Derivative Spreads: Evidence from SPX Options*

Jie Cao[†] Kris Jacobs[‡] Sai Ke[§]

This Version: 28th December 2023

Abstract

We document the intraday patterns of spreads, implied volatilities, market order flows, and trading volume. Consistent with the classical models describing dealer trading behavior, we find a significantly positive relationship between volatilities and SPX options spreads. A positive relationship between the deviation from balanced buy-sell orders from end-users and SPX options spreads before market close is also found, coherent with the predictions of inventory control models. However, we observe a diminishing pattern of the impact of end-user demands near market close, which dealer market power models can explain. We also report a negative relationship between spreads and supply imbalances. Finally, we compare the effects of market order pressure with end-user demand imbalances.

Keywords: Options Spread, Market Maker, SPX, Volatility, Order Flow

JEL Classification: G12, G13, G20

*We thank Hitesh Doshi, Matthew Flynn (discussant), Thomas George, Guanglian Hu (discussant), Albert J. Lee (discussant), Yifei Li (discussant), Paola Pederzoli, Rauli Susmel, Jun (Jonathan) Wang (discussant), Ruixin Yang (discussant), seminar participants at the University of Houston, and participants at Academy of Behavioral Finance and Economics 2023 Annual Meeting, Asia-Pacific Association of Derivatives 2023 Annual Conference, CFRI & CIRF 2023 Joint Conference, the Chinese Economists Society 2023 China Annual Conference, Conference on Financial Economics and Accounting 2023, IRMC 2023, Pacific Basin Finance Economics Accounting and Management 2023 Annual Conference, and Southern Finance Association 2023 Annual Meeting for helpful comments.

†Hong Kong Polytechnic University School of Accounting and Finance, Hong Kong. jie.cao@polyu.edu.hk

‡Bauer College of Business, University of Houston, Houston, TX, USA. kjacobs@bauer.uh.edu

§School of Business Administration, University of Mississippi, Oxford, MS, USA. ske@bus.olemiss.edu

1 Introduction

Recent years have witnessed the thriving of the options market. Although deemed as redundant assets in a perfect market (Black and Scholes (1973) and Merton (1973)), options expand investors' investment opportunity set (Ross (1976) and Hakansson (1978)) and contribute to capital-efficient hedging and speculation. The rising prosperity and the critical role of options in financial markets have attracted the attention of academia to explore the functioning mechanism of options markets and the patterns of options returns, risks, and order flows.

Looking into the transactions in the options market, we would have a naturally arising question: How do market makers behave? How do they absorb the order flows from end-users, set up spreads, and price the volatilities? Hasbrouck and Sofianos (1993) discuss the two major market maker behavior models: asymmetric information models and inventory control models. Chan et al. (1995) document the intraday patterns of stock and options spreads and attribute the differences to the contrasting market-making system. Wei and Zheng (2010) explore the determinants of equity options liquidity and emphasize the critical role of volatilities. Christoffersen et al. (2018) find that end-user demand imbalances contribute to explaining effective spread variation.

We first document some stylized facts of how options spread, and other variables related to transactions, change intraday. We compare the 15-minute quotes with the average for each trading day to capture the intraday evolution. Options percentage spreads are high at the market open and shortly before the market close, with an acute decline after the opening. The wide bid-ask spread at the market open can be explained by the adverse selection exposure of market makers after the non-trading hours with new information that has not been disseminated. The large spreads close to the market close might come from market makers' response to the heavy and inelastic demand near the close.[1] The shrinking of spreads after this peak might result from depleted trading demand after the transactions. A remarkable height of the trading volume near the market close is found, consistent with the time of inelastic trading demand. We also document the intraday patterns of dollar spreads, implied volatilities, order imbalances, quote depth, and supply imbalances. Proxied by absolute returns due to data limitations, we record the intraday trends of SPX index return volatilities and discover a U-shaped pattern with a high left tail.

Guided by these theoretical analyses and empirical work, we focus on this research question: Do volatilities and order flows have any effects on spreads? We narrow our sample range and focus on SPX options, which are the most liquid, and the underlying covers a bunch of representative stocks. We start by characterizing the panel relationship between spreads and volatilities. We also explore the effects of order flows from options "consumers" on spreads for calls and puts separately. We first investigate the contemporaneous relationship between volatilities and spreads. Volatilities are measured by the annualized standard deviations of 15-minute SPX index returns, while spreads are the difference between ask and bid prices of SPX options divided by quote midpoints, usually referred to as percentage spreads in the literature. We also consider dollar spreads in the empirical analysis, which are not scaled by the midpoints. We find a positive relationship between volatilities and options spreads, which is consistent with the hypothesis that the market makers of call options require compensation for their exposure to underlying market risks. The finding is also coherent with the model predictions of Biais (1993).

We observe that both call and put spreads, averaged with quote depth, positively correlate with absolute demand imbalances, proxying undesirable demand shocks that push market

[1] Such inelastic trading demand has been documented in the stock market. For example, Bogousslavsky and Muravyev (2023) confirm that the passive investment strategy fuels the large and growing closing volume.

makers away from their optimal inventory level. These observations are in alignment with the predictions of inventory control models (Amihud and Mendelson (1980) and Ho and Stoll (1981)) that the market makers will increase spreads when facing extreme orders. Then, we zoom into the intraday microstructure and document the effects of imbalances across the trading day, where we witness a diminishing pattern when the time is approaching the market close. Why is timing so important in the effects of imbalances on spreads? Following Brock and Kleidon (1992), we argue that market makers have more substantial bargaining power at the close since the demand for trading is more inelastic. Therefore, they price discriminate the investors with eager trading needs by wider spreads, and the extra profits relieve the inventory pressure. During the day, however, market makers cannot earn these additional profits and are more concerned with the demand pressure. Cross-sectional investigations also support our hypothesis since the demand effect is weak among ITM and long-maturity options, which are more illiquid. In those options, market makers have a more inelastic trading demand to accommodate. We perform a similar intraday investigation of the effect of supply imbalances on spreads and observe a negative correlation. Under a similar mechanism of inventory pressure, market makers tend to attract liquidity consumption when they have an excessive trading supply.

We also perform robustness checks and confirm our findings in different econometrical settings. One notable robustness test is that we investigate the effects of order pressure from the whole market on spreads, which are the imbalances computed from market orders. The unbalanced market order pressure presents a stronger positive relationship with options spreads at the close. The results suggest the differences between the two imbalance measures: demand imbalances contain end-users only, while market order imbalances also reflect the trading needs of market makers. As Muravyev and Ni (2020) document, the correlations between order and end-user imbalances are low. After these tests, we investigate the time-series relationships of spreads, volatilities, and demand imbalances.

The paper contributes to the literature mainly from two perspectives. First, we empirically test the hypotheses of how market makers set up spreads. There is some evidence in the previous literature illustrating the variations of spreads. Wei and Zheng (2010) find the average panel regression estimates between spreads and volatilities negative. Christoffersen et al. (2018) report negative cross-sectional relationships between ATM options spreads and underlying volatilities and positive relationships between spreads and absolute imbalances. Our observations of panel relationships between spreads and the variables of interests are not always in the same direction as the previous empirical findings but are in alignment with the predictions of inventory models describing dealer trading behavior, including Amihud and Mendelson (1980), Ho and Stoll (1981), and Biais (1993). We also extend the classical models with the demand factor by investigating the potential effects of supply, which could be helpful to develop more comprehensive models of market maker behavior in the future.

Second, we supplement the empirical evidence in the previous literature documenting the intraday patterns of spreads, such as Chan et al. (1995). Compared to the early work, the length of our sample period offers more time-series variations and makes our conclusions more convincing. We investigate the differences in the impacts of underlying volatilities and demand imbalances on spreads at different time points during the trading day. The time-varying features of the relationships deepen the understanding of the intraday dynamics of spreads and support the market power model proposed by Brock and Kleidon (1992).

Also, we explore the detailed effect of order pressure on spreads. Some prior literature employs order imbalances as controls, such as Christoffersen et al. (2018). However, we examine the impact of order flows in various settings and directly provide empirical evidence to the models of dealer behavior regarding inventory pressure. We study the intraday evolvement of the relationship between inventory pressure and spreads. The evolution shows how the applicability of dealer behavior models changes with timing and market conditions, which contributes to the future development of a more comprehensive model. Also, our paper is the first to compare the influence of options order flows on spreads using both intraday OPRA data and CBOE open-close data, which extends the studies on the relationships of the two measures, such as Muravyev and Ni (2020). The imbalances from OPRA data provide a panoramic view of all traders in the market, while CBOE open-close data focus on the subset of non-market makers. Comparing the differences between these two helps a deeper understanding of each fraction of investors and their interaction.

The remainder of the paper proceeds as follows. The following section discusses the literature on the behavior of options liquidity providers and develops the hypotheses of this paper. Section 3 describes our sample selection and measure construction. Section 4 reports the empirical benchmark results of the impact of volatilities and order flows on spreads. Section 5 investigates how market makers' bargaining power affects the demand imbalance effect on spreads. Section 6 compares end-user demand imbalances and market order imbalances. Section 7 conducts several robustness tests. Section 8 concludes.

2 Literature Review and Hypothesis Development

The previous literature paid some attention to the behavior of market makers, and spread is one of the proxies for inference. Hasbrouck and Sofianos (1993) summarize the two principal models of dealer trading behavior: Asymmetric information models focus on the adverse selection exposure of the liquidity providers who issue their orders publicly to a market consisting of indistinguishable informed and uninformed traders. Inventory control models consider the problem of keeping securities holdings within certain bounds determined by the dealer's risk aversion. Ho and Stoll (1981) explicitly model the optimal pricing of dealers and examine the relationship of stock spreads to the inventory of market makers and the return volatility. Garleanu et al. (2008) propose a model of demand-pressure effects on option prices and notice the unhedgeable risks faced by market makers.

To illustrate the behavior of market makers, the literature resorts to intra-day transactions and explores the patterns of spreads. McInish and Wood (1992) document higher spreads at the beginning and end of the day. Focusing on the changes in spreads around earnings announcements, Lee et al. (1993) highlight the role of information asymmetry risk in liquidity providers' risk management and decision-making process. Chordia et al. (2002) document the time-series properties of aggregate market spreads.

The literature also tries to explain the empirical findings with the theoretical models in the options market. Chan et al. (1995) compare the intraday patterns of NYSE stock spreads and CBOE options spreads. Stock spreads show a U-shape pattern during the day, while options spreads are the widest at market open, sharply decrease after that, and become narrow at market close. They attribute the differences to the different market-making mechanisms of stocks and options. Stock specialists increase spreads at market openings and closings to deter imbalanced order flows at that time. In contrast, the competing market makers of options can avoid excessive long or short positions. Wei and Zheng (2010) investigate the determinants of equity options liquidity, measured by proportional spreads, and find the option return volatility to be a key determinant. Following George and Longstaff (1993)'s insight that traders view calls and puts as substitutes, they find traders substitute medium-term options with short-term options when the former is unavailable. They also document that traders substitute ITM options with OTM options when the underlying market is volatile. Christoffersen et al. (2018) find the illiquidity premia of equity options and investigate the key drivers of effective spreads. Compared with Wei and Zheng (2010), Christoffersen et al. (2018) highlight the influence of end-user demand imbalances on spreads.

