High-Frequency Trading in the Options Market

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Abstract

Despite structural differences between the options and stock markets, few studies have discussed the behavior and impact of high-frequency traders (HFTs) in the options market. Options exchanges identify high-frequency/algorithmic traders as Professional Customers (PCs). In this study, we use granular data that identifies trades by customers, PCs, and Market Makers (MMs). We find that PCs mainly trade as a counterparty to customers, similar to MMs. However, the liquidity provision by PCs leads to order flow toxicity: PCs use a "cream skimming" strategy that imposes adverse selection costs on MMs. PCs mainly trade with uninformed customers, most likely leveraging their speed and algorithmic advantage. PCs provide less liquidity when the market and stock volatility are high. Customer call option trades made with PCs have one-tenth of price impact and no return or volatility predictability, while there is significant price impact in addition to return and volatility predictability when executed against MMs during the next 30 minutes. Our finding on HFTs' non-arbitrage channel of order flow toxicity is new and suggests that the role of HFTs should be better understood in the context of the options market structure.

Keywords: Options Market, Professional customers, HFTs, Cream skimming, Big Data

JEL Classification: G14, G18

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1 Introduction

Equity options have recently become popular among investors, surpassing the daily stock trading volume for the first time in history on July 21, 2020. In particular, the quarterly options trading volume (Figure 1) has demonstrated a significant upward trend since the first quarter of 2020. Options trading has increased exponentially from $1 billion in the first quarter of 2015 to $2.5 billion in the fourth quarter of 2021. The options to stock (O/S) volume ratio has also increased by 60% from Q1 of 2015 to Q4 of 2021.

[Insert Figure 1 Here]

This increase in options trading volume coincides with extended work-from-home dynamics, meme stock phenomena, and a zero-commission policy being gradually implemented by major brokerage firms. Robinhood, for example, introduced zero-commission options trading in December 2017, followed by Charles Schwab, TD Ameritrade, E*Trade, and Fidelity in October 2019. The reduction in direct trading costs has resulted in increased retail trader participation and increased liquidity supply from third parties, such as algorithmic traders, who take advantage of unsophisticated retail trades.[1] With the rise of retail investors, studying the implications of high-frequency traders (HFTs) or algorithmic traders (ATs) in the options market is more important and timelier than ever.

The notion of high frequency in the options market is slower compared to the stock market. Options exchanges identify HFTs and ATs by the trading frequency of customer accounts, which is at least 390 orders per day or one order a minute, and define such traders as professional customers (PCs or professionals).[2] In this study, we address the following questions.

1. What are the main strategies of professional customers in the options market?
2. What is the impact of professional customer trades on liquidity, order flow toxicity, and price discovery?

HFTs keep their trades and strategies closely guarded; however, they profit from short-run arbitrage

[1] According to the CBOE, the increase in single option contracts is most pronounced, from 1.9% to 7.4% of market share, during our sample period (October 2019 to March 2021, 1.5 years), while there was mild growth in the previous interval, from 1.1% to 1.9%. https://www.cboe.com/insights/posts/option-flow-2021-retail-rising/

[2] Options exchanges have given (retail) customers priority of execution before dealers since inception. A series of concerns arose as MMs lost trades against HFTs who had the privilege of customer priority. Due to this concern, the customer priority privilege enjoyed by PCs was removed in late 2009.

opportunities when they demand liquidity or from market-making when they supply liquidity (e.g., Foucault et al. [2017]). Whether HFTs harm or benefit market quality has been extensively discussed with respect to the stock market, and it is generally viewed that market-making by HFTs improves market quality by reducing spreads and price efficiency (O'hara [2015]), though this view is not unanimous. For example, Carrion [2013] and Hendershott and Riordan [2013] found that HFTs provide liquidity when it is scarce and consume liquidity when it is plentiful. Hendershott et al. [2011] and Brogaard et al. [2014] similarly argued that HFTs supply liquidity to the market and thus improve market quality. Furthermore, Jones [2013] surveyed on the role of HFTs and concludes HFTs have substantially improved market liquidity and reduced trading costs. However, others have raised concerns about HFT activities. For example, in the theoretical model, Hoffmann [2014] showed that HFTs could avoid the risk of being adversely picked off before others, which creates a negative externality on other slow traders. Yao and Ye [2018] and Li et al. [2021] found that HFTs provide less liquidity than non-HFTs as adverse selection risk increases. Foucault et al. [2017] discussed the costs of HFT activities as HFTs' arbitrage exposes dealers to the risk of trading at stale quotes (toxic arbitrage). In addition, Nimalendran et al. [2020] argued that HFT activity in the stock market harms option market quality because it increases the hedging costs and toxic arbitrage risk. Budish et al. [2015] further discussed HFTs' socially wasteful arms race due to the mechanical arbitrage opportunity created by continuous trading.

The existing literature on the impact of HFTs on market quality has predominantly focused on the stock market, with few studies on the impact of HFTs on the options markets. There are several notable differences between options and stock market structure that can lead to differences in the impact of HFTs on market quality. First, options market makers (MMs) are relatively slow to update their quotes, which is related to infrequent transactions and exchange-imposed restrictions. Second, listed equity options are only traded on exchanges in the US, while stocks can be traded in other venues (Hendershott et al. [2022]). Third, there are numerous contracts for each optionable stock according to its moneyness and expiration. Fourth, the options market is thought to be MM-dominated, i.e., a quote driven market where bid and ask quotes are posted by MMs. Finally, the transaction costs expressed in quoted/effective spreads are significantly wider compared to underlying stocks; for instance, the average proportional bid-ask spread of a typical stock in the

S&P500 index is 0.07% (7 bps), while the spread for the at-the-money (ATM) options on the stocks in the S&P500 index is 6.39% on average in our sample. Therefore, it is not clear whether the findings and implications regarding HFT activity in the stock market can be extrapolated to the options market.

In this study, we expect PCs' operations to be heterogeneous to MMs due to exchange-imposed regulations on MMs[3] and differences in the fee and rebate schedule based on the trader's identity. Frequent quote revision in particular is costly for MMs, not only due to the monitoring costs (e.g., Foucault et al. [2003]), but also because options exchanges cap the number of quote updates and fine members whose ratios of messages to executions are large (Muravyev and Pearson [2020]). In this regard, PCs have a twofold advantage[4] against MMs: they can selectively participate in market making without committing with two-sided firm quotes and trade faster than MMs.

We consider three hypotheses that predict the trading strategies of PCs and their impact on market quality metrics.

The first is *Toxic Arbitrage* hypothesis (H1). When the trading priority given to PCs was removed, there was concern that the rule would force HFTs to be more opportunistic. Jon Schlossberg, a former product manager at Lime Brokerage, claimed, "There will be a lot more picking off than quoting because quoting will not get you done. You are forcing the customer to adopt a more active trading strategy to pick off the market maker." [5] Foucault et al. [2017] demonstrated that arbitrage strategies used by HFTs—in which the HFTs utilize their speed advantage to pick off stale quotes by MMs based on new information—can be toxic. Under this hypothesis, PCs frequently trade when short-run arbitrage opportunities arise. Arbitrage opportunities are likely to occur when new market information arrives, often leading to higher volatility or vice versa; high volatility in underlying stock can cause MM quotes to be stale. Thus, H1 predicts that PCs' arbitrage activity is more likely for options with relatively low transaction costs and during volatile periods, when short-run arbitrage opportunities are likely to arise. Furthermore, under H1, PCs will trade against stale quotes by MMs; therefore, we expect the correlation between the trading volumes of PCs and

[3] The CBOE rules 5.51/5.52 state that MMs in the options exchange are required to make firm quotes under normal circumstances or will be subject to disciplinary action, suspension, or revocation of registration as a MM. In addition, exchanges have latency limits/penalties on MMs that mitigate peak and overall traffic (Rule 5.25).

[4] However, professionals in CBOE pay a higher fee than MMs for electronic trading in general.

[5] https://www.tradersmagazine.com/news/options-exchanges-knock-high-frequency-traders-down-a-peg/

MMs to be high. As a result of HFTs' arbitrage, it imposes an information asymmetry risk to MMs, which leads to higher spreads in equilibrium.

The second is *Liquidity Provision* hypothesis (H2). Several studies using equity market data have documented that HFTs consume liquidity when it is abundant and provide it when it is scarce (e.g., Hendershott et al. [2011], Hendershott and Riordan [2013]). When HFTs provide liquidity, like MMs, the outcome benefits overall market participants through increased liquidity, lower spreads, and lower price impact. H2 depicts PCs as a source of healthy competition in options market making and predicts that the impact of their trading is analogous to that of MMs. In particular, this hypothesis suggests that they provide liquidity when the underlying stock exhibits higher volatility.

The third is *Cream skimming* hypothesis (H3). Cream skimming refers to the practice of exploiting retail order flows that are largely uninformed liquidity trades. Easley et al. [1996] noted that the purchase agreements (i.e., payment for order flow, PFOF) on retail order flows between dealers and brokers are consistent with cream-skimming behavior. The cream-skimming hypothesis predicts that PCs preferentially provide liquidity to uninformed customer demand. This hypothesis assumes that PCs can identify uninformed orders to some degree with their proprietary algorithms. As a result, they can avoid trading when there is a likelihood of informed traders, such as (i) around earnings announcement days and (ii) when markets are more volatile (more information). PCs can also pick predictably uninformed trades, such as tiny option orders or even very large (i.e., sunshine trading) orders. This hypothesis predicts that as PCs cream skim uninformed order flow, MMs are left with more concentrated informed demand, which leads to an increase in spread and price impact.

A significant amount of the trading in options occurs within the National Best Bid and Offer (NBBO) prices, as customers post limit orders within the spread (i.e., resting orders)[6]. The resting limit orders allow the counterparty to trade when it is advantageous. Furthermore, a trader with a speed advantage can strategically pick off customer demand with a high spread (limit orders placed close to the best bid-ask prices). More importantly, in a market with informed and uninformed

[6] Brokerage firms usually do not encourage customers to use market orders while trading options, even those firms that mainly focus on retail customers, such as Robinhood and Webull. Further, price improvement mechanisms or options auctions explain trade within NBBO. For example, for the SPY options' within NBBO trades, 41% of the volume is from electronic trades and 22% from auctions.

traders, low-latency (i.e., high-frequency) traders can skim the uninformed traders' limit orders with their proprietary algorithm (e.g., Easley et al. [2012], O'hara [2015]). Thus low-latency traders can make order flow toxic for MMs and increase the adverse selection risk faced by MMs (e.g., Kyle [1985], Glosten and Milgrom [1985]) when supplying liquidity through pick-off and cream-skimming strategies.

Table 1 summarizes empirical predictions for the three hypotheses that describe PCs' operating strategies.

[Insert Table 1 Here]

Our empirical investigation of the strategies used by PCs leverages a granular data set from the Chicago Board Options Exchange (CBOE), the largest options exchange in the US,[7] which provides data on each agent's trading activity[8] at 10-minute intervals. HFT activities are conventionally estimated using message-to-transaction ratios in the case of the stock market. Our data obviates the need for the estimation process and minimizes estimation errors, which gives an edge to describe the behavior of HFTs.

We find empirical evidence that PCs participate as MMs by trading as a counterparty of customer option demand. Professionals mainly sell out-of-the-money (OTM) call options against customer call buys. The correlation between customer buy volume and MM (professional) sell volume is 53% (37%), and the correlation between customer sell and MM (professional) buy volume is 51% (38%) while other correlations are near zeros. Specifically, we do not see a strong correlation between professionals' and MMs' trading volumes, suggesting that professionals do not trade against MMs' quotes.

We examine the roles of traders in the options market's price discovery and market microstructure using transactions and quote data aggregated at the 10-minute frequency. We find that customers' long call option demand, especially OTM calls, strongly predicts underlying excess stock returns up to 30 -minutes. Fixed-effects regression estimates show that an increase of one standard deviation in customers' buy call contracts is associated with an increase in underlying 10-minute excess return by 0.0566 basis points (bps), which is 8.15 bps when converted to a daily rate. The predictability

[7] CBOE Options Market Volume Summary, based on market cap, 2022.

[8] Traders are categorized as customers, PCs, MMs, firms, or broker-dealers in the options market.

of future stock returns on options volume suggests that the options market contributes to price discovery over short time horizons. The price discovery could occur through delta hedging by MMs (e.g., Ni et al. [2021]); however, we continue to find a significant predictive power after controlling the hedging channel.

Do PCs provide liquidity against informed customers? If PCs cannot cream skim uninformed customers, we expect to find significance in both PCs' and MMs' trades against customer trades. To determine who is the counterparty to the informed customer trades, we decompose customer trades executed by PCs and MMs with a 2SLS model. For instance, in the case of customer long call trades, we fit the customer volume with PCs' short call and MMs' short call volume, respectively, in the first stage regression. We find that informed customer trades are executed mainly against MMs. Compared to preliminary one-stage regression, customer buy call volumes transacted with MMs show economically and statistically stronger return predictability, while there is no evidence of predictability when fitted with professionals' trading volume. Additionally, we test the degree of the price impact of customer buy call volumes transacted through MMs and PCs. We find that customer buy call options against MMs have a 10 times greater impact than that with professionals as counterparty.

MMs are expected to increase spread to hedge adverse selection risk if professionals skim uninformed orders and make order flow toxic. To test PCs' negative externality on market quality, we extend our analysis and estimate the impact of PC trading on the effective spread with the 2SLS approach. Consistent with the "cream skimming" hypothesis, the estimated coefficients indicate that customer transactions with PCs are positively associated with both quoted and effective spreads, especially when PCs make a large transaction. In contrast, MM volume displays a negative association with spreads. The positive relationship between effective spread and professional trade also implies that PCs selectively provide liquidity in a spread-maximizing manner. The resting orders initiated by customers within the NBBOs wait to be hit by either MMs or professionals. Professionals can maximize the spread profit by strategically picking attractive customer orders close to the best bid/ask with a speed advantage, and their volume is positively associated with effective spreads.[9]

[9] Our discussion on the PCs' order pick-off scheme is indicative and cannot be tested because data do not provide identity at a single transaction level.

PCs can also trade based on future events or conditions, such as underlying stock or market volatility and earnings announcement days. Goldstein and Kavajecz [2004] showed liquidity supply through electronic orders decreases as the market undergoes a more volatile period. Options become attractive when volatility increases, while volatility *per se* poses a risk to liquidity providers. Volatility risk is especially severe for options MMs because it cannot be hedged using the underlying stocks, i.e., the vega (ν) of stock is zero. We formally test PCs' response to increase in underlying and market realized volatility and find that professionals reduce trade during times of high volatility. Also, PCs reduce market participation near public information events such as earnings announcement days (EADs), which is when information asymmetry risk is high. By contrast, customers trading volume increases during high volatility and earnings announcement days, implying that liquidity supply during volatility and near EADs is majorly borne by MMs.

Equity options are also suitable for traders with information about future volatility. Ni et al. [2008] found evidence of informed volatility trading in the options market, though volatility trading through straddles and strangles accounts for a small fraction of option volumes (Lakonishok et al. [2007]). We consider whether customers' volatility demand (i.e., straddle) is informed at a 10-minute level and find that straddle volume has predictive power against the next 10 to 20-minute realized volatility. In addition, customer straddle volume is associated with higher quoted and effective bid-ask spread. We find informed volatility trades are transacted through MMs and not against professionals.

There remains a possibility that professionals might profit from directional bets at intraday frequency level. We test whether PC's options trading leads to price discovery with both in plain regression and 2SLS regression models. In 2-stage regression, we fit PC volumes with MMs and customers as their counterparty. The estimation results reveal insignificant t-statistics and opposite signs for PCs to be profitable, substantiating that professionals' core strategy is in market making with customer orders.

In summary, PCs are unlikely to trade with customer orders containing intraday information, pick trades that maximize their spread profit, and avoid providing liquidity when volatility and information asymmetry risk is high. If not for PCs, economic rents made from those trades would belong to MMs as compensation for taking counterparty risks such as adverse selection cost, inventory cost, and volatility risk. A significant body of research has focused on the aggressiveness of HFTs based on their information and speed advantage against MMs. However, our findings suggest that HFTs can adopt a passive, exploitative market making strategy that has a negative externality on market quality. This trading technique is not generally viewed as a trait of HFTs, especially in the stock market. To the best of our knowledge, these findings are new to the literature.

We conclude that PCs' market-making strategy is consistent with the "cream skimming" hypothesis, aligned with the notion that algorithmic traders maximize against market design and other traders (O'hara [2015]). We do not find evidence that PCs are arbitraging against the MM's stale quotes, nor do we find evidence supporting the liquidity provider hypothesis.

