OSPIN:Informed Trading in Options and Stock Markets

Nick DeRobertis

Yong Jin
Mahendrarajah Nimalendran
Sugata Ray*†

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*Nick DeRobertis (nick.derobertis@warrington.ufl.edu) and Mahendrarajah Nimalendran (mahen.nimalendran@warrington.ufl.edu), University of Florida; Sugata Ray (sugata.ray@cba.ua.edu), University of Alabama; Yong Jin (jimmy.jin@polyu.edu.hk), HongKong Polytechnic University.

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Abstract

To gain a better understanding of the role of information in the price discovery of stock and option markets, we propose and estimate a joint structural model of trading in both markets. The model allows correlated directional informed trading in both markets, informed volatility trading in the options market, and correlated (buy/sell) liquidity trades in both markets. The model parameters and the probabilities of informed and liquidity trading in both markets are estimated using signed high-frequency stock and options trade data for different option contracts. The study finds that moneyness and maturity play an important role in informed trading, and on the microstructure, and price discovery in the stock and options markets. The findings are consistent with the trade off between leverage and liquidity, and the strategic behavior of market makers and traders. The model also allow us to estimate high frequency conditional posterior probabilities of informed trading [$PPIT$]. We find that the high-frequency $PPIT$ measures in the options market lead the stock market measures, and they spike several days before earnings announcements, and remain high for a few days after the announcement. In summary, options markets are very important in price discovery and provide more informative measures of informed trading relative to stock market measures alone.

1 Introduction

The process by which information is revealed through trading has been studied extensively. Most of this research has focused on trading in the stock or options markets about the future direction of the stock. Recent theoretical and empirical studies have suggested that informed agents may trade on both markets simultaneously depending on the trade off between the high leverage in the options market and low transaction costs in the stock market.[1] Also, the options markets provide a venue to trade on volatility information. However, there have been only a few studies that have documented joint trading strategies of informed and liquidity traders in both markets (Johnson and So 2013,Ni, Pan, and Poteshman 2008), based on the direction as well as volatility. In this study, we propose a joint model of trading on the stock and option markets by informed and liquidity traders. The model provides estimates for the probabilities of directional and volatility informed trading as well as correlated (buy/sell) liquidity trading in both markets. Also, based on the model estimates, we provide high-frequency measures of the posterior likelihood of directional and volatility information states, as well as the likelihood of correlated liquidity episodes.

There is a large literature on the relation between future volatility and option implied volatility. Yet we know little about the extent to which new information about future volatility is revealed through option trading in the options market. It is well recognized that private information about the future value of a stock is revealed through trading (Grossman and Stiglitz [1980], Kyle [1985]). Options contracts are volatility sensitive instruments and provide a venue to trade on volatility information.[2] In this paper, we investigate both the joint directional trading in the stock and option markets in addition to volatility information-based trading on the options market.[3]

We propose a structural model in the spirit of Easley, Kiefer, O'Hara, and Paperman 1996, Easley, Hvidkjaer, and O'Hara 2002, and the extended model of Duarte and Young 2009, to jointly estimate the probabilities of both volatility and directional information based trading on the stock and option markets.[4] In addition to jointly

[1] Easley, O'Hara, and Srinivas 1998

[2] Recently there have been ETFs on VIX as well as futures on VIX that are traded. Also, there are a few individual stock volatility indexes such as the CBOE Equity Vixon Apple ($VXAPL$).

[3] In our study, directional information refers to information about whether a stock price is going up or down. Volatility information refers to information regarding the future volatility of a stock either increasing or decreasing.

[4] Ni, Pan, and Poteshman 2008 also investigate informed trading on volatility in the options market using daily net non-market maker trading volume on calls and puts to construct a measure for trading on volatility information. We discuss the differences in our studies and findings in the

modelling informed trades in both the stock and option markets, the model also incorporates time-varying correlated levels of liquidity in both markets as proposed by Duarte and Young 2009.

The model assumes that in each time-period, there are eighteen states representing the presence or absence of different sets of information, as well as the presence or absence of correlated (buy-sell) levels of liquidity trading. Specifically, the probability of directional information has three states: high, low, or no information; volatility information has three states: high, low, or no information; correlated stock market liquidity has two states:high or normal; and correlated option market liquidity has two states high or normal. We assume that the probability of information about the direction in the stock and options market are perfectly correlated. We also assume that the buy/sell correlated liquidity across the stock and options market is perfectly correlated. If there is information in a given period, it can be about volatility or direction, or both. In line with the original PIN model as proposed by Easley, Kiefer, O'Hara, and Paperman 1996, we condition the volatility and directional information based on whether it is bullish (good) or bearish (bad). Also, as proposed by Duarte and Young 2009, we allow for a episodes of symmetrically motivated buy/sell trading (concentrated liquidity trades), in both the stock and option markets. This results in eighteen distinct states, and traders place orders in accordance with this information structure on both stock and option markets, resulting in a rich structural trading model. We use high-frequency transaction-level data and trade direction (buyer initiated and seller initiated) for calls, puts, and the underlying stock to estimate the probabilities of volatility and directional information-based trading as well as concentrated liquidity probability using a maximum likelihood technique.

High frequency signed trades in options and stock is used to identify and estimate the model parameters. Informed directional traders buy stock, buy calls, and sell puts if they are bullish on the price, and they sell stock, sell calls, and buy puts when they are bearish. In contrast, informed volatility traders buy calls and buy puts (straddle/strangle) if they are bullish on volatility, and they sell straddles/strangles if they are bearish. Also, there are correlated (buy and sell) liquidity trades at certain times, and noise or uninformed traders who will be buying and selling the stock, calls, and puts. These trading choices together with observed signed trades in the stock and option markets allow us to estimate separate probabilities of informed trading based on direction for the stock and option markets $(OptDirPIN(\pi_O^D)$,$StkDirPIN(\pi_S^D))$, and volatility trading in the options market, $(OptVolPin(\pi_O^V))$. The direction and volatility $PINs$ are also estimated for "high and "low" states of the stock price and volatility, respectively. In addition we also estimate concentrated probability of

following section.

liquidity trading in the option and stock markets ($OptLIQ(\pi_O^L)$ and $StkLIQ(\pi_S^L)$).

