 option exchange and the NASDAQ ISE exchange—to identify a set of traders who are neither professional customers, brokers, market makers, nor proprietary traders. We follow the existing literature and refer to this category of "public customers" as retail traders. We assume that these traders trade options for directional exposure or speculative purposes and are thus unlikely to hedge their option trades. This dataset allows us to estimate the amount of delta-hedging in the equity market due to retail option trading.[3]

We then measure market liquidity by calculating quoted, effective, and realized spreads and price impact using millisecond resolution data from 2011 to 2019. Our main variable *net* Γ aggregates the risk on all the option contracts by retail investors on an individual stock and captures the intensity of delta hedging of option market makers induced by a change in the stock price. When *net* Γ is positive, it indicates that delta hedgers are net long gamma while retail end-users are net short gamma.[4] We then analyze the relationship between the stock trading required to delta hedge options and stock market liquidity at a daily level.

Our empirical results confirm that when retail traders on net sell (buy) more options, which increases (decreases) net gamma, market liquidity is improved (deteriorates). Quantitatively, a one standard deviation decrease in net gamma causes an 11% increase in realized spreads and a 10% increase in price impact relative to the mean level of these

[3]The granularity of trade classification needed in this study has only been available since 2009 and 2011 from NASDAQ and CBOE, respectively. We refer to the "public customers" in this dataset as retail traders as in de Silva, Smith, and So (2023), Jackwerth (2020), and Eaton, Green, Roseman, and Wu (2022).

[4]In option pricing terminology, the Delta is the first derivative of the option price with respect to the underlying price and is used as a hedge ratio to remove first-order risk from a portfolio of options. Gamma is the term used for the second derivative of the option price with respect to the underlying stock price (equivalently, the first derivative of the delta with respect to the stock price). This Gamma (denoted Γ) captures the change in the hedge ratio induced by changes in prices and will be the main focus of our study.

measures. These magnitudes are particularly large in light of the fact that the mechanism is only activated when there is movement in the underlying security that induces re-hedging of option portfolios by market makers.

To enhance our understanding of how retail trading in the options market impacts market liquidity, we examine market conditions where we anticipate a stronger effect of latent liquidity. Specifically, we posit that when market makers in the equity market are disinclined to provide liquidity, the influence of liquidity demand or supply from intermediaries in the options market will be magnified. In support of this hypothesis, we observe a larger association between our net gamma measure and liquidity in the lead-up to earnings announcements, when market makers face heightened adverse selection or inventory risk, as noted by Johnson and So (2018). In the cross-sectional tests, we also find a stronger correlation between gamma and liquidity in stocks characterized by higher information asymmetry and inventory risk, as gauged by the dispersion in analysts' earnings forecasts and the level of analyst coverage.

We consider several alternative explanations for our results and provide robustness tests. A key concern is that variation in net gamma is driven by information about future liquidity. Because we cannot fully identify the information of options traders, we address this concern in two ways. First, we use the method of Ni, Pearson, Poteshman, and White (2021) to show that our results are robust to removing from our measure variation that could be related to informed trade of options by retail investors. We find that our results are stronger when we isolate the variation that is plausibly related to less informed trade. Another concern is that changes in net gamma predict volatility because traders are informed about option volatility and trade on that information.[5] We rule out this explanation by showing that volatility trading strategies constructed using this information are never profitable, even when we assume that investors can trade at the midpoint of the bid-ask spread and thus don't have to pay large option transaction costs. We also show that the fact that we use an estimate of net gamma has minimal impact on our results and that the result is not driven by the particular measure of net gamma that we use.

Our results are particularly relevant as retail trading in options has increased rapidly

[5]Lakonishok, Lee, Pearson, and Poteshman (2007) show that very little trading is volatility-based—i.e. opening straddles or strangles—this is consistent with anecdotal evidence that trading profitably on volatility information is extremely difficult for non-sophisticated option traders.

recently (Bryzgalova, Pavlova, and Sikorskaya, 2022). While earlier literature has studied whether the listing of options can affect the characteristics of the underlying asset and found mixed results, our findings make clear that these effects may depend on the time-varying level of *net* Γ. Thus, an option introduction could cause an increase in non-informational liquidity supply or demand. Option introduction can improve market liquidity if retail investors are net short options and cause a deterioration in market liquidity if investors are net long options. This means regulators should pay attention not only to the existence of an options market but the current state of the market. Currently, options trading is still dominated by the CBOE C1 exchange and the NASDAQ ISE exchange. However, the number of trading venues is increasing over time, so market fragmentation could make this hedge-rebalancing effect more difficult to track. This incentivizes regulators to aggregate information relating to options trading on multiple exchanges.

2 Related Literature

Our results contribute to a large literature on the relationship between options trading and market quality. Fedenia and Grammatikos (1992) find that options listing decreases spreads on small stocks while increasing spreads on large stocks. Results in Kumar, Sarin, and Shastri (1998) suggest that option listing decreases spreads. Both Conrad (1989) and Detemple and Jorion (1990) find a volatility decrease after option introduction, while Mayhew, Mihov, et al. (2000) find that option introduction increases volatility when one controls for the endogeneity of option listing. A more recent study Hu (2018) finds that option listing increases uninformed trading in the US between 2001 and 2010. Our results add to this literature by explaining why options can affect market quality while explaining that the result can vary over time and depends on the general trading patterns of uninformed option investors.

We also contribute to the debate on unsophisticated investor trading and market liquidity. Kaniel, Saar, and Titman (2008) suggest that individual investors in the equity market provide liquidity, and Ozik, Sadka, and Shen (2021) show that they attenuated the rise in illiquidity during the COVID-19 lockdown. Both Barrot, Kaniel, and Sraer (2016) and Bernhardt, Da, and Warachka (2022) find that individual investors are not compensated for their liquidity provision, which suggests they are uninformed, while Boehmer et al. (2021) suggests that retail trade imbalances can be informed. Eaton et al. (2022) suggests the sophistication of the retail investor matters and find that traders at traditional retail brokerages improve market quality. Less is known about the effects of retail options traders on equity market quality. We contribute to this literature by showing how retail option trading can improve or degrade market liquidity depending on the net-gamma imbalance to be hedged by market makers.

This paper also contributes to burgeoning literature on the effects of derivative hedging on stock market return characteristics. Baltussen, Da, Lammers, and Martens (2021) find evidence that short gamma positions of option hedgers are related to intraday momentum in futures markets, while Barbon, Beckmeyer, Buraschi, and Moerke (2022) show that both momentum and mean reversion are driven by leverage effects and hedge-rebalancing in ETF markets. Like us, Ni et al. (2021) focus on the single stock option market and show that market maker option gamma is negatively related to daily absolute returns suggesting a feedback effect from options trading to return volatility. Relative to this paper, we use a more granular classification of options trading to help isolate trades plausibly made by retail end-users of options and show that the feedback mechanism matters for liquidity and not only extreme return realizations. There is also a large literature on the effects of more exotic derivative products on financial market quality. Boehmer, Chava, and Tookes (2015) show that the introduction of single-name credit default swap (CDS) contracts reduces the market quality of the underlying asset. The results in this paper complement these studies by providing direct evidence that option trading affects market liquidity. A distinct advantage of our setting is that by calculating market liquidity measures using trades and quotes we can link the option gamma to quantities of interest to regulators and prospective traders, allowing us to make statements about likely ex-ante market liquidity rather than ex-post market characteristics.

Finally, we also connect to the theoretical literature on liquidity. Theories of liquidity typically map liquidity to state variables like information asymmetry (Glosten and Milgrom, 1985; Easley and O'hara, 1987), intermediary inventory costs (Amihud and Mendelson, 1980; Ho and Stoll, 1981) and raw trade costs (Demsetz, 1968). Our results suggest that uninformed derivative trading can break the link between primitive state variables and stock liquidity as suggested by these models. Some modern theories include derivatives within models of liquidity. Ronnie Sircar and Papanicolaou (1998) show theoretically how portfolio insurance strategies can increase the volatility of the underlying when program traders must delta hedge their inventory. Wilmott and Schönbucher (2000) also study the feedback effects of option replication trading. In a recent study Huang, Yueshen, and Zhang (2021) embed derivative trading into a model with informed traders and show that delta hedging can reduce price impact in the underlying. Our findings provide empirical evidence in support of these theoretical mechanisms.

3 Option Trading and Latent Liquidity

In this section, we explain how we measure the option positions of various market participants, and explain the relationship between option hedging by intermediaries and the liquidity in the underlying market.

3.1 Retail Trading of Equity Options

The option trades in our dataset can be classified into three broad categories which include customers, firms, and market-makers. Trades initiated by firms can be broken down further into trades by broker-dealers and proprietary traders. Transactions initiated by customers can be further classified into public customers (clients of discount retail brokers or full-service retail brokers) and professional customers. The category of public customers can contain large institutions such as hedge funds and mutual funds, assuming they do not trade enough to be classified as professional customers.