There is also rich literature discussing the patterns of signed order flows and using the order flows to infer the behavior of market makers. In the underlying stock markets, researchers have been linking order imbalance to the conduct of market makers. Studying marketable order imbalance, Lee et al. (2004) identify the types of traders who are de facto liquidity providers, who are likely to be informed, and who are trading for liquidity reasons. In options markets, evidence has also been presented that order imbalance is closely related to various indicators of market conditions. Bollen and Whaley (2004) document a direct relationship between changes in implied volatility and net buying pressure from public order flows. These indicators would affect the decision-making process of options market makers.

We complement the empirical tests of the theoretical models and propose hypotheses to explain the observed patterns of spreads, which are proxies for market maker behavior. Following Ho and Stoll (1983), we mainly consider the inventory risks faced by market makers. When volatilities are high, market makers face higher risks induced by the variation of the underlying prices. Assuming risk-averse, they would require compensation for this uncertainty and increase spreads. In this case, spreads bear risk premia, and the effect of volatilities on spreads is encouraging. Biais (1993) also predict a positive relation between spread and the security's volatility with an inventory model. One caveat with these predictions is that the models are based on the volatility and the spread of the same security, while the focus of our work is the relationship between options spreads and the volatility of the underlying asset. However, given the tight relationship between options prices and the underlying volatility, the inventory risks of options market makers are closely linked to the underlying volatility. We, therefore, formulate the below testable hypothesis:

- $H_0(1)$: SPX options spread is an increasing function of the volatility of SPX index returns. Specifically, it is a time-series relationship.

What about the relationship between spreads and order flows? Motivated by Garleanu et al. (2008), we focus on the demand shocks from the "consumers" of options and examine the influence of absolute demand imbalances from options end-users on spreads. Ho and Stoll (1983) show that spreads exist to compensate market makers for bearing the risk of undesired inventory. Amihud and Mendelson (1980) predict that market makers will respond to more significant deviations from optimal inventory with higher spreads. They show that as long as the market maker attempts to manage his inventory, the spread increases as the inventory imbalance builds up. In our empirical work, demand imbalances are defined as the difference between end-user buying and selling volumes scaled by the total volumes. The absolute value of demand imbalances shows how much the demand for options is skewed to buying or selling. Under inventory control models, this absolute value, which proxies the deviations from optimal inventory, would positively affect spreads as the extreme order flows from non-market makers would push market makers away from their desired inventory level. Market makers would increase the spreads to deter these flows they do not favor. This analysis gives:

- $H_0(2)$: In the panel, an options contract with more imbalanced net demand will have higher spreads.

Having developed the hypotheses regarding the effects of volatility and order flows on options spreads, we discuss the empirical methodology to perform the tests in the next section.

3 Data and Methodology

We mainly rely on high-frequency data from the options pricing reporting authority (OPRA) to conduct our research. The dataset consists of two parts: trades and quotes. The dataset of trades provides intra-day transactional records of each contract, while that of quotes contains the NBBO snapshots of quotes of each contract, sampling at a 15-minute frequency. Besides, the data of quotes have other related information such as greeks, bid-ask size, and implied volatilities. Option Metrics and CBOE open-close C1 exchange volume summary data are also at our disposal. CBOE's open-close database documents non-market makers' daily buy and sell orders to open new and close existing positions. Compared with OPRA data, the open-close database contains the direction of the orders, but with the disadvantage of only being limited to end-users and a higher frequency of data unavailable. We focus on the SPX index options since they are more liquid, and the underlying covers many representative stocks in the market.

We apply the following filters for the data, a standard method to clean the data in the options literature. Transactions and quotes with apparent errors, such as negative prices, negative quotes, bid prices higher than ask prices or negative strike prices, are cleaned. Contracts with extreme deltas are excluded, and we only retain those whose absolute deltas values fall between 0.02 and 0.98. Excessively illiquid options whose bid-ask spread is so large that the ask price is higher than five times the bid price are deleted from our sample. We remove options whose price is less than half the difference between ask and bid prices or larger than the sum of ask and bid. Extremely cheap options with bid-ask midpoints lower than ten cents are also excluded. Finally, we eliminate the observations with zero or negative time value: For call options, the price must be higher than the current price of the underlying minus the strike. For put options, the price cannot be less than the strike price minus the spot price.[2] Following previous literature, we limit our sample to contracts with maturity between 14 to 180 days and do not include weekly options. We focus on regular trading hours. For SPX options, the hours are from 9:30 to 16:15.

[Insert Table 1 approximately here]

Table 1 presents the summary statistics of our sample. The statistics are reported for the changes in the variables, which is the main specification of our regressions. We also report the level statistics of volume, open interests, and maturity to provide an overview of our sample. Generally, the first differencing makes the variables that will attend the regressions have a relatively symmetric distribution. The trading volume of options varies tremendously, and so do the open interests, which is why volume is taken as a natural logarithm when entering the regressions. The maturity of the options in the sample is around two months, and on a typical day, there are about 80 individual call contracts and 120 put contracts. Table 2 reports the correlation matrix of the first differenced variables. The variables are fairly correlated with no extreme correlations.

[Insert Table 2 approximately here]

To infer the behavior of option market makers, we rely on percentage spreads defined as the difference between the bid and ask prices divided by the quote midpoint. Some literature refers to it as proportional spreads to distinguish it from dollar spreads, which can be affected by price level. However, we also report the results with dollar spreads, which are the difference between the bid and ask prices and directly reflect the profits market

[2] Duarte et al. (2022) and Duarte et al. (2023) document the existence of a look-ahead bias when applying filters to $t + 1$ variables at time t. They study the implications for option returns, but the argument may also apply when first-differencing the variables. We discuss these issues in detail in Section 7.6.

makers receive. OPRA data provide synchronous underlying quotes with options quotes, so we compute daily volatilities from 15-minute SPX index quotes to proxy the variations of underlying prices. The indicator of the direction of order flows from end-users is demand imbalances, computed in the below way:

$$Demand = \frac{(OB + CB) - (OS + CS)}{(OB + CB) + (OS + CS)}$$

as the difference between buys and sells, both open and close, divided by the total of buys and sells. *OB* and *OS* refer to open buys and open sells, while *CB* and *CS* denote close buys and close sells. We scale the difference to make the measure comparable across active and inactive options. In the regressions, we aggregate the buys and sells of all end-user groups.

4 Options Spreads, Underlying Volatilities, and End-User Demand Imbalances

4.1 Intraday Patterns

We start the empirical analysis by following Chan et al. (1995) and documenting some stylized facts of the intraday patterns of spreads, implied volatility, order imbalance, and the trading volume for SPX options in our sample. Following Chan et al. (1995) and due to data limitations, the sampling frequency is chosen to be 15 minutes. Our sample starts at 9:30 EST on each trading day, and we take a snapshot of options quotes every 15 minutes. Order imbalances and trading volume are aggregated within this 15-minute interval as well. Note that the first snapshot of quotes is taken at 9:45 EST. In contrast, the order imbalances and trading volume aggregated for the first interval are computed from 9:30 to 9:45. The process repeats until 16:15 EST, the closure of SPX options' regular trading hours.

Table 3 reports the time-series mean values for each standardized variable of interest for each 15-minute interval of the day, where panel A and panel B report call and put options, respectively. Standardization is defined as $(X_{it} - \mu_i)/S_i$, where X_{it} is the raw variable, μ_i is the mean for the day, and S_i is the standard deviation for the day. Figure 1 is the visualization of Table 3 and plots the mean values of the standardized variables with respect to the time horizon.

[Insert Table 3 approximately here]

The first pair in Figure 1 plots the intraday variations of call and put percentage spreads, presenting some similarities with the patterns reported by Chan et al. (1995). Both calls and puts demonstrate resembling intraday patterns, but call spreads seem slightly more volatile than put spreads. Immediately after the market opens, spreads attain the highest level at 10 o'clock without a hump. Then, the spreads decline steadily through the first trading hour and remain relatively stable until 16:00, while call spreads show some trace of further decrease. However, at 16:00, spreads bounce up but fall again at 16:15 when the market closes. As Chan et al. (1995) point out, the high spreads at the open reflect market makers' need to protect themselves from the uncertainty at the open. The information has not been disseminated, and informed investors can trade at the market open to take advantage in advance. The rise of spreads at 16:00 might be the market makers' response to the heavy and inelastic demand near the close. Investors urgently need to adjust their positions when the underlying market stops trading, and the options market faces an imminent non-trading period. For the last 15 minutes, this strong demand has been gradually dissolved by trading, and spreads are shrinking.

[Insert Figure 1 approximately here]

The second pair in Figure 1 exhibits the intraday movements of call and put dollar spreads. Noticeably, the dollar spreads of SPX options are low at market open, then suddenly soar at 10:00 but drop 15 minutes later. For the rest of the day, dollar spreads gradually increase (for calls) and bounce up at 16:00. At market close, however, dollar spreads become small again. The patterns differ from the documentation of Chan et al. (1995), who observe large spreads at market open. However, they also witness two peaks at 10:00 and 16:00. One way to analyze these patterns can be to decompose dollar spreads into percentage spreads and implied volatilities that proxy options prices. The analysis below shows that the patterns of dollar spreads observed here are products of the patterns of percentage spreads multiplied by those of implied volatilities.

The third pair in Figure 1 presents the intraday variations of call and put trading volume. Calls and puts have resembling patterns, but puts variation is more considerable. At the open, the trading is thin but quickly explodes at 10 o'clock. Peaking around 10:00 to 10:15, trading activities cool down in the rest of the morning and remain stable in the afternoon, while volume suddenly rockets at the close. Note that volume is high when the time is close to 10:00 and 16:00, which are the two peaks of spreads. The vicinity of high volume and spread peaks in the time axis is consistent with the claim that demand effects could be one of the drivers of the patterns of spreads. The time of high volumes suggests that of inelastic trading demand when market makers have more substantial market power, which overlaps with when the demand effect decays. The overlay supports the market power story to explain the previous intraday results.

The fourth pair in Figure 1 plots the intraday variations of call and put implied volatilities. Interestingly, both calls and puts have the lowest implied volatilities at the open. Throughout the day, the implied volatilities of calls gradually increase to the peak at 16:00 but with a slight jump at the close. The implied volatilities of puts increase in the morning and remain steady until the close at 16:15, when a slight drop is observed. The patterns contradict the usual patterns of the volatilities of the underlying markets, such as the U-shaped patterns of stock volatilities recorded in Chan et al. (1995). However, some recent studies, such as Muravyev and Ni (2020), suggest that stock volatility is substantially higher intraday than overnight, which can be why implied volatilities are low at market open and increase till market close.

Another possible way to explain the increasing patterns is by relating to the order flows of options and interpreting implied volatilities as prices. The pressure of buying and selling can drive the movement of prices, as Bollen and Whaley (2004) suggest. The last pair in Figure 1 shows the intraday variations of call and put order imbalances. The direction of market orders seems random during the day and does not exhibit any clustering of buying and selling. Therefore, the increasing patterns of implied volatilities during the day might not be motivated by order pressure.