The option markets provide implicit leverage based on their moneyness or $1/\Delta$ for directional traders. This leverage would be useful for informed traders to lever their informational advantage. However, the out-of-the money (OTM) options that have high leverage (low Δ) are very illiquid with high bid-ask spreads. Part of the spread is to compensate market makers for adverse selection costs due the possibility of higher informed trading in these options. Similarly, the at-the-money (ATM) options that have the highest vega (ν) will have the most sensitivity to volatility information, but out-of-the-money (OTM) options will have more leverage, but lower liquidity. Hence, the equilibrium outcome will depend on the precision and the value of the information to the informed traders, transactions costs of the contracts, and strategies employed by other traders and market makers. In this study we hope to provide more information on the strategic trading behaviors of informed agents in the options markets by studying the likelihood of informed, liquidity, and noise trading, for different moneyness and maturity that proxy for the option sensitivities (Greeks), leverage, and transactions costs.

We also use the jointly estimated measures of informed and liquidity trading to study the relation to market microstructure measures in both markets, and also to examine how these measures respond to information sensitive events such as earnings announcements. We find that the probability of volatility informed trading ,$OptVolPIN(\pi_O^V)$, and directional informed trading in options, $OptDirPIN(\pi_O^D)$, are both significantly related to option and stock market microstructure measures, including bid-ask spread, effective spreads, price impact, and cross- market price impact measures. Further, we find that $OptPIN$ measures have more explanatory power than the $StkPIN$ measures in explaining the stock market microstructure metrics. This is consistent with $OptPIN$ measures providing more precise estimates for informed trading relative to $StkPIN$ measures. This may also suggest that price discovery in the option market leads that in the stock market.

Based on the model estimates, we find that the $StkDirPIN$ varies from 3.7% for the largest market value quintile firms to 6.2% for the smallest quintile. The $OptDirPIN$ for $ATM/OTM/ITM$ options are 5.1%/11.4%/15.8% for largest quintile firms and increases monotonically with lower market values to 13.7%/23.2%/26.3% for the smallest quintile firms. The $OptVolPIN$ varies from 5.6%/12.8%/11.7% (large firms) to 12.1%/19.6%/13.6% (small firms) for $ATM/OTM/ITM$ options. Based on our model, the probability of trading in the options market is more than double that in the stock market for directional information. In addition, there is a significant probability of trading on volatility information in the options market. The correlated probability of liquidity trades for the stock market vary between

23.6% for small stocks to 26.4% for large stocks. In the options market the liquidity trading probabilities depend on moneyness with ATM option probabilities varying from 28.5% for large (L) stock options to 30.3% for small (S) stock options. While it is much higher for $ITM(33.6\%(L)/46.0\%(S))$ and for $OTM(28.3\%(L)/35.1\%(S)$ options.

Next we study how the $OSPIN$ measures are related to traditional measures of adverse selection due to informed trading. This includes the bid-ask spread, adverse selection component of spread (AS), and price impact (λ). The $OptDirPIN$ has significant positive relation to option quoted and effective spreads. A one standard deviation (0.096) increase in $OptDirPIN$, increases ATM option effective spread by 3.6% (.0173*.096/0.0462), and an increase of one standard deviation(0.089) in $OptVolPIN$ increases OTM option effective spread by 1.7%. On the other hand an increase of one standard deviation in the underlying stock effective spread increases OTM and ATM option effective spread by 13.9% and 16.2%, and has no impact on ITM option spread. The relatively high impact of stock spreads on option spreads is consistent with the re-balancing cost of hedging their position in the underlying.

Several studies have used informed trading measures derived from the daily data provided by $OptionMetricsData[OM]$.[5] The advantage of OM data is that it is easy to access, but the disadvantage is that it only gives end of day data; quotes/prices, trading volume, and open interest, for options from 1994 to present. The information measures used are based on the imbalance between puts and calls (Put-Volume/Call-Volume) or volume ratios between options and stock (Option-Volume/Stock-Volume). A concern with these measure are that they are not able to separate the directional, correlated liquidity, and volatility informed trading. Our structural model together with more granular transactions level data is able to provide separate estimates for directional, volatility, and correlated liquidity trading. We find that measures such as put/call ratio, option/stock volume ratio, and other metrics based on daily OM data are significantly correlated with option directional $OptDirPIN$, option volatility $OptVolPIN$, as well as option $OptLIQ$ measures estimated from the $OSPIN$ model. Suggesting that one has to use caution in using these measures as proxies for purely directional informed trading.

The OSPIN model estimates can also be used as priors to construct high frequency measures of the posterior likelihood of an informational event Brennan, S. Huh, and Subrahmanyam 2018. We estimate posterior probabilities around earnings

[5] Measures include quoted spreads (Kacperczyk and Pagnotta 2018); Implied volatility spread (Cremers and Weinbaum, 2010); Levered volume ratio (Black, 1975); Cross market price impact (Easley et.al.,1998); option to stock volume ratios (Roll, Schwartz, and Subrahmanyam, 2010, and Johnson and So, 2012); Put/Call volume ratios (Pan and Poteshman , 2006)

announcements to study the trading behavior of informed agents around earnings releases. We find that the likelihood of an information event increases a few days prior to the announcement and remain high for a few days after the announcement. More importantly, the likelihood of informational event is much higher in the option PIN measures compare to stock PIN measures.

The $OSPIN$ model provides a rich characterization of informed and liquidity traders in the options and stock markets. Further, the informed trading metrics using information from both options and stock markets provide more precise estimates of informed trading compared to using only information from the stock market. We also find that informed trading in option markets affect the market microstructure of both the stock market and the options market. While, informed trading measures on the stock market is only related stock market microstructure measures. The study finds that option market PIN measures are superior to stock market measures in detecting informed trading around earning announcements. Overall, the findings are consistent with options market informed trading measures being superior to stock market measures for detecting informed trading.