Our study offers new and interesting insights on the microstructure of options markets. As discussed, prior literature on the implications of algorithmic traders has largely focused on the stock market. Our study also contributes to the literature on price discovery in the options market. Several empirical studies have examined the informativeness of options volume. Chakravarty et al. [2004], for example, estimated the options market's contribution to price discovery to be 17% on average. Other studies have found option predictability on underlying stock returns at various frequencies. For instance, Pan and Poteshman [2006] and Johnson and So [2012] showed that stock returns are predictable on a weekly basis, while Bergsma et al. [2020] demonstrated stock return predictability at a daily frequency. Our finding suggests that buy call volume can predict stock returns in intraday 10-minute frequency after controlling for hedge rebalancing.

The remainder of this paper is organized as follows. Section 2 describes the data and how variables are constructed. Section 3 presents the model estimation results. Section 4 subsequently details additional analysis. Finally, Section 5 provides the research conclusions.

2 Data, Variable Construction and Descriptive Analysis

This section describes our data and explains how variables are constructed. Empirical test results are reported in Sections 3 and 4.

2.1 Data

Our data is constructed from several sources: the Chicago Board of Exchange (CBOE), Center for Research in Security Prices (CRSP), New York Stock Exchange Trades and Quotes (TAQ), Thomson Reuters Institutional Brokers Estimate System (I/B/E/S), and U.S. Department of Treasury. Our main analysis is based on options data from the CBOE, one of the largest options exchanges in the US. We restrict our sample to equity options on S&P 500 firms listed at the beginning of October 2019, obtained from the CRSP. The sample period covers October 2019 to March 2021 (370 business days). The CBOE data includes two products: the first provides detailed transaction volumes organized by trader identities at 10-minute intervals (volume data), and the second includes all trades and quotes of options transactions across 16 U.S. options exchanges (OPRA-trade data). The volume data are aggregated at 10-minute intervals, and representing a cumulative snapshot of signed option trading volumes organized by trader identities: customers, PCs[10] and MMs. We exclude trades assigned to brokers and firms (options-clearing firms). These data also provide additional information on whether an order is opening or closing for the corresponding trader type. All cumulative volumes are first-differenced to obtain the net trading volume for the 10-minute interval. Trading records after the market close (4:00 pm EST) are excluded from the sample. We establish our sample as new contracts by requiring them to have the earliest trading record after the beginning of the sample period. This filtering was performed to estimate MMs' open interest (OI) at 10-minute level. The variable construction section provides a more detailed description of how OI is calculated.

The CBOE trade data include the trade price and quotes of all options at the millisecond frequency across 16 U.S. options exchanges, which amounts to about 1.7 billion observations in our sample period. We exclude non-standard options (e.g., FLEX options) and index options. Observations that have zero or negative (underlying) bid-ask spread, bid-ask spreads that have less than 1 cent (minimum tick), negative trading volume, zero best bid or zero best ask, prices that are not within the best bid, and ask and transaction date after the options expiration date are removed from our sample. Observations that have negative gamma or positive theta are considered erroneous and also excluded. The observations in the quote data are aggregated by 10-minute intervals with

[10] A PC is a person or entity that (a) is not a broker or dealer in securities, and (b) places more than 390 orders in listed options per day on average during a calendar month for their beneficial account(s).

a volume-weighted average. Approximately 30% of the OPRA data is matched to volume data consistent with U.S. proportions of trades in the CBOE.

2.2 Variable Description

For each transaction, we calculate the implied volatility and greeks: delta (Δ), gamma (Γ), vega (ν), and theta (θ). Implied volatility is calculated using stock and option prices, strike price and time to expiration, dividend yield, and the risk-free rate. Both stock and options prices are based on the mid-point of the NBBO. Dividend yields are obtained from the CRSP, and we use month-level interpolated yields from Treasury as the risk-free rate. Greeks are calculated with the implied volatility as an additional input. Because of the computationally intensive nature of calculating greeks, we use the European option base model for theta and vega.[11] The underlying assets' 10-minute realized volatility are estimated using the standard deviation of 1-second return, and 10-minute returns are calculated with the last available best mid-quote at each 10-minute interval. Market return and volatility are estimated from SPY ETF. We measure option liquidity with proportional bid-ask spreads, proportional effective spreads, and the price impact of options volume on stock returns.

Our moneyness measure is based on the classification used by Bollen and Whaley [2004]. We classify an option as OTM if the option's absolute delta is less than or equal to 0.375, in-the-money (ITM) if it is above or equal to 0.625, and ATM if delta is in between 0.375 and 0.625. Moreover, we employ the following variables for testing and controlling our empirical specifications.

2.2.1 Hedging Costs

We consider a channel that relates to the MM's hedge rebalancing. Options MMs can delta-hedge their position associated with the directional risk and hold a delta-neutral portfolio. They adjust their delta exposure at least once a day, and this rebalancing has a non-trivial impact on the underlying stock price (Ni et al. [2021]). To measure the extent of MMs' net exposure at each time

[11] QuantLib, a popular open-source library for quantitative finance, was used for the calculations. We tested the accuracy of QuantLib's European and American models against OptionMetrics data as a benchmark and obtained more than 99% correlations for both.

t for each option j, we calculate the $NetOpenInterest$ volume, similar to Ni et al. [2021]:

$$NetOpenInterest_{j,t} = -\sum_{Y \in \text{Non MM}} \{(OpenBuy^{Y}_{j,t} - CloseSell^{Y}_{j,t}) - (OpenSell^{Y}_{j,t} - CloseBuy^{Y}_{j,t})\}$$

where Y is trader type that is not MM. $OpenBuy$ and $OpenSell$ are volumes that establish a new position for the trader, and $CloseBuy$ and $CloseSell$ are volumes that offset the trader's previous position. The difference between $OpenBuy$ and $CloseSell$ is a buy-side open interest from investor type Y, associated with net contracts opened for Y. Conversely, the difference between $OpenSell$ and $CloseBuy$ is a sell-side open interest which is the net written position for trader type Y. By subtracting sell open-interest from buy open-interest volume and reversing the sign, we obtain $NetOpenInterest_{j,t}$. This measure is the marginal option volume that the MM has to hedge at time t, assuming that investors Y are not involved in hedge rebalancing. The marginal delta hedging cost for the option j at time t can be proxied by weighting the corresponding option's $\Gamma_{j,t}$ and the underlying stock's bid-ask spread.

2.2.2 A Measure of Volatility Demand

We estimate demand for volatility by considering the options volume needed to construct a straddle. First, we match the call and put options with the same strike price K, expiration date T at time t with the same underlying asset. The straddle volume demand by the representative investor type Y is then calculated using the overlap of buy volumes from each call and put option. This value is subsequently weighted by the sum of call/put option vega, ν_C, ν_P, which is the sensitivity of option price to change in (implied) volatility.

$$Straddle^{Y,K,T}_{j,t} = (\nu^{Y,K,T}_{C} + \nu^{Y,K,T}_{P}) * \min\{BuyCall^{Y,K,T}_{j,t}, BuyPut^{Y,K,T}_{j,t}\}$$

$BuyCall$ is the number of a call option with strike K and maturity T purchased by trader type Y, and $BuyPut$ is the purchase volume of put options. We weigh with the vega term to capture the intensity of volatility demand for the straddle.

2.3 Summary Statistics

2.3.1 Descriptive Statistics

Table 2 details the descriptive statistics of the characteristic variables from our 10-minute frequency data, which contains all single-leg S&P 500 firm options traded on the CBOE. Panel 2.A reports the summary statistics for option volumes by trader identity, option price, quoted and effective spreads, proportional quoted and effective spreads, implied volatility, and greeks of options. We include two variables to control delta-hedging by option MMs: GammaExp and RebalCost. GammaExp is a proxy variable for MMs' exposure from delta neutrality, constructed by multiplying $NetOpenInterest$ and option $Gamma$. The rebalancing cost variable is the product of $Gamma$, stock spread, and absolute $NetOpenInterest$. The volume variables indicate each trader's put/call aggregated option contracts. Customers, on average, transact 11.43 contracts in cross-sectional 10 minutes, close to the MM's volume. PCs, on average, trade 0.35 contracts and show a skewed distribution.

Panel 2.B reports underlying stock variables that are matched to our CBOE data: the mid-quote price of the stock, 10-minute stock and market returns, bid-ask spread, proportional spread, and 10 minutes realized volatility. We observe that the proportional bid-ask spread of stocks is significantly less than the options spread; the average stock spread is 7 bps, whereas an average effective spread for options is 470 bps.

[Insert Table 2 Here]

Panel 2.C shows aggregated volumes by 10-minute intervals during the sample period. The average (median) sum of transaction volume from customer accounts is 22,564 (19,637) contracts and from professional accounts is 683 (298) contracts in 10-minute intervals. Notably, total option volumes traded by customers account for most trading, and MMs are the major counterparty of the trade during the sample period. The proportion of professional trades to customers is roughly 3% (669/21,845), suggesting that most customer volume is transacted through MMs. PCs' volume is considerably lower than HFTs' proportion in the stocks market, which is estimated to account for more than 70% of total trades (Hendershott et al. [2011]). The average price of the option is $11.75, and both option volume and price show left-skewed distributions.

[Insert Table 3 Here]

Table 3 shows the summary statistics for options spreads by moneyness groups. The OTM options have 14.9M observations (55%), ATM options have 8.6M observations (31%) and ITM options have 3.8M observations (14%)[12]. On average, OTM options have both the highest proportional quoted and effective spread: 16.88% and 6.75%, followed by ATM (6.39% and 2.43 %) and ITM (5.44% and 1.84%) options. OTM option spreads show the largest dispersion in distribution.

2.3.2 Correlations Among Variables

Panel A in Table 4 shows the correlation coefficients among signed option volumes by trader identity. Each variable represents each trader type's total buy and sell option volume. Notably, the transaction volume correlation between customer buy and MM sell is as high as 53%, and the correlation between customer buy and PC sell is 37%. Furthermore, the correlation between customer sell and MM buy is 51%, and the correlation between customer sell and professional buy is 38%. These high correlations indicate that PCs predominantly trade as a counterparty of customers, like MMs. PCs do not trade with MMs, as their buy and sell correlation with MMs is only 1%. Moreover, the low correlation suggests that PC transactions are unlikely based on arbitrage opportunities against stale MM quotes.

[Insert Table 4 Here]

Panels B and C present the trade-volume correlations by call and put options. We observe higher correlations between customers' buy/sell and professionals' sell/buy for call options (41%/46%) relative to put options (30%/28%). MMs, in contrast, exhibit a higher correlation for buying put (60%) and selling call (69%) relative to selling put (37%) and buying call (48%).

2.4 Professional Customers in the Options Market

Figure 2 displays the time trend of customer and PC transaction volume during the sample period.[13] Both customer and PC trading volumes increased dramatically, especially during the earlier stage of the sample period (late 2019 ~ early 2020) for customers. The customer option trading volume was 17M in October 2019, which increased by 58% to 27M in January 2020. The call (put) volume

[12] We find that many options traded in exchanges are between OTM and ATM. We observe more ATM options (54%) with an alternative moneyness classification, such as stock price being within +-10% of the strike.

[13] For Figure 2, we include existing and new option contracts in our sample.

decreased (increased) during the COVID-19 period and had a very high put-call ratio. Finally, the PC volume exhibits an increasing trend, a 131% increase from 0.45M in October 2019 to 1M in March 2021.

[Insert Figure 2 Here]

Figure 3 show total trading volume by moneyness and trade direction. Customers and professionals trade call options more than put options, and OTM options are most actively traded. Figure 3a shows that customer OTM call option trades account for 52% and 65% for puts. Professionals also trade both OTM calls (puts), which account for 64% (62%) of total volume. Their sell volume of OTM calls represents the most significant portion of their trades, accounting for 71% of the total sell volume.

[Insert Figure 3 Here]

In Figure 4, we visualize the distribution of customer and professional option volumes by expiration date and moneyness. Customers mostly trade options that expire in less than 30 days. For customers, 20% of the entire volume is comprised of OTM options that expire in less than seven days, and 21% expire in 7-30 days. Customer ATM volumes are 10% and 12% each for expiration dates in less than seven days and 7-30 days. The option volume distributions over expiration date exhibit similar patterns across moneyness for both customers and professionals. One notable difference is that professionals are unlikely to trade options with short maturity especially for OTM options. For PCs, the single bin at OTM with 7 to 30 days expiration consists of 35% of overall volumes traded, and ATM options with less than 30 days of expiration come second, accounting for 13% of the entire volume.

[Insert Figure 4 Here]

Next, we aggregate option volumes to show intraday trends by trader type. Figure 5 show average 10-minute interval transaction volume from 9:30 am to 4:00 pm The customers' average trading volume shows a U-shaped pattern that trading is concentrated around the open and the close. The average trading volume by MMs presented in 5c shows a similar pattern and magnitude, confirming that MMs are the major trading counterparty of customers. However, PCs show a relatively flat trend after 10:00 am. They do not participate actively in the open, especially during the first 20 minutes of a day.

[Insert Figure 5 Here]

2.5 Pattern of Trading Around Earnings Announcement Days

This section presents the trading patterns and microstructure around earnings announcement days (EAD) by reference to trading volumes, spreads, and realized volatility. An earnings announcement reveals new information about a company's risk, profitability, and prospect. As such, it impacts underlying stock volatility. As an EAD is a significant information event, one can expect informed trading around the announcement. Figures 6a and 6b illustrate trading volumes by customers and PCs. We observe that options trading by customers sharply increases during the day and the day before the announcements. Though not presented, the MMs' volume is largely similar to customers in size and pattern. PCs, meanwhile, show opposite patterns: they reduce their activity as the EAD approaches and even after a few days. MMs protect against volatility and adverse selection risks by increasing spread, as reflected in Figures 6c and 6d. The average 10-minute proportional effective spread and realized volatility increase on EADs. Furthermore, we observe asymmetry around the EADs; both effective spread and realized volatility are slightly higher after EADs than before EADs, when PCs reduce participation.

[Insert Figure 6 Here]

2.6 Meme Stocks and Options Trading Activity

Meme stocks refer to companies that garnered the public's abrupt attention, especially through online and social media platforms. Online communities propagate and promote narratives and conversations and amplify hype with humorous jokes, videos, and images. Popular platforms for meme stock communities are Reddit, Twitter, and Facebook. Meme stocks first emerged as social phenomenon in early 2020 via the Reddit forum "r/wallstreetbets."[14] This page became a venue for viral word of mouth and coordinated efforts among community members to amplify market sentiment.

GameStop (GME) was the first meme stock that experienced a great boom and bust cycle in early

[14] https://www.investopedia.com/meme-stock-5206762

2021. This response was first motivated by RoaringKitty, an influential YouTuber who announced that GME had high short interest among hedge funds and suggested a short squeeze scheme to drive stock prices even higher. The collaborative scheme from retail investors worked, eventually triggering a short squeeze, and the price of GME skyrocketed in January 2021, exhibiting a more than 1700% increase from $17.69 on January 8, 2021 to $325.0 on Jan 29, 2021. This squeeze caused tremendous loss to hedge funds, and some were forced to shut down. The overwhelming trading volume also caused delays and crashes for brokerage firms such as Robinhood.

[Insert Figure 7 Here]

Meme syndrome also heavily influenced the trading on the options market, resulting in a striking trading volume increase. Figure 7a depicts daily aggregated GME options transaction volume by customers and PCs from December 2020 to March 2021. Transactions from customer accounts significantly increased starting in mid-January. Monthly transaction volume increased from 10,717 contracts in December 2020 to 28,936 in January 2021 and 30,420 in February, marking an approximate 200% increase in volume. PCs' participation followed suit; their transaction volume increased in late January 2021. The PC/customer volume ratio trend illustrated in Figure 7c indicates that PC participation was notably high during the meme period, suggesting that PC participation is highly associated with retail investor activities.

3 Empirical Analysis & Results

3.1 Does Options Trading Predict Stock Returns?

Prior studies have documented that options markets can provide price discovery for underlying stock (Easley et al. [1998])]), and evidence has been documented for various frequencies. For instance,Pan and Poteshman [2006] and Johnson and So [2012] demonstrated the weekly return predictability of put-call ratio and options to stock ratio, and Bergsma et al. [2020] revealed the daily predictability using the first 30-minute option to stock volume ratio. However, it is not obvious whether option volume has predictive power for relatively short-run frequencies, and little is known about whether algorithmic traders are likely to make the market with those likely-informed option demands.

