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High-frequency trading in the stock market and the costs of options market making[☆]

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ABSTRACT

We investigate how high-frequency trading (HFT) in equity markets affects options market liquidity. We find that increased aggressive HFT activity in the stock market leads to wider bid–ask spreads in the options market through two main channels. First, options market makers' quotes are exposed to sniping risk from HFTs exploiting put–call parity violations. Second, informed trading in the options market further amplifies the impact of HFT in equity markets on the liquidity of options by simultaneously increasing the options bid–ask spread and intensifying aggressive HFT activity in the underlying market.

1. Introduction

High-frequency trading (HFT) has significantly altered the functioning of electronic markets.[1] The extensive literature examining the implications of HFT mainly focuses on the market quality effects of HFT within individual markets as opposed to across assets.[2] We attempt to fill this gap by examining the impact of HFT in the stock market on options market liquidity. Our results are relevant given the significant growth in the options market volume in recent years. For instance, between 1996 and 2022, options market volume in the U.S. grew at an annualized compound rate of 15%, outpacing the 10% growth rate

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[1] Throughout this paper, we use the phrase "high-frequency trading" or "HFT" to refer to HFT activity in the stock market unless we explicitly indicate otherwise. The acronym HFT is used interchangeably to refer to high-frequency traders and high-frequency trading.

[2] Hendershott et al. (2011), Brogaard et al. (2015), Van Kervel and Menkveld (2019) and Hagströmer and Nordén (2013) examine the effects on stock market liquidity; Kirilenko et al. (2017) and Lee (2015) investigate the impact in the futures market; Chaboud et al. (2014) and Jiang et al. (2014) focus on FX and fixed-income securities markets respectively.

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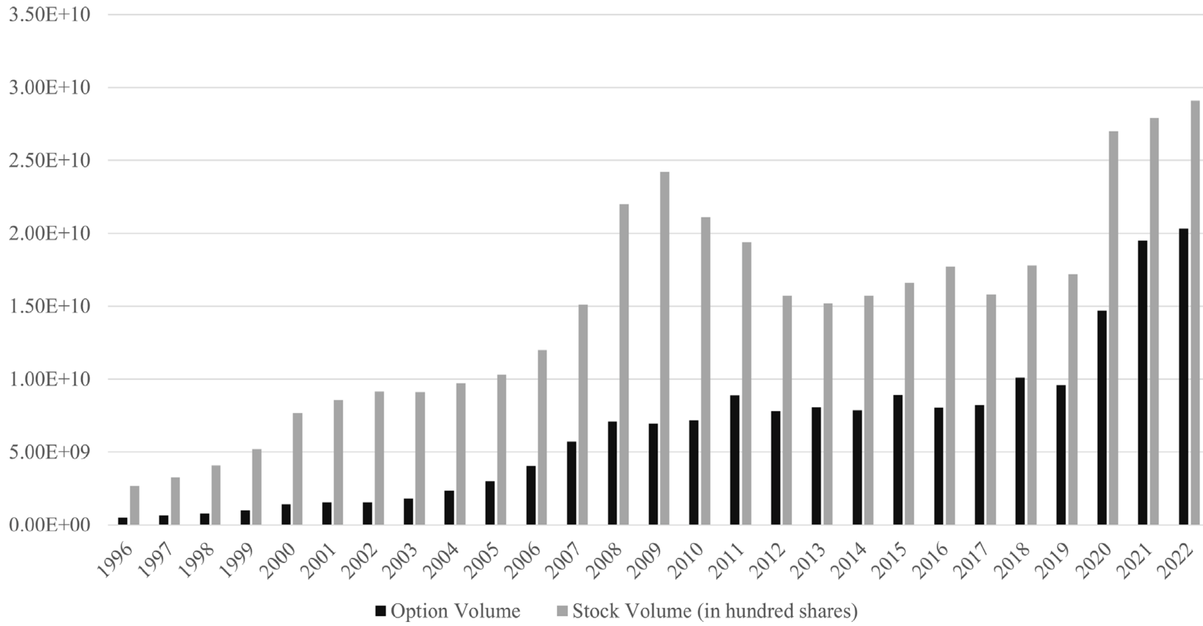

Fig. 1. The evolution of trading volume in the U.S. equity and options market. This figure reports the evolution of trading volume in the U.S. equity and options markets. The gray (dark) bar corresponds to the number of shares (contracts) traded in U.S. equity (options) markets. The sample contains all stocks traded between January 1, 1996 and December 31, 2022 on the U.S. exchanges. The data is obtained from CRSP and OptionMetrics.

observed for the stock trading volume (see Fig. 1).

We investigate whether HFT in stocks impacts the liquidity of options written on those stocks in the U.S. and whether any potential impact differs across liquidity-supplying and liquidity-consuming HFT strategies. We find that HFT activity in the equity markets is associated with a decline in market liquidity – as indicated by an increase in bid–ask spreads – in the options markets. A one-standard-deviation increase in HFT activity in stock markets is associated with a 3.5% higher proportional bid–ask spread in options markets. For a trade of 1000 contracts, our results imply that trading costs increase from USD 85.91 to USD 88.92.[3] To provide a sense of the economic scale of this effect, the volume of stock options trading in the U.S. reached 10.1 billion contracts in 2023,[4] resulting in an estimated total increment in trading costs of approximately USD 30.4 million. This association is exclusively driven by aggressive HFT strategies and not by liquidity-supplying HFT strategies.

We propose two channels to explain the adverse effects of liquidity-demanding HFTs on options market quality. First, our results are consistent with option market makers' quotes being exposed to sniping risk originating from latency races involving arbitrageurs who seek to profit from trading against stale quotes – we call this explanation the *latency arbitrage* channel. Budish et al. (2015), Foucault et al. (2017) and Shkilko and Sokolov (2020) find that fast HFTs with access to speed-enhancing technology can leverage their relative speed advantage to respond more quickly to new information and/or temporary liquidity shocks and profitably exploit arbitrage opportunities. This phenomenon, referred to as "latency" arbitrage opportunities in the relevant literature (e.g., Aquilina et al. (2022), imposes adverse selection costs on market makers to the extent these arbitrage opportunities originate due to arrival of new information.

To test the latency arbitrage channel, we employ cross-sectional analysis and compute the frequency of profitably exploitable put–call parity violations. Our primary hypothesis posits that if options market makers do in fact increase the bid–ask spread in response to cross-market latency arbitrage by HFTs, then the resulting increase in options bid–ask spread should be higher for stocks with a higher frequency of profitable put–call parity violations. We adopt the approach employed by Muravyev et al. (2013) and compare the option-implied stock price (derived from the put–call parity relationship) with the actual stock price. We find that the impact of liquidity-consuming HFT flow on the options bid–ask spread is more pronounced for stocks that exhibit high levels of profitable put–call parity violations.

We also explore a second channel for the positive association between liquidity-demanding HFT in the stock markets and options bid–ask spreads. It is well established that the implicit leverage in options markets makes them very attractive to informed traders (e.g., Easley et al. (1998) and Augustin and Subrahmanyam (2020)). With informed traders in the options market, options market makers widen the bid–ask spread to protect against adverse selection (e.g., Easley et al. (1998)). Simultaneously, informed trading activities may create temporary deviations from put–call parity, allowing aggressive HFTs to intensify their activities in the stock markets to exploit slower traders. If this is the case, informed trading in the options market may amplify the positive impact of HFT in equity markets on the options bid–ask spreads. We call this explanation the *informed trading* channel.

To examine the informed trading channel, we use a unique exogenous shock to informed trading, as employed in Bondarenko and Muravyev (2022): the arrest of Raj Rajaratnam on October 16, 2009. We use the put–call ratio measure calculated from CBOE's open-close options data to proxy for informed trading (Pan and Poteshman, 2006). Our analysis shows that the informed trading channel does indeed play a role in explaining the effects of liquidity-consuming HFTs on the bid–ask spread of options. Economically, we find that informed trading in the options market intensifies the overall effects of HFT in the stock market on the options bid–ask spread by roughly 50%.

While we obtain the above results after controlling for option and stock market factors that are commonly known to influence option market spreads (e.g., options volume and price, option implied volatility, option Greeks, stock liquidity, and realized stock volatility), we acknowledge that the relationship between HFT activity and options market liquidity is likely to be endogenous. This endogeneity may arise because both variables could be jointly influenced by other potentially unobservable factors stemming from the cross-market relationship between options and stock markets (as in Biais and Foucault (2014)), or

[3] Section 3 provides the calculations for these numbers.

[4] https://www.theocc.com/market-data/market-data-reports/volume-and-open-interest/volume-by-exchange.

because the causal link between the two variables goes in the opposite direction (as in Breen et al. (2002)).

To address these endogeneity concerns, we employ the two-stage least squares (2SLS) approach where we use the introduction of flash orders by NASDAQ as an exogenous shock to HFT activity in the stock market. This order type grants market participants the ability to expose their unexecuted marketable orders for an additional 500 ms in the NASDAQ limit order book before eventually routing them to the general marketplace. As only low latency firms are able to monitor order books at such high frequencies and react to the presence of flash orders (Skjeltorp et al., 2016; Harris and Namvar, 2016), our choice of instrument fulfills both criteria for a good instrument: it has a strong correlation with HFT activity in the stock market; and it only affects option market liquidity through its impact on HFT activity in the stock market. The 2SLS estimations confirm the main results. An increase in aggressive HFT activity leads to an increase in quoted spreads in the options markets. Furthermore, the positive relationship between (aggressive) HFT activity and option spreads is stronger for stocks with a high number of profitably exploitable put–call parity violations.[5]

Our primary analysis relies on the NASDAQ HFT data and the options transactions data obtained from the Options Price Reporting Authority (OPRA), which is limited to one year (2009) and 103 stocks. To test the external validity of our results, we complement our primary analysis by examining the correlation between HFT activity and options liquidity using a larger dataset spanning from 2012 to 2019. This analysis, detailed in the Internet Appendix Section C, uses data from the Securities and Exchange Commission's Market Information Data Analytics System (MIDAS) database and OptionMetrics. While this analysis does not provide the same granularity as our main analysis and cannot establish a causal relationship, it consistently shows that the increased total HFT activity in equity markets is associated with a significant decline in options liquidity. Furthermore, both the latency arbitrage and informed trading channels contribute to explaining the positive correlation between HFT activity in the equity market and the bid–ask spread in the options market.

1.1. Related literature and contribution

Our study contributes to understanding the impact of HFTs on the interplay between stock and options market microstructure dynamics. We present evidence on the direct effect of various HFT strategies in equity markets on the options bid–ask spread, and, to the best of our knowledge, our study is the first to address this critical issue.

Studies examining the impact of underlying market liquidity on option liquidity mainly focus on how stock liquidity affects the hedging costs of option market makers. Cho and Engle (1999), Kaul et al. (2004), and Wu et al. (2014) argue that market frictions and imperfections prohibit option market makers from building a perfectly-hedged delta-neutral portfolio, thus necessitating them to seek compensation for the transaction costs and the risks associated with an imperfectly hedged position in the options market. Engle and Neri (2010) and Kaul et al. (2004) establish that the option delta, gamma, and vega affect the hedging capability of option market makers. Boyle and Vorst (1992) and Cho and Engle (1999) in turn demonstrate that the bid–ask spread in the stock market affects the hedging costs of option market makers.

