Risky Intraday Order Flow and Equity Option Liquidity*

Hitesh Doshi† Paola Pederzoli‡ Saim Ayberk Sert§

October 31, 2024

Abstract

We examine the effect of intraday order flow volatility on option market illiquidity. We document a robust positive relationship between order flow volatility and illiquidity, both in time series and the cross-section of short-maturity index and individual equity options. The impact of order flow volatility varies significantly by option maturity, decreasing as maturity increases, underscoring the higher sensitivity of liquidity in ultra-short maturity options. We leverage multi-exchange trading of individual stock options to isolate the direct trade absorption costs from indirect costs. This analysis reveals that, while both cost components are significant, indirect costs dominate, with exchanges adjusting based on aggregate order flow risk across venues. Overall, our results contribute to the understanding of how effectively liquidity providers provide liquidity in this relatively novel market of short-maturity options.

* We thank Rohit Allena, Kevin Crotty, David De Angelis, Kris Jacobs, James Upson (discussant) and the participants to the Lonestar Conference 2024, UQAM Seminar Series in Canada, and seminar at the University of Houston for comments and suggestions. We thank SpiderRock Data & Analytics for providing data. This work was completed in part with resources provided by the Research Computing Data Core at the University of Houston. All errors are our own.

†C.T. Bauer College of Business, University of Houston. Email: hdoshi@bauer.uh.edu

‡C.T. Bauer College of Business, University of Houston. Email: ppederzoli@bauer.uh.edu

§C.T. Bauer College of Business, University of Houston. Email: sasert@bauer.uh.edu

1 Introduction

Investors are turning into short-maturity options, changing the standard trading dynamics in both the SPX options market and the market for individual stock options. In 2023, an impressive 80% of SPX options trading focused on options with expiration less than a month (Dim, Eraker, and Vilkov 2024, Bandi, Fusari, and Reno 2024). The increase in option market liquidity, the rise in investor sophistication, and the growing desire to hedge against specific events have all contributed to the shift towards option strategies with shorter maturities and more frequent rebalancing.[1] In response to this need, exchanges promptly introduced weekly options expiring every Friday for some individual stocks, and daily expirations for SPX options, the so-called 0DTE options.[2]

The surge in short-term options volumes has spurred new research exploring this novel market, its characteristics, and its implications for market stability. The main focus of these papers is, however, on the prices and returns of the options (Bandi et al. 2024; Almeida, Freire, and Hizmeri 2024; Beckmeyer, Branger, and Gayda 2023), or on the impact of option trading on the underlying market (Dim et al. 2024; Adams, Fontaine, and Ornthanalai 2024; Brogaard, Han, and Won 2023), with limited analysis on the quality of the market itself.

This paper aims to fill this gap by studying the liquidity of short-maturity and ultra-short-maturity options and its relation to the intraday order flow distribution, with a particular focus on the intraday volatility of the order flow. According to standard market microstructure models (Glosten and Milgrom 1985; Stoll 1978), trading patterns that increase risks and

[1] See, for example, *https://www.cboe.com/insights/posts/the-evolution-of-same-day-options-trading/*

[2] In 2010, CBOE introduced the first pm-settled SPX Weeklys (SPXW) with Friday expirations. In 2016, CBOE expanded its listings by launching SPXW options that expired on Mondays and Wednesdays. By 2022, CBOE had further broadened its listings to include SPXW contracts expiring on every weekday from Monday through Friday.

costs for liquidity providers should be reflected in the bid-ask spread.[3] Our hypothesis is that these effects should be especially relevant in options with very short maturities. Intuitively, in options markets with very short times to expiration, like 0DTE options, liquidity providers do not have time to earn a premium on their inventory (e.g., in Fournier and Jacobs 2020). They must react quickly to the order flow, monitoring is more intense than in options with longer maturities, and the required premium should be immediately incorporated into the bid-ask spread. Moreover, the daily measures of order imbalances (buy minus sell orders) used in the literature (see Christoffersen, Goyenko, Jacobs, and Karoui 2018; Muravyev 2016, among others) may not fully capture the intraday dynamics of trading, which is important for liquidity providers who continuously rebalance their inventory throughout the day. While buy and sell orders might balance out over the day, resulting in a small net daily order flow, intraday order imbalances can be highly volatile. Inventory models that explicitly account for the stochastic nature of the order flow (see, for example Campi and Zabaljauregui 2020; Bogousslavsky and Collin-Dufresne 2023) recognize the important role of the second moment of the order flow distribution and its positive relation to illiquidity. Intuitively, volatile order flow is linked to the volatility of changes in liquidity providers' inventory, and under the standard assumption that liquidity providers are averse to inventory variance, these models find that more volatile order flow is associated with greater illiquidity in equilibrium. Guided by these insights from bid-ask spread models, we investigate the impact of order flow distribution on bid-ask spread in short-term options, as well as the role of option maturity in this relationship.

We begin by documenting that, while daily order imbalances are relatively small in absolute value (as documented by Dim et al. 2024), the intraday distribution of order flow

[3]See Foucault, Pagano, and Röell (2013) for a review of market microstructure models where the bid-ask spread is endogenously set by liquidity providers to compensate for asymmetric information risk and/or inventory and order processing costs.

has been highly volatile since the years following the financial crisis. Examining the distribution of order flow on days characterized by high trading costs versus those with low trading costs reveals that illiquidity is associated with a distribution with very high volatility and interquartile range. This suggests that more dispersed orders are risky for liquidity providers and detrimental to overall liquidity, consistent with a standard hypothesis of liquidity providers aversion to inventory variance (Ho and Stoll 1981; Stoikov and Sağlam 2009). Formal time-series and panel regressions confirm this pattern: high intraday order flow volatility on day t is positively associated with trading costs on the same day. This result is highly significant, applies to both the SPX options market and the market of individual stock options (time-series and cross-section dimension), and survive the inclusion of numerous controls, including daily measures of volumes, order imbalance, volatility, option greeks, stock characteristics, past measures of spread, and variables that measure market-makers rebalancing needs. Importantly, all our regressions include time-fixed effects such as day-of-the-week, month-of-the-year, and year dummies to account for strong seasonalities in the spread.

Next, we analyze the relation between volatile intraday order flow and illiquidity separately for options in different maturity buckets with one-week intervals, ranging from options expiring on the same day (zero days to maturity or 0DTE), to options expiring in one week (1-6 days), and up to options expiring in seven weeks (42-48 days to maturity). We find that the coefficient of the relation between order flow volatility and spread is positive for all maturity samples and monotonically decreasing in option maturity. Particularly high are the coefficients estimated for 0DTE options and options expiring in one week, which are two times the coefficients estimated for the other maturities. This result confirms our hypothesis that the shorter the expiration of the options, the more sensitive is the bid-ask spread to risky intraday trading patterns.

Volatile order flow can be risky or costly for liquidity providers for multiple reasons. It implies that liquidity providers face a dispersed order flow, varying in both magnitude and sign throughout the trading day. This variability results in increased inventory management costs directly related to trade absorption, such as order processing and inventory rebalancing costs, as well as indirectly related costs, including heightened monitoring and greater uncertainty about future liquidity provision. Since options on individual stocks trade across sixteen exchanges, we can conduct a more granular exchange-level analysis by leveraging the exchange flag in our data that identifies where each trade occurred. This unique feature of the dataset allows us to study heterogeneous exchange-specific liquidity and the role of trade absorption and direct costs in the volatile order flow-illiquidity relationship. Intuitively, the exchange that absorbs the trades and experiences an inventory shock faces both direct and indirect costs of providing liquidity, while other exchanges are only subject to indirect costs. Moreover, if trade absorption costs are the primary driver of the volatile order flow-illiquidity relationship, then exchange-specific liquidity should be more closely related to exchange-specific order flow volatility. Conversely, if liquidity providers' aversion to order flow volatility extends beyond trade absorption, i.e., due to indirect costs, exchange-specific liquidity should be more associated with total order flow volatility.

We conduct two distinct analyses: one at the intraday level and another at the daily level. At the intraday level, we find that after a trade, the exchange where the trade took place raises the spread by approximately 1%, while other exchanges lower their spreads by around 22 basis points. This result suggests that direct costs of liquidity provision are significant and quickly reflected in the spread, while the spread reductions on other exchanges may reflect efforts to attract trading volume. Additionally, past order flow volatility, measured up to the time of trade, positively impacts spread changes across all exchanges, regardless of where the trade occurred. This indicates that the relationship between volatile order flow and illiquidity is largely driven by indirect costs from one trade to the next. At the daily level, we examine whether exchange-specific liquidity is more closely associated with the volatility of total order flow or exchange-specific order flow volatility. The results reveal that, although both factors are significant, total order flow volatility has a stronger influence in both magnitude and significance. Overall, these results suggest that indirect costs have a greater effect on liquidity and that exchanges learn from the total order flow across all exchanges.

Our paper contributes to different strands of literature. It is primarily related to the recent literature that studies the novel market of short-maturity options and ultra-short maturity options (Almeida et al. 2024; Bandi et al. 2024; Dim et al. 2024; Beckmeyer et al. 2023; Adams et al. 2024). The novel aspect of our investigation is the emphasis on option liquidity and its relation to the order flow. Relatedly, Christoffersen et al. (2018) document a substantial illiquidity premium in the option market for longer maturity options. They also analyze the determinants of the bid-ask spread in the cross-section of options and find that the daily absolute value of the order imbalances from non market-makers are positively related to illiquidity. Unlike Christoffersen et al. (2018), we focus on the intraday distribution of the order flow and its impact on liquidity in the time-series and cross-section dimensions of short-term options.

We also contribute to the extensive literature examining order-flow-related measures of trading in options (see, e.g., Bollen and Whaley 2004; Garleanu, Pedersen, and Poteshman 2008; Muravyev 2016; Ni, Pearson, Poteshman, and White 2021; Cao, Jacobs, and Ke 2024; Fournier and Jacobs 2020). Unlike these studies, we introduce in the option market the new measure of risky, volatile intraday order flow and show that this measure is particularly relevant for ultra-short maturity options, while previous research has focused on the first moment of the order flow distribution.

Finally, while order flow volatility has not been explored in the options market, it has been studied in the equity market by Chordia, Hu, Subrahmanyam, and Tong (2019), Bogousslavsky and Collin-Dufresne (2023), and in the bid-ask spread model of Campi and Zabaljauregui (2020). While Chordia et al. (2019) and Campi and Zabaljauregui (2020) emphasize the informational role of order flow volatility, our work is more closely aligned with the inventory model of Bogousslavsky and Collin-Dufresne (2023). We extend their empirical analysis to the options market, specifically examining how option maturity impacts the relationship between order flow volatility and illiquidity. Additionally, we leverage a unique feature of individual stock options data, which records the exchange where trades occurred, enabling us to isolate the role of direct and indirect inventory management costs in this relationship.

The paper proceeds as follows. Section 2 introduces the conceptual framework, and Section 3 describes the data. Section 4 presents the empirical results: Sections 4.1, 4.2 and 4.3 analyze the order flow of SPX options, while Section 4.4 and 4.5 examine the cross-section of options on individual stocks and conducts the exchange-specific analysis, respectively. Section 5 provides additional robustness analysis, and Section 6 concludes.

2 Conceptual Framework

According to standard models of inventory management for option market-makers (Stoikov and Sağlam 2009; Ho and Stoll 1981; Ho and Macris 1984), liquidity providers set the bid-ask spread in the option market to maximize their utility based on their final wealth. This wealth is determined by the cash earned from the bid-ask spread and their inventory position. Standard utility functions typically incorporate an aversion to inventory variance (Stoikov and Sağlam 2009), showing that higher inventory risk leads to wider bid-ask spreads.

Inventory risk, in turn, depends on the dynamics of option prices and order flow. To formalize this, let q_t represent the liquidity providers' position in options at time t and O_t the option price. The value of their inventory I_t at time t is $I_t = q_t O_t$. Assuming both q_t and O_t follow stochastic dynamics governed by Ito processes, applying Ito's lemma gives:

$$dI_t = q_t dO_t + dq_t O_t + d[q_t, O_t].$$

This equation shows that inventory risk arises from two sources: the fluctuations in option prices and the stochastic nature of order flow. Empirical research has primarily focused on the first source, documenting that bid-ask spreads increase with the delta, vega, and gamma of the options traded (Christoffersen et al. 2018; Stoikov and Sağlam 2009).

In this paper we focus on the second source of inventory risk: the stochastic nature of the order flow, and we test the following hypothesis:

H0: *The higher the volatility of the order flow distribution, the higher the trading costs.*

This relationship would indicate that the second component of inventory risk is also significant for liquidity providers and is reflected in bid-ask spreads, with the sign consistent with standard utility functions. In fact, bid-ask spread models that explicitly account for the stochastic distribution of order flow in the stock market find that, in equilibrium, illiquidity is positively associated with order flow volatility (see Campi and Zabaljauregui 2020 and Bogousslavsky and Collin-Dufresne 2023).

3 Data

We obtain options trade data from the CBOE's LiveVol, including timestamp down to milliseconds, trade price and size in contracts, the prevailing NBBO prices, and the contemporaneous best bid and offer prices of underlying security for each trade reported by the Options Price Reporting Authority (OPRA). The dataset spans the intraday trading activity of all equity and index options from January 01, 2004, to July 16, 2021. We merge the LiveVol data with the Center for Research in Securities Prices (CRSP), from which we obtain daily stock returns, trading volumes, prices, and the number of outstanding shares. Additionally, we combine the intraday trade data with OptionMetrics, allowing us to access daily implied volatility and Greeks for option series. For each day, option series are required to be present in all three data sources.