2 Literature review

There is a rich literature covering directional informed trading in the stock market and its link to market microstructure[6]. However, there is much less known about the contemporaneous informed trading in both the stock and option markets and their impact on the microstructure of both markets. Easley, O'Hara, and Srinivas 1998, propose a model, with directionally informed traders choosing between stock and option markets based on the relative transaction costs in the markets, and the "bang-for-buck" in the form of leverage afforded by the options market. The authors conclude that depending on the relative transaction costs in the markets, there can be a separating equilibrium where informed traders trade only in the stock market, or a pooling equilibrium where informed traders trade in both markets. Subsequent empirical work that focused on directional informed trading in these two venues has largely supported the theoretical predictions in the model. For example, Cao, Chen, and Griffin 2005, find informed option trading prior to takeovers. While S.-W. Huh, Lin, and Mello 2012, allow the market makers in the option markets to hedge in the stock market.[7]

6 Bagehot 1971, Glosten and Milgrom 1985, Kyle 1985, Easley and O'hara 1987

7 Several studies have examined informed trading in option markets, for example, Chakravarty, Gulen, and Mayhew 2004, and Kaul, Mahendrarajah Nimalendran, and Zhang 2004 but these authors focus on directional information about the underlying stock price, not information about

The literature examining informed volatility trading is more recent. Johnson and So 2013, estimate a multi-market information asymmetry measure, similar to the PIN, for option markets using aggregate unsigned volume. While simple to compute as it does not rely on estimation of a structural model, it includes both information on volatility, direction, and liquidity in one measure. Ni, Pan, and Poteshman 2008 (NPP), use trades by non-market makers in the option markets to estimate demand for volatility and show that this demand is related to "information about the future realized volatility of underlying stocks." In contrast to our study, which uses intraday quote and transaction data to sign trades, NPP use non-market maker volume ($NMMV$) obtained from the Chicago Board of Options Exchange ($CBOE$) at the daily level for their analysis. Additionally, rather than estimating PIN measures, the study separates option volume into trades that could have been used for constructing straddles and those that were not. In our study, we separately estimate measures for directional and volatility based information trading in the options market. While NPP largely disregard "non-straddle" trading, exclusively focusing on straddle trades, we holistically characterize trades as directional, volatility, liquidity, or noise driven, and separately estimate measures for all these trade types.

Our methodology has several advantages over that used by NPP: (i) using intraday data allows us to sign trades individually, rather than relying on aggregate daily volume; (ii) separately estimating direction, volatility, and liquidity measures allows us to examine the impact of these on market microstructure of the stock and option markets and around information events.

Brennan, S. Huh, and Subrahmanyam 2018 [BHS], use estimates from a PIN model for the stock market to construct high-frequency measures of the posterior likelihood of informed trading around corporate events: merger bids, dividend initiations, SEOs, and quarterly earnings. We extend the BHS methodology to the $OSPIN$ model to estimate high-frequency measures of informed trading around earnings announcements in the option and stock market. The options market provides information on volatility informed traders in addition to directional informed traders. By adding the options market to the stock market, the OSPIN model provides much more information to estimate the various traders' more precisely. The stock market alone has only three pieces of information from the buy stock and sell stock variables (covariance matrix has three unique pieces of information). While the options market has 11 unique pieces of information from the variables BC, SC, BP, and SP. But, once we include both markets, the amount of unique covariances and

the volatility. Simaan and Wu 2007, examine price discovery across option exchanges, but they make no attempt to differentiate between option price changes resulting from underlying stock price changes and those resulting from volatility changes.

variances increase to 21. This allow us to estimate vastly more precise measures of informed and liquidity trading probabilities.

3 OSPIN Model

3.1 Model

In this section we outline our structural trading model that captures both directional information, volatility information, and correlated liquidity trading. Our sequential trade model is a generalization of Easley, Kiefer, O'Hara, and Paperman 1996, and Easley, Hvidkjaer, and O'Hara 2002's probability of information-based trade (PIN) model extended to include correlated liquidity trading in both stock and options markets (Duarte and Young 2009). Our model extends their model to the options market where agents can trade on directional information as well as volatility information on the underlying stock ($OSPIN$). Traders with information about a future increase in stock price can use a long call/short put strategy and those with information about a future decrease in stock price can use a long put/short call strategy. If the information is about volatility, then traders can employ a long straddle/strangle (long call and long put) when the information is about an increase in volatility and they can employ a short straddle/strangle (short call and short put) for a decrease in future volatility.

In our model, every 30-minute period represents a certain arrival rate for each type of order, where traders can buy (B), sell (S), call (C), put (P), options (O), and stocks (S). For example, BC represents a buy call trade, and SS will be a sell stock trade. The set of trades is given by orders, $\Omega = [BC, SC, BP, SP, BS, SS]$. In each period, there may be directional information (D), with a set of probabilities, $p_D = [p_D^u, p_D^d]$. Volatility information (V) with probabilities, $p_V = [p_V^u, p_V^d]$, and information about direction and volatility may be either up or down, signified by the superscript u or d. In addition we allow correlated liquidity trading in either the stock with probability θ_S or in options with probability θ_O.

Specifically, in any given period, there is a p_D^u (p_D^d) probability associated with arrival of information that price will increase (decrease), while there is a $p_D^N = 1 - p_D^u - p_D^d$ probability of no directional information. Similarly, in the same period, there is a p_V^u (p_V^d) probability assigned to arrival of information that volatility will increase (decrease), while there is a $p_V^N = 1 - p_V^u - p_V^d$ probability of no volatility information arrival. In every state described above, we assume that the probability of correlated (buy/sell) large liquidity trading across both stocks and options are equal and set $\theta_S = \theta$ and $\theta_O = \theta$. Hence, there is a $(1-\theta)$ probability of no correlated liquidity trades in both markets. This leads to the following states and associated probabilities.

Orders from informed and uninformed traders to buy and sell call and put options as well as stock follow independent Poisson processes. We assume that there are four types (uninformed, direction informed, volatility informed, and liquidity) of traders, and each type will trade call options, put option, and stocks denoted by subscripts C, P, and S, while superscripts B and S denote buys and sells by the traders. The arrival rates for the different types of trader/orders are described below.

1. Uninformed buyers (sellers) arrive according to independent Poisson processes at rates $\epsilon = \{\epsilon_C^B, \epsilon_C^S, \epsilon_P^B, \epsilon_P^S, \epsilon_S^B, \epsilon_S^S\}$.

2. Orders from traders possessing volatility information arrive at rates $\mu^H = \{\mu_C^B, \mu_P^B\}$ for high volatility, and $\mu^L = \{\mu_C^S, \mu_P^S\}$ for low volatility.

3. Orders from informed directional traders arrive at rate $\nu^H = \{\nu_C^B, \nu_P^S, \nu_S^B\}$ for high direction, and $\nu^L = \{\nu_C^S, \nu_P^B, \nu_S^S\}$ for low direction.

4. Correlated (buy/sell) orders from traders demanding buy and sell liquidity in the option market arrive at a rate $\lambda_O = \{\lambda_C^B, \lambda_C^S, \lambda_P^B, \lambda_P^S\}$, and for the stock market at a rate $\lambda_{\mathcal{S}} = \{\lambda_S^B, \lambda_S^S\}$.

