Cross Market Price Discovery and Selective Delta Hedging in the Option Market

Yunjiang Dong

Queen's University

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Abstract

We study the impact of option trading on equity price discovery using trade-level OPRA and TAQ data for S&P 500 stocks in 2020. On average, an option trade moves the underlying price by 0.56 basis points over five minutes, about one-sixth the effect of a stock trade. The impact is heterogeneous, increases monotonically with moneyness and absolute delta, and concentrates in single-leg and limit-order-book trades, while auction and multi-leg trades have negligible effects. These option trade characteristics associated with high price impact in the underlying are also associated with more stock limit-order-book activity within 100 milliseconds of option trades, consistent with the hypothesis where option market makers selectively delta hedge their orders.

Keywords: Option Market Maker, Vector Autoregression, Price Impact, Delta Hedge.
JEL classification: G11, G12, G14

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[2]This paper supersedes an earlier draft circulated as "The Intertwined Price Discovery Processes in Equity and Option Markets."

1 Introduction

One of the most enduring questions in the option literature is whether option trades convey information about the underlying prices and, if so, how this information is transmitted into prices. Trading theories state that informed investors trade to profit from their private information, while conveying their private information to the market in the process (Glosten and Milgrom, 1985). These informed trades are strategic, and aim to maximize informed investors' profits by optimizing the size of trades, splitting orders across time (Kyle, 1985), across multiple exchanges (Madhavan, 1995), and across multiple markets (Easley et al., 1998). More specifically, informed investors with access to both the equity and option markets should strategically split their orders in both markets. In this case, the presence of option markets complicates the interpretation of stock market price activity, since part of the demand of informed investors may be expressed in options rather than in the stock itself. If informed traders strategically shift a portion of their trading to options, the observed price impact of stock trades will understate the true effect of informed trading on equity prices, as some of the underlying information is revealed through option transactions. This implies that studying equity price movements in isolation risks overestimating the informational role of stock trades while overlooking the contribution of options. For this reason, it is essential to analyze the price impacts of both stock and option trades in a unified framework. In this paper, we use a comprehensive dataset including both option trades and stock trades and quotes data to disentangle the roles of stock and option trades on the price discovery process, with a primary focus on option trades' price impacts on the underlying stock price, and discuss the main mechanical channel of such price impacts. Based on our vector autoregression (VAR) analysis on the aggregated option and stock trades, we find that option trades account for roughly 18 percent of the cumulative price impact on the underlying, while stock trades account for the remaining 82 percent. However, complementary approaches such as variance decomposition (Hasbrouck, 1991) and Vector error correction model (VECM, Hasbrouck, 1995; Chakravarty et al., 2004) yield much smaller contribution estimates (about 1% and 3% respectively). This divergence arises for two key reasons. First, option trading occurs at much lower frequency than stock trading, mechanically reducing their variance share. Second, the estimation of VECM requires the construction of implied stock prices from option prices and the lagged implied volatilities. This tends to underestimate the information content of option trades as the implied stock prices do not contain the updated instantaneous implied volatilities. As a result, estimates based solely on option-implied prices are biased toward attributing price discovery to the stock market, even when option trades exert meaningful impacts in real time. Therefore, our price impact analyses from VAR indicates that, although equities remain the dominant venue for incorporating information, option trades provide a nontrivial share of price discovery that stock-only analyzes would fail to capture. This result reinforces the importance of incorporating option activity when measuring how information is impounded into prices and motivates our focus on the mechanisms through which option trades influence the underlying equity market.

To understand why option trades have measurable price impacts, we next consider the primary mechanism through which option transactions influence equity prices: the hedging activities of option market makers. When a market maker writes a call option, they are exposed to the risk of a price increase which increases the costs of delivering shares at option expiry. More importantly, they are concerned about being adversely selected by informed traders. To hedge against underlying price movements, option market makers can purchase shares in the underlying market, known as delta hedging. Delta, ranging between +1 to 0 for calls, and -1 to 0 for puts, refers to the number of share lots (100 shares) required for hedging per option contract, and can be calculated by option pricing models, e.g. the Black-Scholes option price model. The number of shares required to cover the underlying price risk increases as the magnitude (absolute value) of delta increases. This leads to a mechanical relationship between option moneyness (delta) and price impact, the higher the delta the higher the price impact in the underlying because of more impatient buying.

To test the hypothesis, we match option trades with underlying trades and quotes and calculate the price impacts of option trades. Our empirical analysis confirms this prediction. When we decompose option trades by contract characteristics, we find that in-the-money (ITM) trades generate significantly larger impacts on the underlying stock price than at-the-money (ATM) trades, which in turn exceed the effects of out-of-the-money (OTM) trades. This monotonic relationship between delta and price impact is consistent with the delta-hedging channel: option market makers acquire the largest directional exposures when intermediating ITM trades and therefore must execute larger and more immediate stock-side hedges. By contrast, OTM trades carry smaller deltas and thus require less hedging, resulting in muted underlying price effects.

While moneyness explains why some option trades impose larger hedging needs than others, it does not capture the full heterogeneity in price impacts. The institutional structure of option markets allows market makers to potentially identify whether a trader is informed or not, and to selectively hedge against different type of option orders.

In fully anonymous markets, price impacts will not vary by participant because markets makers are unable to observe the identity of a trader. In option markets, market makers can infer participant types and their motivations for trading. For instance, wholesalers purchase orders from retail brokers and execute these orders in auctions (Hendershott et al., 2025). These orders are profitable because they are less likely to be informationally motivated than orders from institutions or hedge funds. Some orders are also marked when they belong to a complex option strategy. These trades are usually delta-neutral and are not used to profit on directional changes in the underlying price. Therefore, we expect both auction and complex (multi-leg) orders to generate less price impact than orders in their counterparts (limit order book and single-leg orders). These institutional distinctions motivate our next set of tests, where we directly compare auction versus LOB trades and single- versus multi-leg strategies.

In this paper, we exploit the OPRA data feed that identifies different types of option trades: auction versus limit order book, and single versus multi-leg trades. We show that auction trades have about 1/10 the impact on the underlying than LOB trades. A recent literature on retail option trading (Bryzgalova et al., 2023) suggests that auctions are more populated by retail investors and our results confirm this finding. Multi-leg trades have only 1/20 the price impact of single-leg trades. This is consistent with multi-leg trades being mostly driven by non-directional trading strategies. We confirm these results in a regression and using cumulative impulse response functions that control for past trades and autocorrelation in returns.

We then extend our analysis to examine the impact of option trades on option prices themselves, which provides an internal consistency check on our results. The analysis is done for a sub-sample of option trades for which we have at least one trade of the same option contract within the next 4 to 6 minutes. This allows us to measure the impact on the actual traded price of the option and without using stock-implied option prices, but limits our sample to the most liquid options. Here we show similar results: Price impacts increase monotonically with moneyness, while single-leg and limit order book trades have higher price impacts than multi-leg and auction trades, respectively. In general, price impacts are increasing in moneyness, quoted spread, SPY volatility, and the limit order book imbalance in the underlying. This means that option trades impact both the underlying and then the option price.

A central mechanism behind these impacts is the hedging activity of option market makers (OMMs). When OMMs intermediate trades that leave them exposed to directional risk, they often offset this risk by delta hedging. We show that the stock activities (quote updates or trading events) within 100ms of option trades is significantly larger for option trades that are more likely to be price-informed, and with high price impact in the underlying. Our results support the theory that option market makers selectively delta hedge against option trades that are more likely to be price-informed. While previous research using data at lower frequencies has shown that market makers hedging leads to persistent price effects (Ni et al., 2021; Tang et al., 2024). In this paper, we look at trading in the underlying around option trades in a high frequency setting. We find more trading in underlying in the 100 milliseconds post option trade. Connecting to our results on price impacts we show less trading in the underlying, and therefore hedging, after auction trades and multi-legs trades. We find more underlying trading with increasing delta, option trade size, and implied option volatility.

The rest of the paper is structured as follows. Section 2 will review the literature of informed option trading and their impacts on the underlying price discovery process. Section 3 describes the data and the construction process of the equity-option merged sample. Section 4 documents the variation of informativeness between different types of option transactions. Section 5 presents evidence on the selective hedging behavior of the option market maker in the underlying market. Section 6 concludes.