We focus on S&P 500 index options and options on individual stocks which are the constituents of the S&P500 index. We track S&P 500 constituents on a monthly basis following the historical components file from CRSP. A stock is included in our cross-sectional sample for a given month if it was part of the S&P500 index in the previous month.

Our focus lies on short-term options with maturities of up to one month, as these have seen the most significant growth in trading activity over time (Almeida et al. 2024), raising questions about the stability of the option market. Among these options, at-the-money (ATM) options are of special interest, as they have the highest decline in value as maturity approaches, and the highest value of gamma, which is particularly relevant for delta-hedgers liquidity providers (see Ni et al. 2021). Moreover, the prices and spreads of ATM options are less affected by market microstructure noise than out-of-the-money (OTM) options (Duarte, Jones, and Wang 2019).[4] Our main sample is thus composed by ATM options, defined by an absolute delta between 0.375 and 0.625, with up to 48 days to maturity. The delta of each option series is assessed at the close of the preceding business day; for example, an option on day t is considered at-the-money if its absolute delta, as recorded by OptionMetrics at

[4] In the robustness Section 5, we analyze out-of-the-money options and find results consistent with those observed for the at-the-money options in the baseline analysis.

the close of day $t-1$, falls between 0.375 and 0.625.

We examine all options trades recorded by OPRA between 9:30 a.m. and 4:00 p.m US Eastern time. The OPRA database encompasses trades occurring across the sixteen exchanges where investors can trade options. SPX index options are specifically traded only on the CBOE exchange, with regular trading hours concluding at 4:15 p.m. Additionally, they are available for trading during global trading hours before the market opens and after it closes, with this time frame gradually expanding over time.[5] To ensure consistency in coverage across various securities and over time, we concentrate on the standard trading hours of 9:30 a.m. to 4:00 p.m. for all underlying stocks and the S&P500 index.

Following the literature, we apply filters to the intraday trade data to clean obvious errors and outlying records. We filter out the following observations: (1) cancelled trades; (2) trades with zero or negative price, size, and/or bid-ask spread; (3) trades whose sizes are higher than 100,000 contracts; (4) trades whose prices are below bid minus spread or above ask plus spread; and (5) trades whose prices are below $0.10.

4 Empirical Results

This section explores the characteristics of intraday order flow distribution in short-term at-the-money options and its relation with illiquidity. Sections 4.1, 4.2 and 4.3 focus on the order flow of SPX options, while Section 4.4 examines the cross-section of options on individual stocks. The analyses show that in all samples higher variance in intraday order flow is associated with increased trading costs in the time-series and in the cross-section. Section 4.5 performs an exchange-specific analysis to investigate the role of direct and indirect costs

[5] In 2015, CBOE extended trading hours for SPX options to include 3 a.m. to 9:15 a.m. In 2021, the start time moved to 8 p.m. of the day before, and in 2022, CBOE added the 'Curb' session from 4:15 p.m. to 5 p.m.

of inventory management.

4.1 Order Flow and Daily Statistics

Our primary focus is on analyzing the distribution of intraday order flow. To achieve this, we first need to flag every trade as buy (i.e., buyer-initiated) versus sell (i.e. seller-initiated), since the OPRA data does not explicitly provide this information.

Following the literature on high-frequency data of trades and quotes of stocks (Lee and Ready 1991; Bogousslavsky and Collin-Dufresne 2023), trades are categorized as buys or sells based on the quote rule and tick rule. Specifically, if a trade price is closer to the National Best Offer, it is classified as a buy; otherwise, it is classified as a sell. If a trade price falls at the NBBO quote midpoint, we follow Bryzgalova, Pavlova, and Sikorskaya (2023), and apply the quote rule to the Best Bid and Offer (BBO) prices from the exchange where the trade was executed. In cases where the trade price equals the BBO mid price, the tick rule is applied: if the current trade price exceeds the price of the last trade in the same option, the current trade is classified as a buy; conversely, it is classified as a sell.

In the stock market, it is well-known that the quote rule effectively classify trades that occur without any price improvements, resulting in buyer-initiated (seller-initiated) trade prices that are very close to the quoted ask (bid) prices. However, when a trade receives significant price improvement, the trade classification may be prone to misclassification (Ellis, Michaely, and O'Hara 2000). To validate our quote rule on this critical sample, we obtain a sample of about one million option trades executed on 2024-02-02 through auctions.[6] These trades are mostly retail orders which have been automatically routed into auctions to receive the best price-improvement. Within the auction database, we have access to the actual trade

[6]We thank SpiderRock Data & Analytics for providing this auction data.

direction (buy versus sell) along with the prevailing bid and ask quotes of the exchange where the trade occurred. Analysis reveals that, in this sample, the quote rule successfully classifies approximately 85% of the trades.[7]

We then partition the trading day into equispaced time-intervals, and calculate the option order flow on day t in each interval d by subtracting the trade size of seller-initiated trades of all options i from that of buyer-initiated trades:

$$\text{Order Flow}_{t,d} = \sum_i \text{Trade Size of Buys}_{i,t,d} - \sum_i \text{Trade Size of Sells}_{i,t,d}. \tag{1}$$

To obtain the daily order flow, which we label order imbalance and denote it with the variable OI_t, we sum the order flows across the intra-day intervals:

$$OI_t = \sum_d \text{Order Flow}_{t,d}. \tag{2}$$

Several choices for the length of the time intervals are possible. The optimal choice balances the need for high frequency data and option liquidity; if the intervals are too short, we risk having many empty intervals due to insufficient trading activity. While this might not be an issue for SPX options, it could be problematic for some individual stock tickers. Therefore, we opt for a 5-minute interval, which provides a suitable balance as an intermediate high frequency.[8] The first interval spans from 9:30 am to 9:35 am, while the final interval spans from 3:55 pm to 4:00 pm, and in total we have 78 intervals per day.

[7]Another potential source of misclassification could occur with trades that are components of multi-leg strategies. Li et al. (2020) propose an heuristic approach to classify such trades. However, this methodology, relying on manual trade matching, cannot be verified without a sample containing the actual trade direction. Additionally, Li et al. (2020) find that in their sample, 70% of vertical spreads and 60% of straddles can be classified using the quote rule. Therefore, we opt to adhere to the standard quote rule for trade classification.

[8]Qualitatively similar results are obtained if we partition the day into 1-minute intervals or 10-minutes intervals. Results are available upon request.

The order flow measures the buy versus sell pressure in the market. It is positive when investors are, overall, buying more options than selling them, and negative otherwise.

It is crucial to emphasize that our investigation is abstracted from which group of investors initiates or absorbs trades. Options exchanges typically classify traders as customers, firms, and market makers. Market makers, employed by exchanges, primarily provide liquidity in the options market. The roles of other participants are, on the contrary, less clearly defined. Customers and firms can both contribute to market liquidity by placing limit orders, effectively adding to the order book. Conversely, they can also introduce more aggressive orders, thereby depleting liquidity from the market. Often, customers orders are matched with other customers orders, in which case traders in same category are both demander and supplier of liquidity. Our focus lies in examining the characteristics of the intraday distribution of the total net order flow of all participants seeking liquidity in the options market. In Section 5.1, we will closely compare our order flow measure with data on market-makers' inventory. We find that although the two measures are negatively related, the correlation is not notably high, suggesting that market makers are not the sole providers of liquidity in the option market.

[Figure 1 here]

We compute the daily order flow separately for ATM calls and put options with one month to maturity. Figure 1 displays the average daily volume (Panel A) and order imbalance (Panel B) for put and call options in each year of the sample period. We calculate the daily options volume by summing the number of contracts traded across all option series within each option group (calls or puts):

$$\text{Volume}_t = \sum_i \text{Trade Size}_{i,t} \tag{3}$$

Panel A confirms the well-known upward trend in SPX option volumes since the years 2012-2013, observed in both call and put options.

Panel B documents some important characteristics of the daily order imbalances. On average, the order flow is positive for SPX put options and negative for SPX call options, displaying some variability across the years; this trend corresponds with findings from Chen, Joslin, and Ni (2019) and Jacobs, Mai, and Pederzoli (2024), among others. In the aftermath of the financial crisis, the order flow size surged, reaching an average of 2000 contracts as net order flow per day in 2010 (positive for put options and negative for call options). Post-crisis, the daily order flow size remained relatively stable with occasional deviations. For instance, during the years 2015 or 2018, we observe a modest average daily order flow in both call and put options. Particularly noteworthy are the last two years of our sample, 2020 and 2021, where we document an average negative order flow for both call and put options, with a magnitude around 2000.

Overall, the graph illustrates that, despite the surge in option volumes (as evident in Figure 1, Panel A), buy and sell orders remain relatively balanced throughout the day, resulting in no significant increase in the overall size of the daily net order flow, consistent with results documented by exchange analysts and recent literature.[9] The next section will offer a new perspective on order flow patterns by analyzing the intraday distribution, revealing that even when the daily order flow is small, there can be substantial intraday variation.

[9]See, for example, *https://www.cboe.com/insights/posts/volatility-insights-evaluating-the-market-impact-of-spx-0-dte-options/*

4.2 Intraday Order Flow Distribution

In this section, we start our novel analyzes of the intraday distribution of the order flow. Every day we calculate mean, standard deviation, skewness, and quartiles ($q_{0.25}$, $q_{0.5}$, and $q_{0.75}$) of the seventy-eight 5-minute intervals order flows calculated according to equation 1.

[Table 1 here]

Panels A1 and B1 of Table 1 present the average of the daily statistics over the years for ATM SPX call and put options.[10] Figure 2 complements Table 1 by illustrating the time-series of the average 5-minute order flow with intraday confidence intervals.[11]

[Figure 2 here]

The intraday order flow distribution appears largely symmetric over the entire sample period, with an average 5-minute order flow across the years of -6 for ATM call options and 9 for ATM put options. These statistics exhibit variability over the years, ranging from a minimum of -28.76 (recorded in 2020 for ATM calls) to a maximum of 32.65 (recorded for ATM puts in 2016). However, the mean 5-minute order flow does not display any time trend, as apparent from Figure 2. Skewness estimates, which are consistently low in all years, further confirm the overall symmetry of the intraday order flow distribution. Despite the small magnitude, the data indicates that the ATM call market typically exhibits a negatively skewed order flow distribution, whereas the ATM put market shows varying skewness signs

[10] In this preliminary analysis in which we are comparing the intraday order flow distribution over the years, we present results only up to 2020, as our sample ends in July 2021. The first half of 2021 will be included in the formal regression analysis in the subsequent sections.

[11] Specifically, for every day in the sample, we compute the average intraday 5-minute order flow, μ_t, with its confidence interval $\mu_t \pm Z\frac{\sigma_t}{\sqrt{n}}$, where σ_t is the standard deviation of the intraday 5-minute order flows. The figure displays the monthly averages of these daily quantities.

across different years. Standard deviation values have consistently been high, fluctuating from a minimum of 229.68 (recorded in 2004 for ATM calls) to a maximum of 1764.67 (recorded in 2011 for ATM puts), resulting in relatively wide confidence intervals for the average 5-minute order flow. For instance, in 2011, while the average 5-minute order flow for put options stands at 6.22 contracts, the standard deviation averages 1764.67. This leads to a confidence interval for the average order flow in the 5-minute interval of $[-385, 398]$ contracts, indicating a high variability of the 5-minute order flow during the day and across days. The median and the 0.25-0.75 quartiles confirm the overall symmetry of the distribution. By looking at the time-series of the average standard deviation by year, depicted in Figure 2, we find that the distribution initially exhibited a higher degree of concentration in the early years of the sample. Subsequently, it became more dispersed during the financial crisis in 2007, and, for ATM call options, it then stabilizes with some notable spikes around 2018. For ATM puts, the pattern is similar, with notable spikes in 2011 (concurrent to the European financial crisis), and 2018 (concurrent with the Volmageddon incident). The interquantile range, calculated as $q_{0.75} - q_{0.25}$ and presented in Table 1, shows a mild increase over the years.

Overall, this analysis shows that, beginning with the financial crisis in 2007, the distribution of intraday order flow has remained stable over the years. It exhibits high symmetry but also a very high level of standard deviation. Notably, in the ATM put market, this standard deviation peaks during years marked by significant turbulence in volatility markets.

To gain a deeper insight into the relationship between intraday order flow distribution and option market quality, we compare the distribution of intraday order flow during days characterized by high transaction costs with those characterized by low transaction costs. Our goal is to identify the distribution characteristics that are significant for liquidity.

In accordance with Christoffersen et al. (2018) and Bogousslavsky and Collin-Dufresne

(2023), we measure the cost of trading options with the effective spread incurred by option traders. Specifically, for each trade i on day t, we define the percent effective spread as:

$$\text{Effective Spread}_i = 2|\ln P_i - \ln M_i| \tag{4}$$

where P_i is the price of the trade i and M_i is the prevailing midpoint of the NBBO. For each day, the daily effective spread is the volume-weighted average of effective spreads across trades within the same option category (ATM calls and puts), where the volume is the total number of contracts traded.

[Figure 3 here]

Figure 3 displays the time series of the daily effective spread (Panel A) and daily changes in effective spread (Panel B) across the entire sample period for our samples of ATM SPX call (left graphs) and put options (right graphs). We denote the two variables as ES_t and ΔES_t, respectively. The graph illustrates a downward trend in the spread throughout the sample period, along with recurrent spikes that may suggest seasonal patterns in both the spread and the daily changes in the spread. We will account for seasonalities and time-trends in the regression analysis of Section 4.3 and 4.4.