When there is no information in the market (p_N), the orders are purely uninformed, with the set of arrival rates $\epsilon = \{\epsilon_C^B, \epsilon_C^S, \epsilon_P^B, \epsilon_P^S, \epsilon_S^B, \epsilon_S^S\}$ for long call, short call, long put, short put, long stock, and short stock respectively. This would be the baseline rate of order arrivals. An information event occurs in the market with probability $1 - p_N$. The total arrival rate for each order is the sum of the arrival rates from each type of information, added to the baseline uninformed arrival rate based on the assumption that arrival processes are independent. For example, in a single period there is information that volatility would increase, no information about direction, option liquidity trading, but no additional stock liquidity trading. The probability of this state is, $p_V^u(1 - p_D^u - p_D^d)\theta_O(1-\theta_S)$. Then the arrival rates are described in equation 1.

$$
\begin{aligned}
BC &= \epsilon_C^B + \mu_C^B + \lambda_C^B \\
SC &= \epsilon_C^S + \lambda_C^S \\
BP &= \epsilon_P^B + \mu_P^B + \lambda_P^B \\
SP &= \epsilon_P^S + \lambda_P^S \\
BS &= \epsilon_S^B \\
SS &= \epsilon_S^S
\end{aligned}
\tag{1}
$$

Model - State Probabilities and Arrival Rates

Information Type	State	Probability	BC	SC	BP	SP	BS	SS
	Baseline		ϵ_C^B	ϵ_C^S	ϵ_P^B	ϵ_P^S	ϵ_S^B	ϵ_S^S
Volatility	Up	p_V^u	μ_C^B		μ_P^B			
Volatility	Down	p_V^d		μ_C^S		μ_P^S		
Volatility	None	$1 - p_V^u - p_V^d$						
Direction	Up	p_D^u	ν_C^B			ν_P^S	ν_S^B	
Direction	Down	p_D^d		ν_C^S	ν_P^B			ν_S^S
Direction	None	$1 - p_D^u - p_D^d$						
Liquidity	Stock	θ_S					λ_S^B	λ_S^S
Liquidity	Stock-None	$1 - \theta_S$						
Liquidity	Option	θ_O	λ_C^B	λ_C^S	λ_P^B	λ_P^S		
Liquidity	Option-None	$1 - \theta_O$						

The above table gives the probability of a particular state, and the arrival rates for each state of the model. Each panel represents a set of states. A single trading period represents the baseline arrival rates plus the arrival rates from one state from each panel. There are 3 states for volatility information, 3 states for direction information, and 2 states for liquidity trades. In total, there are (3 * 3 * 2 =) 18 states. There are a total of six probability parameters and 22 Poisson arrival rates.

3.2 Restricted Model

The model given in section 3.1 has 28 parameters, and estimating all the parameters using MLE method is challenging. Also, intuition suggest that we can make several reasonable restrictions on the parameters to make the model tractable. First, we set all the uninformed arrival rates to be the same within a market. For options,

$\epsilon_O = \epsilon_C^B = \epsilon_C^S = \epsilon_P^B = \epsilon_P^S$, and for stocks, $\epsilon_S = \epsilon_S^B = \epsilon_S^S$. The assumptions on the uninformed rates are not very restrictive as these traders are non-strategic. Second, we set the informed arrival rates for high and low volatility traders to be the same for the calls and puts, $\mu_O = \mu_C^B = \mu_C^S = \mu_P^B = \mu_P^S$. This is more restrictive as one might expect arrival rates for high volatility to be different from low volatility. Further, we assume that the arrival rates for the high and low directional trader to be the same within a market. For options, $\nu_O = \nu_C^B = \nu_C^S = \nu_P^B = \nu_P^S$, and for stocks $\nu_S = \nu_S^B = \nu_S^S$. We do not expect directional traders to prefer high or low directional trades and hence this assumption is not too restrictive. Finally, we assume that the arrival rates for extra liquidity trading to be the same within a market. For options, $\lambda_O = \lambda_C^B = \lambda_C^S = \lambda_P^B = \lambda_P^S$, while for stocks, $\lambda_S = \lambda_S^B = \lambda_S^S$. Finally, the probability of correlated high liquidity trading is associated with public information events such as earnings announcements. Following an earnings announcement there is very high volume of buys and sells in both option and stock markets. Hence, we can assume that the probability of correlated liquidity trading will be the same for both options and stocks, and set this equal to θ . These assumptions reduce the number of parameters to 12 from 28.

We use the maximum likelihood method (MLE) to estimate the set of parameters of the model, $\Theta = \{p_V^u, p_V^d, p_D^u, p_D^d, \theta, \epsilon_O, \epsilon_S, \mu_O, \nu_O, \nu_S, \lambda_O, \lambda_S\}$, conditional on the observed set of signed orders, $\Omega = \{BC, SC, BP, SP, BS, SS\}$, during a 30-minute interval, for stocks and options on an individual firm.

3.2.1 Likelihood Function

The log likelihood functions consists of the marginal likelihood of the arrival of traders in the options and stock market and the probabilities associated with the state. We have total of 18 possible states based on the up, down, none for the direction and the volatility, and for each of these states we have two other possible states based on the probability of high correlated liquidity trades or none. The likelihood function is described in Appendix A1.

We use a maximum likelihood method (MLE) to estimate the parameters of the model, $\Theta = \{p_V^u, p_V^d, p_D^u, p_D^d, \theta, \epsilon_O, \epsilon_S, \mu_O, \nu_O, \nu_S, \lambda_O, \lambda_S\}$, using signed orders, $\Omega \in \{BC, SC, BP, SP, BS, SS\}$, for individual stock options. From these estimates we construct estimates for the probability of volatility, direction, and liquidity trading in the stock and options markets. See Appendix A1.

3.3 Model Implied Moments

In this section we develop the moments that are implied by our structural model. The PIN model proposed by Easley, Kiefer, and O'Hara 1996, assume only two types of traders: informed and uninformed. The uninformed trades arrive at random and their buy and sell trades are uncorrelated. The informed traders on the other hand will be either buy or sell based on the type of information (good or bad). This will lead to negative model implied correlation between buy and sell trades. However, in the data the correlation between buy and sell trades is positive and quite high. To account for this positive correlation, Duarte and Young 2009, assume an additional source of liquidity trades where the buy and sell trades are correlated. In our model we incorporate this additional correlated liquidity trading in the options and the stock markets. We assume that the probability of the correlated liquidity events is the same for both markets. In addition, we also assume the directional information probabilities are the same for the option and stock markets. These assumptions also provide a linkage between the two markets.