2 Related Literature

2.1 Presence of Informed Trading in Option Markets

The earliest theoretical discussions already noted that options provide a natural venue for informed traders. Black (1975) emphasized that the embedded leverage of options, combined with the difficulty of short-selling in equity markets, makes them especially attractive to traders with private information. Building on this intuition, Easley et al. (1998) develop a sequential trade model of equity and option markets, showing that informed investors optimally split their orders between the two markets. Their model predicts that the likelihood of informed trading is greatest when option contracts have high leverage, low transaction costs, and sufficient liquidity to accommodate informed demand.

On the empirical side, researchers have found evidence that informed trading in options occurs to a great extent during periods of high information asymmetry, especially prior to informational events such as earnings announcements (Amin and Lee, 1997), take-over announcements (Cao et al., 2005; Augustin et al., 2019), Federal Open Market Committee (FOMC) scheduled announcements (Huang et al., 2024), Food and Drug Administration (FDA) announcements (Bohmann and Patel, 2022).

Although this literature establishes that informed trading in option markets is particularly pronounced in the run-up to major firm-level or macroeconomic announcements, it leaves open the question of how option trades affect the underlying market in real time outside of such event windows. In contrast to studies that focus on the timing of informed trading, our paper examines the microstructure mechanisms through which option trades transmit information to equities at high frequency. By combining OPRA trade data with TAQ stock quotes, we are able to measure the instantaneous price impacts of option transactions, disentangle their heterogeneity across moneyness, execution venues, and trading strategies, and link these impacts to market makers' delta-hedging activity. In this way, our study complements the event-driven literature by showing that option trades can contribute to price discovery not only around major announcements, but also in the continuous intraday trading process.

2.2 Information Content of Informed Option Trades

Apart from establishing that informed trading exists in option markets, a second strand of research focus on investigating the information carried by option market activities. One set of studies examines the predictive content of option volume for subsequent stock returns. Pan and Poteshman (2006) analyze differences in call versus put volume and find that net buying pressure in options helps predict future stock returns. Johnson and So (2012) show that option volume conveys negative information about future stock returns, and attribute this pattern to the presence of short-sale constraints in equity markets: informed traders who face difficulties shorting the stock may instead exploit their signals by trading in put options. Muravyev et al. (2018) provide a complementary explanation, linking the information content of option activity to the stock loan market. They demonstrate that option-implied prices reflect stock borrowing fees, which creates a channel through which option trading embeds information about future returns. Their evidence supports the notion that informed traders use options to express directional views that are not immediately reflected in stock prices. In addition to information on future stock returns, Ni et al. (2008) document that option order flow, especially in straddles, predicts future realized volatility, consistent with informed investors strategically trading volatility through options.

A complementary line of work investigates how option demand pressures affect option markets themselves. Bollen and Whaley (2004) show that net buying pressure in options has persistent effects on the implied volatility surface, suggesting that order flow conveys both information and inventory risk to market makers. This finding further reinforces the idea that option markets play a dual informational role, transmitting both price and volatility information to the broader market.

Taken together, this body of work demonstrates that option markets are informationally rich, influencing both the mean and variance of underlying returns. Yet much of the existing evidence relies on aggregated measures of option volume or net order flow, which may mask important heterogeneity across contracts and execution mechanisms. Our paper builds on this literature by shifting the focus from aggregate activity to the price impacts of individual option transactions in high-frequency data. By studying how trades differ across moneyness, execution type, and trading strategy, we provide a more granular view of how option trades influence the underlying equity market.

2.3 Information Contribution of the Option Market

A parallel line of research directly investigates how much option markets contribute to price discovery in the underlying. Chakravarty et al. (2004) use Hasbrouck's information share methodology (Hasbrouck, 1995) and find that, on average, option markets account for about 17% of the price discovery in the underlying equities, with variation across firms depending on liquidity and trading activity. Holowczak et al. (2006) propose a portfolio approach that nets out the confounding effects of stochastic volatility and higher moments by constructing synthetic forwards from pairs of options. Using second-by-second data for 40 heavily traded U.S. equities in 2002, they report that the option market's average information share is only 12.7% for NYSE-listed stocks and 3.1% for NASDAQ-listed stocks. Both papers suggest that, while statistically significant, options contribute much less to directional price discovery than stocks, and their informativeness is concentrated during periods of heavy option trading activity or when order flow creates strong directional pressure. More recent work using international data further highlights the heterogeneity: Muravyev et al. (2013) find little evidence that options lead in U.S. markets, while Hu (2014) and Patel et al. (2020) show that under specific conditions, such as when studying disaggregated option trades or international settings, option markets do play a meaningful role. Together, these studies underscore that the empirical evidence is mixed and often sensitive to sample period, methodology, and microstructure features.

Our paper revisits this debate by taking advantage of the complete OPRA trade feed and TAQ quotes for the underlying. Unlike much of the prior literature that focuses narrowly on at-the-money contracts or selected subsets of options, we include the full universe of listed options, covering all option contracts across the entire moneyness and maturity spectrum. As emphasized by Duarte et al. (2024), restricting attention to narrow samples of contracts can generate biases in inference about information shares, particularly by overemphasizing the role of the most liquid options while ignoring the contribution (or lack thereof) of less-traded but informationally relevant contracts. By incorporating all available trades, our analysis avoids these biases and provides a comprehensive, high-frequency view of how option transactions transmit information to equity markets.

2.4 Hedging Activities of Option Market Makers

A large strand of the literature studies how option market makers (OMMs) manage the risks that arise from providing liquidity in derivatives markets. Traditionally, option literature emphasized delta hedging as the canonical tool for neutralizing directional exposures (Black and Scholes, 1973), and early empirical work assumed that OMMs continuously hedge their inventories in the underlying market. More recent studies, however, reveal a more complex picture.

Huh et al. (2015) show that hedging demand from OMMs contributes to stock return predictability, especially when delta exposures are imbalanced. Tang et al. (2024) develop the measure of expected hedging demand (EHD) and show that stocks with high EHD tend to have volatile fundamentals, active option trading, and deltas highly sensitive to price changes, implying frequent and sizable hedging needs. Related work links hedging frictions to other outcomes: Ni et al. (2021) find that option demand shocks spill over into volatility markets, while Baltussen et al. (2021) show that systematic end-of-day rebalancing by OMMs creates predictable intraday return patterns. Finally, Hu et al. (2025) document that only a minority of market makers hedge consistently, while most rely on rapid inventory rebalancing rather than continuous delta hedging.

Overall, this literature suggests that OMM hedging generates short-term feedback effects in underlying prices but operates through both delta hedging and inventory management. Our paper adds to this area of literature by examining the limit order book activity within 100 milliseconds of option trades, providing suggestive evidence of delta-hedging by market makers at high frequency. Moreover, we are the first to document selective hedging behavior across trade types, highlighting that OMMs hedge against potentially informed option trades aggressively while treating others as uninformed and requiring minimal adjustment.

3 Data and Sample Construction

To study the cross-market relationship between the equity and option markets, we assemble a comprehensive dataset of stock and option transactions combining option data from the Option Price Reporting Authority (OPRA) and equity data from the NYSE Trades and Quotes (TAQ). Daily stock closing prices are collected from Center for Research in Security Prices (CRSP). The full sample includes approximately 280 million option trade observations. We also define a filtered sample of about 146 million trades for which we can compute 5-minute option price changes (requiring at least one subsequent trade in the same option contract within 4–6 minutes). This filtered subsample, while roughly half the size of the full sample, focuses on more liquid option contracts where short-horizon price impact on the option itself can be measured. The filtered sample allows for inspection of the 5-minute price impact on prices of individual option contracts without relying on option pricing models and lagged implied volatilities. In both samples, roughly two-thirds of option trades are on call options, and the distribution of trade directions is about 50% buyer-initiated vs. 50% seller-initiated. We focus on options on the stocks that are included in the S&P 500 index[1]. We remove records that are likely associated with data errors: 1) trades and quotes with non-positive prices, 2) quotes with negative spread, 3) trade condition IDs indicating an out-of-sequence, re-opened, or canceled trade[2]. We also remove all floor trades records as they occur at a very low frequency (about 0.12% of the sample), and are likely associated with highly specific responses from option market makers that may add noise to our results. Finally, to analyze price discovery jointly between markets, we complement the sample with daily stock prices from CRSP when looking at price discovery processes at daily or slower frequencies.

OPRA option transaction data record all standardized option transactions in the US

[1] ETF and index options (such as SPY and SPX) are not included in the sample. We also remove firms that went through ticker change during 2020 to facilitate matching of OPRA and TAQ databases. Tickers removed are: IR, RTX, UTX, ARNC, HWM, CTL, and LUMN.