We use a regression model to determine whether high frequency option volume predicts future stock returns. We estimate the information content of options volume using the following fixed-effects regression specification:

$$\alpha_{i,t+m} = \beta_1 V_{i,j,t}^{BuyCall,C} + \beta_2 V_{i,j,t}^{SellCall,C} + \beta_3 V_{i,j,t}^{BuyPut,C} + \beta_4 V_{i,j,t}^{SellPut,C} + X'\beta + \Lambda_t + \Omega_i + \epsilon_{i,j,t} \quad (1)$$

where i is the underlying equity asset, j is the option series, t is the 10-minute time identifier. $\alpha_{i,t+m}$ refers to the market-adjusted holding return from time t to $t+m$. The market adjustment is performed by taking the difference between stock and market return. The $V_{i,j,t}^{BuyCall,C}$ is customer's buy transaction volume for call option j at time t for underlying equity i. The other variables are similarly defined. X includes relevant control variables: contemporaneous underlying market-adjusted stock return α_t and α_{t-1}, realized 10 minute volatility $\sigma_{i,t}$, realized 10 minute market volatility $\sigma_{mkt,t}$ and gamma exposure for market maker at t which is constructed by multiplying $NetOpenInterest_{j,t}$ and option gamma Γ_t. The Λ_t, Ω_i are stock and time (day) fixed effects. We report the model estimates up to $m = 30$ minute future returns.

[Insert Table 5 Here]

Our estimation results are presented in Table 5. Among customers' four types of options trading volumes, we observe that buy call volume has the most significant predictability. According to the result in column (1), a one standard deviation increase in customers' buying call contracts (42.6) is associated with an increase in underlying 10-minute excess return by 0.0566 ($42.6 * 1.33 * 10e^{-7}$) basis points, which is 8.15 basis points converted to a daily level. Considering that buy call volume is likely to contain a fairly large amount of noise traders, this strong predictability is surprising even after controlling for the delta hedging portion of options MMs. Though not reported, we continue to observe significant predictability even after 60-minute periods; excess return and overall R^2 also increase. Other option volumes show no strong evidence at a 5% significance level. Customer buy put volume has weak predictability at 10-minute negative future return, and sell put shows significance for the $t + 30$ minutes.

3.2 Who Trades Against Informed Agents in Options?

Given that customer option volume appears to contain information, we estimate who is likely to be the counterparty of those informed trades. As previously discussed, PCs trade as counterparty to customer trades. However, they do not bear exchange obligations as MMs, such as making firm two-sided quotes while benefiting from the speed advantage. We hypothesize that if PCs can recognize the patterns of those likely-informed options traders, they will be unlikely to trade with them, leaving those orders to be transacted by the MMs. We extend model to test this hypothesis by treating customer buy (sell) volumes as endogenous regressors and counterparty sell (buy) as exogenous regressors such that we decompose customer transaction volume with two variations: (1) transacted with professionals and (2) transacted with MMs. We then estimate regression coefficients and t-statistics with fitted values in the 2SLS regression model. We estimate the following model:

$$V_{i,j,t}^{D,C} = \sum_{m} \gamma_m V_{i,j,t}^{m,Y} + X'\beta + \Lambda_t + \Omega_i + \zeta_{i,j,t} \tag{2}$$

$$\alpha_{i,t+m} = \beta_1 \hat{V}_{i,j,t}^{BuyCall,C} + \beta_2 \hat{V}_{i,j,t}^{SellCall,C} + \beta_3 \hat{V}_{i,j,t}^{BuyPut,C} + \beta_4 \hat{V}_{i,j,t}^{SellPut,C} + X'\beta + \Lambda_t + \Omega_i + \epsilon_{i,j,t} \tag{3}$$

Equation 2 specifies the first stage regression, where D in $V^{D,C}$ stands for trade direction and option type combination; $D \in \{BuyCall, SellCall, BuyPut, SellPut\}$. The m in the right-hand equation is each combination for counterparty trader Y, which is either MM or PC; $m \in \{MM, P\}$. Then with each fitted value of the first stage regression $\hat{V}_{i,j,t}^{BuyCall,C}$, $\hat{V}_{i,j,t}^{SellCall,C}$, $\hat{V}_{i,j,t}^{BuyPut,C}$, $\hat{V}_{i,j,t}^{SellPut,C}$, a second stage regression is performed in Equation 3. The estimates of coefficients and t-statistics are reported in Table 6.

[Insert Table 6 Here]

The coefficient and t-statistic estimation results presented in Table 6 indicate which trader is likely to be the counterparty to the informed volume. Columns (1)-(3) show the estimated results for customer volumes fitted by professionals as counterparty, and (4)-(6) are results based on volumes fitted with MMs. We do not find significant predictability evidence for the coefficients in columns (1)-(3), supporting our conjecture that PCs are unlikely to trade with those likely-informed customer demands. Conversely, those informed customer buy call volumes are transacted through MMs, as shown in columns (4)-(6). We continue to observe strong significance in the coefficient of customer buy call volumes, and their economic significance increases: a 66% increase from 1.33 to 2.22 for the next 10-minute return and a 97% increase from 1.56 to 3.08 for the next 30-minute return.

We further examine the option predictability by moneyness. Table 7 presents coefficient estimates by ATM, ITM, and OTM subsamples, fitted with the MM as counterparty. We find that informed call option trading mainly targets OTM options that are strongest in statistical and economic significance. The ATM sample presented in columns (1)-(3) does not show strong significance, whereas the ITM sample is significant at $t + 10$. The economic significance is stronger for the OTM subsample at $t + 20$ and $t + 30$, from 2.94 to 3.21 and 3.08 to 3.74 which is a 9.1% and 21.4% increase, respectively.

[Insert Table 7 Here]

3.3 Price Impact

There is no predictability from PC volume. However, the MM volume for ITM and OTM demonstrate predictive value at t+10. We also test the trades' price impact based on our observation of the informativeness of customers' buy call option volume. Following Amihud [2002], we use contemporaneous absolute stock return as the dependent variable[15] and run a regression with customer buy call volumes fitted with PCs' sell call volumes and MMs' sell call volumes. Each column of Table 8 shows the estimated price impact of customer buy call options through professionals and MMs. The price impact of customer buy calls with MMs is significantly greater (about ten times) than that with PCs. The economic impact is 56.31 basis points for the MM volumes and 5.61 for PCs when measured in standard deviation of volume.

[Insert Table 8 Here]

3.4 Volatility and Professional Customers' Market Making

PCs can selectively participate in market making, unlike MMs. We study how PCs behave when the underlying stock and market volatility changes. Options tend to be more valuable when volatility

[15] Option prices are subject to various factors, such as volatility and remaining time until expiration (i.e., time decay). Therefore, we use the underlying stock return to proxy information content.

is high, as investors' demand for hedging risk increases. The options MMs have limited choice on hedging their positions against volatility per se because the underlying asset has zero vega. As such, MMs increase the spread to protect their loss against volatility risk.[16]. However, as PCs are not bound by exchange regulations imposed on designated market makers (DMMs), their trade participation can be associated with the underlying stocks' volatility . We study this possibility by comparing the trading sensitivity of professionals with customers. A simple model tests how their trading volume depends on changes in realized underlying stock volatility and market volatility:

$$log(1 + V_{i,j,t}^{Professional}) = \beta_1 \sigma_{i,t,STD} + \beta_2 \sigma_{mkt,t,STD} + X'\beta + \Lambda_t + \Omega_i + \epsilon_{i,j,t} \tag{4}$$

where $V_{i,j,t}^{Professional}$ is natural log of option transaction volume from PC with underlying asset i, series j, time t. The $\sigma_{i,t,STD}$ and $\sigma_{mkt,t,STD}$ are standardized 10-minute realized stock and market volatility. The coefficients β_1 and β_2 estimate the sensitivity of PCs' trading to the changes in stock and market volatility. The control variables include days to expire, the option's implied volatility, proportional underlying stock spread, absolute delta, rebalancing cost, and vega of the option. Table 9 presents the sensitivity estimates for each category of trading volume of PCs.

[Insert Table 9 Here]

Column (1) in Panels A and B presents the coefficient estimates of total volume trading by professionals and customers. PCs reduce market participation as underlying stock and market volatility increases. The estimated coefficients in Panel A show that for one standard deviation increase in underlying (market) 10-minute realized volatility, professionals reduce their trading by 0.15% (0.17%) of volume. However, the demand from customers increases dramatically. Panel B estimates in column (1) show that customers' options trading volume increase by 4.13% (2.63%) for one standard deviation increase in underlying (market) volatility. In an aggregate term, this translates to one contract less transaction (669.33 * 0.15%) from PCs and 902 more transactions (21,845.38 * 4.13%) from customers in 10-minute interval. This contrast is striking that had PCs provided liquidity proportionally, they would supply 27 contracts (902*3%) in one standard deviation increase in underlying or market volatility. This result implies that the PCs' liquidity provision

[16] They can also hedge vega risk using options with differing expirations and index options.

model differs from what has been reported on stock market HFTs (e.g., Hendershott et al. [2011]); they exit the market and pass the volatility risk to MMs.

We also include additional dummy variables for earnings announcement days (EAD), the day before and after the earnings announcement. The economic significance of EAD is greater than one standard deviation increase in underlying and market volatility for both PCs and customers. Consistent with Figure 6, PCs reduce their trading as the earnings announcement day approaches. We present other variables of interest in columns (2),(3),(4), and(5): buy call, sell call, buy put, and sell put volumes. Overall, we observe that the signs of the estimated coefficients are consistent with total volume.

3.5 Professional Customer Trades, Cream Skimming, and Liquidity

Bid-ask spread is the major source of income for market making. As with the risk and return relationship, the spreads reveal MMs' perception of the risk of making transactions as counterparty. So far, our analysis suggests that professionals selectively participate in market making. The question emerges, how does their trading impact market liquidity? The "cream skimming" hypothesis predicts that if PCs transact with likely uninformed customer orders, MMs are more exposed to the risk of being adversely selected. If this is the case, professionals' trading volume with customers will be positively associated with effective spread. We estimate the following regression model to study the relationship between PC trades and liquidity.

$$V_{i,j,t}^{MM}, V_{i,j,t}^{P} = \sum_{m} \gamma_m V_{i,j,t}^{m,C} + X'\beta + \Lambda_t + \Omega_i + \zeta_{i,j,t} \tag{5}$$

$$Spread_{i,j,t} = \beta_1 \hat{V}_{i,j,t}^{MM} + \beta_2 \hat{V}_{i,j,t}^{P} + X'\beta + \Lambda_t + \Omega_i + \epsilon_{i,j,t} \tag{6}$$

where i is underlying equity asset, j is the option series, and t is the time identifier. We use a 2SLS approach by first fitting MM volume and professionals volume with customers, then regressing fitted volume on spreads to observe their net effects. The main dependent variable is in proportional terms (in basis points). $\hat{V}_{i,j,t}^{MM}$ and $\hat{V}_{i,j,t}^{P}$ in Equation 6 are fitted total volumes from Equation 5. For control variables, we consider variables that are related to spreads: inverse of option price, option's expiration, implied volatility and underlying realized volatility, market volatility, underlying stock spread, delta, delta hedging cost (rebalancing cost), and vega. $V^{m,C}_{i,j,t}$ in Equation 5 stands for customer option trading volumes: buy call, sell call, buy put, and sell put.

Our main parameter of interest in this model specification is the sign and significance of β_2. With other conditions remaining the same, the transaction cost decreases as transaction volume increases. If there is no significant difference in a professional's market-making strategy, the slope estimate should show the same sign as the MM's, β_1. Table 10 reports coefficients and t-statistic estimates in 2SLS form.

[Insert Table 10 Here]

The first and second row of columns (1) and (3) in Table 10 display slope estimates from MMs and professionals. We observe that PCs' estimated coefficients exhibit opposite signs from MMs. Transaction costs and volume are negatively associated with MMs' effective and quoted spread. In contrast, trading volumes by professionals demonstrate a positive association with both effective and quoted spreads. The estimation model predicts that a one-unit transaction from professionals in a 10-minute interval is associated with a 1.15 basis point increase in effective spreads, which is a 0.32% point (28 * 1.15) increase in terms of one unit of standard deviation of PC volume. The result is consistent with the prediction that as professionals make transactions with customers, it affects the MM's perceived risk. In columns (2) and (4), we specify the regression with a dummy variable interaction form to depict MMs' response to the observed increase in professional trades. The variable $D^{P,small}_t$ takes the value 1 if the PC's trade volume is greater than zero and less than 200 and 0 otherwise. Similarly, $D^{P,large}_t$ is set to 1 if PC volume is greater than 200. Both columns show that small transactions by PCs do not significantly influence effective and quoted spreads. Instead, large PC volumes mainly drive the increase in effective (quoted) spread by 0.41 (1.48) basis points.

Three potential channels can explain the positive link between professionals' trading and spread; the arbitrage channel, short-run informed trading channel, and cream skimming. We do not find evidence supporting the former two channels. Professionals are unlikely to be arbitragers, as our findings show that their trading correlation with the MM is low, and they mainly trade with customers. In addition, PCs reduce activity when volatility is high, when arbitrage opportunity is likely to arise. The results of our empirical test in Table 12 also do not indicate that PCs are trading based on short-run information; the estimated coefficients are opposite and insignificant. Instead, we interpret our result as evidence of a cream-skimming strategy that minimizes market-making risk with proprietary algorithms and latency arbitrage.

In the seminal work of Kyle [1985], risk-neutral MMs infer the degree of toxicity from the observed volume and set the price such that their economic profit becomes zero. In this regard, the positive coefficient on both effective and quoted spread is suggestive that MMs are concerned about professionals' activities because they cream skim the profitable orders for market making. We observe similar results across option moneyness; the details are presented in the Appendix.

Another reason for a positive relationship between professional trades and spreads is PCs' pick-off strategy. Professionals can pick orders near the best bid or ask with their latency advantage, provided the customer order is non-informational. The options market has a relatively large bid-ask spread, and many brokerage firms only accept limited orders from customers. As such, options MMs can observe the resting orders within the best bid and ask, and it is common to see transactions made at a price that is within the best bid and best ask. MMs constantly observe those resting orders and decide to update quotes or transact with them. Therefore, it is also possible for professionals to strategically execute trades on options with a limited price that is close to the best bid or ask with their algorithms. Their transaction with customers is therefore likely to have higher effective spreads because an effective spread is also a measure of price deviation from the midpoint of the best bid and ask.

4 Additional Analysis

4.1 Volatility Predictability

When there is an expected volatility event, options provide a unique channel to profit through the use of straddles, strangles, and other volatility strategies. Studies have shown that options contain volatility information (e.g., Ni et al. [2008]). We test the informativeness of options' implied volatility at a 10-minute level and discuss which counterparty is likely to bear the volatility risk. We limit our focus to simple straddles with ATM options. We proxy a volatility demand from straddle by matching a pair of calls and puts with the same expiration date, strike price, and underlying asset. We require both puts and calls to be ATMs. We also include the inverse of straddle in the model, constructed with selling call and put options.

[Table 11 Here]

Table 11 presents the estimated results. Columns (1) and (2) show results from straddle and inverse straddle volume fitted with market makers as counterparty. The dependent variable in the first column is $t+10$ realized volatility, and in the second column has realized volatility from $t+10$ to $t+20$. We control with current realized and market volatility, and for $t+20$ volatility we include previous $t+10$ volatility. Columns (3) and (4) show straddle volumes fitted with PCs as counterparty. The alternative hypothesis is that investors will increase the straddle (inverse straddle) position when they expect future volatility to be high (low). The coefficient estimate from (1) for customer straddle volume shows positive and significant predictability at a 5% level. However, we do not find significant evidence that both customers and PCs use inverse straddles for a foreseeable reduction in volatility. The estimation results for PCs are presented in the Appendix.

4.2 Professional Customers & Toxic Arbitrage?

This section discusses the possibility of toxic arbitrage by PCs. Toxic arbitrage refers to HFTs' arbitrage when leveraging a speed advantage to trade on stale quotes by MMs after the arrival of new information (Foucault et al. [2017]). We test with a similar regression model described in Equation 2 and 3, with professional volumes fitted with customers and MMs as counterparties. Table 12 reports the estimates for the model specification.

[Insert Table 12 Here]

A profitable options trading strategy implies that buy call and sell put options should be positively related with future returns, and buy put and sell call options should be negatively correlated with future returns. It is notable that in Table 12, the signs of coefficients are opposite for PCs to be profitable, suggesting that PCs' main operating model is market making. Furthermore, the coefficient estimates are overall statistically insignificant. In summary, professionals appear to trade not based on short-run speculation, but for market making, and their trading is unlikely to be informative about future stock returns.

5 Conclusion

In this paper, we explored the strategies of PCs in the options market and their impact on price discovery and market quality. PCs are HFTs that are identified by U.S. options exchanges who place at least 390 orders per day. In this study, we demonstrate that PCs provide liquidity to customer orders, like MMs. However, their trading strategy is consistent with "cream skimming" in that they primarily trade with uninformed traders, which leads to an increase in adverse selection costs for MMs and a deterioration in market quality.