In a closely related study, Mishra et al. (2012) explore the impact of automation on options markets, using high-frequency OPRA data and finding that automation leads to reduced bid–ask spreads and increased liquidity in options markets. Kapadia and Linn (2020) use the August 2012 glitch in Knight Capital's trading platform as an exogenous event to demonstrate that liquidity-related uncertainty in equity markets adversely affects option bid–ask spreads.

Our paper distinguishes itself from the aforementioned studies by focusing on investigating the cross-market arbitrage dynamics between the options and equity markets. We demonstrate that, even after controlling for all variables proposed in previous studies that could influence the hedging costs of option market makers, high-frequency cross-market latency arbitrage forces between options and equity markets significantly impact options market liquidity.

Our study is also related to the literature on informed trading in the options market, a topic reviewed by Augustin and Subrahmanyam (2020). Easley et al. (1998) develop a model where informed traders choose between stock and options markets based on the relative transaction costs in the markets and the "bang-for-buck" afforded by the options market due to its inherent leverage. The authors conclude that, depending on the relative transaction costs in the two markets, there can be a separating equilibrium where informed traders only trade in the stock market or a pooling equilibrium where informed traders trade in both markets. Empirical research focusing on informed trading in these two markets largely validates the theoretical predictions of the model. For instance, Cao et al. (2005) find evidence of informed trading in options before takeovers. Hu (2014) provides evidence of an information channel by demonstrating that the options market-makers' initial delta hedging strategy is reflected in stock prices. Pan and Poteshman (2006), Ni et al. (2008), Cremers and Weinbaum (2010), Ge et al. (2016) and Collin-Dufresne et al. (2021) further document the role of options markets in the price discovery process.

In this context, our work aligns closely with Bondarenko and Muravyev (2022), who employ a unique exogenous shock – the arrest of a trader engaged in insider trading – to investigate informed trading in the options market. Their findings suggest that options volume predicts future stock returns due to its information content before the arrest but not afterwards. Building on this experiment, our results also suggest that options market makers widen the bid–ask spread in the presence of informed trading before the arrest. Importantly, our study extends this line of inquiry by highlighting the potential role of HFTs in transmitting information between the options and stock markets.

Finally, our study contributes to the existing literature on HFT, focusing on speed differentials across traders, sniping, and latency arbitrage. On the one hand, Brogaard et al. (2015) and Ait-Sahalia and Sağlam (2024) show that access to speed-enhancing technology allows market makers to reprice their quotes and better manage adverse selection risk, thereby improving spreads. On the other hand, Budish et al. (2015), Foucault et al. (2017), and Shkilko and Sokolov (2020) provide evidence of (toxic) latency arbitrage opportunities that emerge due to asynchronous adjustments in prices across two (or more) markets upon the arrival of new information. According to Aquilina et al. (2022), the use of latency arbitrage strategies increases trading costs and leads to annual losses of around $5 billion in global equity markets, and Baron et al. (2019) find that HFTs obtain significant profits from these latency arbitrage opportunities. Menkveld and Zoican (2017) show that which of the above two effects dominates depends on a security's news-to-liquidity-trader ratio. In options markets, due to exchange-imposed caps on the number of quote updates, and fines on traders with high message-to-transaction ratios (Muravyev and Pearson, 2020), market makers are particularly vulnerable to sniping risk – an aspect that is consistent with our findings.

Roadmap: The remainder of this paper is organized as follows: Section 2 describes the data; Section 3 presents the estimation results for the main tests and two proposed channels using the OLS setting with fixed effects; Section 4 presents the results for the 2SLS IV approach; and Section 5 concludes. All additional tests mentioned but not included in this paper are available in the Internet Appendix.

[5] While the introduction of flash orders by NASDAQ serves as a useful instrument to mitigate endogeneity concerns, fully addressing these concerns remains challenging in our context. This is largely due to the intrinsic connection between options contracts and their underlying stocks in the equity market, a common issue in the literature on stock and options market dynamics.

2. Data and variables

2.1. Data sources

The primary datasets employed in this study are the NASDAQ HFT data, comprising transactions for 120 randomly selected NASDAQ and NYSE-listed stocks for 2009, and the transaction-level options data obtained from the Options Price Reporting Authority (OPRA). Individual trades in the NASDAQ HFT data have been disaggregated by NASDAQ into those initiated by HFTs and non-HFTs.[6] The NASDAQ HFT data also includes variables such as date, time (in milliseconds), trading volume, price, buy–sell indicator, and the liquidity nature of the two sides of each trade. The nature of the liquidity has been classified as HH, HN, NH, and NN, denoting trades where both liquidity-providers and -takers are HFTs, where an HFT demands liquidity from a non-HFT, where a non-HFT demands liquidity from an HFT, and where two non-HFTs demand and supply liquidity respectively. The total HFT volume has been defined as the sum of HH, HN, and NH, in line with Brogaard et al. (2014). The total trading volume is about 44,800 million shares, of which HFTs account for 31,968 million shares or 71.30% of all trades. The total value of HFT-initiated trades amounts to 1381 billion USD.

We merge the NASDAQ HFT data with the transaction-level options data obtained from OPRA. Although the NASDAQ HFT data covers transactions for 120 stocks, we are only able to match options transactions with the NASDAQ HFT dataset for 103 stocks due to inconsistencies in ticker symbols across the two datasets. We employ the OPRA data for two purposes: (i) to compute the primary measure of trading cost for the options market, specifically the proportional quoted bid–ask spread; and (ii) to estimate the violations of put–call parity. The initial OPRA dataset comprises 19,143,237 transactions. We follow the existing literature and exclude long-term options, i.e., those with maturities greater than 180 days. This allows us to focus on the most actively traded options contracts (e.g., Brenner et al. (2001) and Christoffersen et al. (2017)).

We supplement these two datasets with the open-close options data obtained from CBOE, the NBBO quotes from the Trade and Quote (TAQ), the five-minute intraday stock price data obtained from Refinitiv Tick History, end-of-day option bid and ask prices, trading volumes, Greeks, and implied volatilities[7] from OptionMetrics, put–call implied volatility spreads from Option Suite by Wharton Research Data Services (WRDS), additional HFT measures obtained from the Securities and Exchange Commission's (SEC) Market Information Data Analytics System (MIDAS) dataset, daily ask, bid, trading prices, dividend yield from the Center for Research in Securities Prices (CRSP) dataset, and the daily yield curve from the U.S. Department of Treasury.

2.2. Variable construction

Following the approach of Brogaard et al. (2014), we calculate HFTs' liquidity-demanding trades ($SHFT^{D}_{i,d}$) and liquidity-supplying trades ($SHFT^{S}_{i,d}$) using data from the NASDAQ HFT dataset. $SHFT^{D}_{i,d}$ ($SHFT^{S}_{i,d}$) is computed as the sum of HH and HN (HH and NH) for each stock i and day d. To obtain a measure of total HFT trading volume, we compute $SHFT^{All}_{i,d}$ as the sum of HH, HN, and NH. To ensure that our results are not driven by trading volume attributable to non-high-frequency traders (non-HFTs), we control for non-HFTs' liquidity-demanding ($SNHFT^{D}_{i,d}$) and liquidity-supplying ($SNHFT^{S}_{i,d}$) trading volume in the regression when we use $SHFT^{D}_{i,d}$ and $SHFT^{S}_{i,d}$ as our key explanatory variables (Brogaard et al., 2014). $SNHFT^{D}_{i,d}$ ($SNHFT^{S}_{i,d}$) is calculated as the sum of NN and NH (NN and HN).

Our options market trading cost measure is the proportional bid–ask spread ($OPspread_{i,d}$), which is computed using the transaction-level OPRA dataset. We compute $OPspread_{i,d}$ as the volume-weighted average of the transaction-level proportional bid–ask spread, calculated as the difference between the ask and bid prices divided by the midprice (i.e., the average of ask and bid prices) for each transaction.

In addition to the aforementioned key variables, our study incorporates several control variables to account for the dynamics of both stock and options markets. We include options volume ($Ovolume_{i,d}$), implied volatility ($Oimplied_{i,d}$), inverse option price ($Oinp_{i,d}$), absolute option delta ($|Odelta_{i,d}|$), option vega ($Ovega_{i,d}$), and option gamma ($Ogamma_{i,d}$) as our options market control variables. The $Ovolume_{i,d}$ is the natural logarithm of the daily trading volume (contracts) for each stock i and day d. We compute the daily $Oimplied_{i,d}$, $|Odelta_{i,d}|$, $Ovega_{i,d}$, and $Ogamma_{i,d}$ as the volume-weighted averages of all implied volatilities, absolute deltas, vegas, and gammas across all strike prices and maturities for stock i and day d. We use the absolute value of delta as call and put options and have different signs for deltas, i.e., a call option delta is positive, while delta is negative for put options.

In order to control for the influence of stock market activity, we employ two variables: stock proportional quoted spread ($SPspread_{i,d}$) and realized volatility ($SVolatility_{i,d}$). $SPspread_{i,d}$ is computed as the difference between the best-ask and bid prices for stock i and day d, divided by the midprice of the two prices on the same day. $SVolatility_{i,d}$ is the daily (d) standard deviation of five-minute returns for stock i. Incorporating these control variables allows us to capture the dynamics of the options and stock markets and mitigate the potential confounding effects of unobserved variables on our main results.

To test the latency arbitrage channel, we compute the option's implied stock price by using the OPRA data, and compare it with the contemporaneous stock price. If the discrepancy between the option's implied stock price and the actual stock price allows investors to generate a profit, we flag this discrepancy as a profitable arbitrage opportunity. Our put–call parity violations variable, $Npv_{i,d}$, is then computed as the total number of profitable put–call parity violations for each stock i and day d. The computations are comprehensively detailed in Section 3.2.1.

To measure informed trading in the options market, we adopt a modified version of the put–call ratio metric introduced by Pan and Poteshman (2006). Our informed trading measure, denoted as $Ins_{i,d}$, is computed as the absolute value of the difference between the put–call ratio and 0.5. The put–call ratio itself is computed as the ratio of open-buy put volume to the sum of open-buy put and open-buy call volumes. The underlying rationale driving the selection of this metric is expounded upon in Section 3.3.1.

Finally, we use the SEC's MIDAS data to confirm the robustness of our results; we refer to this as the "MIDAS sample". We detail the main variables employed in this test, the sources from which these variables are obtained, and the results of this test in Internet Appendix Section C.

Table 1 provides an overview of all the main (Panel A) and supplementary (Panel B) variables and their computation methods.

2.3. Descriptive statistics

Table 2 shows the descriptive statistics for the main sample, which comprises the intersection between the NASDAQ HFT and OPRA datasets. Panel A includes the main model variables, where the sample encompasses 103 stocks and their corresponding listed options. Panel B includes supplementary variables. We winsorize all variables at the 1st and 99th percentile values to mitigate the influence of outliers.

The daily average trading volume of HFTs, as measured by the stock-day average of $SHFT^{All}_{i,d}$ is 1.36 million. This suggests that HFTs typically serve as counterparties for a substantial number of shares traded on a given day. HFTs are also net suppliers of liquidity, as evidenced by their stock-day average $SHFT^{D}_{i,d}$ and $SHFT^{S}_{i,d}$

[6] Brogaard et al. (2014) provide full details of the disaggregation.