The estimate of $Net\Gamma$ depends on our assumption about the identities of likely delta hedgers. The literature either uses market-makers and broker-dealers or market-makers, broker-dealers, and firm proprietary traders as the likely delta hedgers. Since our focus is on trades of retail investors with intermediaries we follow Chen, Joslin, and Ni (2019) to merge firms and market-makers as one group and observe how their trades with public investors affect the market.

We note that the definition of an informed investor in our context is an investor who has information on volatility and delta hedges a purchased or sold option to capture the difference between the price of volatility in the market (the option implied volatility) and their estimate of expected realized volatility. Because public customers are not likely to delta hedge their inventory, we consider them to be uninformed retail investors. For this reason, these public customers are classified as retail traders in the context of options markets by de Silva et al. (2023), Jackwerth (2020), and Eaton et al. (2022) and we also refer to this category as retail traders.[6] Some small institutions that trade options infrequently could also be classified as customers. A series of papers on the institutional use of options suggests they use options for hedging, income generation, or return amplification (Natter, Rohleder, Schulte, and Wilkens, 2016; Cici and Palacios, 2015; Kaniel and Wang, 2022) but not for sophisticated volatility trading strategies. Nonetheless, any misclassification will bias us against finding any result: if our measure mistakenly includes quantitative investors who trade options for the purpose of exploiting volatility mispricing, they would need to delta hedge the options in a similar way to intermediaries (but in the opposite direction) and thus would bias us against finding any effect.

Our classification of traders benefits from a unique feature of options markets; unlike equity markets, options markets do not have any off-exchange trading (and thus no Trade Reporting Facility). Because retail orders are segmented on the exchange and prioritized, their trades must be classified at the origin (i.e. if an entity trades on behalf of a customer and on their own book the trade will not be classified in the same way). The ability to distinguish customers by sophistication was enhanced when the ISE proposed a rule change to separate customer orders into public customers and professional customers, with the practical outcome that only public customers get the marketplace advantages of priority in the order book and fee waivers. The SEC approved this proposed rule change and noted that "The ISE states that the purpose, generally, of providing these marketplace advantages to Public Customer Orders is to attract retail investor order flow to the Exchange by leveling the playing field for retail investors over market professionals and providing competitive pricing."[7] The CBOE had a similar proposal accepted and made clear that the classification separates retail traders from sophisticated traders, commenting "The purpose of this new order type is to distinguish between those public customer orders routed to CBOE which are for non-professional, retail investors, and those public

[6] Bryzgalova et al. (2022) also use this measure to verify their transaction based measure of retail trade. This measure of retail trade exploits a flag for price improvement mechanisms introduced by the Options Price Reporting Authority (OPRA) in November 2019 for transaction-level data.

[7] SEC Release No. 34-59287, January 23rd 2009 and quotation source here

customer orders which are for persons or entities that have access to information and technology that enables them to professionally trade listed options".[8,9] The "professional customer" designation ultimately prevents market-makers at these exchanges from competition with sophisticated retail investors who would take advantage of their public customer designation to trade with priority and lower fees against unsophisticated customer orders. Later amendments to the rule further clarify that professional customers capture sophisticated traders.[10]

We note that our classification of retail traders is immune to the criticism that the OCC misclassifies trades of market makers and other sophisticated arbitrageurs as retail trades. Figure 2 shows exactly how broker-dealers and market makers from the CBOE can be misclassified in the OCC classification scheme. We also note that the CBOE data is classified according to the account type so that the splitting of large institutional orders into multiple smaller-sized orders will not affect the classification of the trade. Furthermore, incorrect classification of origin codes can result in fines and penalties.[11]

Our focus is on the effect of uninformed retail investors on market liquidity through delta hedging of net option positions. However, our measure for $Net\Gamma$ assumes that likely delta hedgers absorb the demand of retail traders and "professional customers" who may be considered more sophisticated investors. To alleviate the concern that our measure is distorted by these investors, we show that they make up a negligible portion of overall public customer trading volume. Table 1 shows that they make up 2% of volume in the average firm. We also show in Table A1 that our results strengthen when we focus on firms with less professional customer and proprietary trader volume.

[8] The CBOE proposal was accepted largely on the basis of being identical to the proposal of the ISE. Release No. 34-61198, December 17th, 2009, and comment letters on the proposal are found at https://www.sec.gov/comments/sr-cboe-2009-078/cboe2009078.shtml

[9] See regulatory circular RG09-148

[10] "the Exchange no longer believed that the definitions of customer and non-customer properly distinguished between the kind of nonprofessional retail investors that the order priority rules and fee exemptions were intended to benefit and non-broker-dealer professional traders with access to advanced market data information and sophisticated trading platforms that were not intended to benefit from those rules and exemptions"https://www.sec.gov/files/rules/sro/cboe/2016/34-77049.pdf

[11] see https://www.findknowdo.com/news/10/25/2021/broker-dealer-settles-charges-exchanges-origin-code-violations

3.2 The Link between Equity Options Trading and Stock Liquidity

While equity securities have a net-positive supply, equity options have a net-zero supply—for every option buyer, there must be an option writer. The classic theory of option pricing of Scholes and Black (1973) and Merton (1973) shows that option pricing is intimately linked with stock trading through a delta hedging argument in which a dynamically varying position in the stock is used to offset the risk exposure of the option position. Thus, options are created by replication and this replication activity will require liquidity to be demanded or supplied depending on the risk exposure. Early theories ruled out any market impact of the trading needed for option replication by the assumption of frictionless markets without transaction costs.[12] Removing the assumption of frictionless markets allows the stock trading from dynamic delta hedging to impact the market for the underlying.

Financial technology combined with a lack of sophistication can obscure this activity of market makers from many option end-users. In particular, retail investors often don't appreciate that as long as a market maker is net-long or short options in a particular stock, their option trade has the same effect as submitting a particular liquidity demand or supply schedule to the market with their order. The delta hedging program of the intermediary will be a function of the underlying asset price change.[13]

To fix ideas we focus on an individual stock and detail the relationships between the liquidity supply and demand from options trading and market liquidity. First, consider the delta of a given option contract

$$\Delta_{i,t} = \frac{\partial C_{i,t}}{\partial S_{i,t}}.$$

$\Delta_{i,t}$ represents the rate of change of the option price ($C_{i,t}$) with respect to the stock price

[12] In reality, equity option market-makers act as producers in the options market rather than mere matching mechanisms, market makers for equities aim to make the spread and end the day without holding any stock inventory. In an ideal world, equity option market makers would operate in a similar fashion, matching equity option buyers and sellers, and taking the spread as compensation for risks such as inventory, operational costs, and information asymmetry risk.

[13] Another example of a latent factor affecting liquidity is the existence of margins - Foley, Kwan, Philip, and Ødegaard (2022) find that sudden increase in margin requirements during the COVID-19 crisis resulted in withdrawn liquidity.

$(S_{i,t})$ and is the hedge ratio of first-order importance for an options market maker. The hedging of options would be trivial if not for changes in this hedge ratio, but since the option price is a nonlinear function of the stock price, this hedge ratio will change over time. The first derivative of the option delta with respect to the stock price tells us how much the hedge ratio will change when the stock price changes, and thus, allows us to predict the mechanical trading of the options market maker given what we know about their net option position and total net gamma,

$$\Gamma_{i,t} = \frac{\partial \Delta_{i,t}}{\partial S_{i,t}} = \frac{\partial^2 C_{i,t}}{\partial S_{i,t}^2}.$$

Later we will detail the calculation of the net option position to be hedged by market makers, for now, we take this as given and use an example to fix ideas. To operationalize this idea that changes in price will induce trading we start with a measure of net share gamma which captures the number of shares that need to be purchased by the market makers given a \$1 increase in the stock price. Here it is crucial that we use the net open interest (the net option position) of the option market makers (or more generally delta-hedgers). The Net Share Gamma is:

$$\text{Net Share Gamma}_t = \sum_{j=1}^{J_t} \text{Net Open Interest}_{j,t}^{\Delta \text{ hedgers}} \Gamma_j(t, S_t),$$

where J_t is the number of open option series on the stock. We then rescale this measure so that it is expressed in terms of dollar volume traded per 1% move in the stock price, a measure commonly used by practitioners

$$\$ \text{ Gamma } 1\%_t = \text{Net Share Gamma}_t \times S_t \times \frac{S_t}{100}.$$

This tells us the dollar volume of stock that would be traded given a hypothetical move of 1% in the stock price. We can compare this to the total dollar volume traded in the stock on a given day

$$\$ \text{ Volume} = Volume_t \times S_t.$$

Finally, we can also calculate the realized dollar volume of stock traded on day t due to delta hedging, by combining the Net Share Gamma_t and the realized return:[14]

$$\$ \text{ Gamma Realized}_t = \text{Net Share Gamma}_t \times S_t \times R_t.$$

Figure 1 contains two visual examples of the relationship between Dollar Net Gamma and liquidity (Percent Price Impact) for one of our sample firms (Meta Platforms Inc.). Figure 1 Panel A contains a kernel density estimate for the distribution of price impact in two different states - when Dollar Net Gamma is greater than zero, and less than zero respectively. Given the discussion above, we expect liquidity conditions to be better when market maker Net Gamma is higher because of increased liquidity supply. It is clear from the graph that the distribution of Price Impact is much tighter and concentrated closer to zero when Dollar Net Gamma is positive; when Dollar Net Gamma is negative we see a much longer tail in the distribution of price impacts, suggesting that the mechanical liquidity demand of option hedgers in the stock market affects market liquidity. Panel B contains a time series plot of the Net (dollar) Gamma and Price Impact. We calculate one-month moving averages of the variables to make the data easier to visualize (we also lag the Dollar Net Gamma by one day relative to the realization of price impact). We can see that on average periods with high Net Gamma have relatively lower price impact which suggests that the results in Panel A are not coming from some time effects (such as both dollar gamma and price impact being subject to a time trend).