The cream skimming hypothesis of PCs' market-making strategy is supported through several tests. First, we found that the price impact of customer transactions through MMs is ten times greater than that through PCs. Second, PCs avoid market-making during high volatility periods when information asymmetry and potential informed trading are high. Third, PCs make the order flow toxic by cream skimming uninformed traders, leading to higher adverse selection costs for MMs and higher quoted/effective spreads.

The impact of HFTs on market quality in the stock market has been extensively studied. However, the impact of HFTs on the quality of the options market is less well understood. This study is the first to document liquidity deterioration through a non-arbitrage channel in the options market. Furthermore, PC participation in the options market has grown significantly during a relatively short period, and the implicit cost borne by MMs is expected to grow. Our findings suggest that the implications of algorithmic trading are dependent on the market structure and highlight the need to understand the costs and risks of HFTs in the options market.

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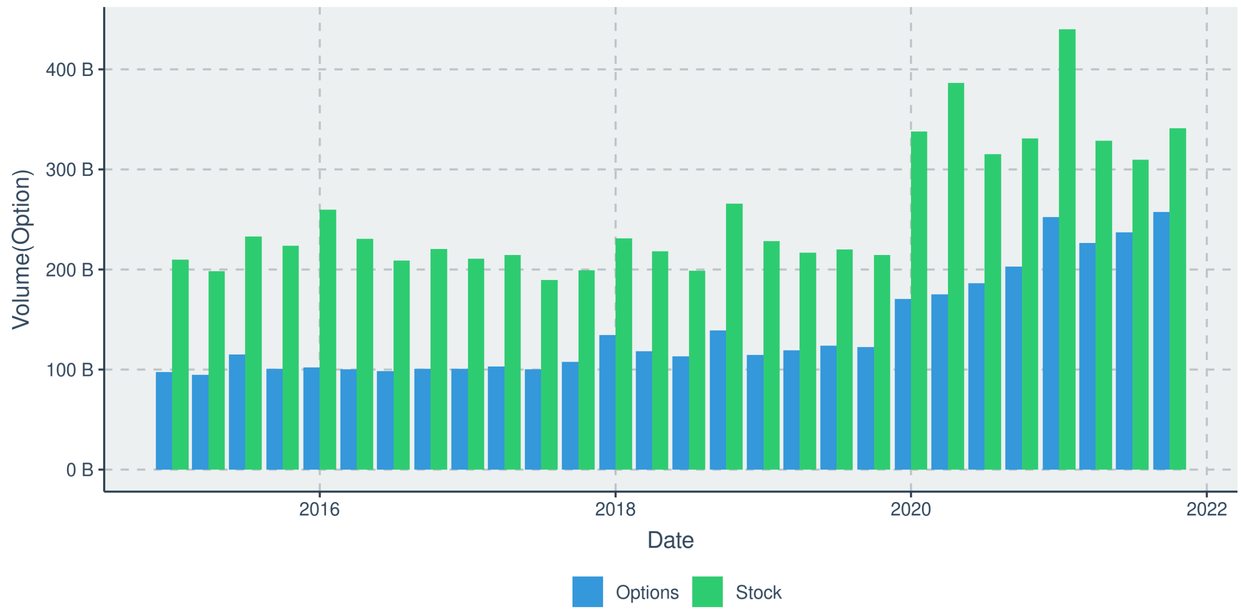
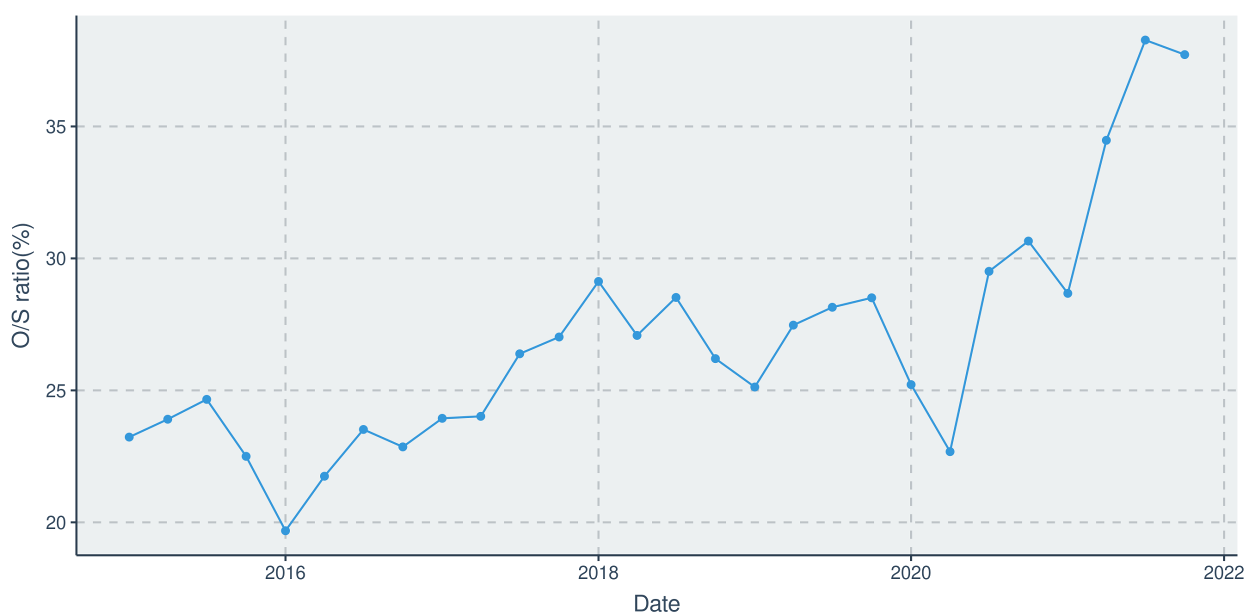
6 Figures



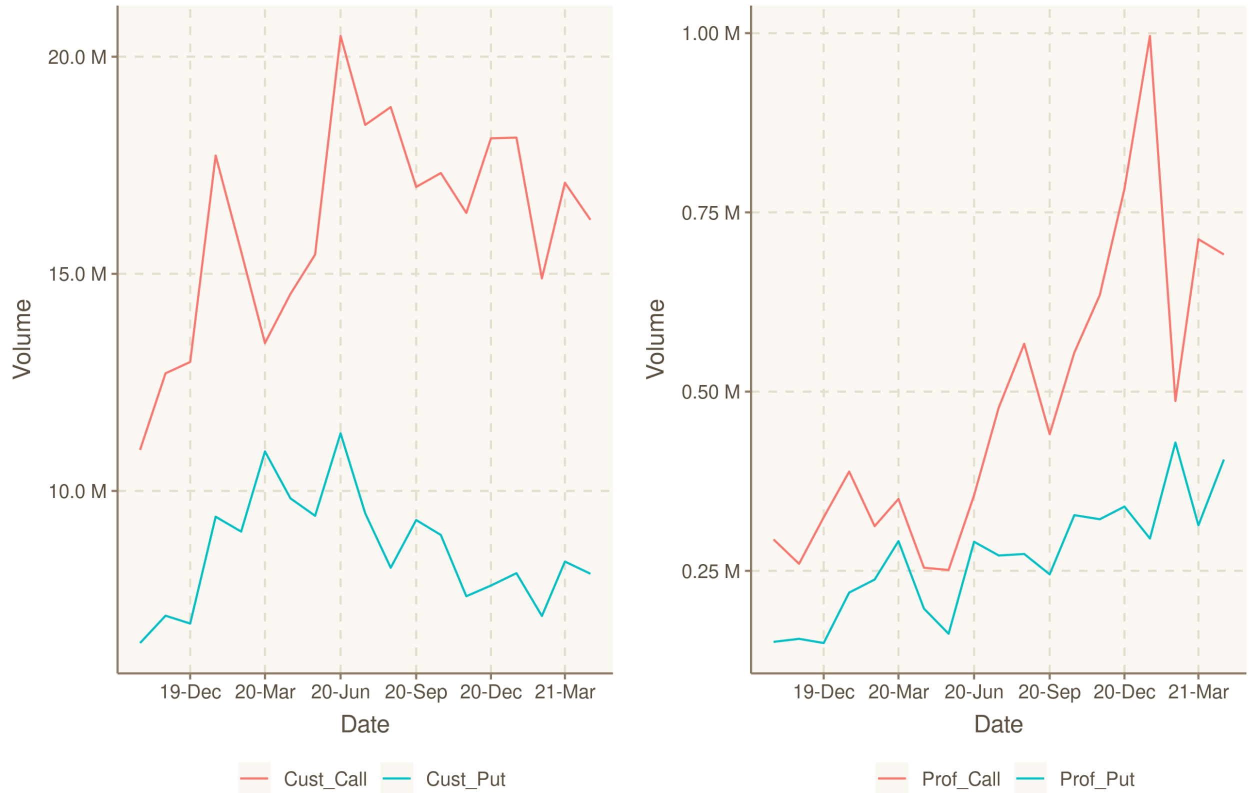
(a) Quarterly Option and Stock Volume Traded in U.S.



(b) Options to Stock ratio trend

Figure 1: Option and Stock Trade Volume Trend

Note: The figure above shows the quarterly volume trend from Q1 of 2015 to Q4 of 2021 for the all U.S. exchange and NASDAQ listed equities and equity options provided by OptionMetrics. Options volume is expressed in the number of contracts traded times the number of underlying (*100). Each option contract represents 100 shares of the underlying equity. The figure below shows the quarterly trend of options to stocks (O/S) ratio in percentage.

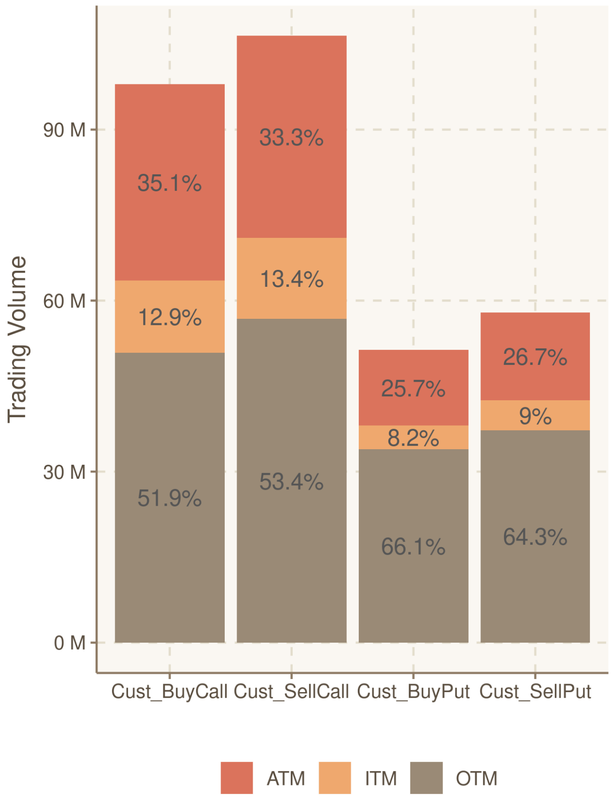


(a) Customer Volume

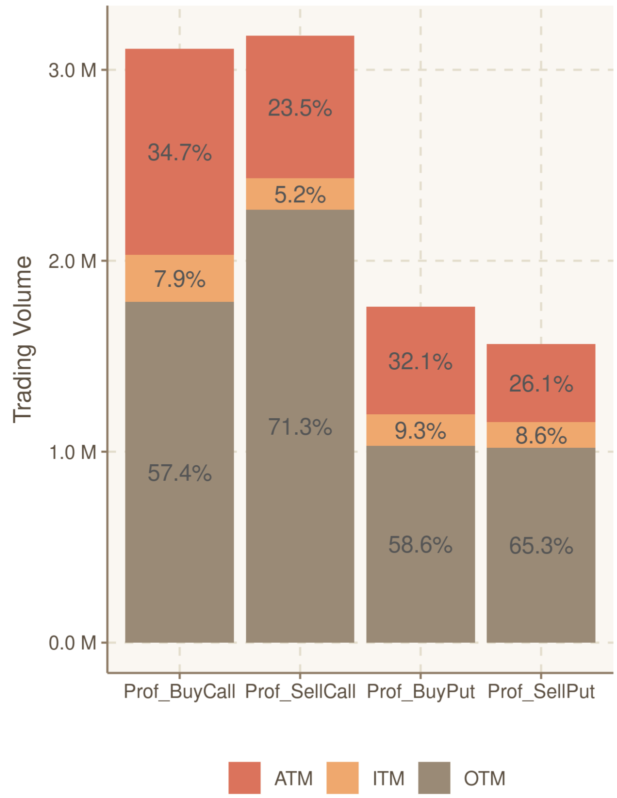
(b) Professional Volume

Figure 2: Option Trade Volume Trend

Note: The above figure shows each trader type's monthly trend of options transaction volume. The figure on the left displays the trend of customer option transaction volumes and professionals on the right. The variable Cust_Call (Prof_Call) represents customers' (professionals') call options transaction volume. Cust_Put and Prof_Put are defined similarly. The figure on the right is the monthly trend of professional customer volume by option types. The sample consists of all CBOE options with S&P500 stocks as their underlying trades from October 2019 to March 2021.



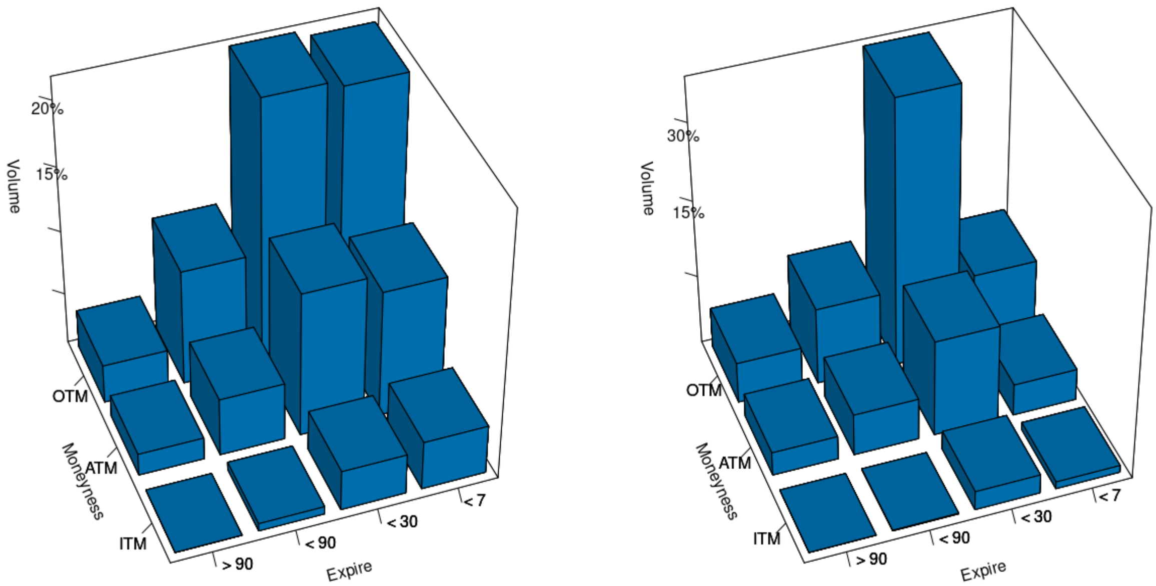
(a) Customer Volume



(b) Professional Volume

Figure 3: Option Trading Volume by Moneyness

Note: The above figures show cross-sectional options transaction volumes by option type and moneyness. The figure on the left is options transaction volume from customers and on the right presents professional customers option volume. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021, with data filtering described in the data section. We define option's moneyness as Out-of-The-Money (OTM) if the corresponding option's absolute delta is less than or equal to 0.375, as In-The-Money (ITM) if absolute delta is above or equal to 0.625, and ATM if absolute delta is in between 0.375 and 0.625.