[7] Greeks and implied volatilities are computed using a binomial tree with a constant interest rate.

Table 1
Definitions of variables.

Variable	Description	Data source
Panel A: Main model variables		
$SHFT^{All}_{i,d}$ (000,000s)	Measure of total HFT trading volume for firm i and day d computed as the total number of shares traded by all HFTs.	NASDAQ
$SHFT^{S}_{i,d}$ (000,000s)	Measure of liquidity-supplying HFT trading volume for firm i and day d computed as the total number of shares traded by liquidity-supplying HFTs.	NASDAQ
$SHFT^{D}_{i,d}$ (000,000s)	Measure of liquidity-demanding HFT trading volume for firm i and day d computed as the total number of shares traded by liquidity-demanding HFTs.	NASDAQ
$SNHFT^{S}_{i,d}$ (000,000s)	Measure of liquidity-supplying non-HFT trading volume for firm i and day d computed as the total number of shares traded by liquidity-supplying non-HFTs.	NASDAQ
$SNHFT^{D}_{i,d}$ (000,000s)	Measure of liquidity-demanding non-HFT trading volume for firm i and day d computed as the total number of shares traded by liquidity-demanding non-HFTs.	NASDAQ
$SPspread_{i,d}$ (%)	Relative quoted spread firm i in day d computed as the difference between the best-ask and bid prices for stock i and day d, divided by the midpoint of the two prices on the same day.	CRSP
$SVolatility_{i,d}$	Volatility measure for firm i in day d is computed as the daily standard deviation of five-minute returns.	Refinitiv
$OPspread_{i,d}$ (%)	Option market proportional spread for stock i and day d computed as the volume-weighted average of the proportional spread (the difference between the best-ask and bid prices divided by the midpoint of the ask and bid prices).	OPRA
$Ovolume_{i,d}$	Option volume for stock i and day d computed as the natural logarithm of the daily trading volume (contracts).	OptionMetrics
$Oimplied_{i,d}$	Option-implied volatility for stock i and day d computed as the volume-weighted average of the implied volatility provided by OptionMetrics.	OptionMetrics
$\lvert Odelta_{i,d}\rvert$	Absolute option delta for stock i and day d computed as the volume-weighted average of the absolute value of delta provided by OptionMetrics.	OptionMetrics
$Ogamma_{i,d}$	Option gamma for stock i and day d computed as the volume-weighted average of gamma provided by OptionMetrics.	OptionMetrics
$Ovega_{i,d}$	Option vega for stock i and day d computed as the volume-weighted average of vega provided by OptionMetrics.	OptionMetrics
$Oinp_{i,d}$	Inverse option price firm i in day d computed as the one divided by the option midprice.	OPRA
$Npv_{i,d}$	The number of profitable put–call parity violations for each stock i and day d. The put–call parity identification method is described in Section 3.2.1.	OPRA
$Ins_{i,d}$	The informed trading measure for each stock i and day d computed as the absolute difference between the put–call ratio and 0.5. The put–call ratio itself is computed by dividing the open-buy put volume by the sum of open-buy put and call volumes.	CBOE
Panel B: Supplementary variables		
$QT_{i,d}$	Quote-to-trade ratio for stock i and day d computed as the sum of order volume for all order messages divided by the sum of trade volume for all trades that are not against hidden orders.	MIDAS
$Ivs_{i,d}$	Absolute value of the put–call implied volatility spread for each stock i and day d.	OptionMetrics
$Oins_{i,d}$	The informed trading measure for each stock i and day d computed as the standard deviation of the minute-to-minute percentage changes in the put–call ratio. The minute-to-minute put–call ratio is calculated by dividing the buy-put volume by the sum of buy-put and buy-call volumes for each minute.	OPRA
$Mins_{i,d}$	The informed trading measure for each stock i and day d computed as the absolute difference between the put–call ratio and 0.5. The put–call ratio itself is computed by dividing total put volume by the sum of total put and call volumes.	OptionMetrics

This table reports the notation, description, and source of variables. The units of the variables are in parentheses following the variable names.

of 0.77 million and 0.93 million shares respectively. The average spread between ask and bid prices in stock markets, as measured by $SPspread_{i,d}$, is 0.12%, lower than the average options market bid–ask spread ($OPspread_{i,d}$) by a factor of approximately 177; the average $OPspread_{i,d}$ is 21.24%.

The mean value of $Ovolume_{i,d}$ is 6.80, indicating that the average number of option contracts traded each firm and day is 897. The mean and median values of $Ovolume_{i,d}$, $Oimplied_{i,d}$, $\lvert Odelta_{i,d}\rvert$, and $Ogamma_{i,d}$ are close to each other. This suggests that these variables have a relatively symmetrical data distribution. On the other hand, the mean value of $Ovega_{i,d}$ is 4.91, and the median is 3.76, indicating that the distribution of $Ovega_{i,d}$ is right-skewed. The variable $Npv_{i,d}$ has a mean of 4.49 and a large standard deviation of 11.83; thus, there is significant variation in the number of profitable put–call parity violations across firms. For $Ins_{i,d}$, the mean and median values are 0.25 and 0.24 respectively.

Table IA.1 in the Internet Appendix presents the correlation between $OPspread_{i,d}$ and the control variables used in the analysis, providing insights into the magnitude and direction of these associations. The associations between the control variables and options spreads are statistically significant and generally align with the existing literature.

3. Baseline results

3.1. The impact of HFT on option spread

We begin our analysis by testing the impact of total HFT activity on the options market bid–ask spread and estimating the following model:

$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{All}_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (1)$$

where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT^{All}_{i,d}$ is the measure of HFTs' total activities, and α_i and β_d are stock and time (day) fixed effects. The $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $\lvert Odelta_{i,d}\rvert$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. All these variables are defined in Table 1.

The estimation results of Eq. (1) are reported in column (i) of Table 3. Standard errors are double clustered by firm and day. To facilitate better economic interpretation, we standardize all variables, as suggested by Foucault and Fresard (2014). We find a positive relationship between $SHFT^{All}_{i,d}$ and $OPspread_{i,d}$, with statistical significance at the

Table 2
Summary statistics.

Panel A: Main model variables				
	Mean	Median	Std. dev.	N
$SHFT^{All}_{i,d}$ (000,000s)	1.36	0.20	2.81	20,639
$SHFT^{S}_{i,d}$ (000,000s)	0.93	0.10	2.11	20,639
$SHFT^{D}_{i,d}$ (000,000s)	0.77	0.14	1.48	20,639
$SNHFT^{S}_{i,d}$ (000,000s)	0.98	0.27	1.67	20,639
$SNHFT^{D}_{i,d}$ (000,000s)	1.13	0.23	2.27	20,639
$SPspread_{i,d}$ (%)	0.12	0.08	0.12	20,639
$SVolatility_{i,d}$	0.003	0.003	0.002	20,639
$OPspread_{i,d}$ (%)	21.24	13.09	24.77	20,639
$Ovolume_{i,d}$	6.80	6.80	3.16	20,639
$Oimplied_{i,d}$	0.54	0.48	0.23	20,639
$\lvert Odelta_{i,d}\rvert$	0.52	0.52	0.13	20,639
$Ogamma_{i,d}$	0.10	0.08	0.06	20,639
$Ovega_{i,d}$	4.91	3.76	4.08	20,639
$Oinp_{i,d}$	1.27	0.91	1.22	20,639
$Npv_{i,d}$	4.49	0.00	11.83	8344
$Ins_{i,d}$	0.25	0.24	0.20	4892
Panel B: Supplementary variables				
$QT_{i,d}$	42.07	33.73	29.43	1,862,924
$Ivs_{i,d}$	0.04	0.02	0.06	1,862,924
$Oins_{i,d}$	0.22	0.01	0.94	18,994
$Mins_{i,d}$	0.46	0.25	0.76	1,862,924

This table reports the summary statistics (mean, median, and standard deviation) of the variables across all firms/stocks. The units of variables are in parentheses following the variable names in the first column, and the number of firm-day observations for each variable is in the last column. For detailed definitions of variables refer to Table 1.

Table 3
The impact of HFT activities on option spread – OLS.

	$OPspread_{i,d}$ (i)	$OPspread_{i,d}$ (ii)	$OPspread_{i,d}$ (iii)
$SHFT^{All}_{i,d}$	0.03*** (2.66)		
$SHFT^{S}_{i,d}$		0.01 (0.73)	
$SHFT^{D}_{i,d}$			0.03*** (3.11)
Controls	Yes	Yes	Yes
Stock fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
N obs.	20,639	20,639	20,639
R^2	0.38	0.38	0.38

This table reports the results of estimating the impact of HFT in equity markets on the options bid–ask spread using the following models:

$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{All}_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$$
$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{S}_{i,d} + \sum_{k=1}^{9} \delta_k C_{k,i,d} + \varepsilon_{i,d}$$
$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{D}_{i,d} + \sum_{k=1}^{9} \delta_k C_{k,i,d} + \varepsilon_{i,d}$$

where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT^{All}_{i,d}$ is the measure of HFTs' total activities, $SHFT^{S}_{i,d}$ is the measure of HFTs' liquidity-supplying activities, and $SHFT^{D}_{i,d}$ is the measure of HFTs' liquidity-demanding activities. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $\lvert Odelta_{i,d}\rvert$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. In addition to these variables, we also control for non-HFTs' liquidity-demanding ($SNHFT^{D}_{i,d}$) and liquidity-supplying ($SNHFT^{S}_{i,d}$) trading activities when we use $SHFT^{D}_{i,d}$ and $SHFT^{S}_{i,d}$ respectively. All models include both firm and day fixed effects (α_i and β_d respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

1% level and a t-statistic of 2.66. This suggests that HFT in equity markets has a detrimental impact on the liquidity of options markets. The magnitude of the impact is also economically important, with a one-standard-deviation increase in $SHFT^{All}_{i,d}$ corresponding to a 3.5% higher $OPspread_{i,d}$.[8] To understand the economic significance of the 3.5% increment in $OPspread_{i,d}$, consider a trade of 1000 contracts. As the average price for a contract is USD 0.79 in our sample, the average effective dollar spread is about USD 0.17 (0.2124*0.79). Given that the cost of trading is half of the dollar effective spread, the average total trading cost for 1000 contracts is USD 85.91 (1000*0.17*0.5). A 3.5% increment in $OPspread_{i,d}$ is associated with the trading cost for 1000 contracts rising to around USD 88.92.[9] To provide a sense of the total economic scale of this increment, the volume of stock options trading in the U.S. reached 10.1 billion contracts in 2023,[10] resulting in an estimated total increment in trading costs of approximately USD 30.4 million.

Next, we investigate the underlying mechanism of the positive association between total HFT activities and the option bid–ask spread. As suppliers of immediacy, market makers are exposed to adverse selection, inventory holding, and order-processing costs. Research in microstructure has examined these costs while focusing on equity markets. Models of asymmetric information, such as Kyle (1985), Glosten and Milgrom (1985) and Easley and O'Hara (1987) argue that market makers recover the losses incurred from trading against better-informed counterparties by charging a bid–ask spread. Similarly, models of inventory-holding costs, such as Stoll (1978) and Ho and Stoll (1980) suggest that the bid–ask spread compensates risk-averse market makers for losses incurred due to suboptimal inventory positions, even in the absence of asymmetric information. Order-processing costs typically include variable costs such as trading and clearing fees and fixed costs such as exchange membership fees, IT costs, and administrative costs.