[2] Trade Condition IDs removed for this criteria are 2, 6, 7, 13, 21, 40, 41, 42, 43.

option market. For each transaction, OPRA data provides the following information: 1) Details of the option contract, including the underlying ticker, option type (call or put), strike price, and contract expiration date. 2) Quoted prices of the underlying stock and the option contract at the time of the transaction. 3) Transaction details, including the trade price and volume of the transaction. 4) Trade condition IDs, offering additional order information such as execution type (auction vs limit order book) and trading strategy (single-leg vs multi-leg), which are crucial characteristics when studying informativeness in option trades.[3]

We make use of the TAQ database in multiple angles to supplement the sample with information from the equity market. First, for each option transaction, we collect mid price of underlying stock at the time of the option transaction, and at regular intervals after the option transaction. Second, we create a dataset combining both option and stock transaction records. This dataset is used to estimate the VAR model, the impulse response function, and the variance decomposition of stock and option trades on the underlying return. Third, we use 1-second interval stock and option mid price data to estimate the VECM model as in Chakravarty et al. (2004).

3.1 Descriptive Statistics of Option Transactions

We begin by summarizing the main features of the option trade data. Table 1 reports descriptive statistics for both the full sample of trades and the filtered sample used in the main analysis. The overall distribution of option prices is similar across the two samples. The mean option trade price in the full sample is \$6.77 compared to \$6.63 in the filtered sample, with medians of \$1.93 and \$1.87, respectively. Trade sizes also remain broadly comparable, averaging 5.5 contracts in the full sample and 5.4 contracts in the filtered

[3] In recent option market microstructure literature, Bryzgalova et al. (2023) uses a specific trade condition ID, SLAN (Single-leg non-ISO improvement mechanisms), as a proxy to identify transactions that are likely initiated by retail investors. Trade condition IDs were also used to classify option transactions that are priced by auctions in Hendershott et al. (2025).

sample. Implied volatilities average around 53 percent in both samples, indicating that filtering does not materially change the risk profiles of the option contracts represented.

The most notable differences between the two samples arise in time-to-maturity and spreads. In the full sample, the average time-to-maturity is over 40 days, whereas in the filtered sample it falls to 19 days. This difference reflects the limited trading activity in longer-dated contracts, which are frequently excluded by the liquidity filter. Similarly, quoted and effective spreads are smaller in the filtered sample, with average effective spreads declining from 2.9 percent to 2.1 percent. This indicates that the filtered sample correctly captures the more liquid segment of the market where spreads are narrower and transactions are more competitive.

Insert Table 1 here.

3.2 Option Trade Characteristics

We assign option trade characteristics to each option trade based on the OPRA data, which are reported in Table 2. Trade directions are inferred using the Lee and Ready (1991) tick test on option quotes. In addition to the trade direction, each option trade is assigned an underlying exposure direction. We label each trade as *bullish* if it reflects a positive exposure to the underlying (buying a call or selling a put) or *bearish* if it reflects a negative exposure (selling a call or buying a put).

In both samples, calls dominate puts, though the imbalance is more pronounced in the filtered sample. While calls represent about two-thirds (65%) of the full sample, their share rises to over 70% once the liquidity filter is applied. Despite this difference in contract type, the directional composition of option trades remains remarkably stable across the two samples: bullish and bearish exposures are nearly evenly split at around 50%. Thus, while the filtered sample tilts more heavily toward calls, it preserves the balance between trades expressing positive versus negative views on the underlying. The underlying exposure direction is crucial for signing the option trade's price impact on the underlying (PIU). For example, a bullish option trade should have a positive(negative) PIU when the underlying stock price increases(decreases) after the option trade.

Moneyness is defined as $\frac{S}{K} - 1$ for calls and $1 - \frac{S}{K}$ for puts. We then categorize option trades based on their moneyness: in-the-money (ITM) trades are those with moneyness greater than 3%, out-of-the-money (OTM) if moneyness is less than –3%, and at-the-money (ATM) for those in between. Moneyness distributions, however, differ more substantially. In the full sample, 9% of trades are in-the-money (ITM), 48% are out-of-the-money (OTM), and 43% are at-the-money (ATM). In the filtered sample, the share of ITM trades drops by almost half (to under 5%), while ATM trades expand to a majority (53%). This suggests that more liquid contracts tend to cluster near the money, while deeper ITM contracts are thinner and less likely to appear in the filtered dataset.

We use OPRA's trade condition IDs to distinguish each option trade's pricing mechanism and trading strategy. Table A3 maps each trade condition ID to the pricing mechanism and trading strategy dimensions of option trade characteristics. These classifications allow us to test hypotheses about which trades are likely to be information-driven. For instance, auction trades are predominantly retail order flow handled by wholesalers (Bryzgalova et al., 2023; Hendershott et al., 2025, and thus expected to be less informed, while multi-leg trades often implement arbitrage or hedging strategies that carry minimal directional exposure.

For pricing mechanism, trades marked as "auction" (price-improvement auctions as described in Hendershott et al., 2025) versus those executed in the limit order book (LOB). Approximately 21% of trades are executed through auctions in both full and filtered samples, with the remaining 79% routed through the limit order book (LOB).

For trading strategy, multi-leg trades (e.g. calendar spreads, strangles, covered calls and puts) comprise about 20% of trades, whereas the remaining 80% are single-leg transactions. The percentages lean slightly in favor to single-leg trades in the filtered sample. Likely due to some multi-leg strategies involve less often traded option contracts.

Insert Table 2 here.

3.3 Option Transaction's Price Impact on Underlying

To measure the price impacts of option trades on the underlying stock price, we measure an option trade's 5-minute price impact on underlying (PIU) as the signed change in the underlying stock's midquote price from the moment just before the option trade to five minutes after the trade, multiplied by the trade's directional sign (+1 for bullish, –1 for bearish trades). By construction, a positive PIU indicates that the underlying moved in the direction consistent with the underlying exposure direction of the option trade (e.g. stock price increases/decreases after a bullish/bearish option trade), vice versa.

Table 3 presents descriptive statistics for the five-minute price impact of option trades on the underlying stock (PIU), measured in basis points, across various trade categories in the filtered sample. The average 5-minute PIU is 0.56bps (1.55¢). Call and put options exhibit similar average impacts, at 0.57 and 0.54 bps respectively, but put trades show heavier tails, suggesting more extreme price responses. When further segmented by trade direction, buy-initiated trades produce roughly double the average price impact of sell-initiated trades. In terms of moneyness, ITM and OTM trades have highest average PIUs, at 0.83 and 0.63bps respectively, while ATM trades have the lowest PIU at 0.48bps. PIU also rises monotonically with time-to-expiration: 0DTE options show the smallest effects (0.38 bps), while trades in contracts expiring in more than one year produce nearly four times the impact (1.46 bps). Execution mechanisms and strategy type also show strong differences. Trades routed through auctions have significantly lower mean impacts (0.24 bps) than those executed on the limit order book (0.65 bps), and multi-leg trades exhibit virtually no impact (0.08 bps) compared to single-leg trades (0.66 bps), possibly due to the delta-neutral nature of most complex strategies.

Insert Table 3 here.

4 Informativeness across Option Trade Types

To assess whether the large cross-sectional differences in underlying price impacts documented in Table 3 reflect systematic variation in the informativeness of option trades, we begin by estimating stock-day level ordinary least squares (OLS) regressions of price impacts on option trade characteristics. The OLS framework allows us to control for observable factors such as trade size, implied volatility, quoted spreads, and prevailing market conditions, isolating the incremental contribution of each trade type to immediate and short-horizon price changes. Based on the descriptive evidence, we expect informed option trades are more likely to come from single-leg, in-the-money, and limit order book executions, which are associated with larger and more positive signed price impacts on the underlying (PIU). Conversely, trades typically associated with uninformed or hedging-related flow (such as multi-leg strategies and auction executions) should exhibit smaller or negligible price impacts. We then extend the analysis using a vector autoregression (VAR) framework to examine the dynamic interaction between option and equity markets. The VAR impulse response functions capture how shocks from different option trade types propagate into underlying prices over time, while the variance decomposition quantifies the share of underlying price variation attributable to each trade category, providing a complementary measure of their relative informativeness. Finally, we also implement a vector error correction model (VECM) following the methodology of Chakravarty et al. (2004) to estimate information shares based purely on the joint price movements of the option and stock markets, without conditioning on trade-level data. This approach measures the contribution of stock and option markets to the efficient price by exploiting the co-integration relationship between the two price series, providing a benchmark for the total information content in option prices relative to equities.