The theoretical model implied moments for buy and sell orders in the option and stock markets based on the structural model parameters are provided in Appendix A2. The expected values are defined as $\mu_x \in \Omega$ and the variance and covariance terms are defined as $\sigma_{x,y\in\Omega}$, where, $\Omega = \{BC, SC, BP, SP, BS, SS\}$. The sample moments and the model implied moments provide an important check of our structural model estimates based on the ML method.

The model implied moments are consistent with positive variance for all positive parameters values, which is the case given that all the probabilities will be positive (or zero) and all the Poisson arrival rates will also be positive (or zero). However, the covariances depend critically on the relative values for the correlated liquidity trading and the expected informed trading. For example, the covariance between buying and selling call options is $\sigma_{BC,SC} = \lambda_O^2\theta(1-\theta) - \mu_O^2 p_V^d p_V^u - \nu_O^2 p_D^d p_D^u$, and the correlated liquidity trading will determine whether the covariance is positive or negative. In the extreme case when $\theta = \lambda = 0$, there is no correlated buy and sell liquidity trades, and the covariance between call option buys and sell trades and put options buys and sells will be negative, but in the sample the correlations are significant and positive and this requires the correlated trading to be significant and large for the sample moments to be consistent with the model moments, or $\lambda_O^2\theta(1-\theta) > \mu_O^2 p_V^d p_V^u - \nu_O^2 p_D^d p_D^u$. This is consistent with significant trading due to differences in opinion in both the options and stock markets.

3.4 Informed Trading Measures

3.4.1 Restricted Model OSPIN Measures

The probability of informed or liquidity trading (π) for a type of information or liquidity, $i = \{D = Direction, V = Volatility, L = Liquidity\}$ in a market $m = \{O = Option, S = Stock\}$ is constructed from the expected arrival rate of orders in that market m, (π^m) , and type of information or liquidity traders i, is $\pi_i^m = \frac{\pi_i^m}{\pi_m}$. For example, the probability of volatility information (includes both high and low volatility regimes) event is $p_V^u + p_V^d$, and conditional on this the volatility-informed arrival rate across options is $2\mu_O$. Hence the expected rate of volatility information arrival is $2\mu_O(p_V^u + p_V^d)$. The total expected arrival rate in the options market is $2(2\epsilon_O + 2\lambda_O\theta_O + \mu_O p_V^u + \mu_O p_V^d + \nu_O p_D^u + \nu_O p_D^d)$. Based on this, the probability of volatility information measure in the options market is given by equation (2).[8]

$$\pi_V^O = \frac{\mu_O \left(p_V^d + p_V^u\right)}{2\epsilon_O + 2\lambda_O\theta_O + \mu_O p_V^d + \mu_O p_V^u + \nu_O p_D^u + \nu_O p_D^d}. \tag{2}$$

In appendix 1 we provide the formulas for all the measures based on the parameters from our OSPIN model.

3.5 High Frequency Posterior Likelihood of Informed Trading

To estimate $OSPIN$ measures using ML method requires a large number of observations. This only provides the probabilities of informed trading over the estimation period. For, example when we use monthly data the OSPIN estimates are the average over a month. However, to study the dynamics of informed trading around an event such as earnings announcements, one would require higher frequency (daily or higher) metrics for informed trading. Brennan, S. Huh, and Subrahmanyam 2018, propose using the posterior probabilities associated with informed trading conditional on OSPIN model parameters. The posterior probabilities can be calculated using the marginal likelihood of a particular state conditional on the estimated parameters and the signed order flow that is observed for a particular day. Let,

$$\begin{aligned} \Omega_t &= \{BC_t, SC_t, BP_t, SP_t, BS_t, SS_t\}, \\ \hat{\Theta} &= \{\hat{p_V^u}, \hat{p_V^d}, \hat{p_D^u}, \hat{p_D^d}, \hat{\theta}, \hat{\epsilon_O}, \hat{\epsilon_S}, \hat{\mu_O}, \hat{\nu_O}, \hat{\nu_S}, \hat{\lambda_O}, \hat{\lambda_S}\}. \end{aligned} \tag{3}$$

[8] We have also calculated separate probability measures (OSPIN) for both markets for positive or negative information about direction and volatility.

In equation (3), Ω_t is the observed order flow for the high frequency time interval t and $\hat{\Theta}$ is the model parameters estimated over the time period T (one month). Let the posterior marginal likelihood of state s be $\{l_{s,t}|\hat{\Theta}, \Omega_t\}$. There are 18 states; and one example would be the state where the direction is high, volatility is high, and the liquidity trading is high. Based on the conditional likelihoods, the posterior probability of a state "s" for time "t" is given by equation (4).

$$\pi_{s,t} = \frac{\{l_{s,t}|\hat{\Theta}, \Omega_t\}}{\sum_{s=1}^{S}\{l_{s,t}|\hat{\Theta}, \Omega_t\}}. \tag{4}$$

4 Monte Carlo Simulation

We follow the approach used by Mahendrarajah Nimalendran 1994 to carry out our Monte Carlo simulation for estimating and analyzing the finite sample properties of the estimators.

1. Set the values for the parameters $\eta \in \{p_V^u, p_V^d, p_D^u, p_D^d, \theta, \epsilon_O, \epsilon_S, \mu_O, \nu_O, \nu_S, \lambda_O, \lambda_S\}$ using independent Uniform distribution and with minimum and maximum supports that are chosen to be close to $25^{th.}$ and $75^{th.}$ percentiles of the the estimated parameters for our sample of 200 firms.

2. Determine the terminal node for a state based on simulated probabilities.

3. Simulate Poisson arrival rates to generate the number of trades for buy call (BC), sell call (SC), buy put (BP), sell put (SP), buy stock (BS), and sell stock (SS), for a certain fixed time period.

4. Simulate, $T = 250$, observations per simulated firm ($i = 200$). This gives a sample including $T \times i$ observation of orders, $\Omega \in \{CB, CS, PB, PS, BS, SS\}$.