Battalio and Schultz (2011) posit that option market makers' exposure to adverse selection and inventory risks is typically greater. First, option market makers' inventory positions may be highly volatile due to implicit leverage in options contracts and uncertainty surrounding stock return volatility (Jameson and Wilhelm, 1992). Second, the option market makers have limited control over their inventory positions due to option market dynamics. For example, traders are more inclined to write call options than to purchase them, while they use buy and sell orders relatively evenly in equity markets (e.g., Lakonishok et al. (2007)). As a result, options market makers hedge their inventories by taking an offsetting position in the underlying cash market (e.g., Black and Scholes (1973)).

In a discrete-time setting, the hedging costs of option market makers entail two components: the cost of setting up and liquidating the initial delta-neutral position; and the cost of continuously rebalancing the portfolio to maintain a delta-neutral position (e.g., Jameson and Wilhelm (1992)). In Black and Scholes (1973) model, it is assumed that equity markets are frictionless and without imperfections, allowing options market makers to perfectly hedge their exposures. However, in a real-world context, they can only partially hedge their positions, leading to imperfect hedging. Consequently, Boyle and Vorst (1992) and Cho and Engle (1999) demonstrate that equity market frictions such as the bid–ask spread force options market makers to require compensation for the transaction costs and the risks associated with imperfectly hedging their exposure (e.g., Kaul et al. (2004) and Wu et al. (2014)). This connection between the equity and options markets is commonly referred to as the *hedging* channel in the literature.

Based on the literature discussed above, the most prominent equity market factor influencing the cost of options market makers' hedging is the bid–ask spread in the equity market (e.g., Boyle and Vorst (1992), Cho and Engle (1999) and Engle and Neri (2010)). The implication

[8] All the variables are standardized in the regression. Therefore, we calculate the economic impact by multiplying the estimated coefficient of $SHFT^{All}_{i,d}$ with the standard deviation of $OPspread_{i,d}$ and divide it by the mean of $OPspread_{i,d}$.

[9] For comparison, Brogaard et al. (2015) and Shkilko and Sokolov (2020) report a 2% and 2.6% change in effective spreads due to HFT activity.

[10] https://www.theocc.com/market-data/market-data-reports/volume-and-open-interest/volume-by-exchange.

of this for our study is that HFT activity in the stock market likely affects option market makers' hedging costs through its effect on the bid–ask spread in the stock market. On the one hand, HFTs that provide liquidity in the stock market leverage their speed advantage to mitigate adverse selection and inventory-holding risks, thereby increasing liquidity provision (e.g., Hendershott et al. (2011) and Brogaard et al. (2015)). On the other hand, liquidity-consuming HFTs may pick off slower traders and impose adverse selection costs on liquidity providers (e.g., Foucault et al. (2017) and Shkilko and Sokolov (2020)). The resulting impact on the bid–ask spread may be either positive or negative for the hedging costs of option market makers, depending on the underlying strategy pursued by HFT firms.

To test the significance of the hedging channel in explaining our findings, we employ a set of models to separately explore the effects of HFT strategies that demand or supply liquidity on the bid–ask spread of options. The models used for this analysis are as follows:

$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^S_{i,d} + \sum_{k=1}^{9} \delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (2)$$

$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^D_{i,d} + \sum_{k=1}^{9} \delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (3)$$

where $SHFT^S_{i,d}$ and $SHFT^D_{i,d}$ are the measures of liquidity-supplying and liquidity-demanding HFTs' activities respectively. The empirical specifications of Eqs. (2) and (3) are akin to that of Eq. (1). The only deviation lies in our adoption of the approach followed by Brogaard et al. (2014), where we introduce the liquidity supplying (in Eq. (2)) and demanding (in Eq. (3)) activities of non-HFTs as an additional control variable.

The findings are reported in columns (ii) and (iii) of Table 3. $SHFT^D_{i,d}$ exhibits a positive and statistically significant relationship with $OPspread_{i,d}$. To provide a sense of the economic significance of this effect, we note that a one-standard-deviation increase in $SHFT^D_{i,d}$ relates to a 3.5% increment in $OPspread_{i,d}$. Nevertheless, we observe no statistically significant correlation between HFTs' liquidity-supplying trading activity ($SHFT^S_{i,d}$) and the bid–ask spread of options.

At first glance, the non-significant association between $SHFT^S_{i,d}$ and $OPspread_{i,d}$ is perplexing. However, this finding is not unexpected as our empirical specifications control for all plausible determinants of the hedging channel. The literature suggests that the most significant equity market determinants of the options bid–ask spread are the equity bid–ask spread (e.g., Boyle and Vorst (1992)) and the volatility of the underlying asset (Engle and Neri, 2010). Both these variables are included in Eqs. (2) and (3). Therefore, the lack of a significant relationship between $SHFT^S_{i,d}$ and $OPspread_{i,d}$ is unsurprising. Nonetheless, this explanation raises a very important and interesting question about why HFTs' liquidity-demanding activities are still significantly associated with the bid–ask spread in options markets. We propose two new channels – the *latency arbitrage* and *informed trading* channels – in the next two sub-sections to answer this question.

3.2. The latency arbitrage channel

The payoffs of a stock and its listed European option contracts are correlated through put–call parity. This parity condition dictates that a portfolio comprising a short put option and a long call option with identical strike prices and maturity dates generates equivalent returns to a forward contract with the same maturity and forward price equal to the option strike price. Failure to satisfy this parity relationship results in a violation of the law of one price, thereby creating an arbitrage opportunity between the stock and option markets. Empirical evidence from the options market microstructure literature, such as Ofek et al. (2004) and Muravyev et al. (2013), confirms the existence of profitable arbitrage opportunities that stem from put–call parity violations.

A dominant trading strategy used by HFTs is latency arbitrage (cross-market or single-market), where HFTs use their relative speed advantage to quickly respond to new information and/or temporary liquidity shocks and execute trades against stale quotes before slower market participants can revise their prices.[11] Budish et al. (2015) demonstrate that these latency arbitrage opportunities are flaws in market design, leading to increased trading costs.

Foucault et al. (2017) show that when cross-market latency arbitrage opportunities are "toxic",[12] liquidity-consuming HFTs' trading adversely affects liquidity in the market that is slower to adjust (e.g., Rzayev et al. (2023)). Similarly, Shkilko and Sokolov (2020) find that when price changes in futures markets generate arbitrage opportunities between futures and equity markets, liquidity-consuming HFTs exploit their microwave connections to pick off stale quotes, thereby increasing adverse selection risk in equity markets. Baron et al. (2019) further demonstrate that liquidity-demanding HFTs actively exploit latency arbitrage opportunities and obtain significant profits (e.g., Boehmer et al. (2018)). This finding is consistent with the evidence provided by Aquilina et al. (2022), who document that aggressive HFTs conduct the majority of trading activity in latency arbitrage races.

This discussion implies that liquidity-consuming HFTs engaging in cross-market latency arbitrage strategies may exploit violations of the put–call parity relationship by sniping stale quotes in the options market. Options market makers are particularly exposed to such toxic arbitrage losses due to the exchange-imposed caps on the number of quote updates and fines on traders with higher messages-to-transactions ratios (see Muravyev and Pearson (2020)). These restrictions may significantly constrain option market makers' capacity to revise their quotes in response to the cross-market trading activity of liquidity-consuming HFTs, thereby necessitating a compensatory mechanism. We call this channel the *latency arbitrage* channel.

If this mechanism plays a role, then the relationship between liquidity-consuming HFT activities and options bid–ask spread should be more prevalent when there are more profitable put–call parity violations. We follow a three-step procedure to test this. First, we identify the profitable put–call parity violations between equity and options markets. Second, for each day, we allocate stocks to the $High$ group if the realization of the number of profitable arbitrage opportunities for that stock is above the median number of profitable arbitrage opportunities across all stocks. In the third step, we estimate our baseline regression by interacting the $High$ variable with our HFT measures. Our expectation is that the impact of liquidity-consuming HFTs on the options bid–ask spread will be more pronounced in the $High$ group.

3.2.1. Identifying profitable (high frequency) put–call parity violations

To identify profitable put–call parity violations, we adopt the methodology proposed in Muravyev et al. (2013). This approach involves comparing the option-implied stock prices with the actual stock prices. We first extract second-level stock NBBO quotes from the TAQ database and match them to call and put option transaction prices obtained from the OPRA at the same second-level time. The implied

[11] We use the term "relative speed" in the same sense as Foucault et al. (2017)) and Baron et al. (2019). These studies demonstrate that increasing *absolute* speed in financial markets does not provide high-frequency arbitrageurs with any advantage. For example, if financial markets adopt new technology that uniformly increases order submission speed for all participants, including slow dealers and fast arbitrageurs, then arbitrageurs do not gain any advantage over slower dealers. However, if the speed of fast arbitrageurs increases relative to slower traders, then fast arbitrageurs can adversely select slower traders due to their higher speed, even if the information is made public to everyone simultaneously. Consequently, a relative speed advantage is necessary for latency arbitrage to occur.

[12] Arbitrage opportunities are deemed "toxic" when they result from asynchronous adjustments in the price of related assets due to the arrival of new information.

stock price S^* based on the put–call parity equation for dividend-paying European options is given by the following equation: $S^* = C + Xe^{-(r-q)T} - P$, where S^* is the option implied stock price, C (P) is the call (put) price, r is the risk-free annual rate, q is the annual dividend yield, T is the time to maturity in years, and X is the strike price. The daily yield curve from the US Department of Treasury is used to obtain the annualized risk-free rates for various maturities such as 30 days, 90 days, 180 days, and 1 year. For options that expire between 30 and 90 days, we use linear interpolation to calculate the respective risk-free rates. For options with less than 30 days maturities, we use a 30-day risk-free rate. The expiration is calculated based on the time difference between the transaction time and the maturity date at 16:15:00 PM EST and expressed in years using 365 calendar days. The yearly dividend yield is generated by using the difference between *ret* and *retx* variables from CRSP. The most recent dividend yield is matched to each option.

If the implied stock price is within the bid–ask bound of the stock price, there is no arbitrage opportunity. However, there are arbitrage opportunities when the implied stock price is either above the ask or below the bid price of the stock. The arbitrage gap should also be large enough to cover transaction costs (the bid–ask spread). The first arbitrage case is when the option implied stock price is less than the current stock price at the bid. In this case, an investor can build a long position in the portfolio of options and the risk-free bond and a short position in the stock to make an arbitrage profit. With transaction costs, this would mean an investor can long a position by buying a call option at the ask, buying the risk-free bond, and selling the put option at the bid. When the implied stock price is larger than the current stock price at the ask, an investor can short the options portfolio and buy the stock to gain arbitrage profit. With transaction costs, investors go short by selling a call option at the bid, selling the risk-free bond, and buying a put option at the ask.