We compare the intraday distribution of order flow on days characterized by low and high trading costs as follows: for each year in the sample, we identify the days falling in the bottom 10% and top 10% based on their ΔES_t values.[12] We then calculate the summary statistics (mean, standard deviation, skewness, and quartiles) shown in Table 1 for each of these subsamples. Panels A2 and B2 of Table 1 present the difference in these statistics between days with low and high transaction costs, segmented by year.

[12]Similar results are obtained when splitting the sample according to ES_t instead of ΔES_t. Results are provided in the Online Appendix. We use ΔES_t as the main measure of trading costs in this preliminary analysis to be consistent with the regression analysis of section 4.3.

The results are qualitatively similar across the years for both call and put options markets. Days with low transaction costs have a distribution of intraday order flow that consistently shows lower standard deviation and smaller interquartile range compared to days with high transaction costs. Meanwhile, the distribution remains symmetric in both subsamples, as evidenced by the minimal change in skewness and median. The table also reports the results of testing whether the differences reported are statistically significant within each year. Although these statistical tests have limited power, we find that for half of the years, the differences in standard deviations and first and third quartiles are statistically significant. None of the other statistics show the same consistent pattern. The table also reveals no time-trend in the difference between the standard deviation of order flow on days with low and high trading costs, indicating that extreme distribution days have not become more pronounced over time. However, the current high levels of volumes in the option market represent a mass of traders which could potentially generate a very volatile order flow. This underscores the importance of understanding the implications of volatile intraday order flow distributions.

In summary, the findings of this section suggest that the distribution of intraday order flow holds significant economic implications for market liquidity. Specifically, days in which the average 5-minute order flow is more volatile, as measured by the standard deviation of the distribution and the interquantile range, appear to coincide with days with low option market liquidity. Next section formally tests this pattern through a regression analysis.

4.3 Volatile Order Flow and Option Market Liquidity

In this section, we conduct a formal examination of the relationship between option market liquidity and the standard deviation of the intraday order flow distribution, which were shown to be highly related in the previous section.

We conduct separate time-series regressions for SPX calls and put options using the following specification:

$$\Delta ES_t = \alpha + \beta_1 log(SD_t) + \beta_2 log(\text{Volume}_t) + \beta_3 |OI_t| + \text{Time Controls} + \text{Other Controls} + \epsilon_t, \tag{5}$$

where ΔES_t measures the daily change in the effective spread paid by investors for trading options on day t, $log(SD_t)$ denotes the logarithm of the standard deviation of the intraday order flow distribution on day t, $log(\text{Volume}_t)$ is the logarithm of the daily volume calculated according to equation 3, and $|OI_t|$ is the absolute value of the daily order imbalance calculated according to equation 2. We use the absolute value of the order imbalance, following the findings of Christoffersen et al. (2018), who demonstrated that this measure is strongly related to illiquidity through a market-maker inventory channel. Time controls include day-of-the-week, month-of-year, and year dummies, while other controls include the market return and VIX level on day t, the absolute value of the average delta, vega and gamma of the options on day t, and one-day and two-day lags of ΔES_t. We further segment call and put option samples into maturity buckets with one-week intervals, ranging from options expiring on the same day (zero days to maturity or 0DTE), to options expiring in one week (1-6 days), and up to options expiring in seven weeks (42-48 days to maturity). All variables are calculated separately for ATM calls and put options in each maturity bucket on day t[13], and standard errors are calculated using Newey-West with the optimal lag suggested by Andrews and Monahan (1992).

[Table 2 here]

[13]For 0DTE options we considered the greeks recorded on day $t-1$.

Table 2 presents the summary statistics of the dependent and independent variables included in the regressions, and Panels A1 and B1 of Table 3 presents the regression results segmented by option maturity buckets.

[Table 3 here]

The results consistently reveal a positive and statistically significant relationship between the intraday volatility of order flow $log(SD_t)$ and the effective cost of trading, indicating that days characterized by greater volatility of intraday order flow correspond to lower liquidity. This result holds across various maturity buckets and put call samples, and remains robust after accounting for numerous controls. The breakdown of results into maturity buckets reveals a significant trend in the coefficient of $log(SD_t)$: the coefficient is higher for short-term options and decreases almost monotonically with option maturity.

[Figure 4 here]

Figure 4 presents the coefficient plot of the estimates for increasing maturities along with their confidence bounds. The statistical significance is so high that the confidence bounds are remarkably narrow, and the monotonicity of the estimates stands out clearly from the picture. This pattern indicates that the liquidity of the market for short-term options is more heavily influenced by the intraday distribution of order flow. To formally test for differences in coefficients between the ultra-short maturity sample, including 0DTE options, and other maturities, we conduct a pooled regression of ΔES_t on $log(SD_t)$, with dummies identifying each maturity bucket. Specifically, we introduce seven dummies, D_{1-6}, D_{7-13}, D_{14-20}, D_{21-27}, D_{28-34}, D_{35-41}, and D_{42-48}, representing each maturity bucket except 0DTE. The coefficient of $log(SD_t)$ measures the sensitivity of illiquidity to volatile order flow in 0DTE options, while interactions of $log(SD_t)$ with these dummies assess whether the coefficient differs in other maturity buckets compared to the 0DTE bucket. Panels A2 and B2 of Table 3 present the results. The $log(SD_t)$ coefficient is positive and significant, with a magnitude consistent with the estimate for the 0DTE sample alone. The interaction term coefficients are all negative and significant, confirming the lower sensitivity to order flow volatility in options with longer maturities.

The coefficients in Table 3 related to volumes and the absolute value of order imbalance also offer important insights and connection with the literature. We find that $log(Volume_t)$ is generally positively related to option illiquidity with few exceptions (call options with 1-6 days to maturity and 28-34 days to maturity, and puts with 0 days to maturity and 1-6 days to maturity). While standard market-microstructure models posit that volume should be negatively related to market illiquidity (Kyle 1985), in the options market, higher volumes may also increase inventory risk for liquidity providers, thereby diminishing their beneficial impact on market quality.[14] The absolute value of daily order imbalance, $|OI_t|$, captures the imbalances between buy and sell trades throughout the entire day. It has been utilized in the literature as a measure of demand pressure (Bollen and Whaley 2004; Garleanu et al. 2008) or as an indicator of changes in option market-maker positions and their associated inventory risk (Muravyev 2016). While this variable proves significant in certain specifications, it does not overshadow the significance of order flow volatility, particularly for options in very short maturity buckets. Essentially, these two variables gauge distinct aspects of order flow and are not interchangeable. For instance, a day could witness balanced buy and sell orders, resulting in a very low absolute value of order imbalance, yet the orders may be distributed

[14]Specifically, we find that volumes are generally positively related to the bid-ask spread and daily changes in the bid-ask spread in the time-series analysis of SPX options (see Table IA.3 in the Online Appendix and Table 3). This positive relationship also appears in the panel regression of individual stocks (Table 4). Conversely, in the Fama-MacBeth regression (reported in Tables IA.5 and IA.6 in the Online Appendix), volumes are negatively related to the bid-ask spread and daily changes in the bid-ask spread, consistent with the findings of Christoffersen et al. (2018).

in a highly dispersed manner throughout the day.

4.4 Volatile Order Flow and Option Market Liquidity in Individual Stock Options

The previous section documents a strong positive relationship between the time-series of the cost of trading SPX options and the volatility of the intraday order flow distribution. The relationship is stronger for ultra-short maturities and decreases for longer maturities. This section documents that the same relationships also hold in the market for options on individual stocks.

We consider the constituents of the S&P 500, tracking them monthly from the beginning of our sample. A stock-day is included in our sample if the stock was part of the S&P 500 index in the preceding month. Figure 5 illustrates the number of individual stocks within our sample over the years. At first, the count varies between 100 and 200 during the initial years, and later settles between 300 and 400 from 2009 onward. This trend indicates an expansion in the options market, incorporating a larger number of individual stock tickers.

[Figure 5 here]

Panel B of Figure 1 displays the average daily volumes and order imbalances of at-the-money call and put options with up to 48 days to maturity written on the stocks that are part of the S&P500 index. Unlike SPX options, we find that investors trade more call options than put options on individual stocks, with the difference in volumes significantly increasing from 2020 onwards. The bar graph on the right indicates that the daily order imbalance is, on average, positive for both call and put options. Our findings are novel but qualitatively align with the summary statistics provided by Bryzgalova et al. (2023) and Bogousslavsky and Muravyev (2024) on retail trading, which accounts for a substantial portion of volumes in options on individual stocks in recent years.

Our primary variable of interest, $log(SD_{s,t})$, is the logarithm of the daily standard deviation of the seventy-eight 5-minute order imbalances. It is constructed separately for each stock s using the same procedure as for SPX outlined in section 4.1. Since options on individual stocks may not be traded as frequently as SPX options, we include a stock-day option type (call/put) in the sample if the option group has at least ten non-empty intervals out of the seventy-eight. The other variables related to daily volumes, order imbalance, and effective cost of trading are also constructed separately of each stock-day option-type following equations 3, 2, and 4, respectively.

We perform a panel regression of $\Delta ES_{s,t}$ on $log(SD_{s,t})$ with stock-fixed effect, controlling for volumes and the absolute value of the order imbalance on day t.[15] Other controls include the average implied volatility of options on stock s and day t, $IV_{s,t}$, and the average of the options greeks, i.e., gamma, vega, and the absolute value of delta on stock s and day t.[16] We also control for stock characteristics, as stock return, firm size and stock volume. Time fixed-effects include day-of-the-week, month-of-the-year, and year controls. Standard errors are computed are clustered at the day and stock level.

[Table 4 here]

Table 4 presents the results for call options (Panel A) and put options (Panel B). The samples are further divided into options with maturities of up to 24 days and those with maturities between 25 and 48 days. The results are robust, showing a strong positive relationship between the standard deviation of the order flow and illiquidity for both call and

[15] Qualitatively similar results are obtained using a cross-sectional Fama-MacBeth regression instead of the panel regression, and they are presented in the Online Appendix.

[16] For 0DTE options, we use the greeks recorded on day $t - 1$.

put samples. This relationship remains robust even after controlling for volumes and order imbalance. Additionally, the coefficient is higher for very-short maturity options (up to 24 days to expiration), confirming that the term structure observed in SPX options also applies to the individual stock option market: the shorter the option's maturity, the higher the sensitivity of the trading cost to intraday order flow volatility.

4.5 An Analysis by Exchange

The previous sections document a robust positive relationship between volatile order flow and illiquidity in the time series of SPX options and options on individual stocks. This section examines the mechanism behind this relationship and investigates the role of inventory shocks. Indeed, inventory management costs include costs directly related to trade absorption and inventory shocks, such as transaction costs and those associated with inventory rebalancing, as well as indirect costs, such as monitoring and anticipatory inventory management. In an ideal setting, where we could track the spreads quoted by individual liquidity providers, if costs related to inventory shocks are driving the relationship, those absorbing more trades would quote higher spreads when order flow is volatile. Conversely, if liquidity providers' aversion to order flow volatility extends beyond actual trade absorption, the relationship between liquidity and volatile order flow would remain consistent across providers.

While we do not have this granularity of data on liquidity providers, we can exploit the fact that individual stock options are traded simultaneously across sixteen exchanges. The OPRA database provides the exchange identifier for each trade, along with the contemporaneous best bid and offer quotes across all exchanges. Every exchange designates a primary market-maker, which generally differs across exchanges.[17] As long as liquidity providers are

[17]The current list of designated market makers for each ticker on CBOE and NASDAQ, for example, is publicly available on the website of the exchanges.

heterogeneous across exchanges, exchanges are heterogeneously exposed to inventory shocks, allowing us to isolate the role of inventory shocks in the observed relationship. Muravyev (2016) utilizes a similar multi-exchange setting to quantify the inventory and non-inventory components of a trade's price impact. In contrast, our focus is on the spread and its relation to the standard deviation of the order flow.

We conduct two separate analyses: (i) a trade-by-trade analysis that investigates the differential change in spread after a trade between the exchange that absorbed the trade and the other exchanges, and (ii) a daily analysis that tests whether changes in effective spread across exchanges are more closely linked to the volatility of the total order flow or to exchange-specific order flow volatility. For these analyses at the exchange level we focus on the constituents of the Dow Jones which have been part of the index since the start of our sample period, January 2004. Our sample comprises the following sixteen tickers: AXP, BA, CAT, DIS, DOW, HD, IBM, INTC, JNJ, JPM, KO, MMM, MRK, MSFT, PG, WMT. As in the main analysis, we consider the sample of one-month (up to 48 days to maturity) at-the-money call and put options, with moneyness determined by the delta recorded by OptionMetrics at the end of the preceding day.

For the trade-by-trade analysis, we track, for every ticker and trade, the change in the quoted spread across all exchanges. For simultaneous trades occurring on the same option and exchange, we consolidate them into a single observation. This aggregated observation has a trade size equal to the signed sum of the individual trade sizes and a trade price that is the average of the individual trade prices. All other filters align with those previously applied in the daily analysis. We analyze an average of ten million records for call trades and six million of records for puts trades per stock. Microsoft (MSFT) has the largest option market, with forty million records in the call option sample and eighteen million records in the put option sample. DOW and 3M (tickers DOW and MMM) have the smallest option markets, but their sample still encompass approximately two million records in the call market and one million records in the put market.