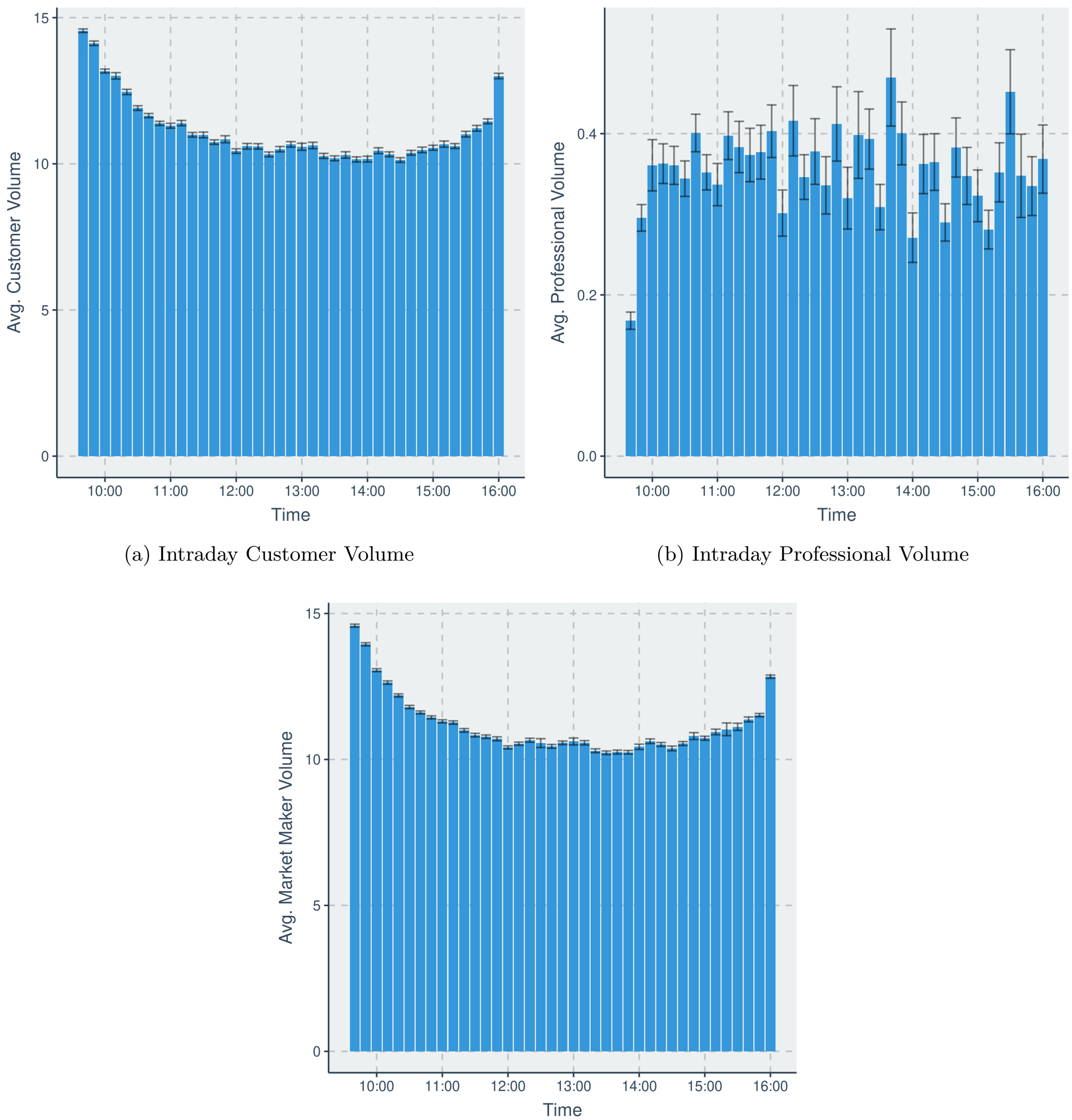


(a) Customer Volume

(b) Professional Volume

Figure 4: Option Trading Volume by Moneyness and Expiration

Note: The above 3D histogram shows proportional options volume by customers and professional customers, and all 12 bins sum up to 100%. The customer option transaction volume is on the left, and professional customers on the right. The Y-axis represents the option's moneyness, and the X-axis represents the remaining option's expiration days. The labels "<7","<30","<90",">90" stand for "less than 7 days", "less than 30 days", "less than 90 days", and "more or equal to 90 days" each. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021, with data filtering described in the data section. We define option's moneyness as Out-of-The-Money (OTM) if the corresponding option's absolute delta is less than or equal to 0.375, as In-The-Money (ITM) if absolute delta is above or equal to 0.625, and At-The-Money (ATM) if absolute delta is in between 0.375 and 0.625.



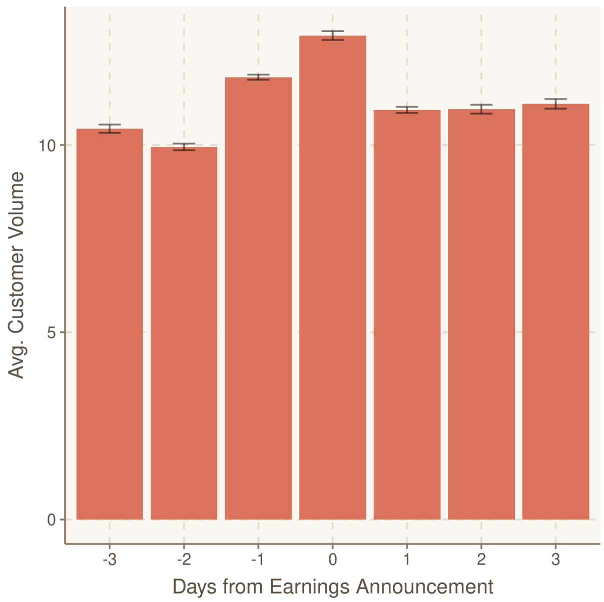
(a) Intraday Customer Volume

(b) Intraday Professional Volume

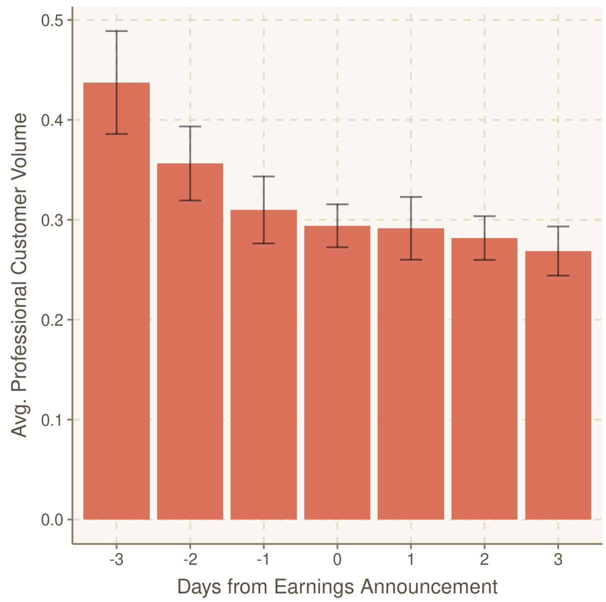
(c) Intraday Market Maker Volume

Figure 5: Intraday Average Option Trading Volume by Trader Type

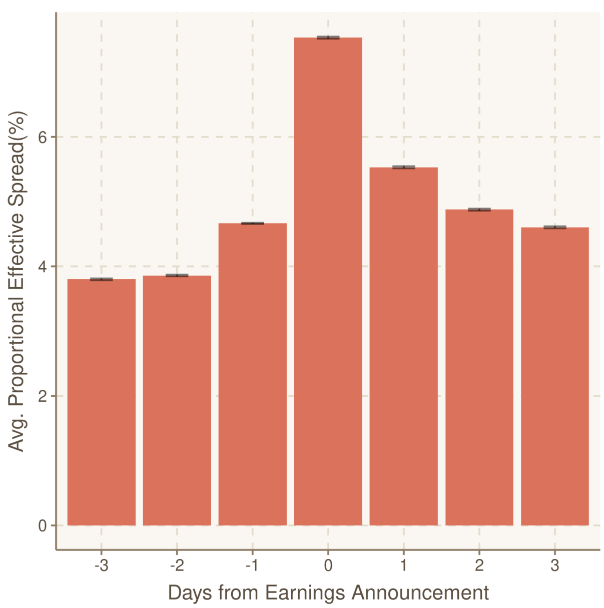
Note: The above figures show intraday average options transaction volumes by trader type. The figure on the upper left is options transaction volume from customers and on the upper right presents professional customers option volume, and the bottom presents market makers. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021, with data filtering described in the data section. Error bar represents the standard error of the mean.



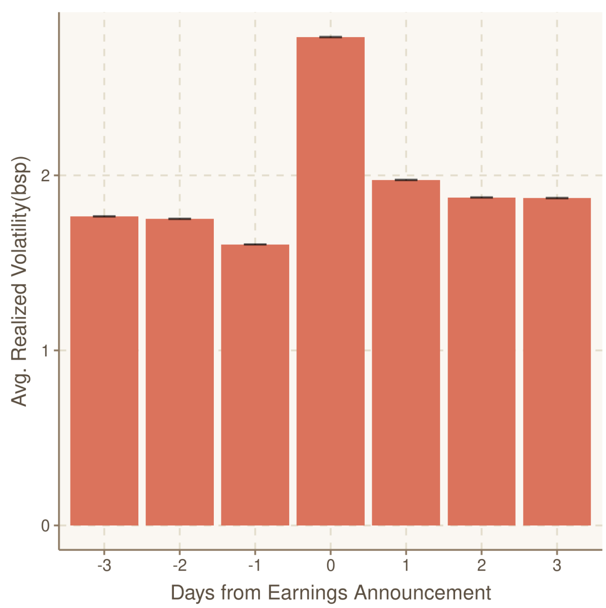
(a) Customer Volume



(b) Professional Volume



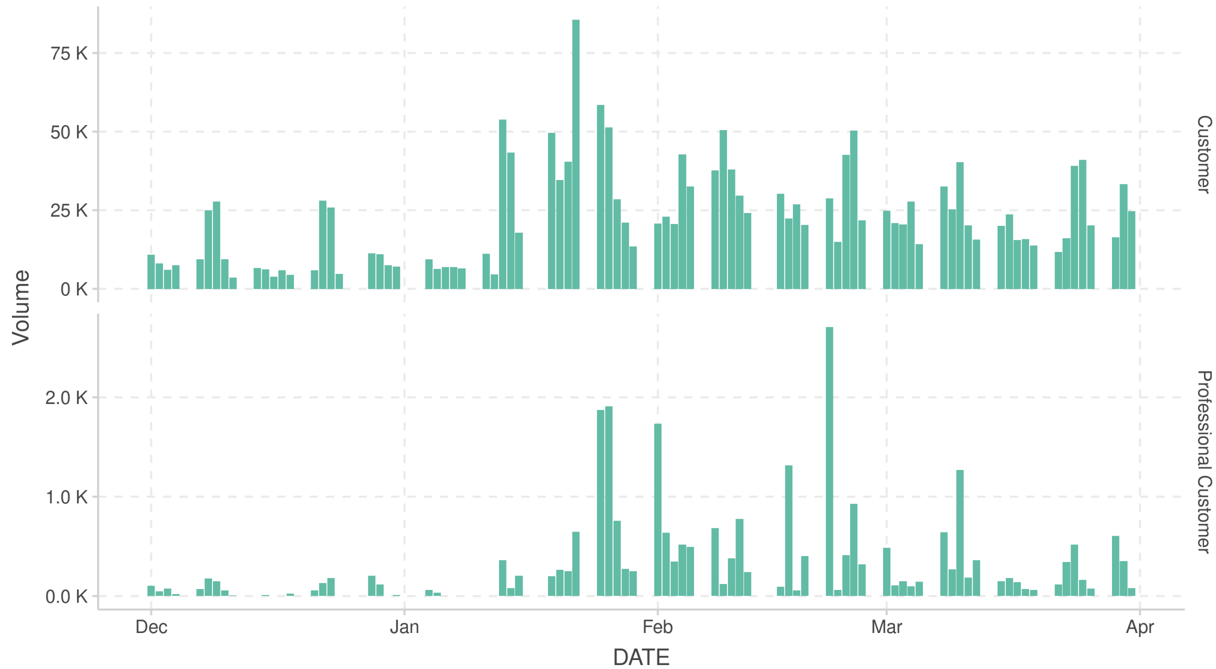
(c) Effective Spread



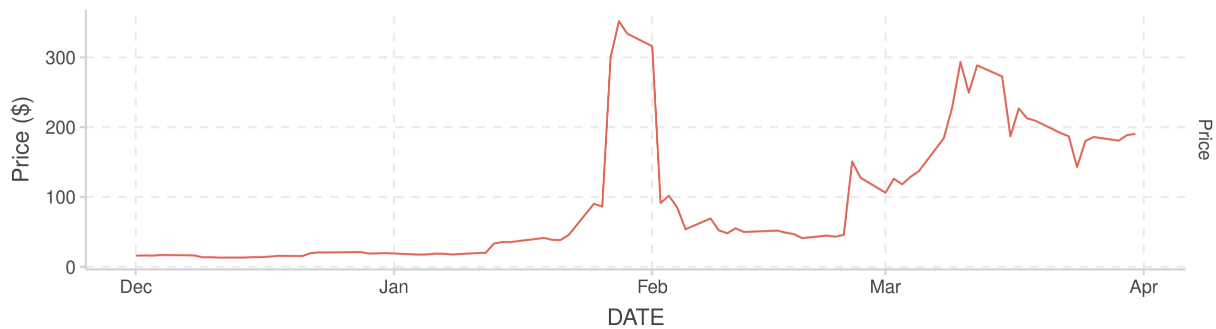
(d) Realized Volatility

Figure 6: Trading Volume, Spread and Volatility around Earnings Announcement

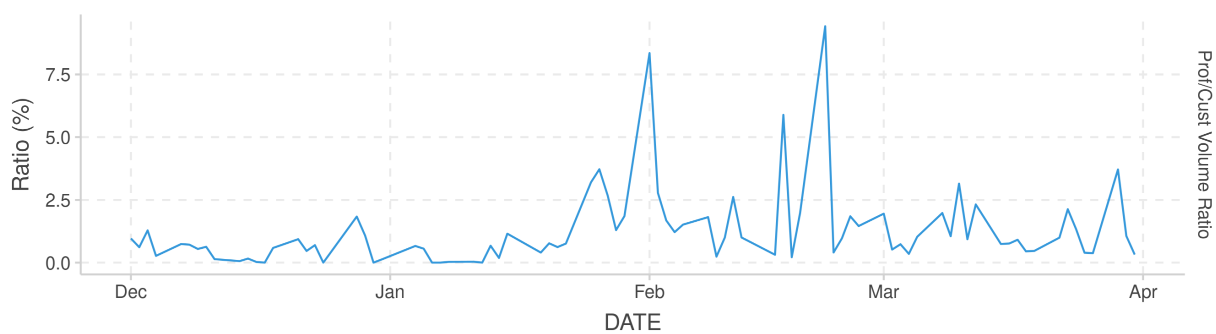
Note: The above figures show options trading volumes, proportional effective spreads and 10-minute realized volatility around earnings announcement date. The figure on the upper left and right is options transaction volume from customers and professional customers. The bottom left and right figure present proportional effective spread and realized volatility each. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021, with data filtering described in the data section. Error bar represents the standard error of the mean. Earnings announcement date 0 is the first business day that is affected by the announcement.



(a) Customer and Professional Customer's Options Trading Volume



(b) GameStop Stock Price Trend



(c) Professionals and Customers Trading Volume ratio

Figure 7: Options Trading Patterns during Meme period (GameStop:GME)

Note: The figure above shows options trading volume from Customer and Professional Customers accounts, underlying stock price movement, and volume ratio (Professionals / Customers) of Meme stock (GME) from Dec 2020 to Mar 2021. Options volume is expressed in the number of contracts traded, and each option contract represents 100 shares of the underlying equity. The volume ratio is in percentage terms.

7 Tables

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Table 1: Hypotheses Predictions

Hypothesis	Main Trading Counterparty	Trade Volume with Increased Volatility	Return Predictability	Price Impact	Impact on Spread
H1: Toxic Arbitrageurs	Market Makers	Increase	High	High	Increases
H2: Liquidity Suppliers (Market-making)	Customers (Both Informed & Uninformed)	Proportional to customer demand	Similar to Market Makers	Similar to Market Makers	Decreases
H3: Cream-skimming (Market-making)	Customers (Uninformed)	Decreases	Lower than Market Makers	Lower than Market Makers	Increases

Note:
The table summarizes three hypotheses that explain trading patterns/strategies of professional customers in the options market. Professional customers are exchange-identified high-frequency traders in the options market that are not market maker or dealers, who place orders at least 390 orders per day (i.e. one order per minute) on average.