These long and short positions in S^* can be presented using the put–call parity relationship: $S^{*Ask} = Buy(C^{Ask}) + Buy(X) + Sell(P^{Bid})$, and $S^{*Bid} = Sell(C^{Bid}) + Sell(X) + Buy(P^{Ask})$. If the underlying stock quotes at the same time as the options quotes are S^{Bid} and S^{Ask}, then arbitrage opportunities arise if the following price differentials exist in the market: $S^{Bid} > S^{*Ask}$ or $S^{*Bid} > S^{Ask}$. It is important to note that we are interested in identifying *profitable* put–call parity violations. For this, we apply the criteria described in Muravyev et al. (2013):

$$S^{Bid} - S^{*Ask} \geq \$0.02 \text{ and } \frac{S^{Bid} - S^{*Ask}}{S^{Bid}} \geq 0.05\% \quad (4)$$

$$S^{*Bid} - S^{Ask} \geq \$0.02 \text{ and } \frac{S^{*Bid} - S^{Ask}}{S^{Ask}} \geq 0.05\% \quad (5)$$

We use the violations described in Eqs. (4) and (5) to identify arbitrage opportunities in the options and stock markets. Based on this, we calculate our key arbitrage variable – the number of profitable put–call parity violations ($Npv_{i,d}$) – for each stock and day. The descriptive statistics provided in Table 2 show that, on average, our sample has 4.49 profitable arbitrage put–call parity violations with a standard deviation of 11.83. Moreover, the median value for $Npv_{i,d}$ is 0, implying that there are many stock-day observations with no profitable put–call parity deviations.

3.2.2. Testing the latency arbitrage channel

We test the latency arbitrage channel by conducting a cross-sectional analysis. Our hypothesis posits that the impact of HFTs on the options bid–ask spread is amplified when there are a greater number of profitable arbitrage opportunities. On each day, we allocate stocks to the $High$ group depending on the number of profitable put–call parity violations. For each day, the stock is allocated to the $High$ group if its $Npv_{i,d}$ value is above the median number of profitable put–call parity violations for all stocks. We then re-estimate Eqs. (1) and (3) by introducing interactions between their respective HFT proxies and the $High$ group:

Table 4
Testing the latency arbitrage channel – OLS.

	$OPspread_{i,d}$ (i)	$OPspread_{i,d}$ (ii)
$SHFT^{All}_{i,d}$	−0.06*	
	(−1.89)	
$SHFT^{D}_{i,d}$		−0.05
		(−1.40)
$High_{i,d}$	−0.05***	−0.06***
	(−4.43)	(−4.45)
$SHFT^{All}_{i,d}High_{i,d}$	0.06***	
	(3.67)	
$SHFT^{D}_{i,d}High_{i,d}$		0.07***
		(3.59)
Controls	Yes	Yes
Stock fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
N obs.	8344	8344
R^2	0.28	0.28

This table reports the results of testing the latency arbitrage channel using the following models:
$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{All}_{i,d} + \gamma_2 High_{i,d} + \gamma_3 SHFT^{All}_{i,d}High_{i,d} + \sum_{k=1}^{8}\delta_k C_{k,i,d} + \varepsilon_{i,d}$
$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{D}_{i,d} + \gamma_2 High_{i,d} + \gamma_3 SHFT^{D}_{i,d}High_{i,d} \sum_{k=1}^{9}\delta_k C_{k,i,d} + \varepsilon_{i,d}$
where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT^{All}_{i,d}$ is the measure of HFTs' total activities and $SHFT^{D}_{i,d}$ is the measure of HFTs' liquidity-demanding activities. $High_{i,d}$ is a dummy variable equal to one in day d if its $Npv_{i,d}$ (the number of put–call parity violations) value is above the median number of profitable put–call parity violations for all stocks. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. In addition to these variables, we also control for non-HFTs' liquidity-demanding activities ($SNHFT^{D}_{i,d}$) when we use $SHFT^{D}_{i,d}$. All models include both firm and day fixed effects (α_i and β_d respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{All}_{i,d} + \gamma_2 High_{i,d} + \gamma_3 SHFT^{All}_{i,d}High_{i,d} + \sum_{k=1}^{8}\delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (6)$$

$$OPspread_{i,d} = \alpha_i + \beta_d + \gamma_1 SHFT^{D}_{i,d} + \gamma_2 High_{i,d} + \gamma_3 SHFT^{D}_{i,d}High_{i,d} \sum_{k=1}^{9}\delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (7)$$

where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT^{All}_{i,d}$ is the measure of HFTs' total activities and $SHFT^{D}_{i,d}$ is the measure of HFTs' liquidity-demanding activities. $High_{i,d}$ is a dummy variable equal to one when there is a higher number of profitable put–call parity violations. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. All these variables are defined in Table 1.

The results are presented in Table 4. We find that the positive association between HFT and option spread shifts to the interaction variable. The coefficients of $SHFT^{All}_{i,d}$ and $SHFT^{D}_{i,d}$ are no longer positively related to the options bid–ask spread; however, the coefficients for $SHFT^{All}_{i,d}High_{i,d}$ and $SHFT^{D}_{i,d}High_{i,d}$ are positive and statistically significant. This result indicates that the proposed latency arbitrage channel can indeed explain the association between HFT in stock markets and options bid–ask spread. Nevertheless, as elaborated in the next sub-section, the latency arbitrage channel is not the sole factor contributing to this relationship.

3.3. The informed trading channel

Our results so far show that HFT in the stock market is associated with an increase in the bid–ask spread in the options market. We also relate our findings to the latency arbitrage channel, suggesting that liquidity-consuming HFTs increase bid–ask spread in the options market by exploiting cross-market arbitrage opportunities between equity and options markets. We employ put–call parity violations as a means of testing the latency arbitrage channel and find corroborating evidence. In this section, we explore the second non-mutually exclusive channel to explain our findings.[13]

The existing body of literature underscores the attractiveness of options markets to informed traders, primarily due to two key factors: the substantial leverage they offer and the absence of shorting constraints (e.g., Easley et al. (1998), Ge et al. (2016), Augustin and Subrahmanyam (2020) and Bondarenko and Muravyev (2022)). While options market makers often widen the bid–ask spread to compensate for the risk associated with trading against informed agents (e.g., Easley et al. (1998) and Kaul et al. (2004)), informed traders may still choose to execute transactions within the options market if the information they possess is sufficiently profitable.

The transactions initiated by informed traders themselves could arguably lead to temporary deviations from the put–call parity. For example, consider a scenario where an informed trader purchases a call option due to positive information about a particular stock. In response, the market maker may adjust the price of the call option as well as the bid–ask spread associated with it. However, if the price of the put option (with the same strike price and time to maturity) remains unchanged, the implied stock price derived from option prices could be higher than the actual stock price observed in the stock market.

This increase in put–call parity violations could potentially serve as an arbitrage signal for liquidity-consuming HFTs, enabling them to exploit slower traders in the stock market. If this hypothesis holds true, it has two implications for the focus of our study. First, it suggests that HFTs play a role in transmitting information between the options and stock markets. Second, informed trading in the options market may heighten the association between liquidity-consuming HFTs in the stock market and the bid–ask spread in the options market. We call this explanation the *informed trading* channel.

3.3.1. Testing the informed trading channel

To explore the informed trading channel, we undertake three tests as follows. In the first test, our aim is to assess the influence of informed trading within the options market on the options bid–ask spread. In the second test, the correlation between informed trading activities in the options market and HFT in the stock market is investigated. Finally, we verify whether the positive effect of liquidity-consuming HFTs in the stock markets on the options bid–ask spread remains significant after accounting for the presence of the informed trading channel.

Empirically conducting the three aforementioned tests presents a challenge, primarily due to the difficulty of observing investors' information sets – a limitation shared with other studies examining the impacts of informed trading on market quality. Ideally, the most robust approach would involve leveraging an exogenous shock that directly influences the trading activities of informed investors to conduct such tests. However, such shocks are infrequent and not easily available. Fortunately, our sample covering 2009 did witness one such unique shock, providing us with an opportunity to explore the informed trading channel.

Using the put–call ratio measure developed by Pan and Poteshman (2006) and Bondarenko and Muravyev (2022) find a strong predictive relationship between options trading volume and future stock returns before October 2009. However, this predictive power disappears beyond that point. Bondarenko and Muravyev (2022) analyze the reasons for this shift, ultimately attributing it to a significant event – the arrest of Raj Rajaratnam, an investor charged with insider trading on October 16, 2009. Building on their work, we also employ the arrest of Raj Rajaratnam as an exogenous shock that disrupts informed trading dynamics.[14] Our objective is to investigate the effects of informed trading in the options market on both the options bid–ask spread and the activities of HFTs in the stock market, both before and after this event. To do so, we estimate the following regression model:

$$OPspread_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1} Event_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (8)$$

$$SHFT_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1} Event_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (9)$$

where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT_{i,d}$ is one of two HFT measures ($SHFT^S_{i,d}$ and $SHFT^D_{i,d}$), and $Ins_{i,d}$ is the measure of informed trading discussed below. $Event_{i,d}$ is a dummy variable equal to one before October 16, 2009 (Rajaratnam's arrest). To have a clean setting, we exclude five trading days before the event. We also include the same control variables as those employed in the main analyses. We only include stock fixed effects because $Event_{i,d}$ does not have a time variation across stocks.

$Ins_{i,d}$ is calculated using the following equation:

$$Ins = \left| \frac{OBPV}{(OBPV + OBCV)} - 0.5 \right| \quad (10)$$

where $OBPV$ represents the open-buy put volume, and $OBCV$ represents the open-buy call volume obtained from CBOE.[15] As seen, the first part of the right-hand side of this equation is the original put–call ratio, defined in Pan and Poteshman (2006).

We slightly modify this original put–call ratio because both an increase and a decline in the put–call ratio indicate informed trading activity. The original ratio is suitable for the analysis linking informed trading in the options market to stock returns, as demonstrated by Bondarenko and Muravyev (2022). This is because stock returns tend to decrease (increase) in response to negative (positive) news. However, regardless of the nature of the news, we anticipate that both the bid–ask spread in the options market and HFT in the equity market increase with informed trading in the options market. Consequently, for the purpose of our study, we employ a modified version of this ratio, $Ins_{i,d}$, which captures the magnitude of informed trading irrespective of the direction of the information.

To explain, consider a scenario where the open-buy put volume equals the open-buy call volume (indicating no information). In this case, the put–call ratio is 0.5, resulting in $Ins_{i,d}$ being zero. We set the put–call ratio to 0.5 and $Ins_{i,d}$ to zero when both open-buy put and call volumes are zero. This ensures that cases where both open-buy put and call volumes are zero are included in the analysis and

[13] Our thanks to an anonymous referee for this suggestion.

[14] Bondarenko and Muravyev (2022) go a step further by distinguishing between informed traders who use private information and those who rely on public information. Their research shows that the prediction of stock returns through option volume is primarily attributed to private information. However, we do not make this distinction, as it lies outside the scope of our study.

[15] CBOE categorizes the data into "customer" and "firm" groups. In our analysis, we employ customers' trades to calculate the put–call ratio. This choice aligns with Pan and Poteshman (2006) and Bondarenko and Muravyev (2022), who underscore the heightened predictive capabilities of customer trades in forecasting future stock returns.