We perform the following pooled regression separately for each stock:

$$\Delta Spread_{i,j,\tau} = \alpha + \beta_1 Dummy_{i,j,\tau-1} + \beta_2 log(SD_{0,\tau}) + \beta_3 log(SD_{0,\tau}) Dummy_{i,j,\tau-1} + \epsilon_\tau, \quad (6)$$

where $\Delta Spread_{i,j,\tau}$ is the change in the quoted spread in exchange i for option j from the trade time $\tau - 1$ to the next trade time τ. We measure the quoted spread as the difference between the quoted ask and bid prices on the exchange, divided by the exchange mid price. $Dummy_{i,j,\tau-1}$ is a dummy variable which equals one for exchange i where the trade in option j occurred at time $\tau - 1$. It is zero for all other exchanges. The dummy variable thus captures the differential liquidity response between the exchange that absorbed the trade versus the others. $log(SD_{0,\tau})$ measures the logarithm of the standard deviation of the order flow from the start of the day until time τ.[18] The primary measure considers the order flow across all exchanges, though we will also examine an exchange-specific measure later. Finally, the variable $log(SD_{0,\tau}) Dummy_{i,j,\tau-1}$ is the interaction between the standard deviation of the order flow and the dummy.

[Table 5 here]

Table 5 presents the results, segmented by stock and option-type (Panel A for calls and Panel B for puts). All regressions include day fixed effect, and the standard errors are clustered at the day and exchange levels. $\Delta Spread_{i,j,\tau}$ are also winsorized at the 1% and

[18] The first trades of the day lack sufficient trading history to calculate $log(SD_{0,\tau})$ using the 5-minute order flow as done in the daily analysis. Therefore, we will only consider trades recorded after 10 a.m. Additionally, we implement a higher frequency version of $log(SD_{0,\tau})$ by considering the standard deviation of all signed trade sizes from the start of the day until time τ. Similar results are obtained by calculating $log(SD_{0,\tau})$ using 1-minute order flow.

99% levels to eliminate instances of apparently unrealistic quotes reported by OPRA. All coefficients are multiplied by 100.

The first specification includes only a constant and the dummy, and thus tests if the change in spread after a trade is the same between the exchange where the trade occured and all the other exchanges. We find consistent and robust results across stocks, as well as across call and put samples, indicating that the constant is negative while the coefficient of the dummy variable is positive. Following a trade, the spread decreases by ten to twenty basis points across all exchanges, while it increases in the exchange where the trade was recorded. The actual change in spread in the trading exchange is the sum of these two coefficients, approximately amounting to 1%. Thus, the primary impact of a trade on illiquidity stems from inventory costs, while the non-inventory impact is smaller and negatively related to illiquidity. This last result might indicate an effort from the exchanges that did not absorbed the trades to attract volumes.

In the second specification, we augment the regression with the addition of the standard deviation of the order flow up to time τ. We introduce the variable $log(SD_{0,\tau})$ and its interaction with the dummy variable. The hypothesis we test is whether uncertain order flow, previously shown to be positively associated with illiquidity in the main analysis, plays a more significant role in the liquidity of the exchange that just experienced an inventory shock. The results consistently document a positive coefficient for $log(SD_{0,\tau})$ and an insignificant coefficient for the interaction, indicating that all exchanges are affected similarly by order flow volatility, with no distinction for the exchange that just absorbed the trade.

Finally, we re-estimate the panel regressions using an exchange-specific measure of uncertain order flow, $log(SD_{i,0,\tau})$. Specifically, for each exchange, we calculate the standard deviation of the order flow up to time τ by considering only the trades that occurred on that exchange. Similar to before, our hypothesis to test is that if uncertain order flow is primarily related to illiquidity through an inventory shock channel, we would expect exchanges with the highest levels of $log(SD_{i,0,\tau})$ to revise their spreads more. Moreover, this effect should be more pronounced for the trading exchange. Specification 3 in Table 5 presents the results, documenting that both the coefficients of $log(SD_{i,0,\tau})$ and its interaction with the dummy are insignificant.

Overall, the high-frequency analysis by exchange confirms that exchanges adjust their spreads more when order flow volatility is high, consistent with our earlier findings. Additionally, the results show that it is the volatility of the total order flow, rather than exchange-specific order flow, that correlates with illiquidity, with no difference between the exchange that just absorbed the trades and the others. These findings highlight an aversion to volatile order flow by liquidity providers that extends beyond inventory shock-related costs.

From these results alone, we cannot conclude that trade-related costs do not play any role in the daily relationship documented in the main analysis, as daily rebalancing requirements may not be fully captured by this intraday analysis. Therefore, we also perform a daily analysis.

Specifically, to examine the role of trade absorption at the daily level and align closely with the analysis in Section 4.4, we investigate the heterogeneous changes in daily effective spreads across exchanges and their relationship with $log(SD_{s,t})$ (total order flow volatility) and $log(SD_{s,i,t})$ (exchange-specific order flow volatility).

[Table 6 here]

The results are presented in Table 6. The dependent variable, $\Delta ES_{i,s,t}$ measures the change in effective spread calculated using only trades recorded on exchange i for stock s on day t. The results show that, for both call and put options, the strongest relationship, in terms of both magnitude and significance, is between the spread and $log(SD_{s,t})$. The coefficient for $log(SD_{s,i,t})$ is also significant, indicating that at the daily level the distribution of exchange-specific order flow has also an impact on the exchange liquidity, however the coefficient is nearly ten times smaller than that for $log(SD_{s,t})$.

In summary, the results of this section show that exchange-specific liquidity is mainly driven by the volatility of the total order flow, regardless of whether the order flow was absorbed by the exchange or by others. While exchange-specific order flow dynamics are significant in the daily regressions, their impact is smaller compared to the effect of global order flow. These findings suggest that volatile order flow imposes costs and risks on liquidity providers that extend beyond those solely related to trade absorption, and exchanges are revising their spread based on the distribution of the total order flow.

5 Robustness

This section presents the findings from various robustness analyses. Section 5.1 tests the robustness of our results by including variables commonly used in the literature to capture market-maker inventory size and rebalancing needs. Section 5.2 provides results using the spread in levels rather than changes, as well as the volatility of order flow scaled by volume. Section 5.3 shows that the results also hold in the out-of-the-money options sample. Finally, Section 5.4 presents additional analysis documenting that the relationship between volatile order flow and illiquidity is not driven by i) retail trading, ii) market opening and closing sessions, and that it remains robust when time fixed effects are excluded. The tables of Sections 5.2, 5.3, and 5.4 are reported in the Online Appendix.

5.1 Market Makers Rebalancing Needs

As discussed in Section 4.1, our analysis is abstracted from which group of investors initiates or absorbs trades, as our main focus is on the overall market liquidity supplied by those investors who absorb initiated trades, referred to here as liquidity providers.

Among market participants, market-makers are unique in that they are employed by exchanges specifically to provide continuous liquidity in the market. The literature has documented that variables measuring the order flow absorbed by market makers (Cao et al. 2024; Christoffersen et al. 2018; Muravyev 2016) and their inventory risk (Fournier and Jacobs 2020; Ni et al. 2021) are significant determinants of option market liquidity and future returns.

In this section, we complement our main analysis of Table 3 and test if our results are robust to the inclusion of variables that more precisely measure the inventory and the rebalancing needs of market makers. We consider the following variables: i) the absolute value of the non market-maker order imbalance on day t instead of the absolute value of the order imbalance calculated from the signed order flow as in Section 4.3, ii) the market-makers cumulative net inventory at time $t-1$, and iii) the overall gamma of the market-makers inventory at $t-1$, calculated following Ni et al. (2021). We calculate these variables using the CBOE's Open-Close database[19], which provides the daily numbers of buy and sell orders for SPX options from non-market makers.

[Table 7 here]

Table 7 presents the results and show that, for all options maturities, the relationship between the volatility of the intraday distribution of order flow and liquidity remains robust

[19]See Jacobs et al. (2024) for a detailed description of the Open-Close database along with filtering and merging procedure.

even with the inclusion of new controls. When comparing the non-market-maker order imbalance with our measure of order imbalance from the order flow in Section 4.1, we find a positive relationship between the two measures. However, the correlation is notably low (less than 10%), indicating that market-makers are not the sole liquidity providers in the options market.

5.2 Spread in Levels and Scaled $log(SD_t)$

In this section, we first assess the robustness of our findings by using the daily effective spread ES_t instead of ΔES_t as the dependent variable, following Christoffersen et al. (2018). Table IA.1 and Table IA.2 provide the preliminary analysis and the descriptive statistics for ES_t. This analysis shows that on days with low transaction costs, the intraday order flow distribution consistently exhibits lower standard deviation and a smaller interquartile range compared to days with higher transaction costs. Tables IA.3 and IA.4 present time-series regressions for SPX options and panel regressions for individual stock options using ES_t as the dependent variable. The main results and conclusions remain consistent. Figure IA.1 plots the coefficients of $log(SD_t)$ from Table IA.3, confirming the monotonicity of estimates across maturity buckets and illustrating that short-term option market liquidity is more sensitive to the intraday distribution of order flow.

We further test the robustness of our results by scaling the volatility of order flow and order imbalance by daily volume, resulting in $\log(SD/volume)_t$ and $|OI/volume|_t$ variables. Tables IA.7 and IA.8 report the time-series regression for SPX options and the panel regression for individual stock options using these scaled variables. The findings confirm a positive relationship between the intraday volatility of order flow $log(SD/volume)_t$ and illiquidity, consistent with our baseline results.

5.3 Out-of-the-money (OTM) Option Sample

In this section, we assess the robustness of our findings by varying the sample used in the baseline analysis, specifically examining the relationship between option market liquidity and the standard deviation of intraday order flow distribution for out-of-the-money (OTM) options with up to 48 days to maturity instead of at-the-money (ATM) options. An option on day t is classified as OTM if its absolute delta, as recorded by OptionMetrics at the close of day $t-1$, lies between 0.125 and 0.375. Tables IA.9 and IA.10 present the time-series regression for SPX options and the panel regression for individual stock options using OTM options, respectively. The results align with those of our main analysis, showing a positive and statistically significant relationship between the intraday volatility of order flow and trading costs. The effect is even stronger than in the ATM sample, with coefficients decreasing as option maturity increases.

5.4 Additional Robustness

In this section, we further examine if there is any bias in our main results due to controlling for day-of-week, month-of-year, and year fixed effects (see Jennings, Kim, Lee, and Taylor (2024)). Tables IA.11 and Table IA.12 report the time-series regression for SPX options and the panel regression for individual stock options excluding day-of-week and month-of-year controls. While the adjusted R^2 values mildly decrease after removing these time controls, the primary results and inferences remain consistent.

Finally, we assess to which extent our results are due to: i) retail trading, and ii) the opening and closing trading sessions. Tables IA.13 and IA.14 present the results of Table 3 re-estimated by excluding retail trades (identified with the 'SLAN' flag following Bryzgalova et al. 2023) and excluding the first and last half an hour of trading, respectively. The results consistently demonstrate a positive relationship between intraday order flow volatility and illiquidity, indicating that retail trading and the opening and closing trading sessions are not the main drivers of this effect.

6 Conclusion

The recent surge in volumes in option contracts with increasingly shorter expirations has raised concerns among academics and regulators about the stability of this expanding market. A key characteristic of the options market is its high level of intermediation, leaving an open question as to how effectively liquidity providers can absorb large, potentially imbalanced order flows while maintaining an efficient and well-functioning market.

Our analysis documents economically and statistically significant positive relationship between intraday order flow volatility and illiquidity in options market. The absolute magnitude of the effect decreases with maturity, highlighting the importance of order flow volatility for very short-term options. The effect is pervasive: it holds in the time-series and cross-sectional dimension, and it significantly outweighs the significance of more traditional daily first-moment measures of order flow dynamics, such as volumes or absolute order imbalances. Indeed, even if buy and sell orders balance over the day, resulting in a small net order flow, substantial intraday volatility can still occur. An exchange-specific analysis further shows that liquidity providers are averse to unpredictable order flows even when they do not directly absorb them, highlighting the role of indirect costs and future liquidity provision risk in the observed relationship.

Our findings underscore the potential risks posed by high volumes in short-term option contracts, which can amplify intraday order flow volatility and challenge market stability. We show that as intraday order flow volatility rises, liquidity providers widen bid-ask spreads to manage the elevated risk, resulting in higher hedging costs for investors increasingly dependent on short-term rollover strategies over long-term hedges. This spread widening, in turn, can impair market efficiency by reducing liquidity and price discovery, which may in turn elevate systemic risk. These dynamics highlight critical aspects that regulators should consider to maintain stability and market quality in financial markets.

References

Adams, Greg, Jean-Sebastien Fontaine, and Chayawat Ornthanalai, 2024, The market for 0-days-to-expiration: The role of liquidity providers in volatility attenuation, *Available at SSRN* .

Almeida, Caio, Gustavo Freire, and Rodrigo Hizmeri, 2024, 0dte asset pricing, *Available at SSRN* .

Andrews, Donald WK, and J Christopher Monahan, 1992, An improved heteroskedasticity and autocorrelation consistent covariance matrix estimator, *Econometrica: Journal of the Econometric Society* 953–966.

Baltussen, Guido, Zhi Da, Sten Lammers, and Martin Martens, 2021, Hedging demand and market intraday momentum, *Journal of Financial Economics* 142, 377–403.

Bandi, Federico, Nicola Fusari, and Roberto Reno, 2024, 0dte option pricing, *Available at SSRN* .