Although we cannot compute the intraday volatilities of SPX index returns due to the limitation of our data, we plot the intraday pattern of the absolute 15-minute returns in lieu. The standardized values of the absolute returns are reported in Table 3 with a blank at 16:15 as the SPX index ceases trading at 16:00. Figure 2 is the visualization of the reported values. Generally, the absolute returns exhibit a U-shape pattern with a high left tail. The shape is consistent with the documentation of Chan et al. (1995), which also employs absolute returns to proxy intraday volatilities. We find more significant absolute returns at the open than what they document. The differences between this figure and the figure on implied volatilities suggest that the information on volatilities consumes some time to flow from the underlying market to the options market.

[Insert Figure 2 approximately here]

We also include the intraday patterns of depth and supply. The visualization of standardized intraday depth and supply imbalances is presented in Figure 3. The bid and ask sizes show the opposite patterns to that of trading volume, with two troughs after the market opens and before the market closes. The two troughs are indicators of large liquidity consumption, consistent with the timing of inelastic trading demand and the increase of the bargaining power of market makers. The signed supply imbalances fluctuate across the day, but the absolute supply imbalances present similar troughs with depth. Perhaps it is more convenient for market makers to manage their supply and inventory when the quote size is primarily consumed. As the inventory level is lower, it is easier to balance the trading supply in the buying and selling directions.

[Insert Figure 3 approximately here]

4.2 Percentage Spreads

We then perform the empirical analysis by regressing percentage bid-ask spreads on the volatilities and order flow variables. To mitigate the concerns that some spreads are inactive, we average the intraday spreads with their depth across the trading day, as the inactive spreads would have shallow quote sizes. It is known that spreads and volatilities are subject to high persistence, which could undermine the validity of our empirical analysis. Therefore, we apply first-differencing to both the dependent variable and the regressors in our main results. Specifically, we run the following panel regressions to obtain the baseline results of the impacts of realized volatilities and end-user demand imbalances on SPX options percentage spreads:

$$\Delta Spread_{it} = \alpha + \beta_1 \Delta STD_t + \beta_2 \Delta |Demand|_{it} + \beta_3 \Delta Controls_{it} + FE_i + \epsilon_{it}$$

where Δ denotes first-differencing, and Spread is the percentage spread in this subsection. STD is the realized volatilities of SPX index returns, and |Demand| is the absolute end-user demand imbalances. The method to compute these variables has been discussed in Section 3. The frequency of the regressions is daily. We include contract fixed effects to capture the potentially omitted characteristics of options, which resemble firm fixed effects in the literature on stocks. We do not consider time-fixed effects as they will absorb the impact of realized volatilities, which is of vital interest. The t-statistics are computed from Driscoll and Kraay (1998) standard errors, robust to general forms of cross-sectional and temporal dependence. These settings of fixed effects and standard error adjustment also apply for later analyses unless explicitly stated.

Controls include several measures suggested by previous literature. Trading volume is one of the controls because McInish and Wood (1992) document a significant relationship between stock volume and stock spreads. Delta is in the set of controls since it tells how options prices change concerning the fluctuation of the underlying prices. We include vega since the option price sensitivity to the underlying volatility might be related to the spread sensitivity to the underlying volatility. Engle and Neri (2010) point out that hedging costs can be one of the determinants of options spreads, and the costs are related to gamma; therefore, gamma enters the cohort of controls. Although spread is a popular measure of liquidity, we would like to focus on the part reflecting market maker behavior and control the part of market liquidity changes. We intend to measure liquidity from another perspective and apply the measure of price impact as the absolute return divided by dollar trading volume to capture liquidity differences across options. We also include maturity and moneyness, some of the most crucial characteristics of an options contract. Moneyness is defined as $S/K - 1$, where S is the spot price, and K is the strike price. The control variables are also averaged in the same manner as the two variables of interest.

Regressions (1) and (3) of Table 4 show the results of this panel regression of the impact of volatilities and imbalances on percentage spreads, which are run within calls and puts separately. Panels A and B reveal the univariate regression results of volatilities and imbalances, respectively, while Panel C discloses the multivariate results of volatilities, imbalances, and other control variables. Columns (1) and (3) in Panel A suggest a positive relationship between the underlying realized volatilities and call spreads, although the relationship to put spreads is insignificant. In Panel B, we can see a positive correlation between end-user imbalances and options spreads.

Multivariate regression results are more consistent with our expectations, potentially due to controlling some important options' characteristics, such as trading volume and greeks. Realized volatilities demonstrate positive effects on spreads with coefficient estimates of 0.026 for calls and 0.014 for puts, both of which are significant at the 1% level. Economically, one standard deviation growth of realized volatilities increases percentage spreads by 0.25% for calls and 0.14% for puts, around 5 to 7% of the standard deviation of spreads. Option spreads seem to be larger when the underlying market is more volatile. This is consistent with the hypotheses that market makers require risk compensation for facing risks from the underlying price movement and increase spreads to obtain the reward. These results also support the positive relationship between volatilities and spreads predicted by Ho and Stoll (1983) and Biais (1993). However, the observations are opposite to the empirical findings of Wei and Zheng (2010), which document negative relationships between equity options spreads and underlying volatilities. They perform panel regressions of options for each stock in their sample and report the cross-sectional means of the panel regression coefficients by stocks. The inconsistency might come from the difference between SPX index calls and equity calls. The reason can also be that they do not include contract fixed effects in their panel regressions, and the results might be affected by potentially omitted options features. Another possible reason would be that they do not apply first differencing to mitigate the problems caused by persistence. Chan et al. (1995) find that NYSE stocks' intraday spreads and volatilities move in the same direction. Although they argue that the monopolistic power of NYSE specialists mainly drives the similarities, they notice the possible effects of uncertainty on spreads, which supports the above explanation of the positive impact of volatilities.

[Insert Table 4 approximately here]

Similarly, end-user demand imbalances demonstrate strong positive influences on spreads, suggesting that market makers would widen spreads when facing excessive demand pressure. The evidence is coherent with the prediction of the inventory control models proposed by Amihud and Mendelson (1980), which are usually used to explain market maker behavior. As the order pressure from the end-users increases, market makers are pushed further away from their optimal inventory level and face higher inventory risks. To discourage the undesired order flows and cover the higher inventory risk exposure, options market makers would increase bid-ask spreads, resulting in a positive relationship. The witnessed positive relationship is also consistent with the prior empirical work, such as Christoffersen et al. (2018).

4.3 Dollar Spreads

When studying spreads, the previous literature shows some divergence in the definition. George and Longstaff (1993) focus on the difference between ask and bid prices, usually referred to as dollar spread. Wei and Zheng (2010) examine the impact of trading activities on the liquidity of equity options by the proportional bid-ask spread, which is a dollar spread scaled by the quote midpoint. We implement the same way as Wei and Zheng (2010) in our main regressions, as percentage spreads are less affected by options price levels than dollar spreads. However, dollar spreads can directly reflect the profits received for market-making and the compensation required by market makers. It is known that market makers are less flexible in choosing the number of contracts that flow in and need to be absorbed. Therefore, given their wealth constraints, they are more affected by the dollar value of the orders processed. We repeat the empirical analyses in the previous Subsection 4.2 to investigate the influences of volatilities and imbalances on dollar spreads.

Regressions (2) and (4) of Table 4 show the regression coefficients with dollar spreads aggregated daily with depth weight. The univariate results, Columns (2) and (4) in Panel A, suggest a positive relationship between the underlying realized volatilities and options spreads. Panel B shows a positive correlation between end-user imbalances and call spreads, although the relationship to put spreads is insignificant.

As we expect, the multivariate regressions present strongly positive correlations between dollar spreads and realized volatilities, consistent with the results of percentage spreads. The coefficient estimates are 0.650 and 1.987 for calls and puts, with significance at 1% level and very high t-statistics. Economically, one standard deviation growth of realized volatilities increases percentage spreads by 2.22 cents for calls and 5.80 cents for puts, around 5% and 9% of the standard deviation of dollar spreads. The impact of absolute end-user demand imbalances is significant for dollar spreads with a positive sign.

5 Market Makers' Bargaining Power

5.1 Spreads at Different Times

Our next step is to zoom into the intraday and investigate if the effects persist throughout the day. We repeat the regression analysis with the spread at each available time point during a trading day, starting from 14:15 EST to 16:15 EST, with a sampling frequency of 15 minutes.[3] Following the empirical setup in the prior subsections, all the regressions include the same cohort of control variables as in the baseline regressions. They are measured up to the time of retrieving the spread. The results are reported in Table 5. For conciseness, the coefficient estimates of controls are omitted, and only the estimates of percentage spreads are shown. We notice a stable effect of volatilities on spreads while the impact of imbalances largely decays (especially in magnitude) when the market is about to ring the closing bell. The effect of imbalances becomes scant or even negative near the close.

[Insert Table 5 approximately here]

The pattern of the estimates of imbalances suggests that market makers are more concerned with excessive demand pressure during the trading day. When it is close to the end of trading, end-user demands become less influential in their decision-making process. One possible explanation is that inventory control models provide a more fitting description of

[3]End-user imbalances are measured daily due to data availability. Therefore, we report the intraday results starting from 14:15 EST. Before 14:00 EST, the coefficient estimates of underlying volatilities are stable. The estimates of imbalances have a relatively large magnitude of approximately 0.1. However, the estimates need to be interpreted cautiously since imbalances are measured at the end of the day.

market maker behavior in the middle of the day: Market makers increase spreads to discourage the undesired order flows and obtain compensations for the absorption of the demand shocks. However, the models assume that the profits of market-making barely cover the costs, while the assumption could be loosened around the market close.

An alternative model of the market power of market makers, proposed by Brock and Kleidon (1992), could be applied to depict the actions of market makers at the close when transaction demand is heavier and less elastic. Due to the imminent non-trading period, optimal portfolios at the close could differ, and investors are more eager to adjust their positions. Also, institutional fund managers tend to trade near the close. Therefore, market makers gain higher bargaining power than end-users and are able to effectively price discriminate by charging a higher price in response to the heavy and inelastic demand. Expanding spreads can be found near the end of the trading day in the previous Subsection 4.1. Chan et al. (1995) also employ this model to explain the intraday patterns of spreads at the close. As market makers are better off from this greater market power, their wealth is less constrained. The extra profit from the rising bargaining power buffers the demand shocks and serves as part of the required compensation. Therefore, market makers are less distressed with demand imbalances at the close, and we witness attenuating influences of imbalances on spreads when the trading is close to stopping.

The market power model seems to suit the pattern of imbalances, but why are the estimates of underlying volatilities more resistant to this enervating effect? The dissimilarity might come from the features of volatilities and imbalances. Underlying volatilities enter into the rational prices of options as a component in the pricing formula. Changes in underlying volatilities directly affect the liquidating values of market makers' inventory, while imbalances do not. The extreme order flows are more related to the funding tightness and cash flows of market makers but do not boost or reduce the reasonable prices of options. Therefore, the extra profit at the close can mitigate much of the demand shock but not volatility. However, the significance of the volatility effect disappears at a time with highly inelastic trading demand (16:00 EST). The extra profit from very high bargaining power might compensate for all the risks born by market makers: any way they can reap a large sum of profits.