Table 5
Testing the informed trading channel – main analysis (part I)

	$OPspread_{i,d}$ (i)	$OPspread_{i,d}$ (ii)	$SHFT^S_{i,d}$ (iii)	$SHFT^S_{i,d}$ (iv)	$SHFT^D_{i,d}$ (v)	$SHFT^D_{i,d}$ (vi)
$Ins_{i,d-1}$	−0.01	−0.04**	−0.01	−0.01*	0.00	−0.01
	(−0.67)	(−2.33)	(−0.87)	(−1.72)	(0.23)	(−1.30)
$Event_{i,d}$		−0.03		−0.01		−0.05**
		(−1.41)		(−0.82)		(−2.27)
$Ins_{i,d-1}Event_{i,d}$		0.04**		0.01		0.02**
		(2.43)		(0.84)		(1.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	No	Yes	No	Yes	No
N obs.	4892	4892	4892	4892	4892	4892
R^2	0.38	0.39	0.03	0.06	0.03	0.08

This table reports the results of testing the informed trading channel using the following models:
$OPspread_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1} Event_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \epsilon_{i,d}$
$SHFT_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1} Event_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \epsilon_{i,d}$
where $OPspread_{i,d}$ is the proportional option bid–ask spread, $Ins_{i,d}$ is the measure of informed trading, and $SHFT_{i,d}$ is one of two HFT measures ($SHFT^S_{i,d}$ and $SHFT^D_{i,d}$). $Event_{i,d}$ is a dummy variable equal to one before October 16, 2009 (Rajaratnam's arrest) and zero thereafter. The sample encompasses a period of two months before and after the event date, with the exclusion of the five trading days preceding the event date. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. In columns (i), (iii), and (v), both firm and day fixed effects (α_i and β_d respectively) are included, while columns (ii), (iv), and (vi) include only firm fixed effects. The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

not omitted. When the open-buy put volume surpasses the open-buy call volume (indicating negative information), both the put–call ratio and $Ins_{i,d}$ increase. Conversely, if the open-buy call volume exceeds the open-buy put volume (indicating positive information), the put–call ratio diminishes, and $Ins_{i,d}$ increases. This implies that any elevation in $Ins_{i,d}$ indicates an uptick in informed trading.

We use the first lag of $Ins_{i,d}$ ($Ins_{i,d-1}$) in Eqs. (8) and (9) for two main reasons. First, the literature on the equity markets suggests that informed investors strategically choose to trade when there are more liquidity traders, and they use limit orders instead of market orders. Collin-Dufresne and Fos (2015) show that this generates a negative contemporaneous association between information trading and standard liquidity measures, such as the bid–ask spread. Along this line, Degryse et al. (2016) document that for large firms, the liquidity metrics exhibit a lagged response to informed trading activities. Second, the open-buy data (provided by CBOE) that we use to calculate $Ins_{i,d}$ is available at the end of the day during our sample period.[16] Hence, market makers are not able to observe the data in real-time and adjust ask and bid prices. Consistent with this, Pan and Poteshman (2006) demonstrate that price adjustments to the open-buy volume tend to take more than a day.

We present the estimation results of Eqs. (8) and (9) in Table 5. The sample period encompasses a two-month window both preceding and following the event date of October 16, 2009, due to our data availability. In column (i), our findings indicate that $Ins_{i,d-1}$ is not statistically significantly related to $OPspread_{i,d}$. However, after incorporating the event dummy, $Event_{i,d}$, in column (ii), the interaction term $Ins_{i,d-1}Event_{i,d}$ is positively and statistically significantly associated with $OPspread_{i,d}$. In economic terms, a one-standard-deviation rise in $Ins_{i,d-1}$ leads to an approximately 5.8% increase in $OPspread_{i,d}$ before the arrest of Raj Rajaratnam. Similar results are observed when we employ $SHFT^D_{i,d}$ as our dependent variable, as indicated in columns (v) and (vi). A one-standard-deviation uptick in $Ins_{i,d-1}$ corresponds to roughly a 2% increase in $SHFT^D_{i,d}$ before the arrest of Raj Rajaratnam. Nonetheless, such a significant relationship is not evident when we employ $SHFT^S_{i,d}$ as the dependent variable.

These empirical results suggest that our informed trading metric predicts higher options bid–ask spreads and greater levels of liquidity-consuming HFT activity in the stock market during the period leading up to the arrest of Raj Rajaratnam. Intriguingly, this predictive capacity dissipates post-arrest. These findings are consistent with Bondarenko and Muravyev (2022), who show that option trading volume predicts the future stock return before the arrest of Raj Rajaratnam only.

As mentioned above, in our main specification, we use the first lag of our informed trading measure. This choice is motivated by the literature suggesting a negative association between informed trading and liquidity in the contemporaneous relationship. However, we also extend the horizon of predictability by regressing the options bid–ask spread on informed trading observed at various lags (0, -1-day, -2-day, -3-day, -4-day, and -5-day). The slope coefficients and their 95% confidence intervals are presented in Fig. 2.

Two points are worth discussing here. First, before the arrest of Raj Rajaratnam, the contemporaneous effect of informed trading on the bid–ask spread is negative (albeit not statistically significant). This finding aligns with Collin-Dufresne and Fos (2015), who demonstrate that informed traders strategically choose the timing of their trading and opt for limit orders over market orders to hide their information (Kaniel and Liu, 2006). Second, the magnitude of the coefficients appears to decay, consistent with Pan and Poteshman (2006). These results support our choice to use the first lag of informed trading in the main specification.

Our informed trading channel postulates a dual impact of options-informed trading on the options and equity markets. First, in response to the risk of trading against informed participants, options market makers widen the bid–ask spread. Second, informed trading increases temporary violations in the put–call parity, a phenomenon detected by liquidity-consuming HFTs, prompting an upsurge in their activities in the underlying markets. Consequently, we anticipate observing a positive correlation between informed trading and both the bid–ask spread in options and the trading activities of liquidity-consuming HFTs in the underlying markets. The findings presented in Table 5 corroborate these predictions, underscoring the relevance of the informed trading channel as a second explanation for the positive relationship between liquidity-consuming HFT activity in the underlying markets and the options bid–ask spread.

Therefore, in the subsequent analysis, we assess the effects of liquidity-consuming HFTs on the bid–ask spread of options, taking into account the effects of the informed trading channel. To do this, we modify Eq. (8) by including $SHFT^D_{i,d}$ and its interaction with $Event_{i,d}$ ($SHFT^D_{i,d}Event_{i,d}$) as explanatory variables. Our rationale for

[16] CBOE's intraday open-buy data is available since January 2011.

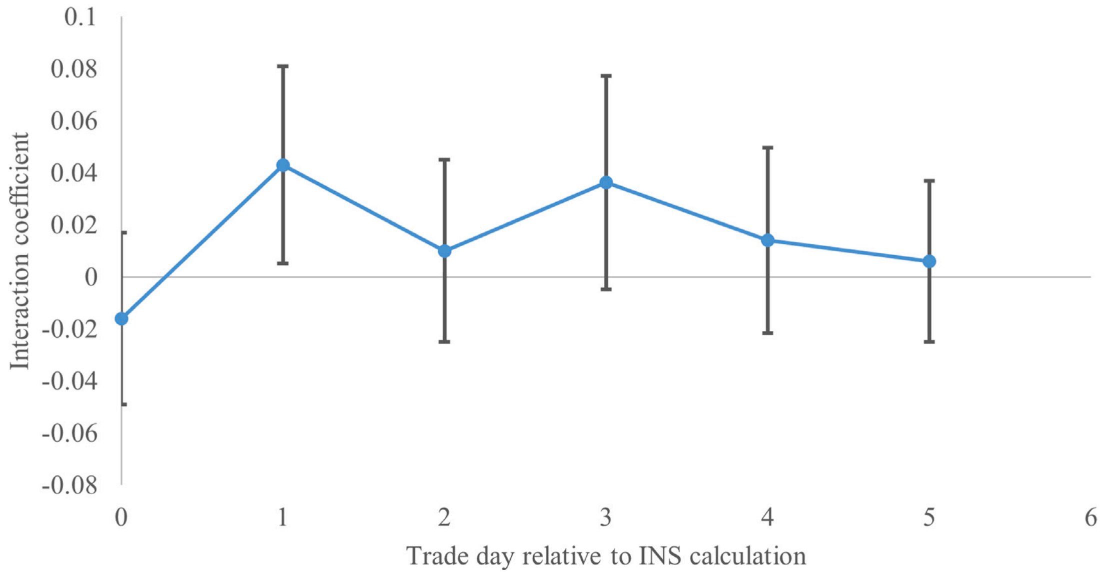

Fig. 2. The predictability of open-buy option volume signal for options bid–ask spread. This figure reports the coefficient and the 95% confidence intervals of the model regressing bid–ask spread on informed trading observed at various lags (0, -1-day, -2-day, -3-day, -4-day, and -5-day) before the arrest of Raj Rajaratnam.

Table 6
Testing the informed trading channel – main analysis (part II)

	$OPspread_{i,d}$
$Ins_{i,d-1}$	−0.04** (−2.31)
$Event_{i,d}$	−0.04 (−1.55)
$Ins_{i,d-1}Event_{i,d}$	0.04** (2.40)
$SHFT^D_{i,d}$	0.04*** (5.52)
$SHFT^D_{i,d}Event_{i,d}$	0.02** (2.03)
$Controls$	Yes
Stock fixed effect	Yes
Time fixed effect	No
N obs.	4892
R^2	0.40

This table reports the results of testing the informed trading channel using the following model:
$OPspread_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1}Event_{i,d} + \gamma_4 SHFT^D_{i,d} + \gamma_5 SHFT^D_{i,d}Event_{i,d} + \sum_{k=1}^{8}\delta_k C_{k,i,d} + \varepsilon_{i,d}$
where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT^D_{i,d}$ is the measure of HFTs' liquidity-demanding activities, and $Ins_{i,d}$ is the measure of informed trading. $Event_{i,d}$ is a dummy variable equal to one before October 16, 2009 (Rajaratnam's arrest) and zero thereafter. The sample encompasses a period of two months before and after the event date, with the exclusion of the five trading days preceding the event date. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. The table includes only firm fixed effects. The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

this test is that if the informed trading channel accounts for the entire relationship between HFT in the equity markets and options bid–ask spreads, then the impact of liquidity-consuming HFTs on options bid–ask spreads should only be significant before the arrest of Raj Rajaratnam. This is because informed trading does not predict HFT activities in the underlying markets after that date.

Table 6 presents the results of this analysis, revealing two findings. First, the coefficient for $SHFT^D_{i,d}Event_{i,d}$ is statistically significant and positive. This implies that, in line with the informed trading channel, the effects of liquidity-consuming HFT are more pronounced before the arrest of Raj Rajaratnam, i.e., when there is more informed trading. Second, the coefficient of $SHFT^D_{i,d}$ remains significant after accounting for total informed trading ($Ins_{i,d-1}Event_{i,d}$) and the impact of informed trading through HFTs ($SHFT^D_{i,d}Event_{i,d}$). This suggests that the informed trading channel alone does not fully explain the association between HFT activity in the stock market and options bid–ask spreads.