Table 2: Descriptive statistics

Variable	N	Mean	SD	p1	p25	p50	p75	p99
Panel A: Options								
Cust vol (contracts)	27,437,233	11.43	76.34	0.00	1.00	2.00	7.00	147.00
Prof vol (contracts)	27,437,233	0.35	28.04	0.00	0.00	0.00	0.00	3.00
MM vol (contracts)	27,437,233	11.44	63.76	1.00	1.00	2.00	8.00	149.00
Mid quote ($)	27,437,233	11.75	36.57	0.04	0.78	2.45	7.97	158.32
Quoted Spread ($)	27,437,233	0.47	1.07	0.01	0.05	0.15	0.40	5.20
Quoted Spread (%)	27,437,233	11.98	20.99	0.67	2.50	4.97	11.43	117.65
Effective Spread ($)	27,437,233	0.14	0.37	0.00	0.01	0.04	0.11	1.54
Effective Spread (%)	27,437,233	4.70	10.65	0.00	0.68	1.69	4.16	57.78
Implied volatility (%)	27,437,233	46.17	30.22	13.56	27.31	37.36	55.56	160.91
DELTA	27,437,233	0.11	0.42	-0.86	-0.20	0.14	0.44	0.93
GAMMA	27,437,233	0.05	0.08	0.00	0.01	0.02	0.06	0.40
THETA	27,437,233	-0.52	1.42	-6.60	-0.36	-0.11	-0.04	0.00
VEGA	27,437,233	30.98	77.27	0.27	3.48	9.54	25.97	364.55
GammaExp	27,437,233	0.04	8.75	-5.43	-0.04	0.00	0.06	6.18
RebalCost	27,437,233	0.04	0.82	0.00	0.00	0.00	0.01	0.60
Panel B: Stocks								
Mid quote ($)	3,053,078	156.15	273.27	7.04	42.24	85.14	169.70	1,562.75
Stock return (10min, %)	3,052,842	0.00	0.59	-1.39	-0.16	0.00	0.16	1.39
Market return (10min, %)	3,053,078	0.00	0.21	-0.62	-0.06	0.00	0.07	0.62
Quoted Spread ($)	3,053,078	0.14	0.45	0.01	0.01	0.03	0.10	1.91
Quoted Spread (%)	3,053,078	0.07	0.40	0.01	0.03	0.05	0.08	0.37
Volatility (10min, *1e5)	3,052,949	20.03	18.68	4.22	10.15	15.13	23.66	87.13
Mkt Volatility (10min, *1e5)	3,053,078	6.06	5.58	1.25	2.82	4.40	7.11	30.97
Panel C: 10 minute Aggregated								
Cust vol (contracts)	14,358	21,845.38	13,626.68	285.00	13,776.00	18,928.50	26,687.75	71,420.06
Prof vol (contracts)	14,358	669.33	1,566.12	0.00	127.00	288.00	555.00	7,063.16
MM vol (contracts)	14,358	21,852.53	13,291.12	355.99	14,113.25	19,230.00	26,603.00	70,633.86

Note:
The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. Each column represents number of observations(N), mean, standard deviation(SD), and percentiles of (1%,25%,50%,75%,99%) each. Panel A show variables from to option contract and Panel B show variables related to matched underlying equities. "Cust vol", "Prof vol" and "MM vol" represent the number of options contracts transacted by Customer, Professional customer and Market maker. Each option contract has 100 underlying equity assets. Theta and Vega are estimated using European Options based model. Theta is reported in per business day basis (252 days). Quoted spread is difference between best ask and best bid and proportional bid ask spread is quoted spread expressed in percentage proportion of bid-ask midpoint . Effective spread is two times absolute difference between trade price and midpoint. Propotional effective spread is effective spread expressed in percentatge proportion of midpoint. GammaExp is proxy variable for market maker exposure, defined by NetOpenInterest multiplied by Gamma. Rebalancing cost is defined as mutiplication of gamma, proportional stock spread and absolute value of open interest. Volatility and market volatility are measured by 1 second standard deviation of returns for previous 10 minute interval, and multiplied by 1e5 for scaling.

Table 3: Option Spreads by Moneyness

Moneyness	Variable	N	Mean	SD	p1	p25	p50	p75	p99
At the Money Options									
ATM	Quoted Spread (%)	8,651,412	6.39	10.01	0.61	1.88	3.46	6.90	47.35
ATM	Effective Spread (%)	8,651,412	2.43	4.61	0.00	0.58	1.25	2.62	19.51
ATM	Quoted Spread ($)	8,651,412	0.57	1.16	0.01	0.07	0.20	0.52	6.00
ATM	Effective Spread ($)	8,651,412	0.17	0.39	0.00	0.02	0.06	0.16	1.76
In the Money Options									
ITM	Quoted Spread (%)	3,824,543	5.44	8.10	0.48	1.77	3.12	5.94	38.14
ITM	Effective Spread (%)	3,824,543	1.84	3.53	0.00	0.36	0.92	2.01	15.27
ITM	Quoted Spread ($)	3,824,543	0.88	1.66	0.01	0.12	0.30	0.90	8.15
ITM	Effective Spread ($)	3,824,543	0.23	0.58	0.00	0.03	0.07	0.22	2.30
Out of the Money Options									
OTM	Quoted Spread (%)	14,961,278	16.88	26.08	0.94	3.51	7.27	17.61	140.74
OTM	Effective Spread (%)	14,961,278	6.75	13.53	0.00	0.99	2.50	6.33	66.67
OTM	Quoted Spread ($)	14,961,278	0.30	0.74	0.01	0.03	0.10	0.26	3.70
OTM	Effective Spread ($)	14,961,278	0.09	0.25	0.00	0.01	0.03	0.07	1.04

Note:
Each column represents number of observations (N), mean, standard deviation (SD), and percentiles of (1%,25%,50%,75%,99%). The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. We define option's moneyness as out of the money (OTM) if the corresponding option's absolute delta is less than or equal to 0.375, as in the money (ITM) if absolute delta is above or equal to 0.625, and at the money (ATM) if absolute delta is in between 0.375 and 0.625. Quoted spread ($) is the difference between best ask and best bid, and proportional bid-ask spread (%) is quoted spread expressed in percentage proportion of bid-ask midpoint. Effective spread ($) is two times the absolute difference between the trade price and midpoint. Proportional effective spread (%) is the effective spread expressed in a percentage proportion of midpoint.

Table 4: Correlation Coefficients

Panel A: Total Volumes

Variable	Cust Buy	Prof Buy	MM Buy	Cust Sell	Prof Sell	MM Sell
Cust Buy	1.00	0.00	0.03	0.04	0.37	0.53
Prof Buy		1.00	0.05	0.38	0.00	0.01
MM Buy			1.00	0.51	0.01	0.04
Cust Sell				1.00	0.00	0.03
Prof Sell					1.00	0.04
MM Sell						1.00

Panel B: Call Volumes

Variable	Cust BuyCall	Cust SellCall	Prof BuyCall	Prof SellCall	MM BuyCall	MM SellCall
Cust BuyCall	1.00	0.06	0.00	0.40	0.04	0.69
Cust SellCall		1.00	0.41	0.00	0.48	0.06
Prof BuyCall			1.00	0.00	0.04	0.01
Prof SellCall				1.00	0.00	0.06
MM BuyCall					1.00	0.07
MM SellCall						1.00

Panel C: Put Volumes

Variable	Cust BuyPut	Cust SellPut	Prof BuyPut	Prof SellPut	MM BuyPut	MM SellPut
Cust BuyPut	1.00	0.03	0.00	0.28	0.03	0.37
Cust SellPut		1.00	0.30	0.00	0.60	0.02
Prof BuyPut			1.00	0.00	0.05	0.02
Prof SellPut				1.00	0.02	0.02
MM BuyPut					1.00	0.03
MM SellPut						1.00

Note:
The sample consists of all CBOE options trades on S&P500 stocks from October 2019 through March 2021. Total sample size is 27,437,233. Each variable in Panel A represents each trader type's total call / put transaction volume in a 10-minute interval. The volume variables are named with trader type, the direction of trade, and option type. Cust, Prof, and MM represent Customers, Professional customers, and Market makers. For example, "Cust BuyPut" represents customers' buy transaction volume for put options. Panels B and C show each trader's call/put options signed volume correlations.

Table 5: Stock Return Predictability by Option Volume

Dependent Variables:	α_{t+10}	α_{t+20}	α_{t+30}
Model:	(1)	(2)	(3)
Variables			
$V_t^{BuyCall,C}$	$1.33 \times 10^{-7***}$	$1.47 \times 10^{-7***}$	$1.56 \times 10^{-7***}$
	(2.858)	(3.307)	(2.750)
$V_t^{SellCall,C}$	-2.78×10^{-9}	-9.85×10^{-9}	-2.42×10^{-8}
	(-0.1192)	(-0.2367)	(-0.3714)
$V_t^{BuyPut,C}$	$-9.9 \times 10^{-8*}$	-7.31×10^{-8}	-5.82×10^{-8}
	(-1.875)	(-0.9741)	(-0.6857)
$V_t^{SellPut,C}$	4.88×10^{-8}	$9.95 \times 10^{-8*}$	$1.27 \times 10^{-7*}$
	(1.335)	(1.810)	(1.693)
α_{-10m}	-0.0004	0.0015	0.0010
	(-0.5553)	(1.168)	(0.8634)
α_t	-0.0568**	-0.0473***	-0.0674***
	(-2.284)	(-3.403)	(-5.245)
$log(1 + \sigma_t)$	-0.0058	0.5633	0.5516
	(-0.0113)	(0.7618)	(0.5713)
$log(1 + \sigma_{mkt,t})$	4.016***	6.388***	10.01***
	(2.664)	(2.668)	(3.248)
GammaExp	-1.59×10^{-7}	-1.97×10^{-7}	-2.72×10^{-7}
	(-1.149)	(-1.025)	(-1.514)
Fixed-effects			
Stock	Yes	Yes	Yes
Day	Yes	Yes	Yes
Fit statistics			
Observations	24,148,714	23,428,639	22,777,141
R^2	0.00802	0.00806	0.01185
Within R^2	0.00570	0.00320	0.00484

Clustered (Stock & Day) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports coefficient estimates and t-statistics for the fixed effects model on equation 1 with 10-minute frequency. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. Each dependent variable stands for up to 10 minutes, 10 minutes, and 30 minutes holding period excess returns for the underlying stock, expressed in digits. Regression using full sample is reported, and results using ATM, ITM, OTM subsamples are reported in the Appendix. $V_{i,j,t}^{BuyCall,C}$ is the number of call options bought by customers, and other volumes are similarly defined. σ_t is realized 10 minute minute volatility, $\sigma_{mkt,t}$ is realized 10 minute market volatility. GammaExposure is $NetOpenInterest_{j,t}$ multiplied by option gamma Γ_t. The regression includes stock and time fixed effects and double clustered by stock and time.

Table 6: Options Return Predictability, 2SLS regression by Professionals and Market Makers

Dependent Variables:	α_{t+10}	α_{t+20} With Profs	α_{t+30}	α_{t+10}	α_{t+20} With MM	α_{t+30}
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\hat{V}_t^{BuyCall,Cust}$	4×10^{-8}	-8.14×10^{-9}	-3.03×10^{-8}	$2.22 \times 10^{-7**}$	$2.94 \times 10^{-7***}$	$3.08 \times 10^{-7***}$
	(0.7984)	(-0.1448)	(-0.4572)	(2.531)	(3.143)	(2.673)
$\hat{V}_t^{SellCall,Cust}$	-3.37×10^{-8}	2.78×10^{-8}	-1.31×10^{-9}	1.46×10^{-8}	-2.04×10^{-9}	-7.6×10^{-8}
	(-1.541)	(0.3478)	(-0.0098)	(0.2642)	(-0.0246)	(-0.7136)
$\hat{V}_t^{BuyPut,Cust}$	-1.08×10^{-7}	6.34×10^{-9}	-1.41×10^{-7}	-5.03×10^{-8}	3.05×10^{-8}	7.19×10^{-8}
	(-1.080)	(0.0727)	(-0.8094)	(-0.4341)	(0.2035)	(0.4053)
$\hat{V}_t^{SellPut,Cust}$	1.23×10^{-8}	9.65×10^{-8}	6.53×10^{-8}	2.12×10^{-8}	1.2×10^{-7}	1×10^{-7}
	(0.2239)	(1.110)	(0.5740)	(0.3364)	(1.109)	(0.6527)
α_{-10m}	-0.0004	0.0015	0.0010	-0.0004	0.0015	0.0010
	(-0.5555)	(1.168)	(0.8631)	(-0.5552)	(1.168)	(0.8635)
α_t	-0.0568**	-0.0473***	-0.0674***	-0.0568**	-0.0473***	-0.0674***
	(-2.284)	(-3.403)	(-5.244)	(-2.284)	(-3.403)	(-5.245)
Volatility (stock)	-0.0054	0.5635	0.5522	-0.0061	0.5627	0.5512
	(-0.0105)	(0.7623)	(0.5720)	(-0.0119)	(0.7610)	(0.5709)
Volatility (market)	4.016***	6.388***	10.01***	4.016***	6.388***	10.01***
	(2.664)	(2.668)	(3.248)	(2.664)	(2.668)	(3.248)
GammaExp	-2.06×10^{-7}	$-3.5 \times 10^{-7*}$	$-4.81 \times 10^{-7*}$	-5.71×10^{-8}	-2.78×10^{-8}	-8.89×10^{-9}
	(-1.235)	(-1.684)	(-1.832)	(-0.3107)	(-0.1001)	(-0.0365)
Fixed-effects						
Stock	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	24,148,714	23,428,639	22,777,141	24,148,714	23,428,639	22,777,141
F-test (1st stage), $\hat{V}_t^{BuyCall,Cust}$	1,174,740.7	1,166,604.5	1,129,090.9	5,196,816.4	5,035,751.2	5,025,711.1
F-test (1st stage), $\hat{V}_t^{SellCall,Cust}$	1,305,184.6	1,191,682.3	996,339.4	1,442,741.1	1,361,648.7	1,345,053.0
F-test (1st stage), $\hat{V}_t^{BuyPut,Cust}$	538,883.6	519,714.7	492,587.9	661,380.2	621,336.9	565,848.3
F-test (1st stage), $\hat{V}_t^{SellPut,Cust}$	574,268.6	613,417.3	563,825.0	3,475,316.4	3,633,674.8	3,592,234.0
R^2	0.00802	0.00806	0.01185	0.00802	0.00806	0.01185

Clustered (Stock & Day) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports coefficient estimates and t-statistics for fixed effects model on equation 3 with 10-minute frequency. In columns (1)-(3) and (4)-(6), dependent variables are 10 minutes through 30 minutes holding period excess returns for the underlying stock, expressed in digits. Regression using the full sample is reported and results using ATM, ITM, and OTM subsamples are reported in the Appendix. All customer volumes are fitted values from equation 2. Columns (1)-(3) are fitted by professional volumes, and (4)-(6) are fitted by market makers. $\hat{V}_{i,j,t}^{BuyCall,C}$ is the fitted value of the number of call options bought by customers with corresponding counterparty trader, and other volumes are defined similarly. σ_t, $\sigma_{mkt,t}$ are realized 10 minute minute volatility and realized 10 minute market volatility. GammaExposure is $NetOpenInterest_{j,t}$ multiplied by option gamma Γ_t. The regression includes stock and time fixed effects and double clustered by stock and time. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021.