One concern with these results is that end-user demands are measured daily, which might be inaccurate for intraday analysis. We redo the analysis with market order imbalances, which are computed from transactions and can be measured intraday. The diminishing pattern of coefficient estimates is also observed. As market order imbalances represent the demand of all market participants apart from end-users, we report the results of end-user demand imbalances instead of market order imbalances.

5.2 Moneyness and Maturity

Although this paper focuses on panel relationships, we also look at the cross-sectional and time-series variations. We first explore the cross-sectional relationships between spreads and the variables of interest. As the underlying volatilities are the same at each time point for every contract, it is impossible to employ the usual Fama MacBeth regressions. Therefore, we sort options into moneyness groups and redo the baseline panel regressions. Moneyness is defined as $S/K - 1$, where S is the underlying price and K is the strike price. OTM options are calls and puts that are 5% out-of-the-money. DOTM options are calls and puts that are 10% out-of-the-money. ATM options are calls and puts that are +/-5% at-the-money. ITM options are calls and puts that are 5% in-the-money. Table 6 displays the results. The volatility effect is always positive and primarily significant across moneyness groups.

[Insert Table 6 approximately here]

In contrast, the imbalance effect is more driven by OTM options, which are more liquid. Trading demand can be easily absorbed by either market makers or other market participants who place limit orders. When the moneyness of options goes in the direction of ITM, the options are less actively traded, and market makers have a more considerable bargaining power to fulfill the trading need. Analogously to what we see in the intraday patterns, we also observe a weaker relationship between spreads and imbalances among ITM options.

We perform a similar analysis to options maturity. Options are divided into short-maturity, medium-maturity, and long-maturity groups, and we redo the baseline panel regressions. Short-maturity options are calls and puts with a maturity of fewer than 60 days. Medium-maturity options are calls and puts with a maturity of more than 60 days but fewer than 120 days. Calls and puts with more than 120 days of maturity are long-maturity options. Akin to what we observe in moneyness, the underlying realized volatility homogeneously has a significantly positive effect on spreads across maturity groups, while short-maturity options drive the demand effect. The difference also indicates that market makers are less concerned about excessive demand when the demand is inelastic and have a more assertive stance on negotiating the deals.

5.3 Supply Effects

The effects of demand on spreads have been solidly established by theoretical papers such as Ho and Stoll (1981) and verified by a series of empirical papers. However, some recent studies suggest the potential effects of supply on the behavior of intermediaries. A growing literature, such as Brunnermeier and Pedersen (2009), Adrian et al. (2014), and He and Krishnamurthy (2018), shows theoretically and empirically that intermediaries and their capital constraints affect prices and risk premiums. It is reasonable to infer that the ability of market makers to supply options would impact spreads. On the one hand, market makers might be willing to attract more options consumption when they have an extra supply. On the other hand, offering excessive liquidity in one direction (buy or sell) might indicate some constraints in the other direction. Such constraints might pressure market makers to discourage the demand for trading. Therefore, how the supply from market makers accommodates the buying and selling demand of options remains an interesting question to explore and answer.

We intend to perform some initial exploration and shed some light on this question. To the best of our knowledge, we are the first study to pay attention to the supply effects of market makers on spreads. To make the results comparable to the demand effects in the previous Subsection 5.1, we construct the supply imbalance measure similar to the demand imbalances. Specifically, we apply the bid and ask depth as the proxy for the supply of options from market makers. Then, the supply measure is defined as the absolute difference between the bid and ask depth, denominated by the sum of the two to facilitate the cross-sectional comparison:

$$Supply = \frac{BidSize - AskSize}{BidSize + AskSize}$$

A higher measure shows a more lopsided supply, and market makers might have excessive inventory. The depth data are based on the synchronous size provided by OPRA associated with quotes.

Inspired by demand results, we employ an intraday analysis of the supply effects. In particular, we regress the intraday spreads on the supply measure, where the timestamp categorizes the sample at the 15-minute frequency, and the regressions are performed within each group. Other empirical settings are the same as the previous regressions. The results are presented in Table 7. Both call and put options exhibit consistent results of negative correlations between spreads and supply imbalances, which are persistent across the whole trading day. The excessive supply seems to signal that market makers have extra inventory on one side. Market makers are willing to compromise some profits by lowering spreads to reduce the excess inventory. Unlike the demand effects, we do not observe any supply effect pattern; therefore, supply imbalances have persistent effects on spreads.[4]

[Insert Table 7 approximately here]

The supply results extend the classical models of Ho and Stoll (1981), highlighting the volatility and demand effect on the determination of spreads by market makers. The empirical results suggest that the supply is also a potential factor influencing spreads, although it is through a mechanism of inventory pressure similar to the demand. The supply effect echoes the growing literature on intermediaries and suggests that market makers' willingness to provide liquidity could be another factor to consider in the models of market makers. However, one caveat to interpreting the results is that the synchronous depth data are based on the best quotes. If all the quotes were available, the results would give a more comprehensive understanding of the supply.

6 Market Order Imbalances

Bollen and Whaley (2004) point out that market order flows play a role in determining option prices and empirically confirm that net order flows can explain options prices. Analogously

[4]Recall in Figure 3, absolute supply slope drops at 16:00 EST when the trading demand is inelastic. Compared with end-suers who are eager to trade, market makers have less trading pressure with a more balanced inventory.

to the effects of demand imbalances on spreads, the demand pressure from all market participants can influence the behavior of market makers and the movement of options spreads. If the pressure of maintaining optimal inventory level is the primary objective in the decision-making process of market makers when facing excessive market orders, we would expect a positive impact of absolute order imbalances on spreads.

Unlike the CBOE open-close database, which documents end-users' daily aggregated buy and sell volumes, the recorded transactions of all market participants in OPRA tapes do not contain trading directions. Therefore, we follow Lee and Ready (1991) to infer the direction of the intraday transactions from OPRA. If the transaction price is higher than the associated midpoint of the bid and ask quotes, it is classified as a buyer-initiated transaction. If the price is lower than the midpoint, it is identified as seller-initiated. If the price happens to be at the midpoint, then the price is compared with the midpoint and the price of the previous transactions, whichever comes first, to sign the current transaction. In the extremely few cases where the price is still the same, the comparison will proceed to all the previous available transactions until the direction can be determined, by which the probability of a transaction not being categorized is negligible. The indicator of order flow direction is order imbalances, computed as:

$$OIM = \frac{BuyVolume - SellVolume}{BuyVolume + SellVolume}$$

where i denotes each options contract. Buy and Sell volumes are daily aggregated volumes from signed intra-day transactions following the Lee and Ready (1991) algorithm.

When we examine the effects of inventory shocks on spreads in the baseline results of the paper, we focus on demand imbalances instead of order imbalances. One reason is that the data of end-user buying and selling volumes are directly accessible, while the data of market orders need to be processed with inference. We also intend to focus on the inventory effects from end-users on market makers, as they are the final ”consumers” of options. However, it is still interesting how the order shocks from all traders can change the dealers' decision-making. Suppose we assume that other market makers broker the trading activities of market makers, and most market makers would not pick their customers. In that case, we should be able to observe similar effects of order imbalances with demand imbalances.

Our work is the first to compare the influence of options order flows on spreads using both intraday OPRA data and CBOE open-close data. It echoes the comparison of the effects of the two variables on returns by Muravyev and Ni (2020). Table 8 exhibits the results of panel regressions of percentage and dollar spreads with order imbalances. Interestingly, market order imbalances positively correlate with percentage spreads but have a less significant relationship with dollar spreads. In contrast, demand imbalances positively correlate with mid-day spreads but do not present an apparent relationship to end-of-day spreads. Although they have similar structures, order imbalances and demand imbalances measure different order shocks. To shed some light on the impact of order imbalances, we investigate the correlation between the two measures of imbalances. Consistent with Muravyev and Ni (2020), the correlations between order and demand imbalances are surprisingly low, around 10%. A notable part of order imbalance variations can be attributed to market makers under the dichotomy of all traders into market makers and end-users.

[Insert Table 8 approximately here]

7 Robustness

7.1 Relative Risks and Extra Controls

One concern against our hypothesis of the underlying volatility is that market makers care more about the direct fluctuation of options prices. The effect of options price volatility might drive our observed relationship. George and Longstaff (1993) argue that relative risk, the squared delta, is a proxy of options volatilities under the Black and Scholes model. We also follow the paper and include an extended set of control variables in our regressions. The newly added controls include M2,[5] relative risk, and a price dummy, which equals one if the price of an option is greater than or equal to $3.[6] We do not take these variables as controls in the baseline regressions because these variables are more about individual contract attributes and should be absorbed by the fixed effects; however, we would like to see if there is any commonality in these attributes across options, following the previous literature. As is shown in the first part of Table 9, the effects of underlying volatilities on call and put spreads preserve, independent of the effects of options price volatilities.

[Insert Table 9 approximately here]

7.2 Options Return Volatilities

Wei and Zheng (2010) propose an important determinant of options spreads: options return volatilities. In particular, it is defined as the ratio between the underlying and option prices multiplied by the absolute delta and the underlying return volatility.[7] We include the measure

[5]M2 is defined as the squared difference between the S&P 500 index value and the strike of options. It controls the possible non-linear correlations between options spreads and moneyness.

[6]The minimum tick for options trading below 3.00 is 0.05 and for all other series, 0.10. See https://www.cboe.com/tradable_products/sp_500/spx_options/specifications/

[7]See Footnote 4 of Wei and Zheng (2010).

in our analysis to check the robustness of our baseline results. The second part of Table 9 documents the results. The options return volatilities exhibit a positive relationship with percentage spreads but negatively correlate with dollar spreads. Wei and Zheng (2010) claim that the positive sign proves the validity of percentage spreads as a liquidity measure. The negative relationship might also come from options prices being the denominator of options return volatilities. The results of underlying volatilities are generally the same for the dollar spreads, but the coefficients of percentage spreads are affected by the inclusion of options return volatilities. The change might be the consequence that the underlying volatilities are part of the numerator of options return volatilities.

7.3 Alternative Daily Volatility Measure

OPRA data provide synchronous underlying prices with options quotes; therefore, we compute the daily volatilities of the SPX index using the 15-minute returns. One concern is that the sampling frequency is not high enough for daily estimation and could cause some bias. We obtain a daily volatility measure at a higher frequency from the Realized Library of Oxford-Man Institute of Quantitative Finance to mitigate this concern.[8] Specifically, we employ the measure of realized volatility from 5-minute SPX index returns and repeat the regression analysis in our baseline results. The third part of Table 9 presents the replicated results, and the conclusions remain the same as those from the baseline regressions.

7.4 Implied Volatilities

In the previous sections, we employ realized volatilities to explore the effects of underlying volatilities on options spreads. They directly measure market makers' risk exposure to the

[8] We retrieve the data from `https://realized.oxford-man.ox.ac.uk/`

underlying price movement. However, realized volatilities are measured during a period, which in our case, are calculated daily. On the other hand, quote spreads are measured at specific time points. This inconsistency in timing specification can cause some empirical concerns and potentially shadow our conclusions. To address this concern, we repeat the panel regressions with implied volatilities measured simultaneously to the quoted spreads and reflect the volatilities of the SPX index. OPRA data provide synchronous options implied volatilities with options quotes, so we retrieve the data simultaneously as the bid and ask prices timestamps.