Beckmeyer, Heiner, Nicole Branger, and Leander Gayda, 2023, Retail traders love 0dte options... but should they?, *But Should They* .

Bogousslavsky, Vincent, and Pierre Collin-Dufresne, 2023, Liquidity, volume, and order imbalance volatility, *The Journal of Finance* 78, 2189–2232.

Bogousslavsky, Vincent, and Dmitriy Muravyev, 2024, An anatomy of retail option trading, *Available at SSRN* .

Bollen, Nicolas PB, and Robert E Whaley, 2004, Does net buying pressure affect the shape of implied volatility functions?, *The Journal of Finance* 59, 711–753.

Brogaard, Jonathan, Jaehee Han, and Peter Y Won, 2023, How does zero-day-to-expiry options trading affect the volatility of underlying assets?, *Working Paper* .

Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya, 2023, Retail trading in options and the rise of the big three wholesalers, *The Journal of Finance* 78, 3465–3514.

Campi, Luciano, and Diego Zabaljauregui, 2020, Optimal market making under partial information with general intensities, *Applied Mathematical Finance* 27, 1–45.

Cao, Jie, Kris Jacobs, and Sai Ke, 2024, Derivative spreads: Evidence from spx options .

Chen, Hui, Scott Joslin, and Sophie Xiaoyan Ni, 2019, Demand for crash insurance, intermediary constraints, and risk premia in financial markets, *The Review of Financial Studies* 32, 228–265.

Chordia, Tarun, Jianfeng Hu, Avanidhar Subrahmanyam, and Qing Tong, 2019, Order flow volatility and equity costs of capital, *Management Science* 65, 1520–1551.

Christoffersen, Peter, Ruslan Goyenko, Kris Jacobs, and Mehdi Karoui, 2018, Illiquidity premia in the equity options market, *The Review of Financial Studies* 31, 811–851.

Dim, Chukwuma, Bjorn Eraker, and Grigory Vilkov, 2024, 0dtes: Trading, gamma risk and volatility propagation, *Working Paper* .

Duarte, Jefferson, Christopher S Jones, and Junbo L Wang, 2019, Very noisy option prices and inference regarding the volatility risk premium, *Journal of Finance* .

Ellis, Katrina, Roni Michaely, and Maureen O'Hara, 2000, The accuracy of trade classification rules: Evidence from nasdaq, *Journal of financial and Quantitative Analysis* 35, 529–551.

Foucault, Thierry, Marco Pagano, and Ailsa Röell, 2013, *Market liquidity: theory, evidence, and policy* (Oxford University Press, USA).

Fournier, Mathieu, and Kris Jacobs, 2020, A tractable framework for option pricing with dynamic market maker inventory and wealth, *Journal of Financial and Quantitative Analysis* 55, 1117–1162.

Garleanu, Nicolae, Lasse Heje Pedersen, and Allen M Poteshman, 2008, Demand-based option pricing, *The Review of Financial Studies* 22, 4259–4299.

Glosten, Lawrence R, and Paul R Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of financial economics* 14, 71–100.

Ho, Thomas, and Hans R Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial economics* 9, 47–73.

Ho, Thomas SY, and Richard G Macris, 1984, Dealer bid-ask quotes and transaction prices: An empirical study of some amex options, *The Journal of Finance* 39, 23–45.

Hsieh, PeiLin, and Robert Jarrow, 2019, Volatility uncertainty, time decay, and option bid-ask spreads in an incomplete market, *Management Science* 65, 1833–1854.

Jacobs, Kris, Anh Thu Mai, and Paola Pederzoli, 2024, Identifying demand and supply in index option markets, *Available at SSRN 4142582* .

Jennings, Jared, Jung Min Kim, Joshua Lee, and Daniel Taylor, 2024, Measurement error, fixed effects, and false positives in accounting research, *Review of Accounting Studies* 29, 959–995.

Kyle, Albert S, 1985, Continuous auctions and insider trading, *Econometrica: Journal of the Econometric Society* 1315–1335.

Lee, Charles MC, and Mark J Ready, 1991, Inferring trade direction from intraday data, *The Journal of Finance* 46, 733–746.

Muravyev, Dmitriy, 2016, Order flow and expected option returns, *The Journal of Finance* 71, 673–708.

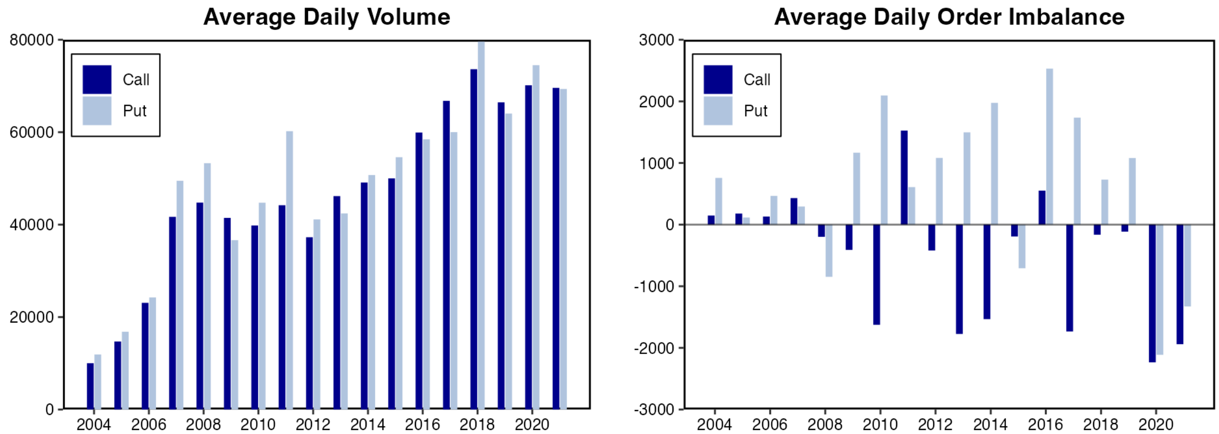
Ni, Sophie X, Neil D Pearson, Allen M Poteshman, and Joshua White, 2021, Does option trading have a pervasive impact on underlying stock prices?, *The Review of Financial Studies* 34, 1952–1986.

Stoikov, Sasha, and Mehmet Sağlam, 2009, Option market making under inventory risk, *Review of Derivatives Research* 12, 55–79.

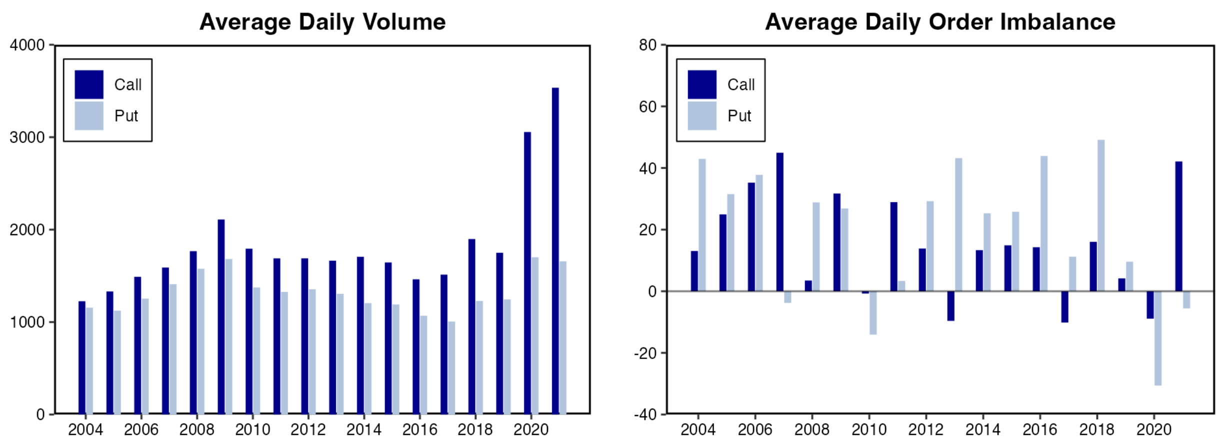
Stoll, Hans R, 1978, The supply of dealer services in securities markets, *The Journal of Finance* 33, 1133–1151.

Figure 1: Daily Volumes and Order Imbalances

Panel A: SPX options

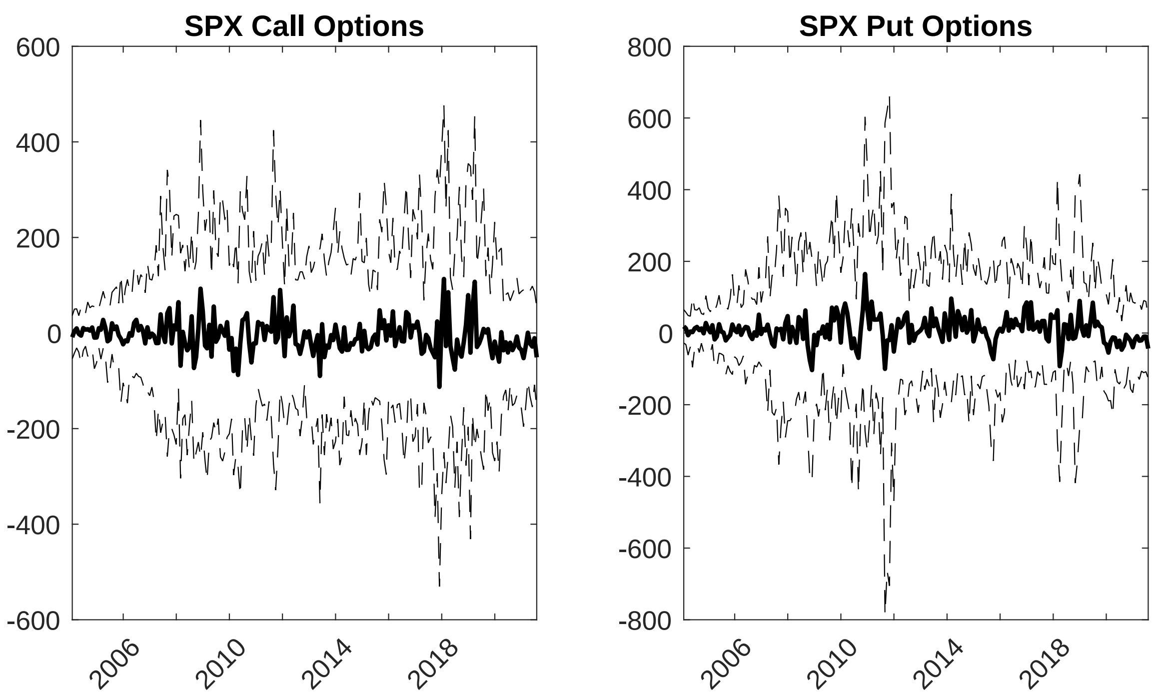


Panel B: Individual Stock Options



This figure displays the average daily volumes and order imbalance for at-the-money (ATM) options with maturities up to one month (48 days), across each year in our sample period. Daily volume is the total number of contracts traded, and daily order imbalance is the difference between buy and sell initiated trades. Panel A displays the average daily volumes and order imbalance for SPX call and put options. Panel B plots for call and put options written on the stocks which are part of the S&P500 index, where we compute average daily volume and order imbalance for each stock-year, and then we take the cross-sectional averages for each year.

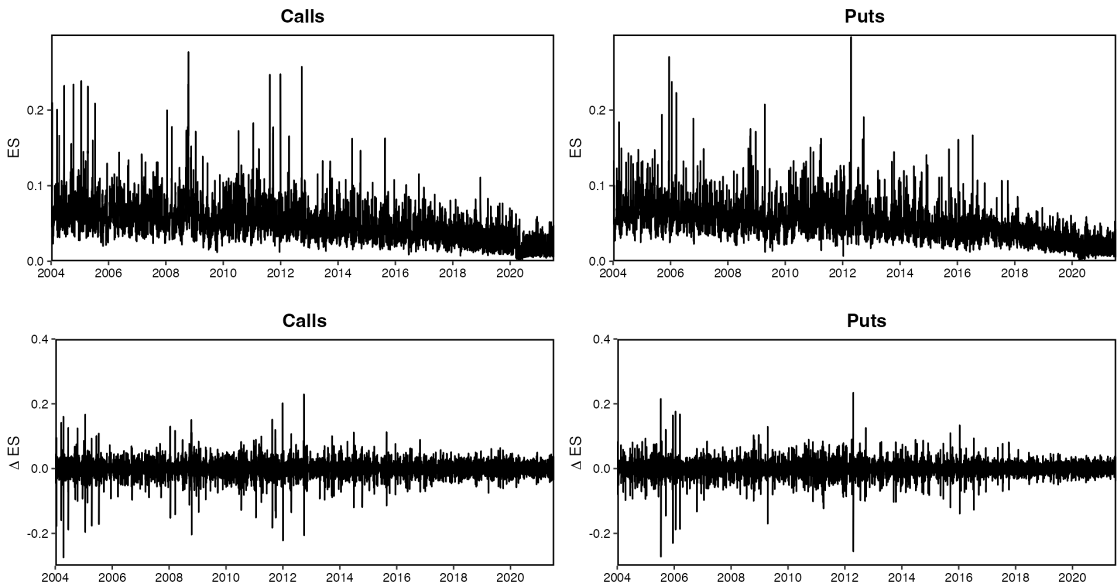
Figure 2: **Intraday Order Flow Distribution Over the Years**