To estimate the economic magnitude of the informed trading channel in explaining the impact of HFT in equity markets on the options bid–ask spread, we can compare the coefficients of $SHFT^D_{i,d}$ and $SHFT^D_{i,d}Event_{i,d}$. When we introduce controls for liquidity-consuming HFT activities before the arrest of Raj Rajaratnam ($SHFT^D_{i,d}Event_{i,d}$), the size of the coefficient for $SHFT^D_{i,d}$ is 0.04, while the coefficient for $SHFT^D_{i,d}Event_{i,d}$ is 0.02. Given that our variables are standardized, this suggests that informed trading amplifies the relationship between liquidity-consuming HFT and options bid–ask spread by roughly 50% (0.02/0.04).

Next, we extend the baseline tests of the informed trading channel in several directions to strengthen our interpretation. First, we conduct a cross-sectional analysis to assess: (i) the empirical relevance of our informed trading measure; and (ii) whether the effects of liquidity-consuming HFTs on the options bid–ask spread persist in situations where informed traders are less active. Our motivation for this extension stems from the findings of Bondarenko and Muravyev (2022), who establish that informed trading in the options market has better predictive power for future stock returns in cases of: (i) out-of-the-money (OTM) options; (ii) days marked by firm-specific unexpected news[17]; and (iii) smaller trades. In this test, we calculate our informed trading measure, $Ins_{i,d}$, for different classes of option contracts and estimate the following model (with all variables as previously defined):

$$OPspread_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1}Event_{i,d} + \gamma_4 SHFT^D_{i,d} + \sum_{k=1}^{8}\delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (11)$$

[17] This specific analysis is omitted in the updated version of the referenced paper.

Table 7
Testing the informed trading channel – cross-sectional analysis.

	$OPspread_{i,d}$ (i) - OTM	$OPspread_{i,d}$ (ii) - ITM	$OPspread_{i,d}$ (iii) - News	$OPspread_{i,d}$ (iv) - Nonews	$OPspread_{i,d}$ (v) - Small	$OPspread_{i,d}$ (vi) - Large
$Ins_{i,d-1}$	−0.05***	−0.00	−0.08***	−0.00	−0.04**	−0.01
	(−2.63)	(−0.09)	(−2.85)	(−0.21)	(−2.51)	(−1.26)
$Event_{i,d}$	−0.04*	−0.01	−0.06*	0.00	−0.03	−0.01
	(−1.74)	(−0.27)	(−1.82)	(0.03)	(−1.25)	(−0.38)
$Ins_{i,d-1}Event_{i,d}$	0.05***	0.02	0.08**	0.01	0.04**	0.02*
	(3.03)	(0.74)	(2.53)	(0.43)	(2.35)	(1.71)
$SHFT^D_{i,d}$	0.04***	0.05***	0.03**	0.04**	0.03***	0.03***
	(3.59)	(3.55)	(2.15)	(2.14)	(2.89)	(3.24)
$Controls$	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	No	No	No	No	No	No
N obs.	4623	4148	2100	2792	4892	4892
R^2	0.40	0.34	0.43	0.37	0.40	0.40

This table reports the results of testing the informed trading channel using the following model:
$OPspread_{i,d} = \alpha_i + \gamma_1 Ins_{i,d-1} + \gamma_2 Event_{i,d} + \gamma_3 Ins_{i,d-1}Event_{i,d} + \gamma_4 SHFT^D_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$
where $OPspread_{i,d}$ is the proportional option bid–ask spread, $SHFT^D_{i,d}$ is the measure of HFTs' liquidity-demanding activities, and $Ins_{i,d}$ is the measure of informed trading. $Event_{i,d}$ is a dummy variable equal to one before October 16, 2009 (Rajaratnam's arrest) and zero thereafter. The sample encompasses a period of two months before and after the event date, with the exclusion of the five trading days preceding the event date. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. In columns 1 and 2, $Ins_{i,d}$ is calculated separately for out-of-the-money (OTM) and in-the-money (ITM) options. A put (call) is OTM if the stock price is above (below) the strike price. In columns 3 and 4, we conduct the regression analysis for unscheduled news (obtained from RavenPack database) and no-news days independently. In columns 5 and 6, $Ins_{i,d}$ is calculated separately for small and large trade sizes (based on the 100 contracts threshold). All models include firm fixed effects only. The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

Columns (i) and (ii) of Table 7 provide the results separately for out-of-the-money (OTM) and in-the-money (ITM) options. We classify option contracts into OTM and ITM categories based on whether the stock price is above or below the strike price. A put option is considered OTM if the stock price exceeds the strike price, whereas a call option is OTM if the stock price is below the strike price. Two observations emerge from our analysis, which are discussed below.

First, our informed trading metric ($Ins_{i,d-1}Event_{i,d}$) exhibits statistical significance exclusively for OTM contracts. This finding is consistent with expectations, as OTM options offer greater leverage, rendering them more appealing to informed investors (Bondarenko and Muravyev, 2022). Most importantly, the correlation between liquidity-consuming HFT activity and the options bid–ask spread is also statistically significant for ITM options, which are not as frequently traded by informed investors.

In columns (iii) and (iv) of our analysis, we differentiate between days with and without firm-relevant unexpected news events, as identified via the RavenPack database. Our rationale is based on the anticipation of more pronounced effects of informed traders prior to days with unanticipated news. In line with our expectations, the results mirror the patterns observed in the moneyness analysis. First, the impact of informed trading on the options bid–ask spread is only evident prior to days with unexpected news. Second, the association between liquidity-consuming HFTs and the options bid–ask spread is statistically significant on days unaffected by such news even though such days are characterized by lower levels of informed trading.

In the final two columns of Table 7, we provide the results for both larger and smaller trades. Following a similar methodology to Bondarenko and Muravyev (2022), we categorize trades into these groups using a threshold of 100 contracts. Bondarenko and Muravyev (2022) establish that small options trades exhibit superior predictive power for future returns, in line with the notion that informed traders prefer to break down their larger parent orders into smaller child trades in the options market. Consistent with this insight, our analysis reveals a more pronounced association between informed trading and the options bid–ask spread in the case of small trades. Importantly, the impact of liquidity-consuming HFTs on the options bid–ask spread remains statistically significant for large trades despite the fact that informed investors prefer to use small orders.

In summary, the cross-sectional analyses presented in Table 7 yield two significant implications. First, our proxy for informed trading demonstrates empirical validity, as evidenced by the greater impact of the informed trading measure on the bid–ask spread for scenarios that are more appealing to informed investors (OTM contracts, days prior to unanticipated news, and small trades). Second, the influence of HFTs on the options bid–ask spread extends beyond the impact of informed trading on the spread. This is evident from the persistent significance of the association between HFTs in the stock market and the options bid–ask spread, even in cases associated with less trading activity by informed investors (ITM contracts, days without unanticipated news, and large trades).

We present the results of two more extensions in the Internet Appendix. First, we employ close-buy option trades to compute the informed trading measure $Ins_{i,d}$, and subsequently re-estimate the effects of informed trading on the options bid–ask spread and liquidity-consuming HFTs' activities employing this revised measure. The rationale for this extension lies in the distinct motivations underpinning these two types of trades. Despite both involving the purchase of options, open-buy trades often signify leveraged bets on the underlying stock, whereas close-buy trades typically occur as a result of profit-taking and other liquidity-related factors (e.g., Pan and Poteshman (2006) and Bondarenko and Muravyev (2022)). Consequently, we do not expect to detect a significant association between $Ins_{i,d-1}Event_{i,d}$ and $OPspread_{i,d}$, or $SHFT^D_{i,d}$ in this particular test. The results presented in Table IA.2 in the Internet Appendix support this expectation.

We acknowledge that our primary dataset for calculating the put–call ratio and the informed trading measure is derived from CBOE's open-close data. This dataset presents three key limitations that are relevant to the specific objectives of our study. First, it only has transactions executed within CBOE, potentially limiting its representativeness. Second, this data is only available at a daily frequency, which might not adequately capture the high-frequency microstructure dynamics we intend to investigate. Third, our data access is constrained to a four-month period, encompassing two months before and two months after the event date. To address these concerns and account for other potential limitations associated with CBOE's open-close data, we introduce a third extension, wherein we employ transaction-level OPRA data to explore the informed trading channel.

To calculate the put–call ratio with the OPRA data, we initially categorize trades into buy and sell directions using the Lee and Ready (1991) algorithm. It is essential to note that the OPRA data does not provide distinctions between opening and closing positions. Consequently, we calculate the put–call ratio as the ratio of buy-put volume to the sum of buy-put and buy-call volumes. In contrast to the daily measurements available from the CBOE data, we shift our focus to the high-frequency microstructure environment in this test. For this purpose, we introduce a new informed trading measure, $Oins_{i,d}$. To compute this measure, we determine the put–call ratio for each minute and calculate the daily standard deviation of minute-to-minute percentage changes in the put–call ratio. This approach is conceptually akin to computing the volatility of stock returns, a common technique employed to capture information arrival in financial markets. In essence, when information flow is more pronounced at the high-frequency level, we expect to observe a higher standard deviation in the changes in the put–call ratio. Subsequently, we replicate the main tests reported in Table 5, using $Oins_{i,d}$ as our new informed trading measure.

The results of this analysis are presented in Table IA.3 in the Internet Appendix. In line with the primary findings reported in Table 5, our informed trading measure positively predicts the options bid–ask spread and liquidity-consuming HFT activity before the event date; however, the positive prediction diminishes after the event date. Thus, our core results, derived from the analysis of CBOE data, align with the newly computed informed trading measure based on the OPRA data.

3.3.2. Out-of-sample test

So far, we have based our analysis on the NASDAQ HFT dataset, which categorizes transactions as either initiated by liquidity-demanding or liquidity-consuming HFTs. However, this dataset is limited to only 120 (103 once merged with the OPRA data) randomly chosen stocks and a single year (2009). To overcome this constraint, we leverage the HFT data obtained from the SEC's MIDAS, encompassing all U.S.-listed common stocks and a broader time period, from 2012 to 2019. This analysis enables us to perform additional out-of-sample assessments to validate our primary findings derived from the NASDAQ HFT data. The results from the analysis of the MIDAS data are consistent with the main findings: there is a positive association between HFT activity and options bid–ask spreads, and this association is likely entirely driven by the interplay of the latency arbitrage and informed trading channels.

The results and further details of this test are reported in Table IA.4 in the Internet Appendix Section C. However, we want to emphasize two limitations in this analysis. First, we do not make any causal inferences in this test. Our primary aim is to demonstrate the correlation between HFT activity in equity markets and the costs of options market making, which remains valid during an out-of-sample test spanning a longer and more recent time period and including a larger number of stocks. Second, the MIDAS data does not directly identify HFT activity but instead provides proxies known to correlate with HFT activity.

4. Addressing endogeneity – instrumental variable approach

One concern is that HFT in the stock market and the option bid–ask spreads may be influenced by common underlying factors, implying that they are jointly endogenous. This concern arises from the fact that option contracts are based on underlying assets traded in the stock markets, creating a cross-market relationship that can introduce endogeneity. To address this concern, we use the two-stage least squares (2SLS) instrumental variable (IV) approach. Given that we employ the NASDAQ HFT dataset from 2009, this involves identifying an exogenous shock to the volume of HFT on the NASDAQ stock exchange during this period as an instrument. Any instrument that we choose must be correlated with the HFT variable and not correlated with the error term in Eq. (1). Skjeltorp et al. (2016) propose a potential instrument satisfying these criteria.