4.1 Ordinary Least Squares with Simple Price Impacts

For each stock-day, we perform an ordinary least squares regression (OLS) of option transactions' price impacts (in basis points) on the underlying (PIU, column 1 through 4) and on the option contract itself (PIO, column 5 and 6) on the option trade characteristics as formulated in Equation 1. Price impacts on underlying (PIU) are signed based on the determined underlying exposure direction (bullish vs bearish), which are determined by the trade direction (inferred from Lee and Ready, 1991 tick test) and the option type (call vs put). For example, both buying a call and selling a put are considered bullish, and the PIU would be positive if the stock price increases after 10 seconds (column 1 and 2) or 5 minutes (column 3 and 4). Whereas for bearish option trades (selling a put or buying a call), positive PIUs are associated with negative changes in stock prices.

$$\text{Price Impact} = \beta_1 D_{\text{Single-leg}} + \beta_2 D_{\text{Auction}} + \beta_3 D_{\text{ITM}} + \beta_4 D_{\text{OTM}} + \Gamma\text{Controls} + \epsilon \qquad (1)$$

The option trade charateristic variables in our analysis include dummy variables representing a type of option trade on the strategy, execution type, or moneyness dimension. $D_{\text{Single-leg}}$ is 1 for single-leg trades, and 0 for multi-leg trades. D_{Auction} is 1 for trades priced through auctions, and 0 for those priced through the limit order book. D_{ITM} and D_{OTM} are dummy variables representing ITM and OTM trades respectively. Multi-leg, limit order book, and ATM trades are absorbed into the intercept term, the estimated coefficients for the dummy variables are the price impact differences of the dummy variable trade characteristic and the absorbed trade characteristics (i.e. single-leg minus multi-leg, auction minus limit order book, ITM/OTM minus ATM). The control variables in our analysis are: *Trade Size* is the number of contracts traded (1 option contract is associated with 100 shares in the underlying stock). *Implied Volatility* (in percent) is computed based on the prevailing stock and option midquotes using the binomial model as in Cox et al.

(1979).[4] *Quoted Spread* (in percent) is the relative half-spread ($\frac{1}{2}\frac{Bid-Ask}{Mid}$) of the option contract traded. *SPY Volatility* (in percent) is the absolute 10-second lagged SPY return (from $t - 10$ to t, where t is the time of the option trade). *Lagged SPY Return* (in percent) is the signed 10-second lagged SPY return. *Underlying Volatility* (in percent) is the absolute 10-second lagged return on the underlying stock. *Lagged Underlying Return* (in percent) is the signed 10-second lagged return on the underlying stock. *Underlying LOB balance* is defined as the $\frac{\text{depth at best bid}-\text{depth at best ask}}{\text{depth at best bid}+\text{depth at best ask}}$, which is positive when the ask-side liquidity of the limit order book is larger and negative when the buy-side liquidity is larger.

Insert Table 4 here.

Table 4 reports the average coefficients of the OLS regressions. The results show significant heterogeneity in price impacts caused by option trades across different types of option trades. In both 10-second and 5-minute horizon for the underlying stock price, single-leg trades are associated with significantly larger PIU: 0.46 bps at the 10-second horizon and 1.07 bps at the 5-minute horizon, relative to multi-leg trades. This is consistent with single-leg trades typically carrying greater directional exposure and therefore prompting more aggressive delta-hedging by the option market makers in the underlying market. For pricing mechanism, auction executions have significantly smaller impacts, reducing PIU by 0.36 bps (10-second) and 0.56 bps (5-minute) relative to LOB trades, consistent with the predominance of retail order flow in auctions and market makers' lower hedging intensity for such trades. In terms of moneyness, ITM trades exhibit larger impacts than both OTM and ATM trades. This is because ITM trades are associated with larger absolute deltas.

The control variables serve to isolate the impact of trade characteristics from other factors that may influence short-horizon price changes. *Trade Size* accounts for the me-

[4] We use the binomial model to account for the nature of American style option in the U.S. option market. In addition, the binomial model allows us to input discrete future dividends. We collect dividend data from CRSP and include the discrete dividends from the trading date to the option contract's expiration date in the model. Our results are robust to using the Black-Scholes Model (Black and Scholes, 1973) with an assumption of continuous dividend to calculate implied volatilities and deltas.

chanical effect of larger option trades generating greater hedging demand in the underlying equity market. *Implied Volatility* captures differences in option value sensitivity and market uncertainty that may influence how aggressively market makers hedge. *Quoted Spread* proxies for the liquidity of the option contract at the time of the trades, where wider spreads are associated with lower liquidity and greater price impacts. *SPY Volatility* and *Lagged SPY return* measure broader market conditions that can amplify or dampen price adjustments in both the option and underlying markets. *Underlying Volatility* and *Lagged Underlying Return* capture short-term return autocorrelation effects, ensuring that estimated effects are not driven by concurrent stock price trends. Finally, *Underlying Limit Order Book (LOB) Imbalance* accounts for prevailing supply–demand conditions in the stock market, which can affect the ease with which market makers offset option positions through hedging trades. Among control variables, *Trade Size*, *SPY Volatility*, *Lagged Underlying Return* and *Underlying LOB imbalance* show statistical significant effect on PIU in 10-second horizon, while the significance for *Trade Size* and *Lagged Underlying Return* is no longer present in 5-minute horizon. Higher quoted spreads are positively associated with both 5-minute PIU, suggesting that option trades executed during less liquid times have greater price effects. *Underlying Volatility* is negatively associated with PIU, this is because as volatility increases, the sensitivity between stock and option prices decreases.

Similar option trade characteristics contribute both to PIU and PIO, but with larger magnitudes in the option market, due to the differences in market sizes. Single-leg trades increase PIO by about 4 bps, suggesting that these trades carry substantial information both in directional and volatility information. In contrast, auction trades reduce PIO by more than 3 bps relative to LOB trades, consistent with their lower informativeness and reduced hedging urgency. ITM trades have the largest positive PIO coefficients (about 5.8 bps), highlighting their high delta exposure. On the other hand, OTM trades have significantly less PIO comparing to ATM trades as ATM options have higher vega exposure. The strong similarity between PIO and PIU results indicates that the same trade characteristics that drive equity market reactions also drive option price adjustments, consistent with rapid cross-market transmission of order flow information and hedging pressures.

The control variables in the PIO regressions exhibit patterns consistent with their role in shaping option price responses. Larger *Trade Size*, *Quoted Spread*, *SPY Volatility* and *Underlying LOB imbalance* are strongly and positively associated with PIO, similar to PIU. *Underlying Volatility* exhibits opposite effect towards PIU and PIO. This is because option price swings are larger during higher underlying volatility, while option trades during this period are volatility rather than directional motivated, hence they affect the underlying price less.

4.2 Vector autoregression with Aggregated Stock and Option Trade Data

To examine the dynamic interaction between option and equity markets, we perform a trade-level vector autoregression (VAR) model following the approach of Brogaard et al. (2019). First we aggregate the TAQ stock and OPRA option trade data for each stock-day, including all stock trades, and all option trades with the same underlying ticker. This combined tradebook is then ordered by the timestamps, where each trade (whether its a stock or option trade) is considered an event time for the purpose of VAR. This event-time framework ensures that price responses are measured relative to the sequencing of trades across both equity and option markets. The VAR model incorporates a set of equations where each variable is written as a linear combination of all other variables and their lags, and its own lags. The following VAR model is estimated for every stock-day:

$$X_t^i = \sum_{k=1}^{5} \beta_k^i X_{t-k}^i + \sum_{j \neq i, j \in N} \sum_{k=0}^{5} \beta_k^j X_{t-k}^j \quad \forall i \in N \tag{2}$$

where N denotes the set of variables involved in the VAR model, including event-time underlying returns, stock trading characteristics, and option trade characteristics. Superscript i and j indicate ith and jth variable within set N. Subscript k indicates the number of lags (in event time, with $k = t$ indicates that the variable is taken at the time of the trading event). For instance, $X_t^i - 2$ denotes the value of the ith variable two trades prior to the current trade. β_k^j is the coefficient to be estimated for the kth lag of jth variable. Note that for $j = i$, we do not include the contemporaneous value of X_t^i on the right hand side, as this would trivialize the coefficient estimates. For $j \neq i$, I allow for contemporaneous effects from other variables.