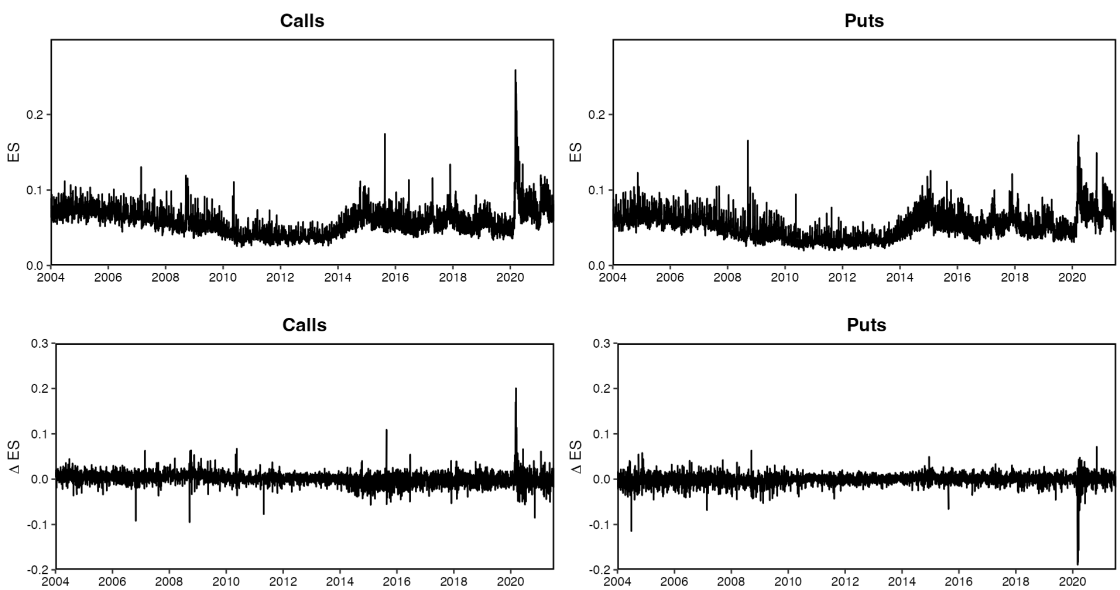
This figure displays the time-series of the average intraday 5-minute order flow for SPX ATM call and put options with confidence intervals. The graph is obtained by dividing each trading day into seventy-eight equal intervals, each covering five minutes, and calculating the order flow (buys minus sells) of put and call options within each interval. The solid lines display the daily average of these 5-minute order flows, μ_t, while the dotted lines depict the 95% confidence intervals, calculated as $\mu_t \pm \frac{Z\sigma}{\sqrt{n}}$, where σ is the intraday standard deviation of the seventy-eight order flows. For readability, the graph displays the monthly averages of these daily quantities.

Figure 3: Time-Series of ES_t and ΔES_t

Panel A: SPX Options

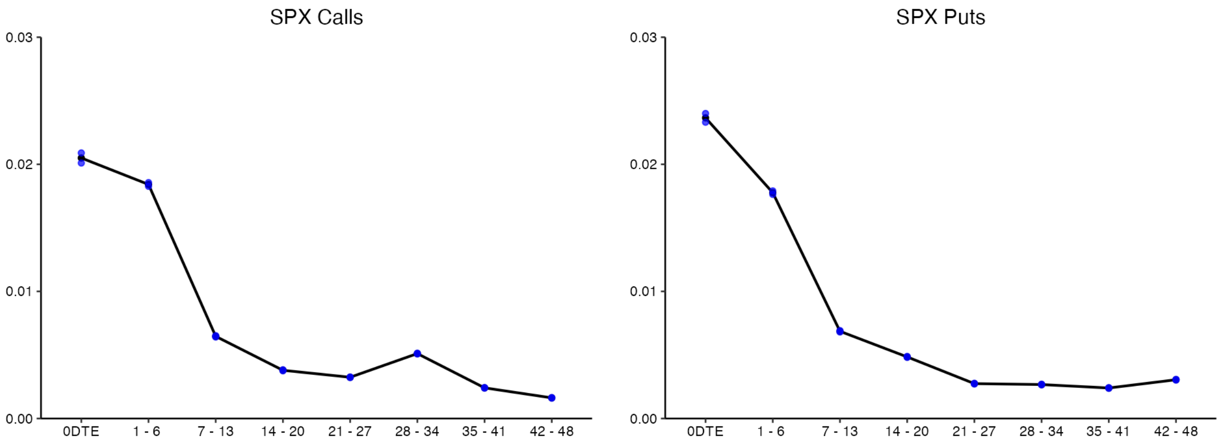


Panel B: Individual Stock Options



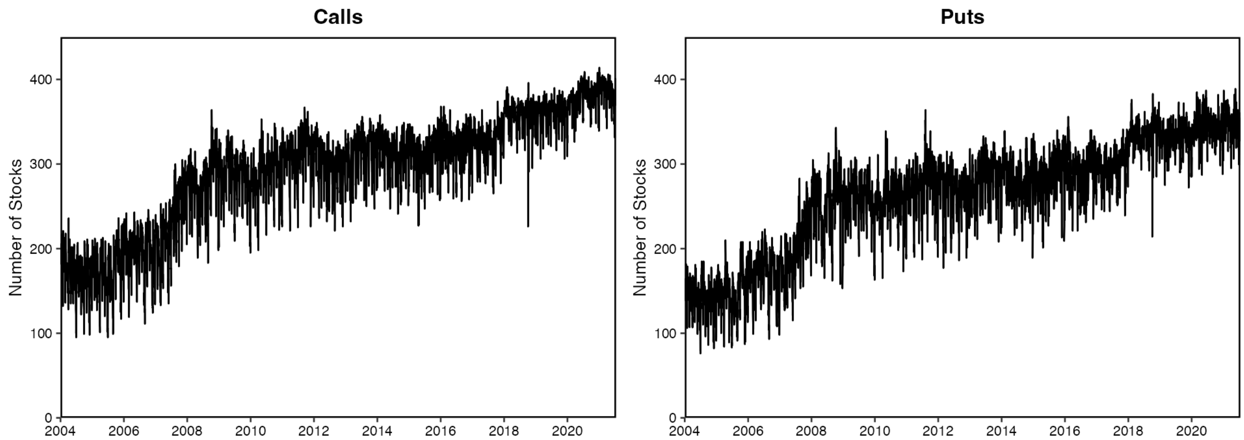
The figure presents the time-series of the daily effective spread and the daily changes in effective spread for ATM call and put options. Panel A presents the graph for SPX options while Panel B presents the graphs for individual stocks options, where a stock-day is included in our sample if the stock was part of the S&P 500 index in the preceding month.

Figure 4: Estimated Coefficients of log(SD_t) Across Maturity Buckets



The figure plots the estimated coefficients for log(SD_t) from the time-series regressions of ΔES_t across different option maturity buckets, as detailed in Table 3. The plot includes 99% confidence intervals, with points highlighted in blue.

Figure 5: Daily Number of Stocks in the Sample



This figure plots the daily number of stocks in the equity options sample for ATM call options and ATM put options. A stock-day is included in our sample if the stock was part of the S&P 500 index in the preceding month. We include equity options with maturities between 0 and 48 days.

Table 1: Intraday Order Flow Distribution Over the Years

Panel A: SPX Calls

	A1: Five-minute Order Flow Summary Statistics						A2: Difference in Distribution Between Low and High ΔES Days					
Year	**Mean**	**Std**	**Skewness**	**Q25**	**Q50**	**Q75**	**ΔMean**	**ΔStd**	**ΔSkew**	**ΔQ25**	**ΔQ50**	**ΔQ75**
2004	2.3	229.7	-0.2	-31.4	3.0	41.9	-20.03	-75.14	0.17	-1.56	-3.70**	-19.54**
2005	3.0	350.2	0.2	-48.6	-0.2	48.5	22.72	-147.68**	1.24	34.85***	2.10	-22.01
2006	1.2	510.3	-0.2	-68.3	2.0	82.3	0.55	-49.53***	0.17	33.18*	-2.77	-27.08
2007	5.0	917.1	-0.2	-129.8	3.2	148.6	-17.52	-400.03	-0.36	65.30	-6.31	-111.37*
2008	-3.4	969.6	-0.5	-128.0	3.1	153.9	-21.21	-290.95	-0.43	53.27	-4.38	-69.80
2009	-6.9	1047.3	-0.1	-113.1	1.3	111.8	-47.94	-217.78	-0.29	4.13	3.06	-16.14
2010	-21.3	971.2	-0.6	-119.9	1.6	125.0	-76.44	-149.49	-0.80	20.41	5.21	-63.75
2011	18.7	922.0	-0.2	-127.6	6.9	151.9	-10.13	-198.46	-0.62	47.00	7.71	-73.89
2012	-6.9	723.4	-0.2	-121.6	3.9	125.0	16.16	-139.37	0.52	18.35	-1.80	-13.82
2013	-24.0	875.9	-0.1	-152.2	-6.6	121.3	-61.56*	-329.71***	-1.43**	31.05	-8.69	-39.49
2014	-19.3	846.8	-0.2	-152.2	-4.9	135.0	-11.94	-200.53**	-0.74	77.78**	9.69	-59.50**
2015	-3.1	792.5	-0.3	-133.6	3.2	140.5	-8.54	-273.39**	-0.07	29.65	0.04	-63.61
2016	6.9	852.8	-0.1	-164.5	2.1	179.9	-68.78**	-94.13	-0.55	23.68	-7.52	-106.34**
2017	-22.2	1157.6	-0.3	-179.1	-4.4	160.3	106.68*	-419.93	1.46	108.29***	8.35	-49.64
2018	-1.6	1121.6	0.0	-196.3	-1.6	189.7	36.70	-716.95*	0.54	125.31***	2.38	-154.20***
2019	-2.1	1020.2	0.1	-161.0	-2.2	148.3	39.55	-501.96*	0.20	81.86***	-7.81	-95.55***
2020	-28.8	597.3	-0.4	-155.8	-12.9	124.1	111.31***	-214.14	0.84	152.23***	48.21***	29.88

Panel B: SPX Puts

	B1: Five-minute Order Flow Summary Statistics						B2: Difference in Distribution Between Low and High ΔES Days					
Year	**Mean**	**Std**	**Skewness**	**Q25**	**Q50**	**Q75**	**ΔMean**	**ΔStd**	**ΔSkew**	**ΔQ25**	**ΔQ50**	**ΔQ75**
2004	10.9	267.7	0.4	-34.2	3.4	50.5	-19.29	-90.45**	0.02	0.16	-1.08	-14.05
2005	0.8	385.8	-0.1	-54.1	2.4	62.7	10.43	-144.95**	-0.28	38.44**	3.94	-16.07
2006	6.7	486.3	0.1	-76.5	1.3	87.6	56.71**	-67.53	1.70**	57.95**	3.25	-14.99
2007	3.9	1011.2	0.0	-163.0	2.3	178.7	-43.73	-279.26*	-0.47	74.28*	-7.63	-106.35***
2008	-12.1	1071.0	-0.3	-186.4	-1.3	180.0	29.80	-406.20**	1.24*	144.97	10.06	-149.65**
2009	15.6	980.6	0.1	-90.8	4.9	111.0	-19.59	-298.88	-0.19	41.76	0.21	-61.96*
2010	28.8	1279.4	0.4	-111.4	9.4	143.7	60.99	-635.74*	1.02	58.80*	-15.13	-85.95*
2011	6.2	1764.7	-0.1	-143.4	10.4	183.5	19.82	-313.39	0.26	52.75	15.90	-71.73
2012	13.5	864.5	0.0	-122.6	3.8	140.2	-89.85**	59.02	-1.25	-4.61	-5.32	-49.92
2013	19.6	811.9	0.2	-118.5	7.2	145.2	-25.11	-305.34**	-1.29	9.17	1.62	-40.78
2014	25.5	858.4	0.3	-131.9	11.3	179.5	-36.73	-154.60	-0.81	70.44**	-11.87	-92.18**
2015	-8.6	803.4	-0.2	-154.0	4.5	161.2	-5.02	-405.08***	0.43	119.59***	-6.44	-143.34***
2016	32.7	756.7	-0.1	-145.8	14.2	214.9	-47.87	-185.71*	0.24	91.71***	-17.73**	-185.39***
2017	22.6	678.1	-0.1	-155.8	8.5	194.3	-19.72	-123.96	-0.59	68.61*	8.17	-83.64***
2018	9.7	1027.6	0.1	-197.5	7.9	232.5	9.52	-197.15	0.77	82.91	13.65	-96.30
2019	14.0	662.5	0.1	-158.1	2.6	171.0	-18.03	-199.89***	0.14	102.56***	-4.87	-121.63***
2020	-27.1	563.1	-0.1	-180.1	-22.9	129.0	30.80	-120.59	-0.94	134.09***	47.06***	-27.03

This table displays averages of intraday order flow distribution statistics for SPX ATM call (Panel A) and put options (Panel B). We divide each trading day into seventy-eight equal intervals, each covering five minutes, and we compute the order flow (buy minus sell orders) within each interval. Panels A1 and B1 display the daily mean, standard deviation (*Std*), skewness, first quartile (*Q25*), median (*Q50*), and third quartile (*Q75*) of the five-minute order flow distribution. Panels A2 and B2 display differences in these average statistics (mean, std, skewness, and quantiles) between low and high liquidity days, classified annually into low liquidity (top 10%) and high liquidity (bottom 10%) days based on ΔES values. Significance levels are denoted by *, **, and ***, representing the 10%, 5%, and 1% levels, respectively.