On June 5, 2009, the NASDAQ stock exchange introduced a new trading feature known as NASDAQ-Only Flash and Flash Enhanced Routable Orders.[18] These orders allow market participants to expose their orders for an additional 500 ms after an unsuccessful execution attempt in the NASDAQ limit order book before reaching the general marketplace.[19] Notably, the time constraint suggests that only qualified low-latency traders – HFTs – are expected to use flash orders (e.g., Harris and Namvar (2016)). This expectation is also consistent with the flash order implementation of Direct Edge – the first company to introduce flash orders on January 27, 2006 – who state that such orders allow HFTs to see and execute flash orders (e.g., Skjeltorp et al. (2016)). Thus, HFTs benefit from flash orders and, consequently, the introduction of the flash order functionality orders is expected to increase HFTs' participation.

Building on the discussion of flash orders and their potential effects on HFT, we use the introduction of flash orders on the NASDAQ stock exchange as an exogenous shock in a 2SLS IV framework to address endogeneity. We specify our 2SLS IV model as follows:

$$SHFT_{i,d} = \alpha_i + \vartheta_1 IV_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d} \tag{12}$$

$$OSpread_{i,d} = \alpha_i + \gamma_1 SH\hat{F}T_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d} \tag{13}$$

where $SHFT_{i,d}$ is one of three HFT measures ($SHFT^{All}_{i,d}$, $SHFT^{S}_{i,d}$ and $SHFT^{D}_{i,d}$) and $SH\hat{F}T_{i,d}$ is the fitted values of three HFT measures ($SH\hat{F}T^{All}_{i,d}$, $SH\hat{F}T^{S}_{i,d}$ and $SH\hat{F}T^{D}_{i,d}$) that are obtained by regressing the respective variables on $IV_{i,d}$ in Eq. (12). Thus, the first- and second-stage models are estimated separately for each HFT measure. The instrumental variable $IV_{i,d}$ is a dummy variable that takes a value of one during the period from June 5, 2009 to August 31, 2009, when NASDAQ introduced its flash order system, and zero for the other periods in our sample. To control for other factors that may affect the options bid–ask spread, we include the same control variables as those employed in the OLS specification (Eq. (1)).

Three crucial considerations require further discussion. First, while NASDAQ initially introduced flash orders on June 5, 2009, subsequent refinements to these orders were implemented on June 8, 2009. Additionally, NASDAQ initially intended to introduce flash orders on June 1, 2009, before rescheduling to June 5, 2009. Hence, to ensure a clean research setting, we exclude a 10-day window before and after the event date. Second, we restrict our sample to data preceding the arrest date of Raj Rajaratnam (October 16, 2009). This step ensures that the shock to informed trading does not impact our results. Third, in this specification, we only include stock fixed effects because our instrument does not have a time variation across stocks.

The estimation results of the first stage are reported in Table IA.5 in the Internet Appendix, where we find that our instrument, $IV_{i,d}$, is statistically significant and positively related to all three HFT measures: $SHFT^{All}_{i,d}$, $SHFT^{D}_{i,d}$, and $SHFT^{S}_{i,d}$. Hence, the implementation of flash orders on June 5, 2009, led to an increase in the activities of both liquidity-demanding and liquidity-supplying HFTs. Furthermore, the F-statistics obtained from the first-stage analysis are statistically significant at conventional levels of significance, confirming the validity of our selected instrument.

The second stage results presented in Table 8 reveal two key findings with respect to the impact of HFT on options market making. First, we find a statistically significant positive relationship between total HFT activities and options spreads, indicating that greater HFT participation in equity markets results in higher trading costs for options

[18] https://www.nasdaqtrader.com/TraderNews.aspx?id=ETA2009-35.

[19] Skjeltorp et al. (2016) provide the implementation details for these orders, and some numerical examples.

Table 8
The impact of HFT activities on option spread – 2 SLS IV – second stage.

	$OPspread_{i,d}$ (i)	$OPspread_{i,d}$ (ii)	$OPspread_{i,d}$ (iii)
$S\hat{HFT}^{All}_{i,d}$	0.08**		
	(2.03)		
$S\hat{HFT}^{S}_{i,d}$		0.01	
		(0.54)	
$S\hat{HFT}^{D}_{i,d}$			0.08**
			(2.02)
Controls	Yes	Yes	Yes
Stock fixed effect	Yes	Yes	Yes
Time fixed effect	No	No	No
N obs.	14,432	14,432	14,432
R^2	0.39	0.39	0.39

This table reports the results of estimating the impact of HFT in equity markets on the options bid–ask spread using the following models:
$SHFT_{i,d} = \alpha_i + \vartheta_1 IV_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$
$OSpread_{i,d} = \alpha_i + \gamma_1 S\hat{HFT}_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$
where $OPspread_{i,d}$ is the proportional option bid–ask spread and $SHFT_{i,d}$ is one of three HFT measures ($SHFT^{All}_{i,d}$, $SHFT^{S}_{i,d}$ and $SHFT^{D}_{i,d}$). $S\hat{HFT}_{i,d}$ is the fitted values of one of three HFT measures ($S\hat{HFT}^{All}_{i,d}$, $S\hat{HFT}^{S}_{i,d}$ and $S\hat{HFT}^{D}_{i,d}$) that is obtained by regressing the respective variables on $IV_{i,d}$, $IV_{i,d}$ is a dummy equal to one from June 5, 2009 to August 31, 2009, and zero for the other periods (from January 1, 2009 to June 4, 2009, and from September 1, 2009 to October 15, 2009). We exclude the 10 days before and after the event date. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. All models include firm fixed effect (α_i). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

Table 9
Testing the latency arbitrage channel – 2 SLS IV – second stage.

	$OPspread_{i,d}$ (i)	$OPspread_{i,d}$ (ii)
$S\hat{HFT}^{All}_{i,d}$	−0.32***	
	(−4.33)	
$S\hat{HFT}^{D}_{i,d}$		−0.29***
		(−4.60)
$High_{i,d}$	−0.03**	−0.03**
	(−2.02)	(−2.12)
$S\hat{HFT}^{All}_{i,d} High_{i,d}$	0.04***	
	(3.82)	
$S\hat{HFT}^{D}_{i,d} High_{i,d}$		0.05***
		(3.69)
Controls	Yes	Yes
Stock fixed effect	Yes	Yes
Time fixed effect	No	No
N obs.	5899	5899
R^2	0.33	0.33

This table reports the results of testing the latency arbitrage channel using the following model:
$OSpread_{i,d} = \alpha_i + \gamma_1 S\hat{HFT}_{i,d} + \gamma_2 High_{i,d} + \gamma_3 S\hat{HFT}_{i,d} High_{i,d} + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$
where $OPspread_{i,d}$ is the proportional option bid–ask spread and $S\hat{HFT}_{i,d}$ is the fitted values of one of two HFT measures ($S\hat{HFT}^{All}_{i,d}$ and $S\hat{HFT}^{D}_{i,d}$) that is obtained by regressing the respective variables on $IV_{i,d}$, $IV_{i,d}$ is a dummy equal to one from June 5, 2009 to August 31, 2009, and zero for the other periods (from January 1, 2009 to June 4, 2009, and from September 1, 2009 to October 15, 2009). We exclude the 10 days before and after the event date. $High_{i,d}$ is a dummy variable equal to one in day d if its $Npv_{i,d}$ (the number of put–call parity violations) value is above the median number of profitable put–call parity violations for all stocks. $C_{k,i,d}$ is a set of k control variables, including variables from both the options and underlying markets. The options market variables are $Ovolume_{i,d}$, $Oimplied_{i,d}$, $Oinp_{i,d}$, $|Odelta_{i,d}|$, $Ogamma_{i,d}$, and $Ovega_{i,d}$, and the stock market variables are $SPspread_{i,d}$, and $SVolatility_{i,d}$. All models include firm fixed effect (α_i). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and day. *, **, and *** denote the significance at 10%, 5%, and 1% respectively. For detailed definitions of variables refer to Table 1.

market makers. Second, this positive effect is sourced from liquidity-demanding HFT orders ($SHFT^{D}_{i,d}$). These results are broadly consistent with the OLS setting findings and they support a causal interpretation of the impact of HFT activities on options market-making trading costs.

Table 9 reports the estimation results for the latency arbitrage channel by using the 2SLS IV approach. Consistent with the results for OLS regressions with fixed effects, we find that the positive and statistically significant association between HFTs' liquidity-demanding trading activity and the option proportional spread is concentrated in stocks with a higher frequency of profitable put–call parity violations.

While we employ the 2SLS IV approach to investigate the latency arbitrage channel, we cannot use flash orders to address endogeneity in the informed trading channel. This is because NASDAQ introduced flash orders in June 2009, but our CBOE open-buy data only covers the period from August 2009 onwards. It is also worth noting that since we use an exogenous shock to the information environment (the arrest of Raj Rajaratnam) to test the informed trading channel, endogeneity is less of a concern for this particular test.

To sum up, our analysis shows that HFTs' trading activities in equity markets affect the trading costs in the options market, and this effect extends beyond the hedging channel documented in previous market microstructure literature. The impact of HFTs in the stock market on the options bid–ask spread can be attributed to a combination of latency arbitrage and informed trading channels. While exogenous shocks to HFT activity in the stock market, and to informed trading in the options market, provide a valuable means of separately mitigating endogeneity concerns for the two channels, we acknowledge the complexity associated with conclusively and fully addressing endogeneity in this setting due to the inherent interconnectedness of the stock and options markets.

5. Conclusion

We find a negative relationship between aggressive HFT strategies in the stock market and options market liquidity: more aggressive HFT activity in the stock market leads to wider bid–ask spreads in the options market. These results hold after controlling for known drivers of stock and option liquidity. We attribute this relationship to two channels: (i) the latency arbitrage channel; and (ii) the informed trading channel. In the first channel, aggressive HFTs engaged in cross-market latency arbitrage strategies expose option market makers to the risk of trading at stale prices. To test this, we measure the frequency of profitably exploitable put–call parity violations and find that the impact of HFT in equity markets on options bid–ask spreads is higher when there are more such violations.

The second channel, the informed trading channel, posits that informed trading activities in the options market may influence the impact of HFT in equity markets on the options bid–ask spread by simultaneously affecting both the options spread and the intensity of aggressive HFT actions in the underlying market. We find that informed trading in the options markets intensifies the positive relationship between liquidity-demanding HFT in the stock market and options bid–ask spread by roughly 50%.

Our study provides important insights into the role of HFTs in explaining the cross-market dynamics between stock and options markets. More broadly, our results have significant implications for market participants, regulators, and policymakers seeking to understand the evolving landscape of financial markets and design effective policies to ensure market stability and efficiency. The findings of this study also underscore the need for a better understanding of the costs and risks associated with HFTs in today's highly fragmented and complex market structures.

CRediT authorship contribution statement

Mahendrarajah Nimalendran: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Khaladdin Rzayev:** Writing – review & editing, Writing – original draft, Software, Resources, Formal analysis, Data curation, Conceptualization, Methodology. **Satchit Sagade:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Replication Package for "High-frequency Trading in the Stock Market and the Costs of Option Market Making" (Reference data) (Mendeley Data).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103900.

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