4 Data and Variables

We use three main databases. We use the Millisecond Trade and Quote data, the "Daily Product" from TAQ, Open/Close data from the Chicago Board Options Exchange (CBOE) and the NASDAQ International Securities Exchange (ISE), and stock price and volume data from CRSP. We include common stocks with share codes 10 or 11 and stocks with exchange codes 1, 2, or 3 corresponding to the NYSE, NYSE MKT (formerly AMEX), and NASDAQ. After calculating liquidity measures, and net gamma for each stock we keep only stocks for which we have at least 500 trading days. Our data spans

[14] This is an estimate which is accurate for small returns, when returns are extreme there may also be changes in implied volatility which will induce more trading through the sensitivity of delta to implied volatility (we ignore this second-order sensitivity which is named vanna in the option trading community).

the period from January 2011 to December 2019.

4.1 Calculation of Delta Hedger Gamma

CBOE and ISE classify trades by trader group and type. Trader groups are public customers (retail traders and professional customers), firms (firm proprietary traders and broker-dealers), and market makers. Trade types are either open buy, open sell (an option is written), close buy (a written option is closed out), or close sell (a purchased option is closed out). By tracking the daily movements of each category and type of trade we can follow the total open interest of each trader group. We are interested in the total open interest of likely delta hedgers which represents the net option demand of retail traders that must be delta hedged by option intermediaries.[15] We define

$$\text{Net Open Interest}_{j,t}^{\Delta\text{hedgers}} = \text{ Open Interest}_{j,t}^{Sell,Retail} - \text{ Open Interest}_{j,t}^{Buy,Retail},$$

where for each option series j

$$\text{Open Interest}_{j,t}^{Sell,Retail} = \text{ Open Interest}_{j,t-1}^{Sell,Retail} + Volume_{j,t}^{OpenSell} - Volume_{j,t}^{CloseBuy},$$

and

$$\text{Open Interest}_{j,t}^{Buy,Retail} = \text{ Open Interest}_{j,t-1}^{Buy,Retail} + Volume_{j,t}^{OpenBuy} - Volume_{j,t}^{CloseSell},$$

where Open Buy and Open Sell represent new purchased and written options by customers and Close Buy and Close Sell represent the closure of existing positions.

To calculate the net gamma for an individual stock, we account for the fact that each option contract is written on 100 shares of the underlying stock and sum the gamma across all open series on day t to get the Net Share Gamma:

$$\text{Net Share Gamma}_t = \sum_{j=1}^{J_t} 100 \times \text{Net Open Interest}_{j,t}^{\Delta\text{ hedgers}} \Gamma_j(t, S_t).$$

[15] Almost all the net-demand of equity options is delta-hedged by equity option market makers. Firm proprietary traders will hedge some of the net demand. We use the word intermediary to refer to the general option delta-hedger and show our results are robust to the assumption of whether firm proprietary traders are included in this group of delta-hedgers or not.

In this form, larger firms with more options trading will mechanically have higher *Net Share Gamma*, so we rescale the net gamma to make the variable comparable across firms, we choose the rescaling in Ni et al. (2021) to make $Net\Gamma_t$ dimensionless. We define:

$$Net\Gamma_t = \sum_{j=1}^{J_t} 100 \left(\frac{S_t}{M_t}\right) \times \text{Net Open Interest}_{j,t}^{\Delta \text{ hedgers}} \Gamma_j(t, S_t), \tag{1}$$

where S_t is the stock price and M_t is the number of shares outstanding all measured at t. Since each individual stock will have somewhat unique liquidity conditions, we don't expect the relationship between $Net\Gamma$ and liquidity to be identical across stocks. For this reason, we will later estimate the relationship firm-by-firm allowing the coefficients for each stock to differ. To summarize, our main variable, $Net\Gamma$ captures the magnitude of re-hedging needed when the underlying stock price changes.

We can only estimate the positions of likely delta hedgers because the trading volume data from the CBOE and ISE together compose only about 50% of the options trading volume. Using data from these two exchanges will induce classical measurement error to our gamma variable which will bias us against finding any relationship between $Net\Gamma$ and liquidity. Consistent with this idea, we show in Table A4 that our results are stronger when we have better data coverage.

Our measure of $Net\Gamma$ depends on whether we include firm proprietary traders in the set of likely delta hedgers. Market makers and broker-dealers are almost certain to hedge their inventory while proprietary traders are assumed to mostly delta hedge their inventory. We include firm proprietary traders in the set of likely delta-hedgers for the main tests and show in Table A3 that our results are robust to excluding them from the set of likely delta-hedgers.

4.2 Liquidity Measures

We use the Daily Trade and Quote (DTAQ) database to calculate the liquidity measures. Holden and Jacobsen (2014) show that DTAQ is the first best solution for calculating liquidity measures and we refer interested readers to their paper for detailed sample cleaning and institutional details.[16]

The percent quoted spread for time interval s is defined as

$$\text{Percent Quoted Spread}_s = \frac{A_s - B_s}{M_s},$$

where A_s is the National Best Ask, B_s is the National Best Bid assigned to time interval s by a particular trade classification technique, and M_s is the midpoint, which is the average of B_s and A_s. We aggregate to the daily level and calculate for each stock the time-weighted average of the Percent Quoted Spread over all time intervals and denote this variable as the *Quoted Spread*.

The percent effective spread for a given stock on trade k is defined as

$$\text{Percent Effective Spread}_k = \frac{2D_k(P_k - M_k)}{M_k},$$

where D_k is an indicator variable that equals +1 if the trade k is a purchase, −1 if trade k is a sale, and P_k is the trade price. We aggregate to the daily level by calculating for each stock the dollar-volume-weighted average of the Percent Effective Spread over all trades and denote this variable as the *Effective Spread*.

The percentage effective spread can be decomposed into a permanent and a transitory component, the temporary component which is the realized spread, and the permanent component which is the price impact.

The percent realized spread of trade k on a given stock is defined as

$$\text{Percent Realized Spread}_k = \frac{2D_k(P_k - M_{k+5})}{M_k},$$

where M_{k+5} is the midpoint five minutes after the midpoint M_k. We aggregate to the daily level by calculating for each stock the dollar-volume-weighted average of the Percent Realized Spread over all trades and denote this variable as the *Realized Spread*.

[16]We thank the authors for making their code available online.

The percent price impact of trade k on a given stock is defined as

$$\text{Percent Price Impact}_k = \frac{2D_k(M_{k+5} - M_k)}{M_k}.$$

We aggregate to the daily level by calculating for each stock the dollar-volume-weighted average of the Percent Price Impact over all trades and denote this variable as the *Price Impact*.

The Percent Realized Spread and Percent Price Impact are a function of D_k which requires the use of a trade classification algorithm. There are three widely used trade classification algorithms: First is that of Lee and Ready (1991) in which a trade is classified buy if $P_k > M_k$, a sell if $P_k < M_k$, or tick test is used if $P_k = M_k$. Using the tick test, a trade is classified as a buy (sell) if the last trade at a different price was at a lower (higher) price than P_k; second is that of Ellis, Michaely, and O'Hara (2000) in which a trade is classified buy if $P_k = A_k$, a sell if $P_k = B_k$, and the tick test is used otherwise; the third method is Chakrabarty, Li, Nguyen, and Van Ness (2007) in which a trade is a buy if $P_k \in [0.3B_k + 0.7A_k, A_k]$, a sell if $P_k \in [B_k, 0.7B_k + 0.3A_k]$, and the tick test is used otherwise. We do not take a stance on the correct algorithm, rather we show the main results for all three methods, and show other results using the Lee and Ready (1991) algorithm while verifying that research conclusions do not change with alternative classification methods.

These various measures tell us about different dimensions of liquidity. Specifically, the quoted spread is a good indicator of trading costs for a small investor who does not expect their trade size to move prices. The effective spread takes into account latent liquidity or movements in the price due to a trade absorbing all of the depth at the given quote and executing on higher or lower limit orders. Realized spreads pick up price changes from the trade price to the post-trade value and can be thought about as a proxy for market maker revenues and price impact reflects the cost market makers face when trading with informed traders, after such a trade the price will not reverse as the information is incorporated into the price. We can see the realized spread is equal to the effective spread less price impact. Some studies refer to price impact and realized spreads as the 'permanent" and "transitory" price impacts of a trade or as the "informational" and "non-informational" impact of trading.