Table 7: Options Stock Return Predictability by Moneyness, fitted with Market makers

Dependent Variables:	α_{t+10}	α_{t+20} ATM	α_{t+30}	α_{t+10}	α_{t+20} ITM	α_{t+30}	α_{t+10}	α_{t+20} OTM	α_{t+30}
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
$\hat{V}_t^{BuyCall,Cust}$	1.23×10^{-7}	$2.42 \times 10^{-7*}$	2.29×10^{-7}	$3.94 \times 10^{-7***}$	$2.69 \times 10^{-7*}$	2.91×10^{-7}	$2.14 \times 10^{-7***}$	$3.21 \times 10^{-7***}$	$3.74 \times 10^{-7***}$
	(0.8590)	(1.841)	(1.549)	(3.017)	(1.860)	(1.510)	(3.024)	(3.192)	(2.803)
$\hat{V}_t^{SellCall,Cust}$	7.61×10^{-8}	-1.76×10^{-7}	-4.22×10^{-7}	-2.11×10^{-8}	-2.59×10^{-8}	-7.08×10^{-8}	2.87×10^{-8}	4.48×10^{-8}	1.81×10^{-8}
	(0.4343)	(-0.8475)	(-1.355)	(-0.1219)	(-0.1488)	(-0.3014)	(0.5385)	(0.5599)	(0.1605)
$\hat{V}_t^{BuyPut,Cust}$	-1.08×10^{-7}	5.9×10^{-7}	1.03×10^{-6}	2.4×10^{-7}	3.31×10^{-7}	4.33×10^{-7}	-1.67×10^{-7}	-1.4×10^{-7}	-2×10^{-7}
	(-0.2723)	(0.9472)	(1.075)	(0.8048)	(0.6940)	(0.9683)	(-1.245)	(-0.9576)	(-1.442)
$\hat{V}_t^{SellPut,Cust}$	2.02×10^{-7}	1.75×10^{-7}	2.55×10^{-7}	3.22×10^{-7}	$8.84 \times 10^{-7**}$	4.9×10^{-7}	-1.23×10^{-7}	-4.87×10^{-8}	-7.3×10^{-8}
	(1.617)	(0.9002)	(1.001)	(1.545)	(2.277)	(0.9479)	(-1.312)	(-0.4063)	(-0.4515)
α_{-10m}	-0.0006	0.0013	0.0008	-0.0008	0.0016	0.0014	-9.25×10^{-5}	0.0016	0.0010
	(-0.9562)	(1.035)	(0.7242)	(-0.8166)	(1.043)	(0.9245)	(-0.1459)	(1.213)	(0.8456)
α_t	-0.0483**	-0.0430***	-0.0659***	-0.0648*	-0.0357***	-0.0624***	-0.0591**	-0.0544**	-0.0702***
	(-1.970)	(-3.665)	(-4.894)	(-1.909)	(-2.973)	(-4.237)	(-2.241)	(-2.465)	(-3.462)
Volatility (stock)	0.1909	0.9857	0.9348	-0.6526	0.0245	-0.1960	0.1143	0.4926	0.5796
	(0.3102)	(1.142)	(0.8526)	(-1.100)	(0.0251)	(-0.1504)	(0.2517)	(0.7656)	(0.6961)
Volatility (market)	3.552*	5.291*	8.682***	5.556***	8.046**	13.07***	3.765***	6.546***	9.876***
	(1.889)	(1.882)	(2.622)	(2.985)	(2.474)	(3.041)	(2.848)	(3.071)	(3.461)
GammaExp	-2.98×10^{-7}	3.69×10^{-7}	6.75×10^{-7}	-3.49×10^{-8}	-5.27×10^{-7}	-6.79×10^{-7}	1.8×10^{-7}	-2.15×10^{-7}	-2.39×10^{-7}
	(-0.7897)	(0.8739)	(1.276)	(-0.1016)	(-0.8007)	(-1.249)	(0.6590)	(-0.6309)	(-0.5318)
Fixed-effects									
Stock	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	7,613,769	7,390,995	7,188,654	3,369,463	3,273,118	3,185,895	13,165,482	12,764,526	12,402,592
F-test (1st stage), $\hat{V}_t^{BuyCall,Cust}$	1,993,137.9	1,953,593.8	1,879,872.9	2,279,748.7	2,214,145.0	2,144,565.6	2,218,220.6	2,134,094.1	2,171,433.0
F-test (1st stage), $\hat{V}_t^{SellCall,Cust}$	236,774.4	219,819.9	212,764.7	1,035,214.1	997,093.7	959,672.9	1,416,347.6	1,352,807.8	1,345,507.9
F-test (1st stage), $\hat{V}_t^{BuyPut,Cust}$	87,215.1	81,131.2	76,114.7	125,474.3	119,242.3	122,026.9	1,699,877.4	1,625,171.3	1,472,429.9
F-test (1st stage), $\hat{V}_t^{SellPut,Cust}$	2,074,119.2	1,992,517.2	1,980,651.6	599,636.5	568,227.5	643,314.6	1,537,442.3	1,653,277.9	1,595,359.6
R^2	0.00633	0.00721	0.01083	0.01204	0.00872	0.01382	0.00833	0.00904	0.01248

Clustered (Stock & Day) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports coefficient estimates and t-statistics for fixed effects model on equation 3 with 10-minute frequency using ATM, ITM, OTM subsamples. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. In columns (1)-(3), (4)-(6), and (7)-(9), dependent variables are 10 minutes through 30 minutes holding period excess returns for the underlying stock, expressed in digits. All customer volumes are fitted values from equation 2. Columns (1)-(3), (4)-(6), (7)-(9) presents ATM, ITM, OTM subsample estimates fitted by market makers. $\hat{V}_{i,j,t}^{BuyCall,C}$ is the fitted value of number of call options bought by customers with corresponding counterparty trader, and other volumes are defined similarly. σ_t, $\sigma_{mkt,t}$ are realized 10 minute minute volatility and realized 10 minute market volatility. GammaExposure is $NetOpenInterest_{j,t}$ multiplied by option gamma Γ_t. Regression includes stock and time fixed effects and double clustered by stock and time.

Table 8: Price Impact of Call Option Volumes

Dependent Variable:	$\lvert\alpha_t\rvert$	
	Fitted with Profs	Fitted with MM
Model:	(1)	(2)
Variables		
$\hat{V}_t^{BuyCall,Cust}$	$9.15 \times 10^{-8**}$	$9.18 \times 10^{-7***}$
	(2.282)	(6.482)
Volatility (Stock)	21.19^{***}	21.19^{***}
	(15.79)	(15.78)
Volatility (Mkt)	-12.64^{***}	-12.64^{***}
	(-4.038)	(-4.039)
GammaExp	$-3.7 \times 10^{-7***}$	$4.42 \times 10^{-7***}$
	(-2.655)	(2.862)
Fixed-effects		
TICKER	Yes	Yes
DATE	Yes	Yes
Fit statistics		
Observations	27,318,273	27,318,273
F-test (1st stage), $\hat{V}_t^{BuyCall,Cust}$	5,392,712.2	22,301,571.5
F-test (2nd stage)	2.4615	674.61

Clustered (TICKER & DATE) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The above table presents coefficient estimates and t-statistics for the price impact of customer buy call options volume. Columns (1) and (2) show regression results when customer trades are fitted to professional customers and market makers. The price impact is measured with the current absolute excess return of underlying equity, expressed in digits. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. The regression includes stock and time fixed effects and double clustered by stock and time.

Table 9: Trading volumes on Realized Volatility

Panel A: Professional Customers

Dependent Variables:	$log(1+V_t^{P})$	$log(1+V_t^{P,BuyCall})$	$log(1+V_t^{P,SellCall})$	$log(1+V_t^{P,BuyPut})$	$log(1+V_t^{P,SellPut})$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\sigma_{t,STD}$	-0.0015***	-0.0003	0.0001	-0.0007***	-0.0005***
	(-3.0090)	(-1.3901)	(0.2944)	(-6.9349)	(-6.0823)
$\sigma_{mkt,t,STD}$	-0.0017***	-0.0005**	-0.0009***	0.0001	-0.0005***
	(-2.7634)	(-2.4153)	(-4.2797)	(0.6121)	(-2.6598)
EAD_{t-1}	-0.0106***	-0.0030***	-0.0029***	-0.0028***	-0.0021***
	(-6.8024)	(-4.5398)	(-5.5417)	(-6.5932)	(-6.6450)
EAD_t	-0.0115***	-0.0057***	-0.0017***	-0.0039***	-0.0003
	(-8.3806)	(-9.2842)	(-3.6926)	(-9.7981)	(-1.1095)
EAD_{t+1}	-0.0031***	-0.0031***	0.0011**	-0.0018***	0.0006**
	(-2.8678)	(-6.7758)	(2.2860)	(-5.1681)	(2.1816)
Fit statistics					
R^2	0.00680	0.00310	0.00274	0.00184	0.00129
Within R^2	0.00180	0.00086	0.00077	0.00034	0.00031

Panel B: Customers

Dependent Variables:	$log(1+V_t^{C})$	$log(1+V_t^{C,BuyCall})$	$log(1+V_t^{C,SellCall})$	$log(1+V_t^{C,BuyPut})$	$log(1+V_t^{C,SellPut})$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\sigma_{t,STD}$	0.0413***	0.0302***	0.0351***	0.0048*	0.0058**
	(8.1138)	(8.1011)	(8.7330)	(1.8862)	(2.3661)
$\sigma_{mkt,t,STD}$	0.0263***	0.0021	0.0099***	0.0162***	0.0215***
	(4.4646)	(0.6888)	(3.0539)	(4.7427)	(6.3225)
EAD_{t-1}	0.1069***	0.1051***	0.0668***	0.0044	0.0123
	(10.0464)	(11.3668)	(6.6548)	(0.5295)	(1.5498)
EAD_t	0.0979***	0.0471***	0.0145**	0.0506***	0.0487***
	(12.0189)	(8.4351)	(2.3660)	(11.1105)	(9.4622)
EAD_{t+1}	0.0365***	0.0115**	-0.0105*	0.0243***	0.0286***
	(4.3641)	(2.1520)	(-1.9180)	(7.9693)	(5.7638)
Fixed-effects					
Day	Yes	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	27,436,649	27,436,649	27,436,649	27,436,649	27,436,649
R^2	0.06931	0.02485	0.02401	0.02934	0.01960
Within R^2	0.02725	0.00653	0.00827	0.01975	0.01277

Clustered (Day & Stock) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Panel A (B) shows estimated regression coefficients of Professional customers (Customers). The dependent variable of the first column is the log of total volume. Each of the second, third, fourth, and fifth columns are buy call, sell call, buy put, and sell put volumes. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. EAD_t is a dummy variable that indicates the first date that is affected earnings announcement. For example, if the announcement was after 4 PM, the next business day is regarded as the announcement date. Control variables include days to expire, implied volatility of option, proportional underlying stock spread, absolute delta, rebalancing cost and vega of the option. Rebalancing cost is defined as mutiplication of gamma, proportional stock spread and absolute value of open interest.

Table 10: Regression on Spreads

Dependent Variables:	Eff Sp (bps)		Qte Sp (bps)	
Model:	(1)	(2)	(3)	(4)
Variables				
$\hat{V}_t^{MM}$	-0.6186***	-0.4153***	-2.531***	-1.831***
	(-9.344)	(-5.696)	(-9.355)	(-12.13)
$\hat{V}_t^{PC}$	1.152***		4.020***	
	(4.031)		(3.268)	
$\hat{V}_t^{MM} \times D_t^{PC,small}$		0.0852**		0.3403***
		(1.987)		(3.033)
$\hat{V}_t^{MM} \times D_t^{PC,large}$		0.3708***		1.487***
		(6.140)		(9.496)
Days_Expire	1.512***	1.511***	3.353***	3.351***
	(9.470)	(9.492)	(10.30)	(10.34)
$log(1/p_t)$	466.1***	465.7***	829.9***	828.6***
	(18.43)	(18.41)	(13.38)	(13.36)
Volatility (stock)	217.7***	217.1***	526.8***	524.8***
	(9.153)	(9.119)	(9.413)	(9.387)
Volatility (market)	103.6***	103.5***	230.6***	230.0***
	(7.779)	(7.774)	(7.213)	(7.210)
Implied Volatility	410.9***	410.6***	660.4***	659.4***
	(18.49)	(18.54)	(11.91)	(11.93)
Stock Spread(%)	9.930*	10.80*	20.82	23.85
	(1.803)	(1.941)	(1.340)	(1.533)
Delta (absolute)	861.3***	859.7***	861.0***	855.3***
	(20.12)	(20.07)	(6.619)	(6.569)
RevalCost	11.67*	6.895*	41.74*	25.08*
	(1.927)	(1.670)	(1.855)	(1.670)
Vega	1.438***	1.440***	1.840***	1.845***
	(3.648)	(3.642)	(3.935)	(3.914)
Fixed-effects				
Day	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes
Fit statistics				
Observations	27,436,649	27,436,649	27,436,649	27,436,649
F-test (1st stage), $\hat{V}_t^{MM}$	1,105,073.5	975,930.1	1,105,073.5	975,930.1
F-test (1st stage), $\hat{V}_t^{PC}$	459,728.2		459,728.2	
F-test (2nd stage)	4,888.5	5,728.2	24,286.4	33,132.6
R^2	0.26043	0.26169	0.35511	0.35958

Clustered (Day & Stock) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Main dependent variables are proportional spreads in basis points. Proportional spreads are calculated by dividing the spread by the midpoint of the best bid and ask. $\hat{V}_{i,j,t}^{MM}$, $\hat{V}_{i,j,t}^{P}$ represents total volume of market maker and professional customers fitted by customer volumes from equation 5. $D_t^{P,small}$ is defined as 1 if PC's trade volume is greater than zero and less than 200 and zero otherwise. $D_t^{P,large}$ is set to 1 if PC volume is greater than 200 and zero otherwise. $log(1/p_t)$ is log of inverse of option price. Realized volatility and market volatility are multiplied by 1e6. Rebalancing cost is obtained by multiplying $NetOpenInterest_{j,t}$, option gamma Γ_t and stock spread.

Table 11: Option Demand for Volatility and Volatility Predictability

Dependent Variables:	$Volatility_{t+10}$	$Volatility_{t+20}$	$Volatility_{t+10}$	$Volatility_{t+20}$
	Traded with MM		Traded with PCs	
Model:	(1)	(2)	(3)	(4)
Variables				
$\widehat{Straddle}_t^C$	$7.7 \times 10^{-9**}$	$5.28 \times 10^{-9*}$	-6.81×10^{-8}	1.17×10^{-7}
	(1.989)	(1.876)	(-1.259)	(0.5808)
$Inv\widehat{Straddle}_t^C$	2.77×10^{-9}	3.96×10^{-9}	-8.55×10^{-10}	-2.48×10^{-8}
	(1.311)	(1.473)	(-0.0474)	(-0.7697)
$Volatility_t$	0.5438***	0.2101***	0.5518***	0.2008***
	(18.42)	(5.596)	(17.31)	(4.699)
$Volatility_t$ (market)	0.8240***	0.5840***	0.8466***	0.5591***
	(4.316)	(3.677)	(4.407)	(3.511)
$Volatility_{t+10}$		0.3091***		0.3089***
		(6.179)		(6.185)
Fixed-effects				
TICKER	Yes	Yes	Yes	Yes
DATE	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,051,049	1,049,280	1,051,049	1,049,280
F-test (1st stage), $\widehat{Straddle}_t^C$	7,530.1	7,515.1	5.5075	5.4994
F-test (1st stage), $Inv\widehat{Straddle}_t^C$	7,776.5	7,764.4	66.556	66.461
R^2	0.21451	0.23047	0.20691	0.21304

Clustered (TICKER & DATE) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The main dependent variables are future realized 10-minute underlying stock volatility in 10 minute and 20 minute after the concurrent period. $\widehat{Straddle}_t^C$ and $Inv\widehat{Straddle}_t^C$ represents customer's straddle volume and inverse straddle volume that are fitted with counterparties. Detailed explanations on variable construction is presented at section 2.2.2. Columns (1) and (2) show estimates when straddles are fitted with market makers, and (3) and (4) show results with professional customers. Volatility represents realized 10-minute underlying and market volatility at time t.

Table 12: Professional Customer Trades and Stock Return Predictability

Dependent Variables:	α_{t+10}	α_{t+20}	α_{t+30}	α_{t+10}	α_{t+20}	α_{t+30}
		2 Stage model			Single stage model	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\hat{V}_t^{BuyCall,P}$	-4.43×10^{-8}	-9.11×10^{-8}	-1.3×10^{-7}	-3.44×10^{-8}	2.77×10^{-8}	-2.5×10^{-9}
	(-0.3926)	(-0.4178)	(-0.3438)	(-1.541)	(0.3459)	(-0.0188)
$\hat{V}_t^{SellCall,P}$	3.26×10^{-7}*	2.23×10^{-7}	2.76×10^{-7}	4.35×10^{-8}	-8.11×10^{-9}	-3.26×10^{-8}
	(1.927)	(1.188)	(1.062)	(0.7967)	(-0.1301)	(-0.4435)
$\hat{V}_t^{BuyPut,P}$	3.46×10^{-7}	5.24×10^{-7}	8.63×10^{-7}	9.77×10^{-9}	8.16×10^{-8}	5.42×10^{-8}
	(1.045)	(1.253)	(1.318)	(0.2192)	(1.228)	(0.6112)
$\hat{V}_t^{SellPut,P}$	-8.73×10^{-7}*	-5.98×10^{-7}	-4.38×10^{-7}	-8.48×10^{-8}	5.38×10^{-9}	-1.08×10^{-7}
	(-1.687)	(-0.8772)	(-0.5481)	(-1.341)	(0.0787)	(-0.9244)
α_{-10m}	-0.0004	0.0015	0.0010	-0.0004	0.0015	0.0010
	(-0.5556)	(1.168)	(0.8630)	(-0.5556)	(1.168)	(0.8631)
α_t	-0.0568**	-0.0473***	-0.0674***	-0.0568**	-0.0473***	-0.0674***
	(-2.284)	(-3.403)	(-5.244)	(-2.284)	(-3.403)	(-5.244)
Volatility (stock)	-0.0055	0.5637	0.5520	-0.0055	0.5637	0.5520
	(-0.0107)	(0.7625)	(0.5718)	(-0.0107)	(0.7625)	(0.5718)
Volatility (market)	4.016***	6.388***	10.01***	4.016***	6.389***	10.01***
	(2.664)	(2.668)	(3.248)	(2.664)	(2.668)	(3.248)
GammaExp	-2.2×10^{-7}	-2.65×10^{-7}	-3.53×10^{-7}*	-2.26×10^{-7}	-2.73×10^{-7}	-3.67×10^{-7}*
	(-1.450)	(-1.295)	(-1.749)	(-1.505)	(-1.340)	(-1.804)
Fixed-effects						
Stock	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	24,148,714	23,428,639	22,777,141	24,148,714	23,428,639	22,777,141
F-test (1st stage), $\hat{V}_t^{BuyCall,P}$	770,094.3	700,284.4	582,642.0			
F-test (1st stage), $\hat{V}_t^{SellCall,P}$	1,001,621.0	994,812.3	969,367.3			
F-test (1st stage), $\hat{V}_t^{BuyPut,P}$	370,577.2	408,687.0	375,468.0			
F-test (1st stage), $\hat{V}_t^{SellPut,P}$	290,728.6	279,907.6	264,285.4			
R^2	0.00802	0.00806	0.01185	0.00802	0.00806	0.01185

Clustered (Stock & Day) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns (1)-(3) and (4)-(6) report estimated coefficient and t-statistics with (and without) 2-stage regression. $\hat{V}_{i,j,t}^{BuyCall,P}$ is the number of call options bought by professionals fitted with customers and market makers as counterparties . The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. Dependent variables are 10 minute to 30 minute market excess return for the underlying stock, expressed in digits. Volatility represents realized 10-minute underlying (market) volatility at time t. GammaExposure is $NetOpenInterest_{j,t}$ multiplied by option gamma Γ_t.