The VAR is estimated in event time, which advances by 1 whenever an option or stock trade takes place. The X variables included are: *Event Time Underlying Return*, *Stock Trade - Price Change*, *Underlying Trade - Same Price*, *Option Trade - Auction*, *Option Trade - LOB*, *Option Trade - Single-leg* and *Option Trade - Multi-leg*. The variables are defined as follows: *Underlying Trade - Price Change* captures all the stock trades with a trade size greater than the NBBO depth and hence moves the NBBO. *Underlying Trade - Same Price* captures all the stock trades with a smaller trade size than the NBBO depth and hence do not move the NBBO. *Option Trade - Auction, LOB, Single-leg, Multi-leg* each captures all the options trades within its specific category based on execution type and trading strategy.

Insert Table 5 here.

Table 5 reports the average cumulative impulse response functions (IRFs) of stock returns to a one trade instance, estimated separately for different categories of option trades. In 20 event time horizon, stock trades have 1.13bps (price change) and 0.71bps (same price) impulse responses on the underlying return respectively. Option trades have lower impulse responses comparing to stock trades. Comparing within option trade types, limit order book executions and single-leg trades exhibit economically significant positive impulse responses, both at 0.38bps. On the other hand, auction and multi-leg trades have near 0 impulse responses. This indicates that a portion of the informed trading is present in the option trades, only through the limit order book and single-leg trades. These option trades shocks the underlying prices, despite traded on a different market. In contrast, auction executions and multi-leg trades have IRFs that are close to zero and statistically insignificant, suggesting little to no dynamic spillover from these categories into the stock market. This pattern is consistent with our selective hedging hypothesis: market makers respond more aggressively to order flow they perceive as potentially informed (e.g., single-leg LOB trades), while trades likely to be non-directional or retail-driven (e.g., auctions and multi-leg strategies) elicit minimal hedging activity and therefore have negligible influence on the evolution of underlying prices.

Insert Table 6 here.

Table 6 shows the information contribution of stock and option trades based on variance decomposing the VAR estimates. Despite contributing to a significant portion of the underlying return process, variance decomposition shows that option trades collectively contribute to about 1% of the variance in the underlying return process. The first reason is that the frequency of option trades happening is much lower than that of stock trades, diluting the contribution of option trades. The second reason is that based on Easley et al. (1998), informed trading activities are likely to happen simultaneously across both markets. This shows that the price information contributed by the option market is likely not unique, and arrives at a delayed fashion due to having to go through the option market maker hedging process. Nonetheless, the option market still contributes a small amount of incremental information on the underlying price discovery process, with a non-negligible fraction of the price impact comparing to stock trades.

While the VAR framework provides event-time evidence of how different types of option trades affect underlying prices, it does not quantify the overall share of price discovery attributable to the option market as a whole. To complement these trade-level dynamics, we turn next to a Vector Error Correction Model (VECM) analysis, which estimates Hasbrouck (1995) information shares based solely on the joint evolution of stock and option prices.

4.3 Vector Error Correction Model Measuring the Information Contributed by Prices from the Stock and Option Markets

While the VAR analysis highlights how individual option trades transmit information to stock prices in real time, it does not measure the overall contribution of option markets to price discovery relative to equities. To address this, we implement the vector error correction model (VECM) as in Chakravarty et al. (2004) and estimate information shares based on the co-integration between option and stock prices. This approach abstracts from trade classification and instead uses the common efficient-price component shared across markets to assess the fraction of permanent price innovations attributable to options.

We construct series of midquote prices from OPRA option data and TAQ stock data, sampled at one-second intervals. For each stock-day, we identify the most actively traded option contract and construct the option-implied underlying midprice based on the option prices of the call-put pair and 30-min lagged implied volatility. The VECM is then estimated using both price series, and Hasbrouck's upper and lower bounds are computed for the option market's share of the efficient price variance. Table 7 reports the distribution of information shares across the sample.

The results indicate that the option market contributes only a modest share to overall price discovery. Across all stock-days, the mean upper bound is approximately 3.3%, while the mean lower bound is close to 0.7%. The median values are even lower, underscoring that for most firms on most days, options play a very limited role compared to equities. The contribution rises somewhat during periods of heightened volatility and for the most liquid options, but remains well below the share attributable to stock markets.

Insert Table 7 here.

It is important to note that, the VECM approach of measuring the contribution of option market on stock price discovery processes is leaving out some information from the option market. First, the 30-minute lagged implied volatilities used to compute the synthetic stock prices would lead to missing information content (i.e., the instantaneous implied volatility) from the option market. Second, only the most traded option contract (usually the ATM option with relatively short maturity) would be used for the construction of the synthetic stock price, leaving out information contained by OTM and longer maturity option contracts.

What the VECM shows is that, the information contribution of option-implied stock price is much lower than the stock price itself. Therefore, from the option market makers perspective, who would suffer large loss from getting adversely selected by informed traders, it is important to identify potential informed option trades from order characteristics. In the next section, we try to identify the heterogeneous reaction from option market makers towards different types of option trades.

5 Stock LOB reaction to Option Trades

We next examine how option trades trigger activity in the underlying stock within the 100 millisecond window following each transaction. Table 8 shows that across the filtered sample, 45% of option trades are followed by at least one stock trade or quote update. The average intensity of response is 4.59 stock trades and 720 shares ($9,000 dollar volume) executed within this narrow window, indicating that option activity does elicit rapid adjustments in the equity market, though not uniformly across all trades.

The magnitude of the response varies across different option trade characteristics. Limit order book executions are followed by 5.41 stock trades and 860 shares ($10,000 dollar volume) on average, compared with only 1.36 trades and 170 shares ($3,000 dollar volume) after auction executions. Similarly, single-leg transactions induce 4.96 trades and 790 shares of stock volume ($9,000 dollar volume), while multi-leg trades are associated with only 3.09 trades and 440 shares ($7,000 dollar volume). The heterogeneity in limit order book reactions aligns with our hypothesized delta hedging channel, where option trades with higher risk of informative trading on future price information, such as single-leg, and LOB trades, lead to more immediate reaction by the market makers, who have to delta-hedge accordingly. The hedging activities are also directly correlates to the moneyness of the option contract, as ITM options have much higher delta, requiring larger volume trade in the underlying to hedge. By moneyness, ITM option trades generate the largest reactions, with 6.85 stock trades and 1,570 shares ($11,000 dollar volume), comparing to 4.71 trades and 790 shares ($10,000 dollar volume) for ATM contracts, and 4.14 trades and 630 shares ($7,000 dollar volume) for OTM contracts.

Insert Table 8 here.

Table 9 confirms these patterns in a regression framework. Relative to baseline ATM, LOB, single-leg trades, auction executions are associated with 158 fewer shares of stock trading within 100ms of option trade, while multi-leg transactions correspond to 160 fewer shares. ITM option trades increase underlying trading by 183 shares relative to ATM contracts, whereas OTM trades reduce subsequent activity by 38 shares. Larger trade size and higher implied volatility both significantly amplify the response: each additional contract traded adds about 0.27 shares to net stock volume, and a one-point increase in implied volatility is associated with 80 more shares. Collectively, these results provide direct evidence that stock market makers hedge selectively and aggressively in response to option trades that carry substantial delta exposure, while largely ignoring trades that are retail-dominated or delta-neutral.

Insert Table 9 here.

6 Conclusion

This paper investigates how option trading contributes to the price discovery of underlying equities. Using trade-level data from OPRA matched with TAQ for S&P 500 stocks from January to October 2020, we show that option trades exert a measurable, though modest, impact on stock prices. On average, an option trade moves the underlying by 0.56 basis points over five minutes, roughly one-sixth the impact of a stock trade. More importantly, the effect is highly selective: single-leg and limit-order-book trades generate substantial and persistent stock price responses, while auctioned and multi-leg trades are almost entirely absorbed without consequence.

Our analysis highlights the central role of market-maker delta-hedging in transmitting information across markets. We document that stock-side trading within 100 milliseconds of an option trade increases sharply following transactions that impose large directional exposures on market makers. The heterogeneity across execution venues and strategies is equally consistent with this mechanism: retail-dominated auction trades and delta-neutral spreads rarely elicit hedging, whereas directional, exchange-executed trades do. This selective response reconciles why only a fraction of the vast option trading volume contributes to equity price discovery.

Complementary VAR and VECM analyses confirm that the option market's aggregate share of price discovery is small. Information share estimates place the contribution of option prices at less than 3 percent of the efficient price variance, underscoring that equities remain the dominant locus of information incorporation. Still, the rapid and durable adjustments following certain option trades demonstrate that options can act as a fast channel for information release when the trades are sufficiently informative.