5. Use non-linear optimization methods to estimate the parameters by maximizing the log-likelihood function, and then record the estimated parameters as,

   $\hat{\eta} \in (\hat{p_V^u}, \hat{p_V^d}, \hat{p_D^u}, \hat{p_D^d}, \hat{\theta}, \hat{\epsilon_O}, \hat{\epsilon_S}, \hat{\mu_O}, \hat{\nu_O}, \hat{\nu_S}, \hat{\lambda_O}, \hat{\lambda_S})$.

6. Repeat steps 2 through 5 for 200 firm replications and for simulated 12 months, and record the estimated set of parameters as $\hat{\eta}_i$, where $i = 1 : 200 \times 12$.

7. The mean estimate, $\bar{\eta}_i = \frac{1}{N_C}\sum_{i=1}^{N_C}\hat{\eta}_i$, and the standard errors of the means $\sigma(\bar{\eta}) = \frac{1}{\sqrt{N_C}}\frac{1}{(N_C-1)}\sum_{i=1}^{N_C}(\hat{\eta}_i - \bar{\eta})^2]^{1/2}$, where N_C is the number of replications that converged to a feasible value.

The results of our simulations are presented in tables 1 and 2, which give the simulated mean and the estimated mean in addition to standard error of the mean and the percentiles for the model parameters. We find that the number of convergence were close to 100%. The estimators have good finite sample properties: the bias for all the estimators are small, and the standard error of the estimates are also small. We also find that the estimates for the option parameters are much more precise and have much less bias than the estimates for the stock parameters. The options model has more degrees of freedom (six covariances and four variances) to identify the nine parameters compared to the stock market, which has only three pieces of information (two variances and one covariance) to estimate six parameters. In our model some of the parameters are the same for the stock and the option markets, probability of liquidity trading (θ), and two directional information probabilities, p_D^u and p_D^d . The efficiency of the estimators improves when more observations enter the simulated sample (not reported). The estimated probabilities for the stock market indicates some bias, while there is no bias for the option market OSPIN measures. This is consistent with the precision and bias of the estimates for the stock and option markets. Overall, the simulations show that the procedure is quite efficient and provide unbiased estimates for the parameters for our Option-Stock PIN ($OSPIN$) model using 250 observations for each of the 200 simulated stocks.

5 Data and Summary Statistics

5.1 Data

The option transaction level data was obtained from $OPRA$ Option Database. This data was provided by the Option Data warehouse, Baruch College, CUNY.[9] The stock transaction level data was extracted from the Trade and Quote (TAQ) database. Other option data such as option Greeks, implied volatility, and realized volatility were obtained from daily $OptionMetrics$ database. Finally, the daily stock data such as end of day price, ask price, bid price, shares outstanding, are obtained from Center for Research in Security Prices ($CRSP$).

[9] Option Price Reporting Authority ($OPRA$) was established as a securities information processor for market information, for collecting, consolidating, and disseminating the option market data from its participants including $AMEX, ARCA, BATS, BX, BSE, C2, CBOE, ISE, MIAX, NASDAQ, andPHLX$. The $OPRA$ Option database contains all the transaction level data (Trades and Quotes) for stock options which are traded in the participants' exchange.

5.2 OSPIN Model Estimation Details

The sample for estimation is created using the following procedure:

1. Compile a list of all the stocks in TAQ and merge this list with $OPRA$ database.

2. Sort the merged list by the option volume in 2010 obtained from $OptionMetrics$, and keep the top 200 stocks (we do not include ETFs). We do this to ensure sufficient option transactions to estimate our $OSPIN$ model.

3. For this study, we consider options in three moneyness groups and two maturity groups.

$$\begin{aligned}
ATM &: Call \in \{0.9 \leq S/X \leq 1.10\}, Put \in \{0.9 \leq X/S \leq 1.10\} \\
OTM &: Call \in \{0.7 < S/X < 0.90\}, Put \in \{0.7 < S/X < 0.90\} \\
ITM &: Call \in \{1.10 < S/X < 1.30\}, Put \in \{1.10 < X/S < 1.30\} \\
STO &: Maturity \leq 30 Days \\
LTO &: 30 Days < Maturity \leq 180\, Days
\end{aligned} \tag{5}$$

The $OPRA$ data has trade and quote data for the options markets time stamped to the nearest second. The option transaction data provided by Option Data Warehouse also includes a buy/sell indicator for the option trades based on the Lee and Ready 1991 (LR) algorithm to sign trades. For the stocks, we merge $NBBO$ and trade data and use the LR algorithm to sign the trades. Finally, we use signed trades aggregated at 30-minute intervals $\Omega = (BC, SC, BP, SP, BS, SS)$ to estimate our model.

The time period of our sample (2011 calendar year) is split into one month estimation periods. For each day we have thirteen 30-minute observations and over one month approximately 273 observations. These 273 observations are used to estimate the parameters using the MLE method. These parameters are then used to compute monthly measures of probabilities of various informed, liquidity, and noise trading.

5.3 Summary statistics

5.3.1 Stock descriptive statistics

Table 3 presents the descriptive statistics for the 200 stocks in our sample. The stocks were selected based on the highest number of trades during the month of December 2010 from the TAQ database. The summary statistics reported are based on the data for 2011. The average market capitalization for the stock is \$45 billion and the interquartile range is from \$13 to \$169 billion. The average price is \$66 and the range is \$31 to \$72. As expected, the number of trade per month is very high with a mean of 1.06 million and a range of 0.47 to 1.35 million. The microstructure properties are consistent with large highly liquid stocks.

The mean quoted, realized, and effective spreads were 4.1 bp, 3.2 bp, and 3.2 bp respectively. The adverse selection (AS) component of the spread based on George, Kaul, and Nimalendran[1994][GKN] model was 1.2 bp. At the 25^{th} percentile, the AS component is 12% of the quoted spread and this increases to 30% of the quoted spread at the 75^{th} percentile. This is in line with smaller market cap stocks having higher spreads and larger fraction of the spread due to AS. Finally, the price impact measure, λ, had a mean estimate of 19.77×10^{-6} and an interquartile range of $.64 \times 10^{-6}$ to 2.01×10^{-6}. Even though the interquartile range is small, the large mean indicates a very skewed distribution for this variable. This is consistent with prior studies that have estimated the price impact measures based on transactions data.