4.3 Descriptive Statistics

Our final sample contains 4,279,421 daily observations for 2,639 unique firms from January 2011 to December 2019.

Table 1 Panel A contains details about trader categories and how they contribute to option volume. We calculate the percentage of total volume for each trader category at the firm level and then calculate averages of each statistic across firms. The average firm has mean retail trading of 47% and we can see that most of this volume is absorbed by broker-dealers, market makers, and proprietary traders. Broker-dealers and market makers make up 38% volume in an average firm while proprietary traders on average make up 2% of volume.

Table 1 Panel B contains summary statistics for the main variable and control variables used in the paper. We calculate the statistics for each firm and then average across firms. We can see that the mean and median of $Net\Gamma$ is positive, meaning that on average for each firm, retail investors are net short options that have to be delta hedged by market makers. We also present multiple spread measures. The average quoted spread is 0.30% while the average effective spread is 0.24% using the method of Lee, Mucklow, and Ready (1993), with alternative trade classification measures giving qualitatively similar values.

5 Empirical Results

In Section 5.1 we introduce and estimate the baseline specification. In Sections 5.2 and 5.3 we show how the effect varies over time and in the cross-section of stocks, respectively. Section 5.4 shows that our results are not likely driven by an information channel. Finally, Section 5.5 shows how our results vary in groups of stocks with different market capitalization and volumes.

5.1 Main Results

Our primary focus is the relationship between variation in delta-hedger gamma from retail trading and measures of the underlying stock liquidity. To this end, we specify, for each stock the following regression model:

$$LIQ_t = a + b \times Net\Gamma_{t-1} + \sum_{l=1}^{L} c_l \times X_{l,t-1} + \varepsilon_t. \quad (2)$$

The regression model is estimated for each stock, and we report the cross-sectional average coefficient estimates. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks (Thompson, 2011). The key prediction is that $Net\Gamma_{t-1}$ is negatively related to measures of liquidity at time t.[17]

As we run the regression stock-by-stock, this coefficient captures the average relationship across all stocks. Although we normalize the net-gamma measure to make it comparable across stocks, we cannot guarantee that the relationship has the same coefficient for each stock, thus we use the same regression specification as Ni et al. (2021). Another advantage of this specification is that we do not need to worry about time-invariant stock characteristics that determine liquidity. For example, some firms may have relatively higher or lower levels of $Net\Gamma$ relative to others which could have a time-invariant level effect on market liquidity and we cannot identify these effects as they can not be distinguished from other time-invariant firm characteristics. We control for volatility by including up to 10 lags of absolute returns and absolute returns interacted with a positive return dummy to account for the asymmetric response of volatility to negative returns, we also control for 10 lags of the dependent variable to account for any persistence in liquidity.

We estimate equation (2) to understand whether net gamma is related to stock market liquidity. Table 2 contains results for the full sample of firms and different measures of liquidity. We can see that for each measure of liquidity, there is a statistically negative relationship between $Net\Gamma_{t-1}$ and the measures of liquidity on day t. The results are

[17] Many authors have noted historical time trends in liquidity as well as sharp drops in spreads related to tick-size changes (from eights to sixteenths in 1997 and decimalization in 2001) which induced them to use changes or deviations from trends in their specifications (see e.g. Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010). The sample from 2011 to 2019 does not display any time trend.

intuitive, first, the economic significance of the relationship between $Net\Gamma$ and the *Quoted Spread* is quite small, amounting to about 1.5% of the daily average value. This is sensible as the liquidity demand and supply mechanism related to options trading needs some movement in the price of the underlying before the option delta is changed and the mechanism is activated. Nonetheless, market makers of the underlying asset who detect greater uninformed trading may be willing to reduce spreads a little. For the regression with *Effective Spread* as the dependent variable the coefficient on $Net\Gamma$ is -0.033, since a one standard deviation move in gamma is 0.006 this translates to a -2 basis point change in the *Effective Spread* for every standard deviation move in gamma which is approximately 8% of the overall average level of the *Effective Spread*. The effect on *Price Impact* is slightly larger at 10% while the largest impact of option trading is on *Realized Spread* with a one-standard-deviation move explaining over 11% of the mean percent realized spread. This result is intuitive - when $Net\Gamma$ is positive the equity option hedge trading represents mechanical liquidity supply that competes with existing market makers.

The overall message from these results is that—on average across stocks—retail option trading that results in changes in the $Net\Gamma$ position of equity option market makers can make a significant difference to the market liquidity of the underlying stock. Increases (decreases) in $Net\Gamma$ lead to improvement (deterioration) in all measured aspects of market liquidity. Market marker profits as measured by the transitory component of the spread as well as the price impact of potential informed traders are most affected. The economic size of these results is large, considering these effects are latent and contingent on sufficient movements in the underlying asset to elicit changes in the optimal option hedge. In the next section, we move on to empirical tests that highlight time periods and stocks where the effect is expected to be particularly large.

5.2 Evidence from Earnings Announcement Periods

Our main results show that delta hedgers in the options market affect underlying market liquidity through their mechanical liquidity demand and supply. In this section, we show the impact of this liquidity plays a more important role when existing market makers are reluctant to provide liquidity.

The period leading up to an earnings announcement is a good setting to test the effect of latent liquidity on measures of liquidity because these effects can only be seen in cases when equity option market makers' delta hedge trades are the marginal trades in the market. This is more likely when traditional liquidity providers have a reduced incentive to make the market. Krinsky and Lee (1996) show that the adverse selection component of the bid-ask spread increases around earnings announcements and Johnson and So (2018) show that market makers supply liquidity asymmetrically leading up to earnings announcements. Lee et al. (1993) show that spreads widen in the lead-up to earnings announcements suggesting liquidity providers use spreads to actively manage information asymmetry risk.

To see why stock-trading coming from the re-hedging of a market maker's options portfolio should have more impact during periods of relatively higher information asymmetry consider typical models of trading with information asymmetry such as Kyle (1985) or Glosten and Milgrom (1985) in which uninformed investors and informed investors trade with an optimizing market maker (or auctioneer). These models rely on a market maker (or auctioneer) who behaves rationally and conditions the price (or the bid-ask spread) on available information about the ratio of informed and uninformed traders. The introduction of an options market maker who is hedging a positive net gamma position would effectively introduce a competitor for the market maker who supplies liquidity at given price points (those points at which the options portfolio is re-hedged) without conditioning on any information. This non-optimizing trader is much more likely to be the marginal liquidity supplier in a market where information asymmetry risk is higher and optimizing market makers hedge this risk by reducing the quantity of shares in the limit order book. Likewise, the introduction of a market maker who is hedging a positive net gamma position would effectively introduce a non-strategic trader who systematically takes liquidity at certain price points (re-hedging the delta) which will impact prices/spreads as long as equity market makers cannot distinguish their non-informational trades from other trades in the market.

To test the hypothesis that latent liquidity effects driven by retail option trading are stronger in the lead-up to earnings announcements we estimate the regression model of the previous section augmented with an interaction term between $Net\Gamma$ and $EARN$ where the variable $EARN$ is equal to 1 in the three trading days leading up to the earnings announcement day, and zero otherwise. The specification is:

$$LIQ_t = a + b \times Net\Gamma_{t-1} + c \times Net\Gamma_{t-1} \times EARN_t + \sum_{l=1}^{L} c_l \times X_{l,t-1} + \varepsilon_t. \qquad (3)$$

To the extent that the impact of latent liquidity is stronger in the lead-up to earnings, we expect the estimated average coefficient $\hat{c}$ to be negative and economically significant.

The results are contained in Table 3. We can see that all four liquidity measures are impacted more heavily by option-hedge trading during earnings periods. This suggests that retail option trading can have a particularly large impact on stocks with already fragile trading environments due to perceived information asymmetry. Adding the baseline effect to the interaction effect we see that the magnitude of the result is twice as large for *Quoted Spread*, *Realized Spread*, and *Price Impact*, while the result is three times as large for the *Effective Spread* measure.

5.3 Evidence from High Information-Asymmetry Stocks

The evidence above suggests that the effect of latent liquidity from retail option trading is stronger at times when perceived adverse selection risk is higher. A related question is the importance of stock-level information asymmetry, we would expect this effect to also be stronger in firms where the overall information environment makes information asymmetry risk a larger concern for market makers in the equity. We test this idea using sample splits on analyst disagreement, a commonly used measure of information asymmetry, namely. Sadka and Scherbina (2007) use this measure to investigate the link between mispricing and liquidity. We calculate analyst disagreement in each year as the standard deviation of all outstanding fiscal year earnings forecasts scaled by the absolute value of the mean forecast. In stocks where analysts disagree more about potential earnings, there is greater scope for informed traders to take advantage of their information, and thus market makers are changing the price of liquidity. However, latent liquidity demand and supply that arises from retail option trader imbalances and delta hedging of market maker inventory must be demanded or supplied as a function of the delta hedging needs, without taking into account adverse selection.