Our findings extend the literature on cross-market price discovery by establishing that the informational role of options is mediated not by aggregate volume, but by the type of trade and its hedging implications. The study is limited to S&P 500 stocks during the volatile COVID period, suggesting caution in generalizing to calmer market regimes or smaller firms.

One promising direction for future work would be to delve more deeply into the volatility information content of option markets. While our results show that stock markets dominate the incorporation of price information, options may still provide early, rich signals about future return distribution, including risk-neutral volatility, skewness, or tail risk, which are often underexploited. Classic theory such as Breeden and Litzenberger (1978) establishes that state-contingent claims implicit in option prices can identify the risk-neutral density of future stock returns; more recent papers (e.g. Chabi-Yo and Loudis, 2020; Chang et al., 2025) show that option-derived measures of variance, skewness, and kurtosis help predict cross-sectional and aggregate stock returns and risk premia. Incorporating such panels of option prices could allow one to test whether information about future volatility (not just directional return moves) is impounded earlier in options than in equity markets, and whether this effect is stronger for high-delta or long-dated options, auction vs. LOB trades, or single- vs multi-leg contracts. Such an extension would help quantify the option market's role in shaping the entire return distribution rather than only short-term price discovery.

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Tables

Table 1: Summary Statistics of Option Trades

This table reports the descriptive statistics of all option trades included in the full sample ($N = 280,014,173$) and the filtered sample ($N = 146,052,544$). The sample period is from January 2nd to October 21st, 2020. *Price* is the reported option trading price. *Trade Size* is the reported option trading volume (in number of contracts). *Mid (Underlying Mid)* are the reported option (stock) midprice inferred from the respective limit order books. *Moneyness* is the difference between underlying midprice and option strike price divided by option strike price, and multiplied by -1 for put options. *Days to Expiration* is the time difference (in days) between expiration date at 4 p.m. and the trading datetime. *Implied Volatility* and *Delta* are computed by using a binomial model for American Options (Cox et al., 1979). *Quoted Spread ($)* is half the dollar difference between option ask price and bid price, and divided by the option mid price to get the relative value (in percentage). *Effective Spread ($)* is the dollar difference between option trade price and midprice, multiplied by the trade direction (+1 for buy, -1 for sell).

	Full Sample			Filtered Sample		
	Mean	Median	SD	Mean	Median	SD
Price ($)	6.77	1.93	16.93	5.26	1.85	11.57
Trade Size (Contracts)	5.47	2.00	12.19	5.39	1.97	12.08
Mid ($)	6.77	1.93	16.93	5.26	1.85	11.57
Underlying Mid ($)	342.17	132.86	655.95	395.34	170.86	719.42
Moneyness	-0.05	-0.03	0.12	-0.04	-0.02	0.08
Days to Expiration	40.77	9.67	90.70	19.01	4.89	47.05
Implied Volatility	52.64%	43.78%	33.37%	53.83%	44.88%	33.56%
Delta	0.13	0.18	0.40	0.16	0.23	0.37
Quoted Spread	4.62%	1.88%	8.43%	3.10%	1.49%	5.26%
Quoted Spread ($)	0.14	0.03	0.33	0.09	0.03	0.20
Effective Spread	2.93%	1.06%	5.92%	2.08%	0.89%	3.93%
Effective Spread ($)	0.07	0.02	0.18	0.05	0.01	0.12

Table 2: Option Trade Characteristics and Frequency

This table reports the frequency of option trade characteristics reported by OPRA. ($N = 280,014,173$). The filtered sample ($N = 146,052,544$) includes only trades where a 5-min volatility can be determined. i.e., there exists a trade of the same option contract between the 4 to 6-min window after. The sample period is from January 2nd to October 21st, 2020. Buying a call option or selling a put option are classified as *Bullish*, while selling a call option or buying a put option are classified as *Bearish*. *ITM*, *OTM*, and *ATM* are defined as option trades with moneyness greater than 3%, less than -3%, and in between -3% and 3% respectively. Moneyness is defined as the difference between the option mid price and the strike price divided by the strike price, multiplied by -1 for put options. *Auction/Orderbook*, *Single-leg/Multi-leg* are determined based on the trade condition ID provided by OPRA as in Appendix Table A2.

	Full Sample		Filtered Sample	
Trade Characteristic	**Frequency**	**Number of Trades**	**Frequency**	**Number of Trades**
Call	65.06%	182,165,547	70.32%	102,708,059
Put	34.94%	97,848,626	29.68%	43,344,485
Bullish	50.05%	140,151,454	50.29%	73,448,241
Bearish	49.95%	139,862,719	49.71%	72,604,303
ITM	8.68%	24,318,222	4.69%	6,849,083
OTM	48.19%	134,951,685	42.11%	61,495,522
ATM	43.12%	120,744,266	53.26%	77,794,752
Auction	20.39%	57,082,121	21.59%	31,533,772
Orderbook	79.61%	222,932,052	78.41%	114,518,772
Single-leg	80.23%	224,658,253	82.98%	121,201,150
Multi-leg	19.77%	55,355,920	17.02%	24,851,394

Table 3: Summary Statistics of Option Trades' Price Impact on Underlying

This table reports the summary statistics of 5-minute price impact on underlying (in bps) of option trades from the filtered sample as defined in table 2. The total number of observations is 146,052,544, subsample frequencies are reported in percentage.

				Percentile				
	Frequency	Mean	SD	5%	25%	50%	75%	95%
Full Sample	100.00%	0.56	50.03	-63.71	-15.81	0.00	16.68	65.67
Option Type								
Call	70.31%	0.57	46.62	-61.31	-15.44	0.02	16.28	63.22
Put	29.69%	0.54	57.30	-68.47	-16.82	0.00	17.70	70.25
*Option Type * Trade Direction*								
BuyCall	35.18%	0.73	46.20	-62.02	-15.05	0.63	16.57	63.44
BuyPut	14.58%	0.79	57.14	-69.93	-17.04	0.01	18.05	71.66
SellCall	35.13%	0.40	47.03	-60.93	-15.81	0.01	15.98	63.33
SellPut	15.11%	0.31	57.46	-67.96	-16.60	0.21	17.38	69.95
Moneyness								
ITM	4.69%	0.83	81.56	-105.40	-22.07	0.00	23.84	107.84
OTM	42.04%	0.63	57.12	-71.88	-17.92	0.00	18.92	74.00
ATM	53.27%	0.48	39.21	-53.45	-14.09	0.07	14.82	54.95
Time to Expiration								
0DTE	9.06%	0.38	44.66	-61.72	-15.57	0.00	16.11	63.03
1-7 days	44.40%	0.46	50.01	-61.94	-16.02	0.03	16.72	63.45
1-2 weeks	20.88%	0.56	48.87	-63.21	-15.69	0.00	16.53	65.12
2-4 weeks	10.11%	0.72	50.32	-66.30	-16.09	0.10	17.29	68.83
1-3 months	11.33%	0.75	53.65	-64.55	-15.39	0.00	16.58	67.21
3-12 months	3.71%	1.07	54.82	-68.65	-15.60	0.00	17.15	72.39
more than 1 year	0.50%	1.46	61.97	-70.52	-14.73	0.00	16.61	75.52
Pricing Mechanism								
Auction	21.60%	0.24	47.06	-61.96	-15.94	0.00	16.30	62.73
LOB	78.40%	0.65	50.82	-63.57	-15.79	0.08	16.78	65.80
Number of Legs								
Single-leg	82.98%	0.66	51.20	-64.52	-16.11	0.09	17.13	66.71
Multi-leg	17.02%	0.08	43.89	-56.67	-14.50	0.00	14.63	56.97

Table 4: Price Impact Heterogeneity Across Option Trade Characteristics

This table reports the average estimates of OLS regressions on the signed price impacts (in basis points) for each stock-day on option trades characteristics. The sample period is from January 2 to October 21, 2020. Only stock-days with at least 100 option trades associated with the same underlying were included in the sample. The dependent variable is 10-second price impacts on underlying (PIU) for column (1) and (2), 5-minute PIU for column (3) and (4), and 5-minute price impacts on options (PIO) for column (5) and (6). Detailed definitions of variables are in Table A1. t-statistics clustering to stock and date are reported in parentheses. *, ** indicate statistically significance at 5% and 1% respectively.