5.3.2 Options Descriptive Statistics

The descriptive statistics for the options on the 200 stocks based on $OPRA$ transactions data is reported in table 4 for option related variables in our sample by moneyness and maturity. The average quoted bid-ask spread for $ITM/ATM/OTM$ options are 2.69%/5.39%/10.43%, while the effective spreads are 1.94%/4.62%/9.10% respectively. The spreads for the options are nearly 100 times larger than the underlying stock spread (quoted average of 0.041%-3). The quoted and effective spreads are also much higher for short term options relative to long term options. In Table 5 we provide quoted and effective spread statistics by market value quintile. The quoted and effective spreads are declining monotonically for all moneyness groups with increase in market value, except for quintile 5 which has a slightly higher spreads for ATM and OTM options.

In table 6 Panel A we report the statistics for number of trades during the half-hour trading intervals from 9:30AM to 4PM, for the 200 firms in our sample in 2011. The number of trades for the average stock is about 30 times larger than for options. What is more interesting is the correlation matrix given in Panel B. Our model and the estimation is based on the structural model and the information in the covariance (correlation) matrix. The correlation between BS and SS is 0.87, in addition the correlations between BC, SC and BP, SP are 0.62 and 0.56. The PIN model proposed by Easley, Kiefer, and O'Hara 1996, assume only two types of traders: informed and uninformed, and the model implied correlation between BS, SS is negative. However, in the data the correlation between buys and sells is positive and quite high. To account for this positive correlation, Duarte and Young 2009, assume an additional source of liquidity trades where the buys and sells are correlated. In our model we incorporate this additional correlated liquidity trading in the options and the stock markets. This provides additional flexibility to match the moments. In table **??** we provide the statistics and correlations by moneyness. We find that trading is concentrated in ATM options, and the correlations are much higher for the ATM options relative to OTM and ITM options. For example ATM_BC and ATM_SC have a correlation of 0.61 and only 0.36 for both ITM and OTM options. Table 7 Panel B provides the correlations for the short and long term maturity options. The correlations are not much different across these maturities.

5.4 OSPIN Model Estimates

5.4.1 All Options

In table 8, we provide summary statistics for our $OSPIN$ model parameters based on all the options and for the entire year by moneyness and maturity. The parameters are estimated over one-month horizons for each stock based on the trade count in each 30-minute interval. The estimates are then averaged across the 12-months for the 200 stocks. On average, the probability of informed directional trading based on "good" information is 0.07 (p_D^u)and based on "negative" information it is 0.06 (p_D^d). This is consistent with directional information being symmetric. The probability of trading on volatility information has much higher probability for high (or up) volatility of 0.15 (p_V^u) compared to 0.06 (p_V^d) for low (or down) volatility information trades. A possible reason is that selling a straddle/strangle is more difficult as selling options require more margin. Table 8 also gives the estimated average for the probability of correlated liquidity trading ($\theta = .21$), as well as Poisson rates for the different types of traders.

The arrival rates for the stock market can be compared from the "ALL" column (the other categories have slightly different estimates due to different availability of data for estimation, or the method did not provide feasible estimates). The estimate for noise traders ($\epsilon_S = 1134$) is smaller than the liquidity rate ($\lambda_S = 1748$) or the informed rate ($\nu_S = 1597$), however, the probability of noise trading ($p_N = .66$) is much higher compared to informed trading ($p_D^{u+d} = 0.13$) and liquidity trading ($\theta = .21$).

The options market provides very interesting results in terms of the different types of traders in the various moneyeness and maturity groups. The rate of noise traders is very low for OTM ($\epsilon_O^{OTM} = 2.27$) and for ITM ($\epsilon_O^{ITM} = 1.01$) compared to ATM ($\epsilon_O^{ATM} = 21.40$), while the probabilities of noise trading are not very different across the groups and is equal to 0.5. The liquidity trading rates are also highest for ATM($\lambda_O^{ATM} = 34.26$) compared to OTM ($\lambda_O^{OTM} = 7.57$) and ITM ($\lambda_O^{ITM} = 3.64$). Given that the expected noise and liquidity trading is very high for ATM options, we would expect the informed traders to also target ATM options. We find that this is indeed the case, with the rates of informed directional and volatility trading being very high for ATM options ($\nu_O^{ATM} = 64.50, \mu_O^{ATM} = 71.36$) relative to OTM ($\nu_O^{OTM} = 14.98, \mu_O^{OTM} = 18.62$) and ITM ($\nu_O^{ITM} = 5.87, \mu_O^{ITM} = 8.41$) options. Even though the informed trading rates are very high for ATM options, the noise and liquidity trading are also very high, therefore the probability of informed trading is low for ATM options. The correlations across the various variables (not reported) are consistent with our intuition, $OSPIN$ measures ($VolPIN$ and $DirPIN$ and $StkPIN$) are negatively correlated with stock and option volume, as well as stock market capitalization. They are positively correlated with stock and option bid-ask spreads. Also consistent with expectations, $OptDirPIN$ is more positively correlated with $StkPIN$ than $VolPIN$.

Table 10 presents selected summary statistics sorted by market capitalization quintile. The probability of directional and volatility informed trading decreases with market capitalization for options and stock markets, reflecting the greater transparency of larger companies. The $OSPIN$ measures of companies in the largest quintile are significantly different from the $OSPIN$ measures of companies in the smallest quintile by market capitalization (test statistics are not reported), and the smallest quintile informed trading probabilities are more than double that of the largest quintile.

6 Results and Analysis

6.1 Bid-Ask Spreads and OSPIN

6.1.1 Option Spread

6.1.2 Adverse Selection Cost

Adverse selection costs play an important role in determining stock spreads. On the options market, the extant evidence is mixed. If informed agents can trade strategically on the stock and the options markets to maximize their returns from private information, and if option market makers cannot instantaneously hedge the option exposure to adverse selection, then the option market makers will face the same information disadvantage as stock market makers do, and the option spread must compensate for this cost.[10]

Black 1975, argues that informed agents might prefer the options market for its high leverage. On the other hand, Easley, O'Hara, and Srinivas 1998, find that informed agents may trade in both the option and the stock markets simultaneously. This has implications for where price discovery occurs. The empirical evidence on this issue is mixed. For example, Vijh 1990, and Cho and Engle 1999, find that option market makers do not face significant adverse selection costs, while Easley, O'Hara, and Srinivas 1998, and Cao, Chen, and Griffin 2005, find evidence consistent with informed trading on the options market.

To proxy for adverse selection costs we will use $DirPIN$, $VolPIN$ and $StkPIN$. These are measures of information based trading in the options and stock markets.