The results are contained in Table 4. We can see that for every measure of liquidity, stocks with high analyst disagreement—which we expect to have more information asymmetry risk for market makers—are more affected by delta hedging of net retail option positions. The difference in the effect size between low and high dispersion stocks is 20% for *Quoted Spread*, for *Effective Spread* the effect size is approximately 4 times as large. For the *Price Impact* variable, the effect size is approximately twice as large, giving an effect size of 13% for high dispersion stocks relative to 6% for low dispersion stocks. This suggests that retail option trading can be particularly impactful in stocks with already fragile trading environments due to perceived information asymmetry.

As an alternative measure of information asymmetry, we also consider analyst forecast coverage, we expect stocks with low coverage to have a poorer information environment which presents better opportunities for informed traders and thus more risk-averse behavior of market makers when providing liquidity. Results in Table 5 show the relationship between $Net\Gamma_{t-1}$ and various measures of liquidity. Except for *Quoted Spread* which has a similar effect size for high and low analyst coverage stocks, the effect sizes for the other variables are three to ten times as large for low analyst coverage stocks relative to high analyst coverage stocks.

5.4 Ruling out the Information Channel

Our results thus far show that our measure $Net\Gamma$—which aggregates the risk in all the option contracts on an individual stock and captures delta-hedging flows—can predict market liquidity. One alternative explanation for these results is that retail investors on aggregate have private information about volatility, which they express by taking positions in the options market. In this section, we show two tests to rule out the possibility that the information channel drives our results.

5.4.1 Isolating Uninformed Trade through a Decomposition of $Net\Gamma$

If informed traders on net buy and sell options in anticipation of changes in volatility which also anticipates changes in liquidity it could bias our estimate. To deal with this we decompose our $Net\Gamma$ measure to remove variation potentially related to informed trading.[18]

Following Ni et al. (2021) we decompose $Net\Gamma$ into three components: a component that comes from net gamma τ periods ago; a component that comes from new options trades between $t-\tau$ and t; and a component that comes from changes in gamma that arise from changing stock prices τ days ago until today. Specifically, we can first decompose $Net\Gamma_t$ into a component that comes from trades in the last τ days and the residual:

$$Net\Gamma_t = \underbrace{Net\Gamma_t(t-\tau, S_t)}_{\text{Residual Gamma}} + \underbrace{[\mathrm{Net}\Gamma_t - \mathrm{Net}\Gamma_t(t-\tau, S_t)]}_{\text{Information Gamma}}. \tag{4}$$

The first term gives the net gamma coming from positions opened $t-\tau$ periods ago using the day t price. A potential concern about this decomposition is that the residual component still may contain long-lived information about liquidity at time t, under the assumption that the investor does not anticipate the change in the net gamma coming exclusively from the change in price between time $t-\tau$ and time t we can further decompose into the gamma at period $t-\tau$ using the stock price at $t-\tau$ and the gamma at period $t-\tau$ using the stock price at t and the gamma at period $t-\tau$ using the stock price at $t-\tau$:

$$\begin{aligned} Net\Gamma_t = & \underbrace{Net\Gamma_t(t-\tau, S_{t-\tau})}_{\text{Period } t-\tau \text{ Gamma}} + \underbrace{[\mathrm{Net}\Gamma_t - \mathrm{Net}\Gamma_t(t-\tau, S_t)]}_{\text{Information Gamma}} \\ & + \underbrace{[\mathrm{Net}\Gamma_t(t-\tau, S_t) - \mathrm{Net}\Gamma_t(t-\tau, S_{t-\tau})]}_{\text{Hedge Gamma}}. \end{aligned} \tag{5}$$

Given $\tau = 5$ the hedge gamma component captures hedge rebalancing trades induced due to movement in the stock price from $t-5$ to t. Under the assumption that the aggregation of options trades to net gamma does not predict price changes over the next five days, this measure is immune to concerns about informed trading.

Table 6 Panel A contains the results of using the first decomposition. We can see that the non-information gamma is negatively related to all four measures of liquidity. The economic and statistical significance is quantitatively similar to the results reported in Table 2. Table 6 Panel B contains the results of using the second decomposition. Using this decomposition we see that the hedge gamma component is not significant for *Quoted*

[18] We do note that to profit from knowledge about changes in volatility informed traders would have to delta hedge their option positions and thus their trading would go in the opposite direction of the intermediaries and bias us against finding any effect.

Spread. However, for the *Effective Spread*, *Realized Spread*, and *Price Impact*, the effect sizes are even larger than in our main specification. The effect size for *Effective Spread* is now 15% which is almost twice as large as the effect size of 8% in Table 2. The effect sizes for the *Realized Spread* and *Price Impact* are larger by 15% and 55% respectively. These results help alleviate concerns that information-driven changes in net-gamma are generating the statistical relationship between net-gamma and liquidity.

5.4.2 Additional Evidence that Aggregate Retail Option Trades are Uninformed

Our measure of $Net\Gamma_{t-1}$ connects the behavior of option delta-hedgers today to the decisions of options traders multiple periods ago. To the extent that the aggregated decisions of options traders reflect information about future outcomes in the market, there is a concern that this variable picks up information as well as a delta-hedging effect.[19] For example, if retail investors expect low volatility, they may sell options on net, leaving market makers net long gamma and if this low volatility environment is associated with low liquidity it could explain the relationship between gamma and liquidity.[20]The mechanism described in this paper will exist regardless of any relationship between private information and volatility, but the policy implications are different if non-informational trading can cause changes in liquidity as we claim.

There is much evidence to suggest much option trading is uninformed and unsophisticated, Bryzgalova et al. (2022) suggests that retail investors lose quite a lot on their options trades, and Lakonishok et al. (2007) estimate an upper bound of approximately 1% of open volume on options devoted to purchased or written straddles which suggest volatility trading. Hu (2018) also find that option introduction disproportionately increases uninformed trading relative to informed trading which is consistent with the findings in this paper. Nonetheless, we test this hypothesis in our paper by considering the profitability of a variety of volatility trading strategies using retail investor data.

[19]It should be noted that the delta hedging effect is mechanical and the question is one of quantifying the effect. The concern is whether the entire coefficient can be attributed to this delta-hedging effect or whether some of the effect should be attributed to another channel such as volatility information trade.

[20]Ni, Pan, and Poteshman (2008) provide empirical evidence to suggest investors trade on volatility information, however, their measure focuses on demand for vega which is concentrated in long-maturity options while gamma is concentrated in short-maturity options.

If the private-volatility-information hypothesis is true, then retail investors should profit from trading on volatility information. For an investor with private information about volatility to profit in the options market, they need to take a position that can profit from information that realized volatility will be above or below market expectations (as captured in option implied volatility). If informed option investors expect realized volatility to be high (low) they should go long (short) volatility by buying (selling) an option and delta-hedging the directional risk.[21] To capture this idea we construct a time series of delta-hedged returns at the stock level and consider a variety of trading strategies that would profit if $Net\Gamma$ is informative about volatility. In particular, we consider strategies that take a long or short position depending on the level of $Net\Gamma$. We consider strategies that are long (short) volatility when $Net\Gamma$ is negative (positive). As levels of $Net\Gamma$ near zero may reflect a lack of conviction by retail investors about the direction of volatility, we also consider strategies when investors only take long-short positions when gamma is at extreme levels such as above the 75th, 90th, and 95th percentile values or below the 25th, 10th, or 5th percentile values. We consider both equal and value-weighted returns and we assume that investors can trade at the midpoint of the bid-ask spread to give the strategy the highest likelihood of achieving economically significant returns.

The results are presented in Table 7. If investors were trading options based on private information on volatility, we would expect strategies based on this information to display economically and statistically significant positive returns. The results in Panels A and B reveal that an investor who tried to exploit information in gamma would typically make significantly negative returns (even in the absence of transaction costs which are large for such option trading strategies).

5.5 Size and Volume Effects

We also consider whether the effects are concentrated in small stocks with relatively low trading volume. Our sample stocks are already quite large and well traded because of the requirements that the stocks have traded options. Nonetheless, it seems likely that the effects of delta-hedging on liquidity should be stronger in smaller stocks that have lower trading volume. We investigate these ideas in Table 8 and Table 9 respectively. Comparing the results for Table 8 Panels A and B we can see that the results exist for

[21] see Ahmad and Wilmott (2005) for a mathematical treatment of volatility arbitrage.

Effective Spread, *Realized Spread*, and *Price Impact* for both large and small stocks. The effect sizes are approximately three times larger for small stocks at 9%, 12%, and 13% of the mean value of the dependent variable. Comparing the results for Table 9 Panels A and B we see that volume seems more important than size for explaining heterogeneity in the main effect size. While the results still hold in high volume stocks for *Quoted Spread*, *Realized Spread*, and *Price Impact*, the effect sizes are much lower.

6 Robustness Tests

In this section, we consider the robustness of our main results to a variety of potential explanations.