8 Appendix

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Table A1: Regression on Spreads by Moneyness

Dependent Variables:	Eff Sp (bps)	Qte Sp (bps)	Eff Sp (bps)	Qte Sp (bps)	Eff Sp (bps)	Qte Sp (bps)
	ATM		ITM		OTM	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\hat{V}_t^{MM}$	-0.3982***	-1.106***	-0.1839***	-0.5481***	-0.5199***	-2.567***
	(-6.039)	(-4.760)	(-7.782)	(-6.450)	(-5.323)	(-8.838)
$\hat{V}_t^{PC}$	1.050***	2.871***	0.7017***	2.148***	0.7364***	2.854***
	(4.256)	(4.048)	(3.168)	(3.240)	(3.571)	(2.844)
Days_Expire	0.2502***	0.5629***	0.1826***	0.4227***	2.006***	3.928***
	(4.704)	(6.773)	(4.293)	(4.843)	(9.500)	(10.67)
$log(1/p_t)$	141.9***	210.8***	108.1***	217.9***	572.2***	867.6***
	(9.019)	(7.492)	(7.930)	(6.933)	(18.07)	(14.13)
Volatility (stock)	161.6***	379.5***	127.3***	267.9***	280.5***	700.3***
	(9.811)	(9.767)	(8.457)	(8.508)	(9.860)	(10.33)
Volatility (market)	63.62***	145.8***	56.36***	151.5***	129.8***	284.2***
	(6.203)	(5.859)	(5.303)	(6.185)	(8.380)	(7.524)
Implied Volatility	47.58***	14.89	14.33*	51.62**	523.3***	614.3***
	(3.314)	(0.4397)	(1.926)	(2.587)	(17.25)	(7.721)
Stock Spread(%)	8.063**	14.87	4.623***	13.89*	17.48	42.95
	(2.013)	(1.349)	(2.876)	(1.689)	(1.620)	(1.645)
Delta (absolute)	66.43***	-207.0***	76.47***	328.0***	1,050.2***	-1,461.2***
	(2.748)	(-5.150)	(3.940)	(5.798)	(6.685)	(-2.880)
RevalCost	19.33**	37.84	4.938***	6.704**	9.001***	33.57***
	(2.267)	(1.594)	(2.951)	(2.313)	(3.151)	(3.830)
Vega	0.1975***	0.2265*	0.1100**	0.2759*	2.548***	3.242***
	(2.786)	(1.884)	(2.462)	(1.936)	(3.365)	(3.500)
Fixed-effects						
Day	Yes	Yes	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	8,651,214	8,651,214	3,824,405	3,824,405	14,961,030	14,961,030
F-test (1st stage), $\hat{V}_t^{MM}$	164,906.8	164,906.8	278,000.8	278,000.8	1,258,367.2	1,258,367.2
F-test (1st stage), $\hat{V}_t^{PC}$	60,205.9	60,205.9	42,748.5	42,748.5	358,830.2	358,830.2
R^2	0.19485	0.31015	0.18701	0.29804	0.27256	0.38181

Clustered (Day & Stock) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The main dependent variables are proportional spreads in basis points. Proportional spreads are calculated by dividing the spread by the best bid and ask midpoint. efeq:spreadeq2. $\hat{V}_{i,j,t}^{MM}$, $\hat{V}_{i,j,t}^{P}$ represents total volume of market maker and professional customers fitted by customer volumes from equation $log(1/p_t)$ is log of inverse of option price. Realized volatility and market volatility are multiplied by 1e6. Rebalancing cost is obtained by multiplying $NetOpenInterest_{j,t}$, option gamma Γ_t and stock spread.

Table A2: Regression on Spreads by Moneyness, Dummy Interaction

Dependent Variables:	Eff Sp (bps)	Qte Sp (bps)	Eff Sp (bps)	Qte Sp (bps)	Eff Sp (bps)	Qte Sp (bps)
	ATM		ITM		OTM	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\hat{V}_t^{MM}$	-0.3083***	-0.8269***	-0.1142***	-0.3262***	-0.3543***	-1.958***
	(-6.878)	(-5.440)	(-7.860)	(-8.101)	(-3.705)	(-10.08)
$\hat{V}_t^{MM} \times D_t^{PC,small}$	0.1121***	0.0308	0.0778***	0.0026	0.0493	0.4364***
	(5.313)	(0.6009)	(4.049)	(0.0240)	(0.8430)	(2.812)
$\hat{V}_t^{MM} \times D_t^{PC,large}$	0.0993**	0.3975***	0.0512*	0.2386***	0.3418***	1.671***
	(2.138)	(3.015)	(1.669)	(3.536)	(3.936)	(8.434)
Days_Expire	0.2486***	0.5584***	0.1821***	0.4211***	2.004***	3.923***
	(4.699)	(6.778)	(4.278)	(4.821)	(9.509)	(10.70)
$log(1/p_t)$	141.4***	209.3***	107.9***	217.3***	571.7***	865.9***
	(8.964)	(7.427)	(7.908)	(6.909)	(18.06)	(14.12)
Volatility (stock)	161.2***	378.7***	127.2***	267.5***	280.1***	698.6***
	(9.811)	(9.769)	(8.446)	(8.492)	(9.830)	(10.31)
Volatility (market)	63.54***	145.5***	56.30***	151.3***	129.6***	283.5***
	(6.202)	(5.857)	(5.302)	(6.184)	(8.370)	(7.518)
Implied Volatility	46.98***	13.15	14.21*	51.22**	522.9***	612.7***
	(3.277)	(0.3879)	(1.909)	(2.567)	(17.25)	(7.693)
Stock Spread(%)	8.581**	16.44	4.686***	14.08*	18.23*	45.88*
	(2.227)	(1.556)	(2.917)	(1.711)	(1.669)	(1.729)
Delta (absolute)	65.66***	-209.2***	76.14***	326.8***	1,045.3***	-1,479.5***
	(2.701)	(-5.213)	(3.933)	(5.795)	(6.676)	(-2.917)
RevalCost	16.51**	29.29*	4.200***	4.437**	5.640**	20.36***
	(2.497)	(1.666)	(3.196)	(2.388)	(2.433)	(3.654)
Vega	0.1981***	0.2287*	0.1103**	0.2767*	2.549***	3.247***
	(2.772)	(1.883)	(2.454)	(1.931)	(3.362)	(3.491)
Fixed-effects						
Day	Yes	Yes	Yes	Yes	Yes	Yes
Stock	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	8,651,214	8,651,214	3,824,405	3,824,405	14,961,030	14,961,030
F-test (1st stage), $\hat{V}_t^{MM}$	142,550.3	142,550.3	259,324.7	259,324.7	1,126,794.3	1,126,794.3
R^2	0.19840	0.31645	0.18830	0.30047	0.27292	0.38352

Clustered (Day & Stock) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Main dependent variables are proportional spreads in basis points. Proportional spreads are calculated by dividing the spread by the midpoint of the best bid and ask. $\hat{V}_{i,j,t}^{MM}$, $\hat{V}_{i,j,t}^{P}$ represents total volume of market maker and professional customers fitted by customer volumes from equation 5. $D_t^{P,small}$ is defined as 1 if PC's trade volume is greater than zero and less than 200 and zero otherwise. $D_t^{P,large}$ is set to 1 if PC volume is greater than 200 and zero otherwise. $log(1/p_t)$ is log of inverse of option price. Realized volatility and market volatility are multiplied by 1e6. Rebalancing cost is obtained by multiplying $NetOpenInterest_{j,t}$, option gamma Γ_t and stock spread.

Table A3: Options Stock Return Predictability by Moneyness, fitted with Professional Customers

Dependent Variables:	α_{t+10}	α_{t+20} ATM	α_{t+30}	α_{t+10}	α_{t+20} ITM	α_{t+30}	α_{t+10}	α_{t+20} OTM	α_{t+30}
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
$\hat{V}_t^{BuyCall,Cust}$	1.98×10^{-8}	-9.02×10^{-8}	-9.25×10^{-8}	4.81×10^{-8}	1.87×10^{-7}	9.35×10^{-8}	4.12×10^{-8}	-5.72×10^{-9}	-3.33×10^{-8}
	(0.1695)	(-0.5506)	(-0.4015)	(0.3414)	(0.9171)	(0.4411)	(0.7055)	(-0.0934)	(-0.4668)
$\hat{V}_t^{SellCall,Cust}$	$-2.03 \times 10^{-7**}$	$-3.82 \times 10^{-7**}$	$-4.46 \times 10^{-7*}$	1.24×10^{-7}	$5.63 \times 10^{-7*}$	3.54×10^{-7}	-1.11×10^{-8}	8.04×10^{-8}	8.99×10^{-8}
	(-2.387)	(-2.219)	(-1.781)	(0.6917)	(1.841)	(0.9129)	(-0.4613)	(0.9314)	(0.7186)
$\hat{V}_t^{BuyPut,Cust}$	-1.55×10^{-6}	1.27×10^{-7}	-1.95×10^{-6}	-6.62×10^{-8}	-1.14×10^{-8}	-3.18×10^{-9}	-3.72×10^{-8}	-5.65×10^{-10}	-5.63×10^{-8}
	(-0.8141)	(0.1155)	(-0.7057)	(-0.5645)	(-0.0418)	(-0.0123)	(-0.6187)	(-0.0073)	(-0.4724)
$\hat{V}_t^{SellPut,Cust}$	7.24×10^{-9}	-9.27×10^{-8}	$-3.14 \times 10^{-7*}$	-1.96×10^{-7}	-3×10^{-7}	-5.04×10^{-7}	4.67×10^{-8}	$2.27 \times 10^{-7*}$	2.85×10^{-7}
	(0.0455)	(-0.5079)	(-1.867)	(-1.465)	(-1.062)	(-1.373)	(0.7283)	(1.653)	(1.296)
α_{-10m}	-0.0006	0.0013	0.0008	-0.0008	0.0016	0.0014	-9.18×10^{-5}	0.0016	0.0010
	(-0.9582)	(1.034)	(0.7215)	(-0.8176)	(1.044)	(0.9244)	(-0.1449)	(1.213)	(0.8466)
α_t	-0.0483**	-0.0430***	-0.0659***	-0.0648*	-0.0357***	-0.0624***	-0.0591**	-0.0544**	-0.0702***
	(-1.971)	(-3.666)	(-4.895)	(-1.910)	(-2.974)	(-4.237)	(-2.241)	(-2.465)	(-3.462)
Volatility (stock)	0.1939	0.9885	0.9396	-0.6522	0.0236	-0.1963	0.1145	0.4928	0.5798
	(0.3151)	(1.147)	(0.8578)	(-1.099)	(0.0241)	(-0.1506)	(0.2521)	(0.7660)	(0.6962)
Volatility (market)	3.557*	5.293*	8.691***	5.556***	8.049**	13.07***	3.766***	6.546***	9.877***
	(1.892)	(1.882)	(2.623)	(2.986)	(2.474)	(3.041)	(2.848)	(3.070)	(3.461)
GammaExp	-5.69×10^{-7}	2.21×10^{-7}	-2.34×10^{-7}	-3.7×10^{-7}	-8.41×10^{-7}	$-1.09 \times 10^{-6**}$	-6.61×10^{-8}	$-8.89 \times 10^{-7***}$	$-1.18 \times 10^{-6**}$
	(-0.7903)	(0.6256)	(-0.2402)	(-0.9358)	(-1.495)	(-2.026)	(-0.2595)	(-2.929)	(-2.267)
Fixed-effects									
Stock	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	7,613,769	7,390,995	7,188,654	3,369,463	3,273,118	3,185,895	13,165,482	12,764,526	12,402,592
F-test (1st stage), $\hat{V}_t^{BuyCall,Cust}$	155,690.5	168,163.7	165,690.7	71,182.2	70,726.7	70,537.4	893,976.6	869,249.9	839,388.9
F-test (1st stage), $\hat{V}_t^{SellCall,Cust}$	191,837.5	188,846.8	186,403.6	76,307.1	74,963.1	73,987.8	997,911.9	892,689.0	711,876.0
F-test (1st stage), $\hat{V}_t^{BuyPut,Cust}$	5,379.0	5,313.8	5,220.0	236,355.3	232,278.0	231,365.9	469,975.4	452,308.6	434,332.5
F-test (1st stage), $\hat{V}_t^{SellPut,Cust}$	163,779.7	186,434.4	156,910.6	157,405.5	153,922.1	167,737.9	295,673.8	310,129.7	284,092.8
R^2	0.00629	0.00721	0.01080	0.01204	0.00870	0.01382	0.00833	0.00904	0.01248

Clustered (Stock & Day) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports coefficient estimates and t-statistics for fixed effects model on equation 3 with 10-minute frequency using ATM, ITM, OTM subsamples. The sample consists of all CBOE options trades on S&P500 stocks from October 2019 to March 2021. In columns (1)-(3), (4)-(6), and (7)-(9), dependent variables are 10 minutes through 30 minutes holding period excess returns for the underlying stock, expressed in digits. All customer volumes are fitted values from equation 2. Columns (1)-(3), (4)-(6), (7)-(9) presents ATM, ITM, OTM subsample estimates fitted by PCs. $\hat{V}_{i,j,t}^{BuyCall,Cust}$ is the fitted value of number of call options bought by customers with corresponding counterparty trader, and other volumes are defined similarly. Volatility is calculated based on 1 second returns during 10 minute interval. GammaExposure is $NetOpenInterest_{j,t}$ multiplied by option gamma Γ_t.

Table A4: Professional Customers' Option Demand for Volatility and Volatility Predictability

Dependent Variables:	$Volatility_{t+10}$	$Volatility_{t+20}$	$Volatility_{t+10}$	$Volatility_{t+20}$
	2 Stage model		Single model	
Model:	(1)	(2)	(3)	(4)
Variables				
$\widehat{Straddle}_t^P$	1.8×10^{-6}	1.33×10^{-6}	-1.33×10^{-9}	2.23×10^{-10}
	(1.074)	(1.086)	(-1.314)	(0.2678)
$\widehat{InvStraddle}_t^P$	2.37×10^{-6}	1.89×10^{-6}	-3.27×10^{-10}	-3.43×10^{-10}
	(1.415)	(1.435)	(-0.4888)	(-0.6081)
$Volatility_t$	0.5524***	0.2165***	0.5448***	0.2109***
	(17.46)	(5.615)	(18.42)	(5.612)
$Volatility_t$ (market)	0.9226***	0.6595***	0.8268***	0.5865***
	(4.475)	(3.897)	(4.319)	(3.681)
$Volatility_{t+10}$		0.3098***		0.3091***
		(6.166)		(6.179)
Fixed-effects				
TICKER	Yes	Yes	Yes	Yes
DATE	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,051,049	1,049,280	1,051,049	1,049,280
F-test (1st stage), $\widehat{Straddle}_t^P$	6.3643	6.3693		
F-test (1st stage), $\widehat{InvStraddle}_t^P$	1.7441	1.7402		
R^2	-1.4420	-0.58233	0.21461	0.23053

Clustered (TICKER & DATE) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The main dependent variables are future realized 10-minute underlying stock volatility in 10 minute and 20 minute after the concurrent period. $\widehat{Straddle}_t^P$ and $\widehat{InvStraddle}_t^P$ represents PCs straddle volume and inverse straddle volume that are fitted with market makers and customers. Detailed explanations on variable construction is presented at section 2.2.2. Columns (1) and (2) show estimates when (inverse) straddles are fitted with market makers and customers, and (3) and (4) show results without first-stage fitting. Volatility represents realized 10-minute underlying and market volatility at time t.