The fourth part of Table 9 shows the daily regression coefficients with implied SPX volatilities. Percentage spreads are negatively correlated with implied volatilities, while the correlations remain strongly positive for dollar spreads. One potential explanation would be that implied volatilities are more closely related to the synchronous options prices, which are in the denominator of percentage spreads. Therefore, the coefficient estimates become negative for percentage spreads.

7.5 Spread Volatilities

Following the logic of realized volatilities, an interesting question is what the effect of spread volatilities would be. Market makers increase spreads to compensate for their exposure to the underlying price changes. What would they do if the spread (the profit itself) is volatile? We perform some initial exploration by examining the relationship between spreads and the volatility of spreads. Specifically, we calculate the daily spread volatility by the standard deviation of the 27 intraday 15-minute spread snapshots. Then, we regress the spreads on the spread volatilities. The second last part of Table 9 displays the positive correlation between respective percentage and dollar spreads with the associated spread volatilities, consistent with the story that market makers are averse to turbulent profits and charge larger spreads for the options with less smooth revenues.

7.6 Look-Ahead Bias

Duarte et al. (2022) and Duarte et al. (2023) study the implications of a potential look-ahead bias in samples of option returns. When computing a return between time $t-1$ and t, ex-post, we know whether a given datapoint satisfies the filters at t, but we do not know this ex-ante (at time $t-1$). If exclusion from the sample based on time t information is not random, this may create biases. While Duarte et al. (2022) and Duarte et al. (2023) focus on option returns, the same remark applies to first-differenced variables. We, therefore, follow Duarte et al. (2023) and investigate the robustness of our results when filters at time t are not imposed. We eliminate most filters at t, but retain the filters that require positive bid and ask prices as well as the requirement that bid prices are lower than ask prices.

The last row of Table 9 reports the results corrected for the look-ahead bias. They are similar to the baseline results in Table 4. Both the volatility and demand effects are estimated with a positive sign, but the demand effect is slightly weaker. This is not surprising. The observations added to the sample as a result of removing filters have lower daily trading volume, fewer daily number of transactions, lower dollar open interest, and higher price impact. The weaker significance may, therefore, result from a noisier sample.

7.7 Time-Series Relationships

Furthermore, we employ the same regressors in our benchmark analysis but with time-series regressions to explore the time-series relationships. On each trading day, we aggregate options with dollar open interests in the previous day, similar to weighting by firms' market capitalization in the stocks' research. Then we run time-series regressions with t-statistics computed from standard deviations adjusted by the Newey and West (1987) method with 16 lags. The results are exhibited in Table 10, with positive correlations observed between spreads and volatilities. Note that the positive effect of end-user demand imbalances is gone. The dissimilarity to what we record in the baseline results indicates that the demand imbalances have a more cross-sectional impact on spreads.

[Insert Table 10 approximately here]

8 Conclusion

We study the variations of SPX options spreads. In particular, we document their significant correlations with volatilities and order flows. Realized volatilities are positively correlated with both call and put spreads throughout the day, while we also observe time-varying impacts of end-user demand imbalances on options spreads. The observations can be explained by the uncertainty compensation required by market makers facing the risks of underlying price movement and the compensation for market makers to deviate from their optimal inventory level. The bargaining power of market makers can model the fluctuations of the effects of imbalances. We investigate the intraday patterns of bid-ask spreads, percentage spreads, implied volatilities, order imbalances, and trading volume and compare them with the description of previous literature (Chan et al. (1995)). We compare the effects of market order imbalances and end-user demand imbalances on spreads. We also check the cross-sectional variations of spreads and the time-series results and confirm the robustness of our baseline results.

Our findings highlight the limits of the theoretical models' applicability to depict intermediaries' decision-making. At the same time, the findings empirically verify some explanations of dealer trading behavior (for example, Ho and Stoll (1983), Brock and Kleidon (1992) and Biais (1993)). Our findings could help develop more comprehensive models in the future. It would be an exciting extension of our work to explore the intraday progressions of non-market makers and compare them with market makers and all the market participants.

References

Adrian, T., E. Etula, and T. Muir (2014). Financial intermediaries and the cross-section of asset returns. *Journal of Finance 69*(6), 2557–2596.

Amihud, Y. and H. Mendelson (1980). Dealership market: Market-making with inventory. *Journal of Financial Economics 8*(1), 31–53.

Biais, B. (1993). Price formation and equilibrium liquidity in fragmented and centralized markets. *Journal of Finance 48*(1), 157–185.

Black, F. and M. Scholes (1973). The pricing of options and corporate liabilities. *Journal of Political Economy 81*(3), 637–654.

Bogousslavsky, V. and D. Muravyev (2023). Who trades at the close? implications for price discovery and liquidity. *Journal of Financial Markets 66*, 100852.

Bollen, N. P. and R. E. Whaley (2004). Does net buying pressure affect the shape of implied volatility functions? *Journal of Finance 59*(2), 711–753.

Brock, W. A. and A. W. Kleidon (1992). Periodic market closure and trading volume: A model of intraday bids and asks. *Journal of Economic Dynamics and Control 16*(3-4), 451–489.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Chan, K., Y. P. Chung, and H. Johnson (1995). The intraday behavior of bid-ask spreads for NYSE stocks and CBOE options. *Journal of Financial and Quantitative Analysis*, 329–346.

Chordia, T., R. Roll, and A. Subrahmanyam (2002). Order imbalance, liquidity, and market returns. *Journal of Financial Economics 65*(1), 111–130.

Christoffersen, P., R. Goyenko, K. Jacobs, and M. Karoui (2018). Illiquidity premia in the equity options market. *Review of Financial Studies 31*(3), 811–851.

Driscoll, J. C. and A. C. Kraay (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics 80*(4), 549–560.

Duarte, J., C. S. Jones, H. Mo, and M. Khorram (2023). Too good to be true: Look-ahead bias in empirical option research. Working Paper, available at `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4590083`.

Duarte, J., C. S. Jones, and J. L. Wang (2022). Very noisy option prices and inference regarding the volatility risk premium. *Journal of Finance*, forthcoming.

Engle, R. and B. Neri (2010). The impact of hedging costs on the bid and ask spread in the options market. Working Paper, available at `https://www.researchgate.net/profile/Breno-Neri/publication/228818078/`.

Garleanu, N., L. H. Pedersen, and A. M. Poteshman (2008). Demand-based option pricing. *Review of Financial Studies 22*(10), 4259–4299.

George, T. J. and F. A. Longstaff (1993). Bid-ask spreads and trading activity in the S&P 100 index options market. *Journal of Financial and Quantitative Analysis 28*(3), 381–397.

Hakansson, N. H. (1978). Welfare aspects of options and supershares. *Journal of Finance 33*(3), 759–776.

Hasbrouck, J. and G. Sofianos (1993). The trades of market makers: An empirical analysis of NYSE specialists. *Journal of Finance 48*(5), 1565–1593.

He, Z. and A. Krishnamurthy (2018). Intermediary asset pricing and the financial crisis. *Annual Review of Financial Economics 10*, 173–197.

Ho, T. and H. R. Stoll (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics 9*(1), 47–73.

Ho, T. S. and H. R. Stoll (1983). The dynamics of dealer markets under competition. *Journal of Finance 38*(4), 1053–1074.

Lee, C. M., B. Mucklow, and M. J. Ready (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies 6*(2), 345–374.

Lee, C. M. and M. J. Ready (1991). Inferring trade direction from intraday data. *Journal of Finance 46*(2), 733–746.

Lee, Y.-T., Y.-J. Liu, R. Roll, and A. Subrahmanyam (2004). Order imbalances and market efficiency: Evidence from the Taiwan Stock Exchange. *Journal of Financial and Quantitative Analysis 39*(2), 327–341.

McInish, T. H. and R. A. Wood (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *Journal of Finance 47*(2), 753–764.

Merton, R. C. (1973). The relationship between put and call option prices: Comment. *Journal of Finance 28*(1), 183–184.

Muravyev, D. and X. C. Ni (2020). Why do option returns change sign from day to night? *Journal of Financial Economics 136*(1), 219–238.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Ross, S. A. (1976). Options and efficiency. *Quarterly Journal of Economics 90*(1), 75–89.

Wei, J. and J. Zheng (2010). Trading activity and bid-ask spreads of individual equity options. *Journal of Banking and Finance 34*(12), 2897–2916.

Figure 1: Mean Values of the Standardized Variables of SPX Options for Each Time Interval during the Day

These figures are intraday time-series mean values of standardized percentage spreads, dollar spreads, implied volatilities, order imbalances, and trading volume reported in Table 3. The standardized variable is defined as $(X_{it} - \mu_i)/S_i$, where X_{it} is the raw variable, μ_i is the mean for the day, and S_i is the standard deviation for the day. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint. Dollar spread is defined as the difference between ask and bid prices. Trading volume is the aggregated number of contracts traded during the interval. Order imbalances are computed from OPRA intraday tapes as the difference between buy and sell orders from all market participants divided by the sum. Red(blue) lines plot the variables of calls(puts). The sample period is from Jan 2004 to Dec 2020.