6.1 Retail Option Trading and Stock Liquidity

One potential concern about our measure is that the group of retail traders contains traders of varying levels of sophistication. We estimate our baseline regression in stocks with different levels of proprietary and professional customer participation to emphasize the importance of trader classification. If professional customers and proprietary traders drive our results, we would expect a stronger relationship between $Net\Gamma$ and liquidity in stocks with a greater level of participation by these investors. Table A1 shows the relationship between the *Effective Spread* and $Net\Gamma$ within groups of firms with different levels of retail trading. We sort firms into groups according to the firm level of non-delta hedger volume accounted for by retail investors which captures the firm-level average of the daily proportion of non-market maker trade that can be associated with retail investors (by definition, firms with lower retail participation have higher professional and proprietary trader participation). In this way, we can understand if the relationship between $Net\Gamma$ and market liquidity is more important for firms with more retail trade in their options. Column (1) shows the baseline result for all firms. The coefficient on $Net\Gamma$ is -0.033, since a one standard deviation move in gamma is 0.006 this translates to a -2 basis point change in the *Effective Spread* for every standard deviation move in gamma which is approximately 8% of the overall average level of the *Effective Spread*. Column (2) contains the results for the sample of firms with below median level of *Retail* the effect size is 4.25% which is approximately half of the effect size in the full sample. Column (3) contains results for the sample of firms with above median level of *Retail* and the coefficient is -0.059 which translates to an effect size of 8.81%. Finally in Column (4) we analyze the relationship within firms that have top quartile level of *Retail*, the coefficient is -0.123 which translates into an effect size of 11.8%. The results in this table provide strong evidence that the effect is stronger in firms with relatively more retail trading. If these "professional investors" were informed and driving the relationship between net demand and liquidity, we would expect the results to be stronger where there are more professional customers. We further rule out the information channel in Section 5.4. Thus, these results also suggest that any sophisticated investors that are classified as "customers" will bias us against finding any relationship between $Net\Gamma$ and liquidity.

6.2 Alternative Trade Classification Algorithms

In Table A2 we assess the impact of alternative trade classification algorithms on our results. We re-run the regression model in equation (2) using the methods of Ellis et al. (2000) (EMO) and Chakrabarty, Jain, Shkilko, and Sokolov (2021) (CLNV) to calculate the Percent Realized Spread and Percent Price Impact which rely on a trade classification algorithm. The results on Percent Price Impact are statistically and economically slightly stronger with the CLNV classification while being weaker with the EMO classification, while the results on Percent Realized Spread are qualitatively similar, and the economic effect sizes are lower with the alternative trade classification algorithms.

6.3 Excluding Proprietary Traders from the Set of Likely Delta Hedgers

Equation (1) makes clear that the measure of net-gamma depends on the group of likely delta hedgers. While it is natural to assume that firm proprietary traders are hedging the options they hold, one can also consider a measure of gamma that considers the firm proprietary traders to be more similar to retail investors and hold naked option positions. We replicate Table 2 using this alternative definition of $Net\Gamma$ in Table A3 and find that the results are largely similar to those using the alternative classification. There is a negative and statistically significant relationship between $Net\Gamma_{t-1}$ and all four liquidity measures as in Table 2. The effect sizes for *Quoted Spread* and *Effective Spread* are almost identical, the effect size for *Realized Spread* is lower at 4% (relative to 11% in Table 2), while the effect size for *Price Impact* is higher at 13% (compared to 11% in Table 2).

6.4 Coverage of Open/Close Data

Our variable $Net\Gamma_{t-1}$ is an estimate of the actual net gamma at any point in time as we do not observe the totality of options trading on our sample stocks on U.S. exchanges. As we do not have any reason to suspect option contracts traded by retail investors are systematically opened or closed on particular exchanges (which would affect our estimate of net gamma), we expect our estimates to contain only classical measurement error that would bias our coefficient estimates toward zero. To verify that our results are robust to using stocks with various levels of data coverage, we calculate coverage by calculating the total option volume for each stock day in our sample traded on the CBOE C1 exchange and the NASDAQ ISE exchange and divide by the total option volume on that stock-day as recorded by OptionMetrics. We then take an average across all days in the sample for each stock to get a stock-level measure of data coverage. We then estimate equation (2) separately for high-and low-coverage stocks.

The results are contained in Table A4. We can see that we lose the power to identify the effect using *Effective Spread* and *Price Impact* for stocks with low data coverage, however, can see that the results for stocks with high data coverage are statistically and economically significant. The effect sizes for the *Effective Spread*, *Realized Spread*, and *Price Impact* are economically significant, a one standard deviation change in $Net\Gamma_{t-1}$ translates into an 11.85%, 10.75%, and 16.35% change in the mean of the respective dependent variables. These results are either similar to or stronger than our baseline results suggesting that measurement error is not driving our results.

7 Conclusion

This paper shows that delta-hedging of net option positions driven by retail trading has a pervasive effect on market liquidity as measured by daily liquidity. These effects are stronger in stocks with low volume or higher information asymmetry and are not explained by informed trading. The impact depends on the net option position of market makers as well as the movement of the underlying stock which means that data from multiple options exchanges need to be centralized and the measure of potential destabilization calculated dynamically for effective oversight by regulators.

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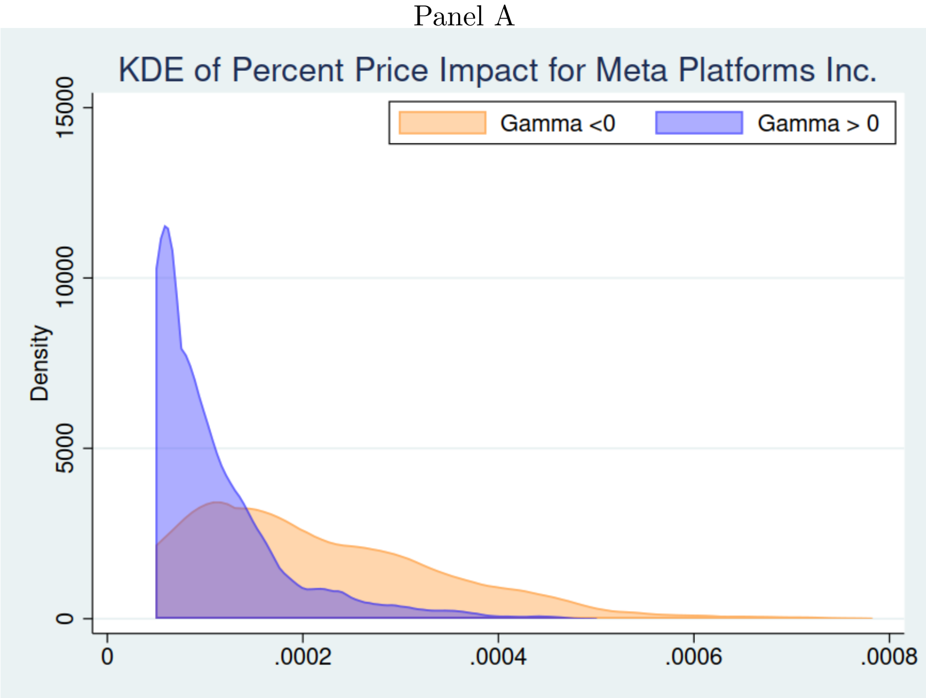
Figure 1: Price Impact and Dollar Gamma for Meta Platforms Inc.

This figure contains in Panel A a Kernel Density Estimate of the distribution of price impact for the case when Dollar Net Gamma is positive and negative respectively. Panel B contains a time series graph of average Price Impact (in basis points) and dollar Net Gamma (in millions of USD) the time series are constructed as 20-period moving averages. Both Panel A and Panel B contain graphs constructed using data for Meta Platforms Inc. (formerly Facebook Inc.).

Panel A



Panel B

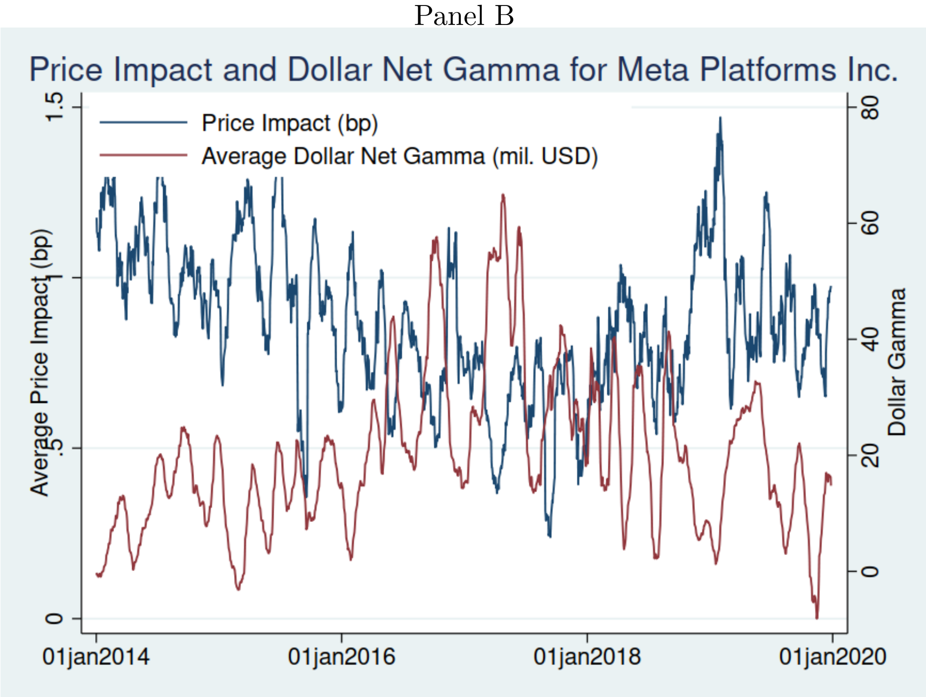


Figure 2: Trade Origin Codes at CBOE mapped to Origin Codes at the OCC.