	10-Second PIU		5-Minute PIU		5-Minute PIO	
	(1)	(2)	(3)	(4)	(5)	(6)
Single-leg	0.46**	0.43**	1.07**	1.06**	3.90**	4.40**
	(42.58)	(35.70)	(18.57)	(16.90)	(81.85)	(81.67)
Auction	-0.36**	-0.36**	-0.56**	-0.51**	-3.22**	-3.20**
	(-44.84)	(-40.59)	(-12.09)	(-10.41)	(-91.43)	(-83.62)
ITM	0.04*	0.04*	0.39**	0.32**	5.86**	5.79**
	(2.26)	(1.99)	(3.96)	(3.00)	(56.23)	(52.83)
OTM	-0.17**	-0.17**	-0.02	-0.08	-1.23**	-1.83**
	(-18.74)	(-16.73)	(-0.42)	(-1.40)	(-32.25)	(-41.17)
Trade Size		0.00**		0.00		0.00**
		(3.22)		(-0.18)		(3.84)
Implied Volatility		-0.01**		-0.04**		0.00
		(-7.97)		(-7.83)		(-0.04)
Quoted Spread		0.00		0.02**		0.29**
		(-1.10)		(4.60)		(68.95)
SPY Volatility		4.47**		6.38**		8.65**
		(18.21)		(5.87)		(12.41)
Lagged SPY Return		-0.57**		0.63		0.75
		(-3.13)		(0.78)		(1.47)
Underlying Volatility		-1.94**		-5.17**		11.36**
		(-25.30)		(-15.55)		(52.82)
Lagged Underlying Return		0.22**		-0.05		-0.29
		(3.60)		(-0.16)		(-1.60)
Underlying LOB imbalance		0.28**		0.31**		0.11**
		(26.26)		(5.76)		(3.59)
Intercept	0.14**	0.37**	0.28**	1.73**	2.80**	0.84**
	(11.75)	(9.21)	(4.39)	(7.74)	(55.02)	(4.02)

Table 5: Cumulative Stock-day Average Return Impulse Response

This table reports the stock-day average return impulse responses upon a stock or option trade. Each trading category is a variable involved in the VAR model and can take the value of +1, 0, or -1. For stock trades, *Price Change* takes the value of +1 if a market buy trade changes the NBBO price, -1 if a market sell trade changes the NBBO price, and 0 otherwise. *Same Price* takes the value of +1 for a market buy trade that does not change the NBBO price, -1 for a market sell trade that does not change the NBBO price, and 0 otherwise. For option trades, *Sing-leg, Multi-leg, LOB, and Auction* each take the value of +1 (-1) for a bullish (bearish) option trade that match the characteristics, and 0 otherwise.

	Stock Trade		**Option Trade**			
t	Price Change	Same Price	Single-leg	Multi-leg	LOB	Auction
1	0.14	0.00	0.17	0.01	0.17	0.01
2	0.41	0.13	0.21	0.02	0.21	0.02
3	0.59	0.23	0.25	0.02	0.25	0.02
4	0.73	0.32	0.29	0.02	0.29	0.03
5	0.83	0.41	0.32	0.02	0.33	0.04
6	0.91	0.47	0.33	0.02	0.34	0.04
7	0.96	0.52	0.34	0.02	0.35	0.04
8	1.01	0.56	0.35	0.02	0.35	0.04
9	1.04	0.59	0.36	0.02	0.36	0.04
10	1.06	0.61	0.36	0.02	0.37	0.04
11	1.08	0.64	0.37	0.02	0.37	0.04
12	1.09	0.65	0.37	0.02	0.37	0.04
13	1.10	0.67	0.37	0.02	0.37	0.04
14	1.11	0.68	0.37	0.02	0.38	0.04
15	1.11	0.68	0.38	0.02	0.38	0.04
16	1.12	0.69	0.38	0.02	0.38	0.04
17	1.12	0.70	0.38	0.02	0.38	0.04
18	1.13	0.70	0.38	0.02	0.38	0.04
19	1.13	0.71	0.38	0.02	0.38	0.04
20	1.13	0.71	0.38	0.02	0.38	0.04

Table 6: Information contribution

This table reports the stock-day average information contributions of each type of option trades. The information contribution is the proportion of variance generated by a specific option trade type out of the total variance generated by all option trades and stock trades.

Order Type	Variance Contribution	Trading Frequency
Limit Order Book	0.91%	6.17%
Auction	0.06%	1.83%
Single-leg	0.94%	6.64%
Multi-leg	0.10%	1.36%

Table 7: VECM estimation of information share by the option market

This table reports the distribution of option market contribution determined by VECM (Hasbrouck, 1995, Chakravarty et al., 2004) across stockdays.

			Percentile				
	Mean	SD	5%	25%	50%	75%	95%
Stockday ($N = 86,179$)							
Upper Bound	3.24%	8.48%	0.00%	0.17%	0.96%	3.09%	11.66%
Lower Bound	2.81%	8.11%	0.00%	0.06%	0.66%	2.53%	10.35%
Stock mean ($N = 491$)							
Upper Bound	3.33%	1.13%	1.96%	2.51%	3.09%	4.00%	5.48%
Lower Bound	2.91%	1.10%	1.56%	2.11%	2.64%	3.58%	5.03%
Stock median ($N = 491$)							
Upper Bound	0.92%	0.34%	0.12%	0.79%	0.98%	1.14%	1.36%
Lower Bound	0.63%	0.26%	0.07%	0.51%	0.68%	0.81%	0.99%
Day mean ($N = 204$)							
Upper Bound	3.24%	0.52%	2.49%	2.92%	3.23%	3.50%	4.09%
Lower Bound	2.82%	0.47%	2.14%	2.51%	2.79%	3.07%	3.59%
Day median ($N = 204$)							
Upper Bound	0.97%	0.15%	0.73%	0.87%	0.97%	1.07%	1.19%
Lower Bound	0.67%	0.12%	0.49%	0.59%	0.67%	0.75%	0.87%

Table 8: Descriptive statistics of stock trading activity around option trades

This table reports the summary statistics of the limit order book activity within 100ms after an option trade, where the stock matches the underlying of the traded option contract. *Stock Activity* is 1 if there is a stock trade or quote update during the 100ms window after an option trade, and 0 otherwise. *Number of Trades* is the total number of stock trades within the 100ms time window. *Volume* is the total number of shared (1000s) traded on the stock markets within the 100ms time window. *Dollarvolume* is the total amount of dollarvolume ($million) traded on the stock markets within the 100ms time window.

	Stock Activity	Number of Trades	Volume (1000 shares)	Dollarvolume ($million)
Full Sample	0.46	4.59	0.72	0.09
Trade Direction				
Buy	0.47	4.64	0.75	0.09
Sell	0.46	4.53	0.69	0.08
Option Type				
Call	0.44	5.75	0.93	0.11
Put	0.47	4.78	0.74	0.09
*OptionType * TradeDirection*				
BuyCall	0.46	4.16	0.70	0.08
BuyPut	0.48	5.57	0.85	0.09
SellCall	0.46	4.80	0.71	0.09
SellPut	0.47	4.05	0.65	0.08
Time to Expiration				
0DTE	0.53	5.28	0.72	0.13
1–7 days	0.48	4.47	0.63	0.09
1–2 weeks	0.48	4.83	0.75	0.09
2–4 weeks	0.44	4.64	0.77	0.08
1–3 months	0.42	4.27	0.72	0.07
3–12 months	0.44	4.57	0.86	0.07
More than 1 year	0.40	4.39	0.88	0.07
Moneyness				
ITM	0.48	6.85	1.57	0.11
OTM	0.45	4.14	0.63	0.07
ATM	0.48	4.63	0.64	0.10
Pricing Mechanism				
Auction	0.35	1.36	0.17	0.03
LOB	0.49	5.41	0.86	0.10
Trading Strategy				
Single-leg	0.48	4.96	0.79	0.09
Multi-leg	0.39	3.09	0.44	0.07
Trader Category				
Retail	0.37	1.48	0.19	0.03
Non-retail	0.48	5.18	0.82	0.10

Table 9: Stock trading activity associated with option trades

This table reports the average estimates of OLS regressions on the limit order book activity within 100ms of option trades for each stock-day on option trade characteristics. The sample period is from January 2 to October 21, 2020. Only stock-days with at least 100 option trades as- sociated with the same underlying were included in the sample. The dependent variable is limit order activity dummy for column (1) and (2), number of stock trades for column (3) and (4), and net volume of stock trades in the direction of option trade exposure for column (5) and (6). Detailed definitions of regression variables are in Table A1. t-statistics clustering to stock and date are reported in parentheses. *, ** indicate statistically significance at 5% and 1% respec- tively.