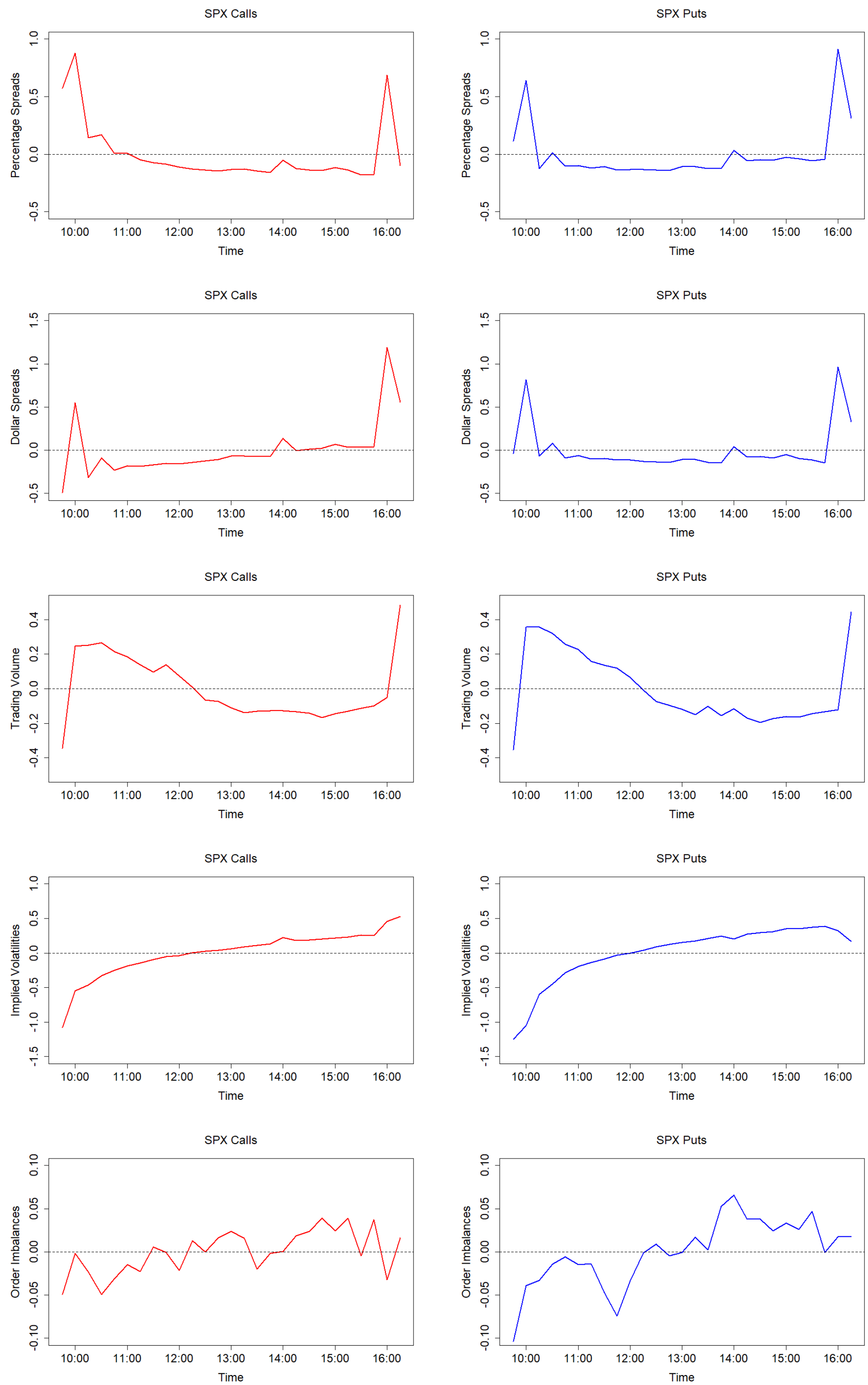

Figure 2: Mean Values of the Standardized Absolute Returns of S&P 500 Index for Each Time Interval during the Day

This figure plots intraday time-series mean values of standardized absolute returns of the S&P 500 index reported in Table 3. The standardized variable is defined as $(X_{it} - \mu_i)/S_i$, where X_{it} is the raw variable, μ_i is the mean for the day, and S_i is the standard deviation for the day. Absolute return is the absolute value of return, a proxy for volatility. The sample period is from Jan 2004 to Dec 2020.

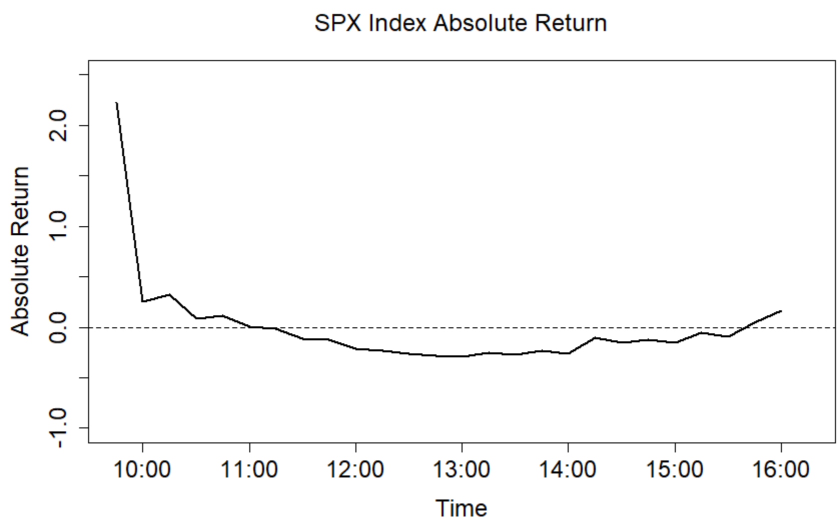

Figure 3: Mean Values of the Standardized Variables of SPX Options for Each Time Interval during the Day

These figures are intraday time-series mean values of standardized bid size, ask size, supply slope, and absolute supply slope. The standardized variable is defined as $(X_{it} - \mu_i)/S_i$, where X_{it} is the raw variable, μ_i is the mean for the day, and S_i is the standard deviation for the day. Bid(ask) size is the depth of bid(ask) price retrieved from OPRA tapes. Supply slope is the difference between bid and ask sizes, divided by the sum. The absolute supply slope is the absolute value of the supply slope. Red(blue) lines plot the variables of calls(puts). The sample period is from Jan 2004 to Dec 2020.

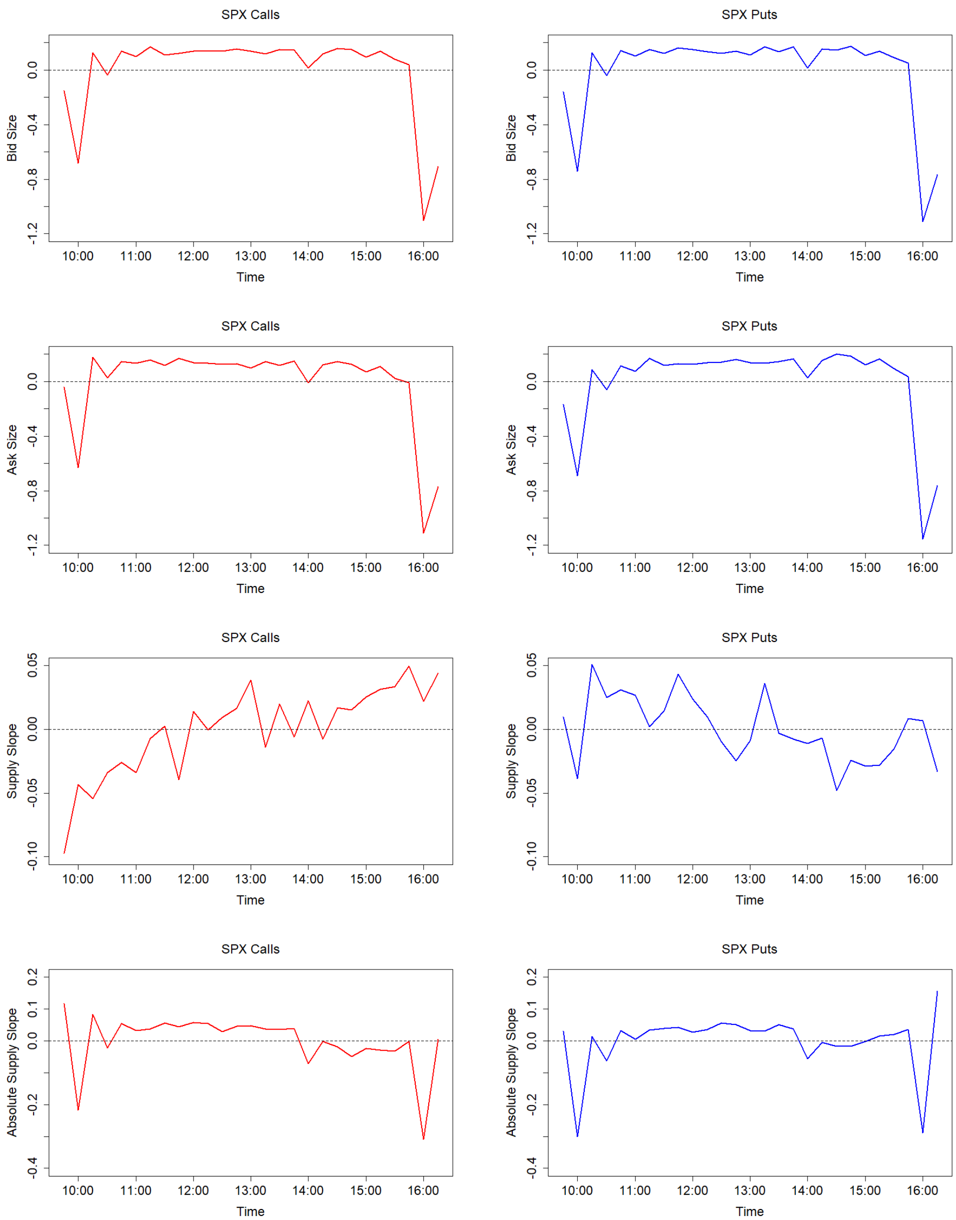

Table 1: Summary Statistics

This table presents the univariate statistics for the key variables in the sample. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. Dollar spread is defined as the difference between ask and bid prices, measured by cents. STD is the daily standard deviation of 15-minute S&P 500 index returns. End-user demand imbalance (Demand) is computed from the CBOE open-close database as the difference between buy and sell orders from all end-users divided by the sum, while |Demand| is the absolute value. Price impact is defined as the absolute return divided by dollar trading volume. Moneyness is defined as $S/K - 1$, where S is the underlying price and K is the strike price. Maturity is the number of days until expiration. The sample period is from Jan 2004 to Dec 2020.

	Obs.	Mean	S. D.	25%	Median	75%
Call Options						
Δ Percentage Spread (%)	315,223	0.16	3.42	−0.59	0.02	0.77
Δ Dollar Spread (cents)	315,223	−0.45	50.29	−11.16	−0.43	9.86
Δ STD (%)	315,223	−0.10	9.53	−3.34	0.04	3.39
Δ |Demand| (%)	315,223	0.00	0.45	−0.28	0.00	0.27
Δ Ln(Volume)	315,223	0.04	2.45	−1.38	0.00	1.44
Δ Delta (%)	315,223	0.29	6.28	−2.30	0.23	3.15
Δ Vega (%)	315,223	−6.95	32.14	−16.15	−4.58	4.17
Δ Gamma (%)	315,223	0.00	0.11	−0.01	0.00	0.02
Δ PriceImpact (%)	315,223	0.01	2.92	−0.01	0.00	0.01
Δ Implied Volatility (%)	315,223	0.00	2.79	−0.34	−0.02	0.31
Δ |OIM| (%)	315,223	0.00	0.20	−0.07	0.00	0.07
Volume	315,223	1403.25	3537.15	20.00	151.00	1075.00
Open Interest (k$)	315,223	539.43	1449.98	12.05	69.82	430.16
Moneyness (%)	315,223	−1.98	4.80	−4.66	−1.91	0.69
Maturity	315,223	58.14	35.66	31.00	50.00	74.00
Put Options						
Δ Percentage Spread (%)	496,307	0.31	2.92	−0.39	0.10	0.81
Δ Dollar Spread (cents)	496,307	−1.70	63.49	−11.91	−1.49	7.33
Δ STD (%)	496,307	−0.02	9.84	−3.33	0.06	3.48
Δ |Demand| (%)	496,307	−0.01	0.44	−0.28	0.00	0.26
Δ Ln(Volume)	496,307	0.05	2.41	−1.35	0.00	1.43
Δ Delta (%)	496,307	0.30	5.21	−1.24	0.37	2.22
Δ Vega (%)	496,307	−7.14	24.98	−15.30	−5.20	1.75
Δ Gamma (%)	496,307	0.00	0.08	−0.01	0.00	0.01
Δ PriceImpact (%)	496,307	0.02	1.23	−0.01	0.00	0.01
Δ Implied Volatility (%)	496,307	0.11	3.31	−0.27	0.05	0.41
Δ |OIM| (%)	496,307	−0.00	0.15	−0.05	−0.00	0.04
Volume	496,307	1505.21	3960.96	23.00	157.00	1171.00
Open Interest (k$)	496,307	408.07	1189.98	9.94	62.95	329.14
Moneyness (%)	496,307	8.33	10.08	1.63	6.18	12.28
Maturity	496,307	60.34	36.90	32.00	51.00	78.00

Table 2: Correlation Matrices

This table presents the correlation matrices for the key variables in the sample. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. Dollar spread is defined as the difference between ask and bid prices, measured by cents. STD is the daily standard deviation of 15-minute S&P 500 index returns. End-user demand imbalance (Demand) is computed from the CBOE open-close database as the difference between buy and sell orders from all end-users divided by the sum, while |Demand| is the absolute value. Price impact is defined as the absolute return divided by dollar trading volume. Moneyness is defined as $S/K - 1$, where S is the underlying price and K is the strike price. Maturity is the number of days until expiration. The sample period is from Jan 2004 to Dec 2020.