This figure contains a map between CBOE origin codes and OCC origin codes as provided in the CBOE Regulatory Circular RG10-12 dated January 14, 2010.

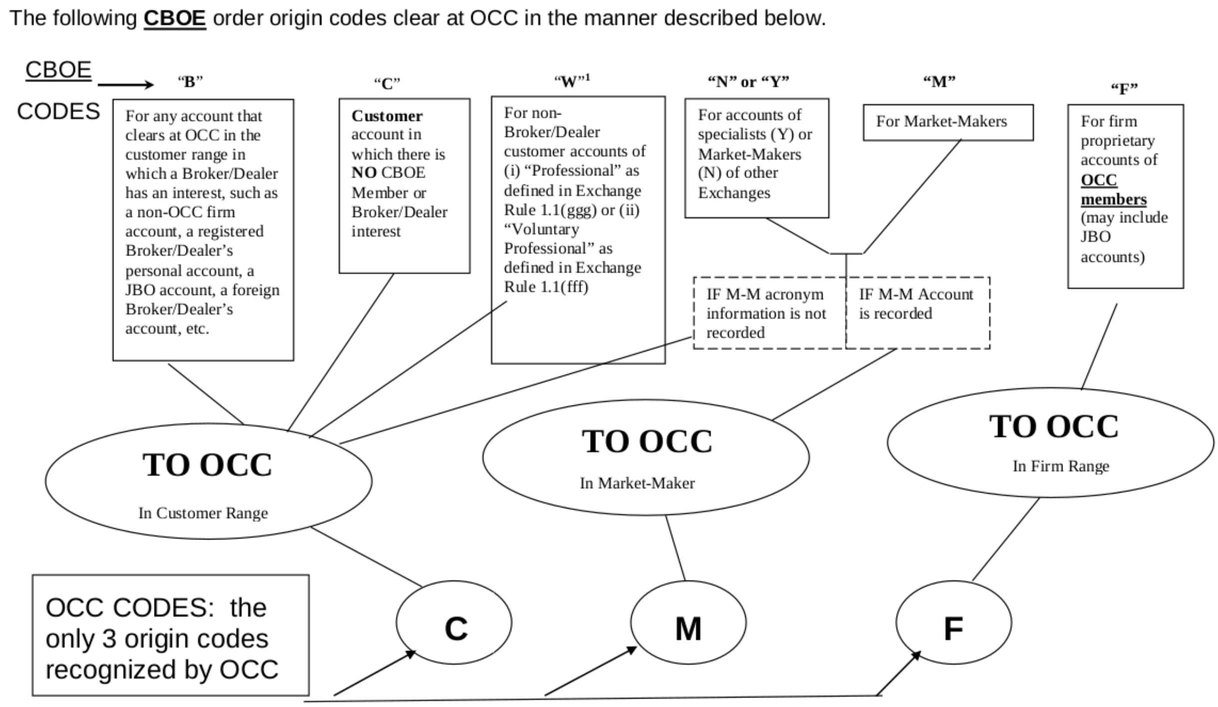


Table 1: Summary Statistics

Panel A contains summary statistics on the percentage of volume accounted for by different groups of traders. Panel B contains summary statistics of the main variables used in the paper. The statistics are calculated at the firm level, and the table contains averages of the firm-level statistics. The Open/Close volume data comes from the CBOE C1 exchange and the NASDAQ ISE exchange. The liquidity measures are calculated using the TAQ database. The sample includes option volume for 2,639 stocks and 4,279,421 stock-date observations.

Panel A: Percentage of Total Volume Accounted for by each Trader Group

	mean	p1	p5	p25	p50	p75	p95	p99
Market Maker & Broker Dealer	0.38	0.07	0.18	0.31	0.38	0.46	0.61	0.67
Proprietary Trader	0.12	0.01	0.03	0.07	0.11	0.16	0.25	0.33
Retail Customer	0.47	0.27	0.33	0.43	0.48	0.52	0.60	0.70
Professional Customer	0.02	0.00	0.00	0.01	0.02	0.03	0.05	0.09

Panel B: Summary Statistics of Regression Variables

	mean	sd	p1	p10	p25	p50	p75	p90	p99
$Net\Gamma$	0.001	0.006	-0.013	-0.003	-0.001	0.001	0.003	0.006	0.019
absolute return	1.813	2.087	0.007	0.210	0.567	1.280	2.396	3.882	9.334
quoted spread (%)	0.302	0.461	0.097	0.138	0.175	0.238	0.339	0.475	0.905
effective spread (%)	0.243	0.237	0.067	0.100	0.131	0.187	0.280	0.421	1.061
realized spread LR (%)	0.078	0.378	-0.373	-0.049	0.004	0.053	0.123	0.227	0.796
realized spread EMO (%)	0.051	0.213	-0.266	-0.050	-0.005	0.034	0.087	0.165	0.525
realized spread CLNV (%)	0.073	0.308	-0.303	-0.046	0.003	0.049	0.114	0.211	0.698
price impact LR(%)	0.160	0.412	-0.294	0.025	0.068	0.121	0.202	0.330	1.052
price impact EMO(%)	0.102	0.191	-0.175	0.012	0.045	0.084	0.138	0.218	0.540
price impact CLNV (%)	0.147	0.339	-0.228	0.023	0.061	0.109	0.183	0.302	0.924

Table 2: Net Option Gamma and Underlying Stock Liquidity

This table contains the results of estimating equation (2) on different measures of liquidity. The regression equations are estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The full sample includes 2,639 stocks and 4,279,421 stock-date observations.

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.008	-0.033	-0.015	-0.029
	(-4.982)	(-7.009)	(-6.914)	(-7.202)
Constant	0.001	0.001	0.000	0.001
	(10.206)	(10.171)	(8.399)	(14.379)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.201	0.394

Table 3: Net Gamma and Stock Liquidity: Earning Announcements

This table contains the results of estimating model (3). EARN is an indicator variable that takes a value of 1 for the period (t-3,t) where t is the firm's quarterly earnings date and is 0 otherwise. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contain the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$ x $EARN$	-0.017	-0.016	-0.006	-0.006
	(-3.823)	(-4.798)	(-2.702)	(-3.166)
$Net\Gamma_{t-1}$	-0.013	-0.007	-0.006	-0.008
	(-7.008)	(-7.477)	(-7.230)	(-7.353)
EARN	0.000	0.000	-0.000	0.000
	(2.540)	(5.526)	(-1.681)	(7.257)
Constant	0.001	0.001	0.000	0.001
	(12.934)	(13.590)	(10.870)	(14.179)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.204	0.409

Table 4: Net Gamma and Stock Liquidity:
Analyst Forecast Dispersion

This table contains the results of estimating model (2) separately for groups of stocks with low (Panel A) and high (Panel B) dispersion of analyst forecasts. Low (High) analyst dispersion firms are defined as those with below (above) median levels of analyst dispersion. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

Panel A: Low Dispersion of Analyst Forecasts

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.005	-0.005	0.000	-0.010
	(-3.481)	(-4.487)	(0.484)	(-5.291)
Constant	0.001	0.001	0.000	0.001
	(8.090)	(8.632)	(8.778)	(11.383)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	1920	1920	1920	1920
Avg. R2	0.194	0.553	0.045	0.479

Panel B: High Dispersion of Analyst Forecasts

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.013	-0.063	-0.022	-0.050
	(-4.431)	(-7.179)	(-6.978)	(-7.500)
Constant	0.002	0.001	0.001	0.001
	(10.593)	(10.913)	(11.023)	(16.230)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.201	0.394

Table 5: Net Gamma and Stock Liquidity:
Analyst Coverage

This table contains the results of estimating model (2) separately for groups of stocks with low (Panel A) and high (Panel B) analyst coverage. Low (High) analyst coverage firms are defined as those with below (above) median levels of analyst coverage. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

Panel A: Low Analyst Coverage Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.008	-0.075	-0.037	-0.061
	(-2.747)	(-5.392)	(-5.338)	(-5.473)
Constant	0.002	0.001	0.001	0.002
	(10.076)	(10.551)	(10.000)	(18.187)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	1467	1467	1467	1467
Avg. R2	0.048	0.235	0.098	0.048

Panel B: High Analyst Coverage Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.005	-0.003	-0.000	-0.004
	(-6.008)	(-5.975)	(-1.641)	(-6.758)
Constant	0.001	0.000	0.000	0.000
	(9.425)	(8.256)	(6.577)	(10.799)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.201	0.394

Table 6: Decomposition of Net Gamma

This table contains results where the dependent variables come from a decomposition of $Net\Gamma$. Panels A and B contain the results of estimating model (2) using the decompositions of $Net\Gamma$ of equations (4) and (5) respectively. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,633 stocks and 4,257,544 stock-date observations.