Table 2: Descriptive Statistics of Δ ES, log(SD), Volume and Order Imbalance. SPX Options

Panel A: Calls

	Δ ES								log(volume)							
	0	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**
Mean	-0.16	-0.24	-0.10	-0.18	-0.19	-0.16	-0.10	-0.26	9.07	8.62	8.77	8.40	8.21	8.36	7.86	7.62
Std	798.58	996.08	275.24	206.24	167.58	173.54	153.62	162.16	1.14	1.59	1.03	1.25	1.38	1.58	1.92	1.98
Skewness	0.20	-0.33	-0.27	0.07	0.04	-0.28	-0.09	-0.07	-0.72	-1.18	-0.68	-0.33	-0.15	-0.15	-0.06	-0.13
Kurtosis	23.21	404.46	16.94	6.15	3.77	12.80	5.11	8.27	0.82	1.03	1.61	0.31	-0.35	-0.54	-1.08	-1.09
ρ	-0.46	-0.49	-0.44	-0.45	-0.40	-0.46	-0.43	-0.48	0.21	0.56	0.42	0.53	0.56	0.58	0.64	0.60
N	1038	2990	2899	2797	2735	2596	2362	2165	1038	2990	2899	2797	2735	2596	2362	2165
	log(SD)								**|OI|**							
	0	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**
Mean	4.79	4.89	5.18	5.05	5.00	5.22	4.86	4.70	1.52	1.87	2.24	2.24	2.14	2.93	2.88	2.37
Std	0.85	1.21	0.98	1.14	1.20	1.29	1.63	1.71	2.01	2.95	3.64	3.82	3.80	5.18	5.37	4.35
Skewness	-0.42	-0.60	-0.17	-0.19	-0.18	-0.34	-0.22	-0.32	3.02	3.97	5.25	4.86	4.22	3.66	3.43	3.48
Kurtosis	0.51	0.47	0.38	-0.11	-0.32	-0.12	-0.72	-0.74	13.68	24.02	46.83	41.30	24.84	17.15	15.82	16.33
ρ	0.06	0.41	0.32	0.41	0.36	0.41	0.50	0.47	0.03	0.17	0.18	0.23	0.20	0.26	0.27	0.25
N	1038	2990	2899	2797	2735	2596	2362	2165	1038	2990	2899	2797	2735	2596	2362	2165

Panel B: Puts

	Δ ES								log(volume)							
	0	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**
Mean	-2.72	-0.19	-0.15	-0.18	-0.14	-0.17	-0.18	-0.12	9.23	8.69	8.78	8.41	8.18	8.27	7.88	7.69
Std	681.15	649.04	251.79	198.32	172.47	149.13	154.74	150.78	1.12	1.54	1.08	1.28	1.40	1.57	1.86	1.92
Skewness	-0.29	-0.35	-0.18	-0.05	-0.10	-0.11	0.00	-0.21	-0.82	-1.11	-0.64	-0.20	0.06	0.02	-0.04	-0.04
Kurtosis	7.43	12.52	4.97	12.59	8.74	4.46	18.85	5.26	1.03	1.00	1.62	0.17	-0.45	-0.57	-0.94	-0.98
ρ	-0.48	-0.47	-0.43	-0.46	-0.43	-0.44	-0.45	-0.44	0.32	0.56	0.41	0.55	0.61	0.66	0.67	0.63
N	1038	2960	2903	2791	2738	2618	2374	2216	1038	2960	2903	2791	2738	2618	2374	2216
	log(SD)								**|OI|**							
	0	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**
Mean	4.88	4.94	5.19	5.06	4.97	5.11	4.82	4.67	1.78	1.91	2.22	2.20	2.20	2.77	2.47	2.43
Std	0.84	1.16	0.98	1.12	1.21	1.30	1.55	1.68	2.17	3.15	3.84	4.67	4.59	6.00	5.20	5.79
Skewness	-0.73	-0.60	-0.20	-0.12	-0.12	-0.15	-0.31	-0.19	2.34	5.77	5.95	7.60	5.90	5.88	5.35	6.21
Kurtosis	1.23	0.60	0.76	0.13	-0.27	-0.07	-0.58	-0.73	7.35	67.03	53.34	85.58	52.17	50.96	42.34	56.23
ρ	0.12	0.37	0.33	0.42	0.45	0.50	0.55	0.54	0.16	0.16	0.21	0.34	0.24	0.33	0.37	0.26
N	1038	2960	2903	2791	2738	2618	2374	2216	1038	2960	2903	2791	2738	2618	2374	2216

The table reports the time-series mean, standard deviation, skewness, excess kurtosis, AR(1) coefficient (ρ), and total number of observations (N) of daily difference in effective spread (ΔES), logarithm of daily volume ($log(volume)$), logarithm of volatility of order-flow ($log(SD)$), and absolute value of daily order flow ($|OI|$) across option matuturity buckets. Panel A presents the results for call options while Panel B presents the results for put options. Absolute value of daily order-flow is divided by 1000 while ΔES is in basis points.

Table 3: Time-series Regressions of ΔES_t on log(SD_t) for SPX Options

Panel A: Calls

	A1: Subsample Regressions								**A2: Pooled Regression with Maturity Dummies**	
Days to Maturity	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**		
log(SD_t)	0.021***	0.018***	0.006***	0.004***	0.004***	0.005***	0.003***	0.002***	log(SD_t)	0.028***
	(4.22)	(5.48)	(5.52)	(5.36)	(6.8)	(8.22)	(5.63)	(4.76)	log(SD_t) D_{1-6}	-0.0202***
log($volume_t$)	0.001	-0.012***	0.002*	0.001	0.0002	-0.002***	-0.0003	0.0001	log(SD_t) D_{7-13}	-0.0194***
	(0.21)	(-3.21)	(1.87)	(0.73)	(0.46)	(-3.85)	(-0.91)	(0.25)	log(SD_t) D_{14-20}	-0.0221***
$\|OI_t\|$	-0.013	0.002	-0.00001	-0.0001	0.002*	0.001	0.002***	0.004***	log(SD_t) D_{21-27}	-0.0228***
	(-1.59)	(0.36)	(-0.01)	(-0.06)	(1.71)	(1.47)	(2.62)	(3.83)	log(SD_t) D_{28-34}	-0.0233***
$R_{M,t}$	-1.955***	0.046	0.006	0.001	0.006	-0.109	0.012	-0.0003	log(SD_t) D_{35-41}	-0.0242***
	(-4.13)	(0.24)	(0.05)	(0.02)	(0.14)	(-1.09)	(0.3)	(-0.01)	log(SD_t) D_{42-48}	-0.0243***
VIX_t	-0.077*	-0.053***	-0.045***	-0.02***	-0.018***	-0.02**	-0.008	-0.004		
	(-1.96)	(-2.59)	(-4.03)	(-2.86)	(-3.01)	(-2.41)	(-0.99)	(-0.55)	Maturity Dummies	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Time Controls	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Other Controls	Yes
N	1038	2990	2899	2797	2735	2596	2362	2165	N	19582
Adj. R^2	0.48	0.43	0.395	0.342	0.31	0.383	0.338	0.364	Adj. R^2	0.388

Panel B: Puts

	B1: Subsample Regressions								**B2: Pooled Regression with Maturity Dummies**	
Days to Maturity	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**		
log(SD_t)	0.024***	0.018***	0.007***	0.005***	0.003***	0.003***	0.003***	0.003***	log(SD_t)	0.022***
	(5.65)	(6.27)	(6.11)	(6.07)	(5.45)	(5.18)	(5.42)	(5.85)	log(SD_t) D_{1-6}	-0.0116***
log($volume_t$)	-0.011**	-0.01***	0.0004	0.001	0.001	0.0002	-0.0001	-0.0003	log(SD_t) D_{7-13}	-0.0138***
	(-2.56)	(-3.7)	(0.38)	(0.93)	(1.3)	(0.41)	(-0.22)	(-0.62)	log(SD_t) D_{14-20}	-0.0157***
$\|OI_t\|$	-0.005	0.009**	0.002	-0.0002	0.004**	-0.0005	0.000002	0.001	log(SD_t) D_{21-27}	-0.0162***
	(-0.48)	(2.56)	(1.39)	(-0.13)	(2.21)	(-0.6)	(0.003)	(0.58)	log(SD_t) D_{28-34}	-0.0178***
$R_{M,t}$	1.661***	-0.054	0.148	0.045	-0.044	0.04	0.157	0.023	log(SD_t) D_{35-41}	-0.0177***
	(4.13)	(-0.44)	(1.59)	(0.97)	(-0.88)	(0.45)	(1.5)	(0.62)	log(SD_t) D_{42-48}	-0.0179***
VIX_t	0.03	-0.024	-0.024**	-0.007	-0.005	-0.017*	0.005	0.01		
	(0.96)	(-1.49)	(-2.56)	(-0.94)	(-0.73)	(-1.67)	(0.75)	(1.26)	Maturity Dummies	Yes
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Time Controls	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Other Controls	Yes
N	1038	2960	2903	2791	2738	2618	2374	2216	N	19638
Adj. R^2	0.47	0.461	0.345	0.348	0.341	0.352	0.316	0.313	Adj. R^2	0.367

Panels A1 and B1 present the time series regressions of ΔES_t on *log(SD_t)* for SPX ATM call (A1) and put options (B1) performed separately for different maturity buckets. ΔES_t is the daily change in the effective spread on day t, *log(SD_t)* is the logarithm of the standard deviation of the intraday order flow distribution on day t, $log(volume_t)$ is the logarithm of the daily options volume, and $|OI_t|$ is the absolute value of the daily order imbalance divided by 10,000. $R_{M,t}$ is daily return on SPX on day t and VIX_t is the level of VIX divided by 100 on day t. Panels A2 and B2 present the results of pooled regressions of ΔES_t on *log(SD_t)* and the interaction of *log(SD_t)* with dummies that identify the different maturity buckets. Time controls include day-of-the-week, month-of-year, and year dummies. Other controls contain one-day and two-day lags of ΔES_t, absolute value of the average delta, vega and gamma of the options on day t. Standard errors are computed using Newey-West with the optimal lag suggested by Andrews and Monahan (1992), and corresponding t-statistics are presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

Table 4: Panel Regressions of $\Delta ES_{s,t}$ on log($SD_{s,t}$) for Individual Stock Options

	Panel A: Calls		**Panel B: Puts**	
	0-24	**25-48**	**0-24**	**25-48**
$\log(\text{SD})_{s,t}$	0.008***	0.004***	0.007***	0.004***
	(46.58)	(48.97)	(39.04)	(41.77)
$\log(\text{volume})_{s,t}$	-0.005***	-0.004***	-0.004***	-0.003***
	(-29.22)	(-44.01)	(-21.55)	(-35.42)
$\lvert\text{OI}\rvert_{s,t}$	-0.003***	0.005***	-0.003***	0.003***
	(-4.75)	(7.78)	(-3.99)	(5.44)
$\text{Return}_{s,t}$	-0.209***	-0.056***	0.098***	0.038***
	(-38.34)	(-24.20)	(17.27)	(15.80)
$\text{IV}_{s,t}$	0.012***	-0.008***	0.014***	-0.006***
	(19.08)	(-18.48)	(22.17)	(-14.16)
Stock FE	Yes	Yes	Yes	Yes
Time Controls	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.431	0.389	0.446	0.356

This table presents the results of panel regressions of $\Delta ES_{s,t}$ on *log($SD_{s,t}$)* for ATM call options (Panel A) and put options (Panel B) written on the stocks that are the constituents of the S&P500. The results are presented for two maturity buckets: 0-24 days to maturity and 25-48 days to maturity. $\Delta ES_{s,t}$ is the daily change in the effective spread on day t for options on stock s. *log($SD_{s,t}$)* is the logarithm of the standard deviation of the intraday order flow distribution on day t for options on stock s, $log(volume_{s,t})$ is the logarithm of the daily options volume, and $|OI_{s,t}|$ is the absolute value of the daily order imbalance (scaled by 10,000). $Return_{s,t}$ is the return of underlying stock on day t, and $IV_{s,t}$ is the average implied volatility of the options on stock s on day t. Other controls include firm size, stock volume, one-day and two-day lags of $\Delta ES_{s,t}$, and absolute values of the average delta, vega and gamma of the options on day t. Time controls include day-of-the-week, month-of-year, and year dummies. Standard errors are clustered at the day and stock level. The corresponding t-statistics are presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