Call Options	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Δ Percentage Spread	1.000										
(2) Δ Dollar Spread	0.076	1.000									
(3) Δ STD	0.139	0.085	1.000								
(4) Δ |Demand|	0.007	0.012	−0.033	1.000							
(5) Δ Ln(Volume)	−0.029	−0.025	0.055	−0.116	1.000						
(6) Δ Delta	−0.331	0.278	−0.161	0.018	−0.030	1.000					
(7) Δ Vega	−0.302	0.040	−0.140	−0.015	0.047	0.368	1.000				
(8) Δ Gamma	−0.050	−0.081	−0.028	−0.009	0.028	0.063	0.210	1.000			
(9) Δ PriceImpact	0.040	−0.020	0.013	0.022	−0.118	−0.029	−0.042	−0.025	1.000		
(10) Δ Implied Volatility	−0.095	0.187	0.140	−0.008	0.004	0.024	0.027	−0.325	−0.020	1.000	
(11) Δ |OIM|	−0.045	0.053	−0.068	0.228	−0.062	0.189	0.046	0.014	0.004	−0.027	1.000
Put Options	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Δ Percentage Spread	1.000										
(2) Δ Dollar Spread	0.133	1.000									
(3) Δ STD	−0.014	0.382	1.000								
(4) Δ |Demand|	0.018	0.002	−0.037	1.000							
(5) Δ Ln(Volume)	−0.025	−0.007	0.054	−0.115	1.000						
(6) Δ Delta	0.217	−0.379	−0.220	0.007	0.004	1.000					
(7) Δ Vega	−0.181	−0.027	0.082	−0.025	0.044	−0.210	1.000				
(8) Δ Gamma	−0.033	−0.046	−0.001	−0.012	0.022	0.008	0.188	1.000			
(9) Δ PriceImpact	0.042	−0.011	0.000	0.041	−0.210	0.026	−0.039	−0.014	1.000		
(10) Δ Implied Volatility	−0.073	0.139	0.162	−0.008	0.010	−0.176	0.121	−0.238	0.003	1.000	
(11) Δ |OIM|	−0.032	0.084	0.023	0.189	−0.051	−0.190	0.020	−0.010	0.008	0.026	1.000

Table 3: Mean Values of the Standardized Variables of SPX Options for Each Time Interval during the Day

This table presents the mean value of the standardized percentage spread, implied volatility, order imbalance, and trading volume of SPX options for each 15-minute time interval during the trading day. The standardized variable is defined as $(X_{it} - \mu_i)/S_i$, where X_{it} is the raw variable, μ_i is the mean for the day, and S_i is the standard deviation for the day. Absolute return is the absolute value of return, a proxy for volatility. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint. Dollar spread is defined as the difference between ask and bid prices. Trading volume is the aggregated number of contracts traded during the interval. Order imbalances are computed from OPRA intraday tapes as the difference between buy and sell orders from all market participants divided by the sum. The sample period is from Jan 2004 to Dec 2020.

Time	Abs. SPX Return	Call % Spread	Call $ Spread	Call Imp. Vol.	Call Order Imbal.	Call Volume	Put % Spread	Put $ Spread	Put Imp. Vol.	Put Order Imbal.	Put Volume
9:45	2.2265	0.5724	−0.4926	−1.0803	−0.0492	−0.3467	0.1153	−0.0387	−1.2497	−0.1036	−0.3542
10:00	0.2568	0.8768	0.5498	−0.5462	−0.0015	0.2460	0.6424	0.8193	−1.0488	−0.0394	0.3557
10:15	0.3242	0.1420	−0.3151	−0.4666	−0.0231	0.2520	−0.1257	−0.0646	−0.5946	−0.0327	0.3573
10:30	0.0884	0.1700	−0.0883	−0.3273	−0.0493	0.2654	0.0119	0.0826	−0.4498	−0.0141	0.3202
10:45	0.1103	0.0055	−0.2303	−0.2529	−0.0311	0.2157	−0.1044	−0.0903	−0.2848	−0.0060	0.2580
11:00	0.0039	0.0065	−0.1819	−0.1888	−0.0147	0.1828	−0.0982	−0.0626	−0.1962	−0.0146	0.2276
11:15	−0.0178	−0.0487	−0.1862	−0.1480	−0.0226	0.1389	−0.1193	−0.1012	−0.1376	−0.0139	0.1574
11:30	−0.1116	−0.0750	−0.1714	−0.0962	0.0055	0.0956	−0.1078	−0.0932	−0.0868	−0.0470	0.1352
11:45	−0.1270	−0.0854	−0.1543	−0.0552	−0.0004	0.1374	−0.1357	−0.1105	−0.0335	−0.0742	0.1186
12:00	−0.2129	−0.1108	−0.1567	−0.0364	−0.0213	0.0747	−0.1333	−0.1095	−0.0013	−0.0333	0.0645
12:15	−0.2289	−0.1286	−0.1391	0.0011	0.0131	0.0071	−0.1308	−0.1317	0.0422	−0.0012	−0.0076
12:30	−0.2603	−0.1363	−0.1234	0.0253	−0.0001	−0.0663	−0.1364	−0.1356	0.0924	0.0092	−0.0729
12:45	−0.2859	−0.1451	−0.1089	0.0361	0.0162	−0.0731	−0.1433	−0.1411	0.1280	−0.0046	−0.0971
13:00	−0.2923	−0.1332	−0.0672	0.0636	0.0236	−0.1109	−0.1069	−0.1075	0.1522	−0.0006	−0.1201
13:15	−0.2479	−0.1301	−0.0679	0.0914	0.0159	−0.1377	−0.1087	−0.1066	0.1747	0.0170	−0.1491
13:30	−0.2736	−0.1462	−0.0730	0.1105	−0.0200	−0.1301	−0.1248	−0.1379	0.2129	0.0024	−0.1021
13:45	−0.2323	−0.1596	−0.0748	0.1349	−0.0017	−0.1266	−0.1257	−0.1451	0.2451	0.0525	−0.1550
14:00	−0.2580	−0.0512	0.1387	0.2255	0.0004	−0.1283	0.0333	0.0392	0.2040	0.0655	−0.1178
14:15	−0.1072	−0.1252	−0.0036	0.1780	0.0188	−0.1326	−0.0570	−0.0808	0.2739	0.0377	−0.1713
14:30	−0.1555	−0.1352	0.0099	0.1881	0.0239	−0.1411	−0.0471	−0.0713	0.2918	0.0377	−0.1956
14:45	−0.1255	−0.1401	0.0220	0.2031	0.0388	−0.1678	−0.0523	−0.0915	0.3075	0.0243	−0.1722
15:00	−0.1523	−0.1172	0.0688	0.2177	0.0244	−0.1460	−0.0277	−0.0526	0.3481	0.0332	−0.1615
15:15	−0.0518	−0.1361	0.0348	0.2284	0.0393	−0.1308	−0.0376	−0.0927	0.3533	0.0261	−0.1632
15:30	−0.0927	−0.1810	0.0340	0.2598	−0.0048	−0.1125	−0.0562	−0.1138	0.3726	0.0472	−0.1452
15:45	0.0493	−0.1748	0.0383	0.2517	0.0375	−0.0982	−0.0423	−0.1483	0.3889	−0.0005	−0.1337
16:00	0.1689	0.6859	1.1884	0.4582	−0.0325	−0.0510	0.9118	0.9617	0.3223	0.0176	−0.1226
16:15	—	−0.0976	0.5580	0.5280	0.0166	0.4852	0.3131	0.3308	0.1681	0.0181	0.4453

Table 4: Daily Panel Regressions of Spreads

This table presents the contemporaneous panel regression coefficients of percentage and dollar spreads on volatilities and imbalances. Panel A(B) shows the results of univariate regressions of spreads on volatilities(imbalances). Panel C shows the results of multivariate regressions of spreads on volatilities, imbalances, and control variables. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. Dollar spread is defined as the difference between ask and bid prices, measured by cents. Control variables include the natural logarithm of trading volume, vega, gamma, delta, price impact, maturity, and moneyness. We also include contract fixed effects in the regressions. The t-statistics are computed from Driscoll and Kraay (1998) standard errors. The sample period is from Jan 2004 to Dec 2020. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	(1)	(2)	(3)	(4)
	Call Δ % Spread	Call Δ $ Spread	Put Δ % Spread	Put Δ $ Spread
Panel A: Univariate results of underlying volatility				
Δ STD (%)	0.049***	0.436***	−0.004	2.438***
	(6.19)	(2.77)	(−0.98)	(6.45)
Δ Controls	N	N	N	N
Contract FE	Y	Y	Y	Y
Adjusted R^2	0.006	−0.003	−0.003	0.130
Panel B: Univariate results of demand imbalance				
Δ |Demand|	0.061***	1.251***	0.122***	0.201
	(3.52)	(3.74)	(7.72)	(0.48)
Δ Controls	N	N	N	N
Contract FE	Y	Y	Y	Y
Adjusted R^2	0.006	−0.003	−0.003	0.130
Panel C: Multivariate results with controls				
Δ STD (%)	0.026***	0.650***	0.014***	1.987***
	(3.71)	(4.03)	(3.68)	(6.50)
Δ |Demand|	0.049***	0.736**	0.080***	1.181***
	(3.20)	(2.19)	(6.11)	(3.19)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Adjusted R^2	0.142	0.095	0.067	0.252
Observations	315,223	315,223	496,307	496,307