	(1)	(2)	(3)	(4)	(5)	(6)
Call	-0.03**	-0.01**	-0.38**	-0.24**	-14.44**	-7.42**
	(0.00)	(0.00)	(0.00)	(0.00)	(1.43)	(1.44)
ITM	0.05**	0.03**	2.28**	2.09**	192.83**	183.27**
	(0.00)	(0.00)	(0.01)	(0.01)	(2.52)	(2.58)
OTM	0.00**	-0.02**	-0.52**	-0.72**	-28.16**	-38.44**
	(0.00)	(0.00)	(0.00)	(0.00)	(1.42)	(1.48)
Auction	-0.22**	-0.22**	-3.98**	-4.00**	-157.82**	-158.93**
	(0.00)	(0.00)	(0.00)	(0.00)	(1.68)	(1.68)
Multi-leg	-0.13**	-0.12**	-1.90**	-1.82**	-159.56**	-155.36**
	(0.00)	(0.00)	(0.00)	(0.00)	(1.71)	(1.72)
Trade Size	0.00**	0.00**	0.00**	0.00**	0.27**	0.27**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	-0.01
Implied Volatility		0.11**		1.58**		80.42**
		(0.00)		(0.01)		(2.06)
Maturity (year)		-0.02**		-0.29**		-16.26**
		(0.00)		(0.01)		(2.75)
Intercept	0.62**	0.57**	6.05**	5.26**	199.68**	159.65**
	(0.00)	(0.00)	(0.00)	(0.01)	(1.49)	(1.84)

Appendix

Table A1: Variable Definition

This table presents the variable definitions for explanatory and control variables used in Table 4 and Table 9.

Variable Name	Description
Explanatory Variables	
Moneyness	The difference between underlying midprice and option strike price divided by option strike strike, and multiplied by -1 for put options.
ITM	In-The-Money: takes the value of 1 if the option contract's moneyness is greater than 0.03 at the time of the trade.
OTM	Out-of-The-Money: takes the value of 1 if the option contract's moneyness is less than -0.03 at the time of the trade.
Single	Single-leg: takes the value of 1 if the option trade is single-leg
Auction	Priced through auction: takes the value of 1 if the option trade is priced through auction and payment for order flow (PFOF) mechanisms.
Control Variables	
Trade Size	Number of option contracts traded
SPY Volatility	The absolute value of the past 10-second return of the S&P 500 exchange-traded fund, SPY (in percent)
Realized Spread	The option's half quoted bid-ask spread relative to the midpoint price at the time of the trade (in percent).
Lagged Underlying Return	The signed 10-second lagged return of the stock midprice (in percent)

Lagged SPY Return	The signed 10-second lagged return of SPY (in percent)
Limit Order Book Imbalance	The option's (depth at best bid price - depth at best ask price)/(depth at best bid price + deaph at best ask price), and multiplied by -1 for sell order.
Implied Volatility	The volatility (in percent) computed by the Binomial Option Pricing Model, given the midprices of the option contract and the underlying at the time of the trade.

Table A2: OPRA Trade Condition ID Description

This table reports the descriptions for the OPRA trade conditional IDs.

Trade Condition ID	Condition Name	Condition Description
18	AutoExecution	Transaction was executed electronically. Prefix appears solely for information; process as a regular transaction.
21	Reopen	Transaction is a reopening of an option contract in which trading has been previously halted. Prefix appears solely for information; process as a regular transaction.
40	Cancel	Transaction previously reported (other than as the last or opening report for the particular option contract) is now to be cancelled.
41	CANCLAST	Transaction is the last reported for the particular option contract and is now cancelled.
42	CANCOPEN	Transaction was the first one (opening) reported this day for the particular option contract. Although later transactions have been reported, this transaction is now to be cancelled.
43	CANCONLY	Transaction was the only one reported this day for the particular option contract and is now to be cancelled.
95	IntermarketSweep	Transaction was the execution of an order identified as an Intermarket Sweep Order. Process like normal transaction.
108	Trade through Exempt	Transaction is Trade Through Exempt. The transaction should be treated like a regular sale.
114	SingLegAuct-NonISO	Transaction was the execution of an electronic order which was "stopped" at a price and traded in a two sided auction mechanism that goes through an exposure period. Such auctions mechanisms include and not limited to Price Improvement, Facilitation or Soliciation Mechanism.

115	SingLegAuctISO	Transaction was the execution of an Intermarket Sweep electronic order which was "stopped" at a price and traded in a two sided auction mechanism that goes through an exposure period. Such auctions mechanisms include and not limited to Price Improvement, Facilitation or Solicitation Mechanism marked as ISO.
116	SingLegCross-NonISO	Transaction was the execution of an electronic order which was "stopped" at a price and traded in a two sided crossing mechanism that does not go through an exposure period. Such crossing mechanisms include and not limited to Customer to Customer Cross and QCC with a single option leg.
118	SingLegFlr	Transaction represents a non-electronic trade executed on a trading floor. Execution of Paired and Non-Paired Auctions and Cross orders on an exchange floor are also included in this category.
119	MultLegAutoEx	Transaction represents an electronic execution of a multi leg order traded in a complex order book.
120	MultLegAuct	Transaction was the execution of an electronic multi leg order which was "stopped" at a price and traded in a two sided auction mechanism that goes through an exposure period in a complex order book. Such auctions mechanisms include and not limited to Price Improvement, Facilitation or Solicitation Mechanism.
121	MultLegCross	Transaction was the execution of an electronic multi leg order which was "stopped" at a price and traded in a two sided crossing mechanism that does not go through an exposure period. Such crossing mechanisms include and not limited to Customer to Customer Cross and QCC with two or more options legs.
122	MultLegFlr	Transaction represents a non-electronic multi leg order trade executed against other multi-leg order(s) on a trading floor. Execution of Paired and Non-Paired Auctions and Cross orders on an exchange floor are also included in this category.
123	MultLegAutoSingLeg	Transaction represents an electronic execution of a multi Leg order traded against single leg orders/ quotes.

124	StkOptAuct	Transaction was the execution of an electronic multi leg stock/options order which was "stopped" at a price and traded in a two sided auction mechanism that goes through an exposure period in a complex order book. Such auctions mechanisms include and not limited to Price Improvement, Facilitation or Solicitation Mechanism.
125	MultLegAuctSingLeg	Transaction was the execution of an electronic multi leg order which was "stopped" at a price and traded in a two sided auction mechanism that goes through an exposure period and trades against single leg orders/ quotes. Such auctions mechanisms include and not limited to Price Improvement, Facilitation or Solicitation Mechanism.
126	MultLegFlrSingLeg	Transaction represents a non-electronic multi leg order trade executed on a trading floor against single leg orders/ quotes. Execution of Paired and Non-Paired Auctions on an exchange floor are also included in this category.
127	StkOptAutoEx	Transaction represents an electronic execution of a multi leg stock/options order traded in a complex order book.
128	StkOptCross	Transaction was the execution of an electronic multi leg stock/options order which was "stopped" at a price and traded in a two sided crossing mechanism that does not go through an exposure period. Such crossing mechanisms include and not limited to Customer to Customer Cross.
129	StkOptFlr	Transaction represents a non-electronic multi leg order stock/options trade executed on a trading floor in a Complex order book. Execution of Paired and Non-Paired Auctions and Cross orders on an exchange floor are also included in this category.

Table A3: Trade Characteristics and Trade Condition ID mapping

This table presents the classification for trade characteristics: Auction and orderbook for pricing mechanism. Single-leg and Multi-leg for trading strategy. Out-of-sequence trades (Trade Condition 2, 6, 7, 13), Reopened trades (Trade Condition ID 21), Canceled trades (Trade Condition ID 40, 41, 42, 43), and floor trades (Trade Condition ID 118, 122, 126, 129) are removed from the sample.

TradeConditionID	Condition Name	Auction	Orderbook	Single-leg	Multi-leg
18	AutoExecution		X	X	
95	IntermarketSweep		X	X	
108	Trade through Exempt		X	X	
114	SingLegAuctNonISO	X		X	
115	SingLegAuctISO	X		X	
116	SingLegCrossNonISO		X	X	
119	MultLegAutoEx		X		X
120	MultLegAuct	X			X
121	MultLegCross		X		X
123	MultLegAutoSingLeg		X		X
124	StkOptAuct	X			X
125	MultLegAuctSingLeg	X			X
127	StkOptAutoEx		X		X
128	StkOptCross		X		X