Table 5: Intraday Change in Spread After a Trade

Regression of $\Delta Spread_{i,j,\tau}$

Panel A: Call Options

Ticker	N obs	Specification 1		Specification 2				Specification 3			
		α	$D_{i,j,\tau-1}$	α	$D_{i,j,\tau-1}$	$log(SD_{0,\tau})$	$log(SD_{0,\tau})\times D_{i,j,\tau-1}$	α	$D_{i,j,\tau-1}$	$log(SD_{i,0,\tau})$	$log(SD_{i,0,\tau})\times D_{i,j,\tau-1}$
AXP	3,326,546	-0.22***	1.15***	-0.63***	1.52*	0.15***	-0.13	-0.16*	1.09**	-0.01	0
BA	25,018,432	-0.14**	2.03**	-0.26***	2.12*	0.05***	-0.03	-0.04	2.08*	-0.06*	0.01
CAT	9,699,156	-0.15***	0.89***	-0.40***	1.80**	0.09***	-0.32.	-0.10**	0.84***	-0.01	0
DIS	16,290,675	-0.14***	1.77**	-0.41***	2.11*	0.10***	-0.12	-0.09***	1.78*	-0.02	0
DOW	2,035,970	-0.32***	1.38***	-0.65***	2.32**	0.11**	-0.28*	-0.30***	1.30***	0	0
HD	7,114,453	-0.18***	1.58**	-0.57***	2.97.	0.15***	-0.48	-0.15*	1.82*	-0.02	0
IBM	9,188,497	-0.13***	1.03***	-0.33***	1.21*	0.07**	-0.06	-0.07.	0.88***	-0.02*	0
INTC	15,281,754	-0.13***	0.85***	-0.42***	1.40**	0.08***	-0.14	-0.13***	0.87***	0	0
JNJ	4,250,672	-0.19***	1.57***	-0.65***	2.29*	0.17***	-0.25	-0.20**	1.83**	0.01	0
JPM	15,712,097	-0.10***	0.69***	-0.28***	1.31*	0.05***	-0.17	-0.05*	0.63***	-0.01.	0
KO	4,091,749	-0.22***	1.59***	-0.62***	2.31*	0.13***	-0.22	-0.23**	2.07**	0	0
MMM	1,972,024	-0.29***	1.58***	-0.77***	2.74*	0.21***	-0.43	-0.32*	1.93**	0.01	-0.01
MRK	2,991,683	-0.22***	1.86***	-0.66***	3.13*	0.14***	-0.37	-0.36.	2.40**	0.01	0
MSFT	41,399,546	-0.07***	1.12***	-0.32***	2.05*	0.08***	-0.27	-0.04.	1.19**	-0.01*	0
PG	3,051,203	-0.19***	1.14***	-0.63***	1.56.	0.15***	-0.14	-0.17.	1.16**	0.01	0
WMT	10,666,867	-0.15***	1.42*	-0.45***	2.24.	0.10***	-0.27	-0.08.	1.54*	-0.02	0

Panel B: Put Options

Ticker	N obs	Specification 1		Specification 2				Specification 3			
		α	$D_{i,j,\tau-1}$	α	$D_{i,j,\tau-1}$	$log(SD_{0,\tau})$	$log(SD_{0,\tau})\times D_{i,j,\tau-1}$	α	$D_{i,j,\tau-1}$	$log(SD_{i,0,\tau})$	$log(SD_{i,0,\tau})\times D_{i,j,\tau-1}$
AXP	2,420,146	-0.23***	1.14***	-0.60***	1.32*	0.14***	-0.07	-0.13*	0.88***	-0.02	0
BA	12,972,646	-0.15***	2.08*	-0.33***	2.49*	0.07***	-0.15	-0.13*	2.36*	-0.02.	0
CAT	7,212,261	-0.15***	0.85***	-0.36***	1.19**	0.07***	-0.11	-0.09***	0.71***	-0.01	0
DIS	7,507,297	-0.15***	1.80*	-0.52***	2.46.	0.14***	-0.23	-0.11	1.87.	-0.02	0
DOW	1,152,225	-0.38***	1.26***	-0.83***	1.86*	0.17**	-0.2	-0.08	0.85***	-0.06	0
HD	4,137,262	-0.18***	1.34**	-0.47***	2.12.	0.11***	-0.26	-0.16*	1.31*	0	0
IBM	7,006,937	-0.13***	1.01***	-0.36***	1.27*	0.08***	-0.09	-0.07.	0.80***	-0.02.	0
INTC	8,912,057	-0.14***	0.83***	-0.44***	1.09***	0.08***	-0.07	-0.12***	0.79***	0.01	0
JNJ	2,382,666	-0.18***	1.28***	-0.69***	1.27*	0.19***	0	-0.13	1.08*	0.01	0
JPM	9,725,906	-0.11***	0.65***	-0.25***	1.01*	0.04***	-0.11	-0.05*	0.54***	-0.01	0
KO	2,172,693	-0.24***	1.29***	-0.63***	1.95*	0.14***	-0.21	-0.27*	1.54*	0.02.	0
MMM	1,341,136	-0.31***	1.46***	-1.08***	2.17**	0.34***	-0.26	-0.19*	1.18***	-0.02	0
MRK	1,657,527	-0.21***	1.55***	-0.72***	2.07.	0.19***	-0.15	-0.25.	1.27***	0.01	0
MSFT	18,485,005	-0.07***	1.08***	-0.38***	1.82*	0.10***	-0.22	-0.07.	1.14**	0	0
PG	2,070,349	-0.20***	1.01***	-0.64***	1.10.	0.16***	-0.04	-0.08	0.68**	-0.01	0
WMT	5,080,495	-0.16***	1.06**	-0.53***	1.51.	0.13***	-0.15	-0.11	0.93*	0	0

The table presents the results of panel regressions of the changes in spread after each trade across exchanges. The dependent variable, $\Delta Spread_{i,j,\tau}$, measures the change in the quoted spread for option j in exchange i from trade $\tau - 1$ to the next trade τ. The change in spread is regressed on the following variables and their interactions: a constant (coefficient α), a dummy variable $D_{i,j,\tau-1}$, which is equal to one if the trade of option j at time $\tau - 1$ was executed on exchange i, and the variables $log(SD_{0,\tau})$ and $log(SD_{i,0,\tau})$ which measure the volatility of the order flow from the start of the day up to trade τ across all exchanges or only for exchange i, respectively. The regressions are computed separately for each ticker and for calls (Panel A) and put options (Panel B). All regressions include day fixed effect, and standard errors are clustered at the day and exchange level. Coefficients are multiplied by 100.

Table 6: Panel Regressions of Exchange-Specific $\Delta ES_{i,s,t}$ on log(SD)

	Daily regressions of $\boldsymbol{\Delta ES_{i,s,t}}$					
	Panel A: ATM Calls 0-48			**Panel B: ATM Puts 0-48**		
	(1)	(2)	(3)	(1)	(2)	(3)
log($SD_{s,t}$)	0.0016***	0.0015***	0.0016***	0.0017***	0.0016***	0.0017***
	(10.05)	(8.88)	(9.75)	(9.37)	(7.91)	(9.74)
log($SD_{s,i,t}$)	0.0002*	0.0002**	0.0002*	0.0003***	0.0002***	0.0003***
	(2.31)	(2.62)	(2.25)	(4.03)	(3.95)	(4.01)
log($Volume_{i,s,t}$)	0.0002	0.0002	0.0002	0.0002	0.0001	0.0002
	(1.06)	(1.23)	(1.2)	(1.13)	(0.87)	(0.94)
$\|OI\|_{s,t}$	-0.0011*	-0.0008	-0.0011*	-0.0018*	-0.0018*	-0.0018*
	(-2.23)	(-1.46)	(-2.22)	(-2.11)	(-2.40)	(-2.10)
Stock $Return_{s,t}$	-0.1476***	-0.0790*	-0.1476***	0.0288	0.0645*	0.0288
	(-3.66)	(-2.36)	(-3.66)	(1.21)	(2.43)	(1.2)
$IV_{s,t}$	0.0027	0.0003	0.0027	0.0044	0.0012	0.0044
	(0.85)	(0.1)	(0.84)	(1.63)	(0.37)	(1.63)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	Yes	No	No	Yes	No
Exchange FE	No	No	Yes	No	No	Yes
Time Controls	Yes	No	Yes	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.06	0.12	0.06	0.04	0.09	0.04

This table presents the results of panel regressions of exchange-specific $\Delta ES_{i,s,t}$ for ATM call and put options with one-month to maturity written on the constituents of the Dow Jones analyzed in Table 5. $\Delta ES_{i,s,t}$ is the daily change in the effective spread on day t for stock s in exchange i, *log($SD_{s,t}$)* is the logarithm of the standard deviation of the intraday order flow distribution on day t for stock s, and *log($SD_{s,i,t}$)* is the logarithm of the order flow volatility using only trades recorded in exchange i. $log(Volume_{i,s,t})$ is the logarithm of the daily options volume for stock s in exchange i, $|OI_{s,t}|$ is the absolute value of the daily order imbalance (scaled by 10,000), *Stock* $Return_{s,t}$ is the return of underlying stock on day t, and $IV_{s,t}$ is the average implied volatility of options on stock s on day t. Other controls include firm size, stock volume, and absolute value of the average delta, vega and gamma of the options on stock s on day t. Time controls include day-of-the-week, month-of-year, and year dummies. Standard errors are clustered at the day, stock and exchange level. The corresponding t-statistics are presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

Table 7: Market-Maker Inventory Variables

Panel A: SPX Calls

Days to Maturity	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**
$\log(SD)_t$	0.02***	0.011***	0.006***	0.004***	0.004***	0.005***	0.003***	0.002***
	(4.33)	(5.51)	(5.43)	(4.88)	(6.92)	(8.36)	(5.94)	(4.87)
$\log(volume)_t$	0.001	-0.0001	0.003**	0.002**	0.001	-0.002***	-0.0001	0.001*
	(0.3)	(-0.03)	(2.3)	(2.28)	(1.55)	(-3.05)	(-0.3)	(1.68)
$\lvert$Order Imbalance$_t\rvert$	-0.008	0.009*	-0.001	-0.001	0.002	0.0001	0.002	0.001
	(-0.58)	(1.9)	(-0.31)	(-0.47)	(1.19)	(0.27)	(1.42)	(0.94)
$\lvert$MM NetInventory$_{t-1}\rvert$	-0.026**	-0.008	-0.001	-0.001	-0.001	-0.001	-0.001*	-0.001
	(-2.01)	(-1.36)	(-1)	(-0.99)	(-1.55)	(-0.81)	(-1.87)	(-1.26)
$\lvert$MM GammaInventory$_{t-1}\rvert$	1.026*	0.575*	0.061	0.0001	0.164	0.146	0.327***	0.257
	(1.71)	(1.77)	(0.57)	(0.0001)	(1.33)	(1.26)	(2.7)	(1.4)
$R_{M,t}$	-1.921***	0.179	0.02	0.0001	0.009	-0.129	0.02	0.025
	(-3.97)	(1.07)	(0.19)	(0.0001)	(0.23)	(-1.26)	(0.5)	(0.6)
VIX_t	-0.084**	-0.094***	-0.04***	-0.017**	-0.014**	-0.015*	-0.007	-0.004
	(-2.13)	(-4.89)	(-3.9)	(-2.48)	(-2.25)	(-1.78)	(-0.94)	(-0.47)
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	996	2642	2838	2747	2685	2542	2307	2111
Adj. R^2	0.471	0.512	0.384	0.358	0.316	0.362	0.33	0.349

Panel B: SPX Puts

Days to Maturity	**0**	**1-6**	**7-13**	**14-20**	**21-27**	**28-34**	**35-41**	**42-48**
$\log(SD)_t$	0.024***	0.014***	0.006***	0.005***	0.003***	0.002***	0.002***	0.003***
	(5.48)	(5.98)	(5.83)	(6.03)	(5.56)	(4.31)	(3.72)	(5.4)
$\log(volume)_t$	-0.011***	-0.0001	0.002*	0.002**	0.001*	0.001	0.0001	0.0001
	(-2.6)	(-0.18)	(1.82)	(2.34)	(1.85)	(1.22)	(0.99)	(0.23)
$\lvert$Order Imbalance$_t\rvert$	-0.009	0.006	0.002	-0.0001	0.001	0.002*	0.002	0.001
	(-0.84)	(1.43)	(0.87)	(-0.11)	(0.57)	(1.67)	(1.49)	(0.66)
$\lvert$MM NetInventory$_{t-1}\rvert$	-0.021	-0.006	-0.001	-0.001	-0.0001	-0.001	-0.001**	-0.001
	(-1.52)	(-1.31)	(-0.64)	(-1.28)	(-0.01)	(-1.07)	(-2.29)	(-1.37)
$\lvert$MM GammaInventory$_{t-1}\rvert$	0.852	0.342	0.05	0.079	0.06	0.024	0.255**	0.252*
	(1.52)	(1.26)	(0.33)	(0.83)	(0.7)	(0.23)	(2)	(1.75)
$R_{M,t}$	-1.921***	0.179	0.02	0.0001	0.009	-0.129	0.02	0.025
	(-3.97)	(1.07)	(0.19)	(0.0001)	(0.23)	(-1.26)	(0.5)	(0.6)
VIX_t	-0.084**	-0.094***	-0.04***	-0.017**	-0.014**	-0.015*	-0.007	-0.004
	(-2.13)	(-4.89)	(-3.9)	(-2.48)	(-2.25)	(-1.78)	(-0.94)	(-0.47)
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	990	2619	2824	2727	2679	2554	2307	2151
Adj. R^2	0.449	0.494	0.342	0.347	0.327	0.302	0.316	0.326

This table presents time-series regressions of ΔES_t on *log(SD$_t$)* and market-maker inventory variables, calculated using the CBOE Open-Close database, for SPX ATM call and put options across different maturity buckets. $|Order\ Imbalance_t|$ is the absolute value of the difference between non-market maker buy and sell orders (divided by 10,000), $|MM\ NetInventory_{t-1}|$ is the absolute value of the net market-maker inventory position on day $t-1$, and $|MM\ GammaInventory_{t-1}|$ is the absolute value of the market-maker inventory position scaled by gamma on day $t-1$. The other variables are analogous to those analyzed in the baseline regression in Table 3. Standard errors are computed using Newey-West with the optimal lag suggested by Andrews and Monahan (1992), and corresponding t-statistics are presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.