Table 5: Intraday Time-Series of Coefficient Estimates of Demand Imbalances

This table presents the intraday time series of the panel regression coefficients of spreads on volatilities and imbalances. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. STD is the daily standard deviation of 15-minute S&P 500 index returns. End-user demand imbalance (Demand) is computed from the CBOE open-close database as the difference between buy and sell orders from all end-users divided by the sum, while |Demand| is the absolute value. Columns (1) and (2) report the multivariate regression coefficients of call percentage spreads on underlying volatility (STD) and end-user demand imbalances in one regression. Columns (3) and (4) report the multivariate regression coefficients of put percentage spreads on underlying volatility (STD) and end-user demand imbalances in one regression. Variables are measured at the specific timestamp on the left, except end-user demand. Control variables include the natural logarithm of trading volume, vega, gamma, delta, price impact, maturity, and moneyness. We also include contract fixed effects in the regressions. The t-statistics are computed from Driscoll and Kraay (1998) standard errors. The sample period is from Jan 2004 to Dec 2020. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	(1) Call Δ % Spread	(2) Call Δ % Spread	(3) Put Δ % Spread	(4) Put Δ % Spread
Time	Δ STD (%)	Δ |Demand|	Δ STD (%)	Δ |Demand|
14:15	0.021***	0.078***	0.020***	0.088***
14:30	0.024***	0.051**	0.021***	0.098***
14:45	0.016*	0.093***	0.024**	0.099***
15:00	0.023***	0.054**	0.025***	0.102***
15:15	0.030***	0.069***	0.029***	0.092***
15:30	0.025***	0.077***	0.029***	0.093***
15:45	0.032***	0.051**	0.042***	0.096***
16:00	0.028	−0.068	0.033	0.005
16:15	0.036***	−0.007	0.033***	0.021

Table 6: Daily Panel Regressions across Moneyness and Maturity

This table presents the contemporaneous panel regression coefficients of SPX percentage spreads on volatilities and imbalances across different moneyness and maturity groups. Panel A(B) shows the results of moneyness(maturity) subsamples. Moneyness is defined as $S/K - 1$, where S is the underlying price and K is the strike price. OTM options are calls and puts that are 5% out-of-the-money. ATM options are calls and puts that are $+/-5\%$ at-the-money. ITM options are calls and puts that are 5% in-the-money. Maturity is the number of days until options expire. Short-maturity options are calls and puts with a maturity of fewer than 60 days. Medium-maturity options are calls and puts with a maturity of more than 60 days but fewer than 120 days. Calls and puts with more than 120 days of maturity are long-maturity options. Control variables include the natural logarithm of trading volume, vega, gamma, delta, price impact, maturity, and moneyness. We also include contract fixed effects in the regressions. The t-statistics are computed from Driscoll and Kraay (1998) standard errors. The sample period is from Jan 2005 to Dec 2020. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Panel A: Moneyness			
	(1)	(2)	(3)
	OTM	ATM	ITM
Call Δ % Spread			
Δ STD (%)	0.041**	0.018***	0.004
	(2.53)	(4.08)	(1.50)
Δ |Demand|	0.130***	0.030**	−0.003
	(2.90)	(2.19)	(−0.25)
Δ Control	Y	Y	Y
Put Δ % Spread			
Δ STD (%)	0.010*	0.015***	0.010***
	(1.81)	(4.04)	(2.58)
Δ |Demand|	0.122***	0.019*	0.076*
	(6.08)	(1.70)	(1.67)
Δ Control	Y	Y	Y

Panel B: Maturity			
	(1)	(2)	(3)
	Short-maturity	Medium-maturity	Long-maturity
Call Δ % Spread			
Δ STD (%)	0.027***	0.025***	0.027***
	(3.48)	(4.03)	(3.50)
Δ |Demand|	0.060***	0.029	0.089**
	(2.97)	(1.19)	(2.20)
Δ Control	Y	Y	Y
Put Δ % Spread			
Δ STD (%)	0.011***	0.016***	0.015***
	(2.64)	(4.00)	(5.34)
Δ |Demand|	0.119***	0.032**	0.025
	(6.19)	(2.17)	(1.12)
Δ Control	Y	Y	Y

Table 7: Intraday Time-series of Coefficient Estimates of Absolute Supply Slopes

This table presents the intraday time series of the panel regression coefficients of spreads on volatilities and supply slopes. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. STD is the daily standard deviation of 15-minute S&P 500 index returns. Market maker supply imbalance (Supply) is computed from OPRA tapes as the difference between bid and ask sizes, divided by the sum, while |Supply| is the absolute value. Columns (1) and (2) report the multivariate regression coefficients of call percentage spreads on underlying volatility (STD) and market maker supply imbalances in one regression. Columns (3) and (4) report the multivariate regression coefficients of put percentage spreads on underlying volatility (STD) and market maker supply imbalances in one regression. Variables, except end-user demand, are measured at the specific timestamp on the left. Control variables include the natural logarithm of trading volume, vega, gamma, delta, price impact, maturity, and moneyness. We also include contract fixed effects in the regressions. The t-statistics are computed from Driscoll and Kraay (1998) standard errors. The sample period is from Jan 2004 to Dec 2020. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	(1) Call Δ % Spread	(2) Call Δ % Spread	(3) Put Δ % Spread	(4) Put Δ % Spread
Time	Δ STD (%)	Δ |Supply|	Δ STD (%)	Δ |Supply|
14:15	0.020***	−1.984***	0.020***	−1.881***
14:30	0.023***	−2.005***	0.020***	−1.975***
14:45	0.016	−2.057***	0.017**	−1.974***
15:00	0.022***	−2.014***	0.025***	−1.988***
15:15	0.029***	−1.944***	0.024***	−1.934***
15:30	0.025***	−1.993***	0.030***	−1.919***
15:45	0.031***	−1.974***	0.040***	−1.995***
16:00	0.028	−1.766***	0.033	−1.778***
16:15	0.036***	−1.786***	0.031***	−1.595***

Table 8: Daily Panel Regressions of Market Order Imbalances

This table presents the contemporaneous panel regression coefficients of percentage and dollar spreads on volatilities and market order imbalances. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. Dollar spread is defined as the difference between ask and bid prices, measured by cents. Order imbalances (|OIM|) are computed from OPRA intraday tapes as the difference between buy and sell orders from all market participants divided by the sum. STD is the daily standard deviation of 15-minute S&P 500 index returns. Control variables include the natural logarithm of trading volume, vega, gamma, delta, price impact, maturity, and moneyness. We also include contract fixed effects in the regressions. The t-statistics are computed from Driscoll and Kraay (1998) standard errors. The sample period is from Jan 2004 to Dec 2020. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	(1) Call Δ % Spread	(2) Call Δ $ Spread	(3) Put Δ % Spread	(4) Put Δ $ Spread
Δ |OIM|	0.212***	0.610	0.146***	4.106***
	(6.08)	(0.77)	(4.78)	(2.81)
Δ STD (%)	0.026***	0.650***	0.014***	1.987***
	(3.73)	(4.02)	(3.67)	(6.51)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Adjusted R^2	0.157	0.108	0.071	0.271
Observations	315,223	315,223	496,307	496,307

Table 9: Various Robustness Checks

This table presents the contemporaneous panel regression coefficients of spreads on volatilities and imbalances in various robustness checks. The relative risk of each contract is equal to squared deltas. Option return volatility (OptRetVol) is measured as the ratio between the underlying price and the option price, multiplied by absolute delta and the underlying return volatility, following Wei and Zheng (2010). Alternative daily volatility measure (RV_5min) is the realized variance based on the 5-minute SPX index. Implied volatilities are synchronous implied volatilities associated with options quotes. Spread volatility (SpreadVol) is the standard deviation of percentage and dollar spreads, respectively. The sample period is from Jan 2004 to Dec 2020. The t-statistics are computed from Driscoll and Kraay (1998) standard errors. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	(1) Call Δ % Spread	(2) Call Δ $ Spread	(3) Put Δ % Spread	(4) Put Δ $ Spread
Relative Risks				
Δ RelativeRisk (%)	0.467***	−3.528***	0.472***	−1.206
	(17.05)	(−5.14)	(15.85)	(−1.55)
Δ STD (%)	0.030***	0.638***	0.015***	1.954***
	(4.41)	(3.93)	(3.54)	(6.53)
Δ |Demand|	0.038***	0.768**	0.060***	1.136***
	(2.63)	(2.48)	(4.86)	(3.31)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Options Return Volatilities				
Δ OptRetVol	0.125***	−1.679***	0.072***	−1.576***
	(3.88)	(−4.36)	(4.44)	(−3.48)
Δ STD (%)	−0.001	1.019***	0.004	2.208***
	(−0.15)	(6.16)	(0.80)	(7.16)
Δ |Demand|	0.051***	0.716**	0.083***	1.101***
	(3.48)	(2.09)	(6.35)	(3.08)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Alternative Daily Volatility Measure				
Δ RV_5min	0.055**	2.110***	0.029**	4.934***
	(2.30)	(5.67)	(2.33)	(10.26)
Δ |Demand|	0.041***	0.579*	0.075***	0.643**
	(2.65)	(1.88)	(5.70)	(2.04)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Implied Volatilities				
Δ Imp Vol (%)	−0.107***	3.146***	−0.024**	1.763***
	(−3.44)	(3.75)	(−2.16)	(2.61)
Δ |Demand|	0.032**	0.499	0.070***	−0.011
	(2.17)	(1.59)	(5.36)	(−0.03)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y

	(1) Call Δ % Spread	(2) Call Δ $ Spread	(3) Put Δ % Spread	(4) Put Δ $ Spread
Spread Volatilities				
Δ SpreadVol (%)	0.272***	0.127***	0.195***	0.168***
	(13.36)	(6.17)	(9.54)	(5.49)
Δ STD (%)	0.021***	0.634***	0.012***	1.900***
	(3.27)	(4.12)	(3.18)	(5.80)
Δ |Demand|	0.069***	1.023***	0.092***	1.209***
	(4.47)	(3.11)	(6.93)	(3.49)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Look-ahead Bias Adjusted				
Δ STD (%)	0.028***	0.776***	0.019***	1.769***
	(2.85)	(3.48)	(3.75)	(5.03)
Δ |Demand|	0.029	1.008***	0.071***	1.012***
	(1.57)	(2.76)	(4.49)	(2.70)
Δ Controls	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y

Table 10: Time-Series Regressions of SPX Options Spreads

This table presents the contemporaneous time-series regression coefficients of spreads on volatilities and imbalances. Percentage spread is defined as the difference between ask and bid prices divided by the quote midpoint, measured by %. Dollar spread is defined as the difference between ask and bid prices, measured by cents. Control variables include the natural logarithm of trading volume, vega, gamma, delta, price impact, maturity, and moneyness. All the variables in the regressions are averaged with the weight of dollar open interest in the previous day. The t-statistics in parentheses are calculated from Newey and West (1987) method with 16 lags for daily regressions. The sample period is from Jan 2004 to Dec 2020. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

	(1) Call Δ % Spread	(2) Call Δ $ Spread	(3) Put Δ % Spread	(4) Put Δ $ Spread
Δ STD (%)	0.025***	1.899***	0.025***	2.462***
	(3.56)	(4.17)	(6.46)	(3.48)
Δ |Demand|	0.193	13.581	−0.737**	−12.541
	(1.00)	(1.24)	(−2.47)	(−1.00)
Δ Controls	Y	Y	Y	Y
Adjusted R^2	0.338	0.150	0.178	0.169
Observations	4,174	4,174	4,174	4,174