Panel A: Decomposition of Net Gamma I

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
Residual Γ_{t-1}	-0.008	-0.037	-0.015	-0.032
	(-5.236)	(-6.941)	(-6.975)	(-7.131)
Information Γ_{t-1}	0.006	-0.019	0.017	-0.045
	(2.328)	(-8.374)	(5.811)	(-9.705)
Constant	0.001	0.001	0.000	0.001
	(10.213)	(10.155)	(8.615)	(14.442)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.201	0.399

Panel B: Decomposition of Net Gamma II

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
Hedge Γ_{t-1}	0.002	-0.085	-0.023	-0.056
	(0.923)	(-4.385)	(-4.552)	(-4.486)
Information Γ_{t-1}	0.007	-0.021	0.019	-0.048
	(2.454)	(-7.355)	(5.911)	(-9.415)
Period $t-\tau$ Γ_{t-1}	-0.013	-0.025	-0.013	-0.024
	(-6.104)	(-5.325)	(-7.141)	(-6.938)
Constant	0.001	0.001	0.000	0.001
	(10.221)	(10.161)	(8.629)	(14.489)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.201	0.399

Table 7: Portfolio Analysis:
Does Net Gamma Contain Information about Future Volatility?

This table contains equal- and value-weighted annualized returns for portfolios that trade using rules derived from the data on $Net\Gamma_{t-1}$. The basic strategy takes a long (short) position in each stock when its gamma level is above or below a given threshold. Column 1 (2) contains results for a long short strategy with a long (short) position when $Net\Gamma$ is above (below) zero (the 50th percentile, p50). Column 3 (4) contains results for a long short strategy that takes a long position when $Net\Gamma$ is above the 75th percentile (90th percentile) and a short position when $Net\Gamma$ is below the 10th percentile (5th percentile). Portfolio returns are averages across stocks in each time period to calculate an average return. Panel A contains results for an equal weight average across stocks while Panel B contains results for a market-capitalization value-weighted average across stocks in each time period. The sample period is from 2011 to 2019. Returns are annualized percentage returns.

Panel A: Equal Weighted Portfolio Returns

	(1) zero	(2) p50	(3) p75 (p25)	(4) p90 (p10)
Return	0.78	-0.87	-0.44	-0.56
	(1.49)	(-1.93)	(-1.30)	(-2.19)

Panel B: Value Weighted Portfolio Returns

	(1) zero	(2) p50	(3) p75 (p25)	(4) p90 (p10)
Return	0.02	-0.46	-0.65	-0.60
	(0.25)	(-1.09)	(-2.22)	(-3.48)

Table 8: Net Gamma and Stock Liquidity:
Sample Split by Stock Size

This table contains the results of estimating model (2) separately for groups of stocks with below median (Panel A) and above median (Panel B) dispersion of analyst forecasts. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

Panel A: Below Median Size Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.017	-0.070	-0.033	-0.061
	(-4.960)	(-6.148)	(-6.143)	(-6.300)
Constant	0.002	0.001	0.001	0.002
	(9.989)	(11.397)	(10.835)	(19.925)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg N. Obs.	1467	1467	1467	1467
Avg R2	0.048	0.235	0.098	0.048

Panel B: Above Median Size Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.000	-0.004	-0.001	-0.003
	(-0.480)	(-5.649)	(-3.687)	(-6.235)
Constant	0.001	0.000	0.000	0.000
	(11.712)	(9.460)	(9.303)	(11.950)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg N. Obs.	2243	2243	2243	2243
Avg R2	0.835	0.850	0.200	0.391

Table 9: Net Gamma and Stock Liquidity:
Sample Split by Stock Trading Volume

This table contains the results of estimating model (2) separately for groups of stocks with below median (Panel A) and above median (Panel B) volume. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

Panel A: Below Median Volume Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.014	-0.071	-0.034	-0.061
	(-3.776)	(-5.508)	(-5.411)	(-5.612)
Constant	0.002	0.001	0.001	0.002
	(10.273)	(10.803)	(10.149)	(19.275)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg N.Obs.	1467	1467	1467	1467
Avg R2	0.047	0.233	0.099	0.046

Panel B: Above Median Volume Stocks

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.003	-0.001	0.000	-0.001
	(-4.341)	(-2.702)	(0.996)	(-5.140)
Constant	0.001	0.000	0.000	0.000
	(9.503)	(7.884)	(6.933)	(10.727)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg N. Obs.	2243	2243	2243	2243
Avg R2	0.835	0.850	0.200	0.391

A Appendix

Table A1: Retail trading and the effect of $Net\Gamma$ on liquidity

This table contains the results of estimating model (2) in groups of firms with different levels of retail trading. We group firms into levels of retail trading using the level of non-delta hedger volume accounted for by retail customers. The dependent variable in all columns is *Effective Spread*. Column 1 contains the full sample, columns 2(3) have firms with below (above) median level of *Retail* while column 4 has a sample of firms where retail is in the top quartile of the cross-sectional distribution. The regression equations are estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The full sample includes 2,639 stocks and 4,279,421 stock-date observations.

	All Firms	Below Median	Above Median	Top Quartile
$Net\Gamma_{t-1}$	-0.033	-0.010	-0.059	-0.123
	(-7.009)	(-4.966)	(-6.934)	(-5.548)
Constant	0.001	0.001	0.000	0.001
	(10.171)	(7.536)	(10.542)	(10.433)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	1664	2243	2243
Avg. R2	0.850	0.512	0.850	0.85

Table A2: Net Gamma and Stock Liquidity: Alternative Trade Classification Algorithms

This table contains the results of estimating model (2) using the trade classification algorithms of Ellis et al. (2000) (EMO) and Chakrabarty et al. (2021) (CLNV) to calculate the Percent Realized Spread and Percent Price Impact. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

	(EMO) Realized Spread	(CLNV) Realized Spread	(EMO) Price Impact	(CLNV) Price Impact
$Net\Gamma_{t-1}$	-0.003	-0.010	-0.007	-0.032
	(-6.050)	(-6.893)	(-7.623)	(-7.196)
Constant	0.000	0.000	0.001	0.001
	(9.886)	(8.649)	(13.381)	(14.001)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.219	0.221	0.357	0.388

Table A3: Net Gamma and Stock Liquidity: Alternative Classification of Likely Delta Hedgers

This table contains the results of estimating model (2) using an alternative definition of $Net\Gamma_{t-1}$ which includes firm proprietary traders in the set of likely delta hedgers. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.009	-0.044	-0.007	-0.052
	(-3.985)	(-4.343)	(-4.160)	(-4.334)
Constant	0.001	0.001	0.000	0.001
	(10.599)	(10.663)	(10.373)	(15.786)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2494	2494	2494	2494
Avg. R2	0.840	0.851	0.196	0.381

Table A4: Net Gamma and Stock Liquidity:
Data Coverage and Estimation Error

This table contains the results of estimating model (2) separately for groups of stocks with below median (Panel A) and above median (Panel B) coverage of data for estimating $Net\Gamma$. The regression equation is estimated for each stock, and the table contains the cross-sectional average coefficient estimates. Avg. N. Obs. and Avg. R2 contains the cross-section average of the R-Squared and the number of observations from the stock-by-stock regressions. Standard errors are constructed from a covariance matrix for the average coefficients that is formed by clustering observations by date and firm with common shocks, as detailed in Thompson (2011). The lag volatility controls and lag liquidity controls use lags from 1 to 10 days before the realization of the dependent variable. The sample includes 2,639 stocks and 4,279,421 stock-date observations.

Panel A: Stocks with Low Data Coverage

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.011	-0.001	-0.010	0.001
	(-5.667)	(-1.382)	(-5.601)	(0.997)
Constant	0.001	0.001	0.000	0.001
	(9.252)	(9.296)	(8.304)	(12.541)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg. N. Obs.	2243	2243	2243	2243
Avg. R2	0.835	0.850	0.201	0.394

Panel B: Stocks with High Data Coverage

	Quoted Spread	Effective Spread	Realized Spread	Price Impact
$Net\Gamma_{t-1}$	-0.004	-0.068	-0.021	-0.060
	(-1.687)	(-6.562)	(-6.290)	(-6.690)
Constant	0.002	0.001	0.001	0.001
	(9.461)	(9.449)	(6.924)	(13.933)
Lag volatility controls	Yes	Yes	Yes	Yes
Lag liquidity controls	Yes	Yes	Yes	Yes
Avg N. Obs.	1467	1467	1467	1467
Avg R2	0.048	0.235	0.098	0.048