6.1.3 Hedging Costs

Black and Scholes 1973 show that in a "perfect" market the payoff to an option can be replicated by continuously rebalancing a portfolio of stocks and bonds. If the conditions necessary for a perfect market hold, then option spreads should only compensate option market makers for order processing costs, and perhaps for informed volatility trading. However, when there are market frictions such as transaction costs, it is no longer possible to replicate the option payoff using a dynamic strategy involving continuous rebalancing. Therefore, option market makers must be compensated for the costs associated with rebalancing at discrete time intervals, as well as costs due to market frictions such as bid-ask spread on the underlying stock, price discreteness, information asymmetry, and model mis-identification.

The costs consist of the cost of setting up and liquidating the initial delta neutral position, and the cost to continuously re-balance the portfolio to maintain a delta neutral position. Several papers, including Leland 1985, Merton and Samuelson 1990, and Boyle and Vorst 1992, have theoretically examined the impact of stock bid-ask spreads on the hedging costs imposed on option dealers due to discrete rebalancing. They show that the option spread (the difference between the prices of long and short calls) due to the discrete rebalancing is positively related to the proportional spread on the underlying asset, inversely related to the revision interval, and positively related to the sensitivity of the option to changes in volatility (ν).

[10] The bid-ask spreads on stocks compensate market makers for order processing, inventory (Ho and Stoll 1981), and adverse selection costs (Bagehot 1971, Glosten and Milgrom 1985, Kyle 1985, Easley and O'hara 1987).

Initial Hedging Cost

An option market maker would set up a delta neutral position by purchasing Δ shares of the stock at the ask price and close the position by selling at the bid price. This would lead to a cost,

$$IC = \Delta(kS). \tag{6}$$

where, IC represents the initial hedging cost, k is the proportional stock spread, S is the stock price, and Δ is the option delta, and the relative initial hedging cost ($RelIC$) is defined as,

$$RelIC = \Delta k. \tag{7}$$

Re-balancing Cost

The initial hedging cost does not include the cost of rebalancing the portfolio to maintain a delta-neutral position. Following Leland 1985 and Boyle and Vorst 1992, we define the rebalancing cost as follows:

$$RC = \frac{2\nu k}{\sqrt{2\pi(\delta t)}}. \tag{8}$$

Where, ν is the option Vega, k is the proportional stock spread, and δt is the rebalancing interval. The relative rebalancing cost ($RelRC$) is defined as,

$$RelRC = \frac{2\nu k}{\sqrt{2\pi(\delta t)}}/S. \tag{9}$$

The rebalancing cost is proportional to the option ν and the spread on the underlying stock, and is inversely related to the rebalancing interval. Since ν is highest when the stock price is equal to the present value of the exercise price, ceteris paribus, we would expect at-the-money options to have the highest rebalancing costs. The expression for the rebalancing costs also has an intuitive explanation; The bid-ask spread on the stock gives rise to an extra volatility when the option is replicated. For example, if you replicate a long call option, then when the stock price increases, rebalancing would require you to purchase more stock. But, this has to be done at the ask price. Similarly, when the stock price falls, the stock has to be sold at the bid price to maintain a delta neutral position. This effectively increases the volatility of the asset, and this increase in volatility would be proportional to the bid-ask spread (Roll 1984).

In constructing the above measure of rebalancing cost we do not observe the rebalancing frequency. Therefore, we assume that this frequency is the same across all option contracts and drop the term $\sqrt{2\pi(\delta t)}$ in our construction of the rebalancing cost. Hence, we obtain the following expression for rebalancing costs and relative rebalancing costs:

$$RC = \nu k \tag{10}$$

and

$$RelRC = \nu k/S \tag{11}$$

<u>Order Processing Costs</u>

Since order-processing costs are likely to be fixed for any particular transaction, the order processing costs should decrease as the expected trading volume increases. Copeland and Galai 1983 suggest a negative relation between bid-ask spreads and trading volume in the long run, and Easley and OHara 1992 provide a model that implies spreads decrease with an increase in expected trading volume. We use trading volume of the option contract (number of contracts traded), denoted as $OptVol$, to proxy for order processing costs. Since we control for adverse selection, we expect the trading volume to be negatively related to spreads.

6.2 A Model of Option and Stock Bid-Ask Spread

We propose the following empirical model for the determinants of option and stock bid-ask spreads to study how our OSPIN measures are related to bid-ask spreads quoted by market makers in the stock and options markets.[11]

$$\begin{aligned}
Opt_Spread &= \beta_0 + \beta_1(StkPIN) + \beta_2(StkLIQ) + \beta_3(OptDirPIN) + \beta_4(OptVolPIN) \\
&\quad + \beta_5(OptLiq) + \beta_6(StkSprd) + \beta_7(DELTA_{option}) + \beta_8(VEGA_{Option}) \\
&\quad + \Gamma(Controls) + \epsilon \\
Stk_Spread &= \beta_0 + \beta_1(StkPIN) + \beta_2(StkLIQ) + \beta_3(OptDirPIN) + \beta_4(OptVolPIN) \\
&\quad + \beta_5(OptLiq) + \beta_6(OptSprd) + \Gamma(Controls) + \epsilon
\end{aligned} \tag{12}$$

[11] We do not include the inventory costs as a determinant for two reasons. First, the literature on stock spreads suggests that its magnitude is trivial (Stoll 1989 and Madhavan and Smidt 1991). Second, option market makers rarely take directional risks. Even if they carry inventory, it is likely to be hedged.

Equation 12 describes the model used to study how the OSPIN measures are related to the option and stock bid/ask spreads. There is a vast body of literature that have linked the bid/ask spread on stocks and options to adverse selections costs of trading against informed agents. When market makers post quotes, they provide an option for informed trader to "hit" the ask price when they trade on information that the price of the asset is higher than the ask and "hit" the bid price when it is below the bid. Market makers will optimally adjust the spread to recoup the losses to the informed from uninformed and liquidity traders.

6.2.1 Stock Quoted Spread

Table 11 shows the estimates for the stock quoted spread on $OSPIN$ measures using firm and month fixed effects and firm and month clustered standard errors. In addition all the models include control variable that are not reported: log of option and stock traded volume each month; standard deviation of mid quote stock returns for each month, and 1/price. We find that the only OSPIN measure that is significant is the $StkDirPin$. The option market $OSPIN$ measure are not related to the stock market spread. The option quoted spread has weak positive effect.

6.2.2 Option Quoted and Effective Spreads

Table 12 provides multivariate regression model estimates for proportional option quoted spread (OQS) and control variables described above. In addition, the OQS models include stock proportional quoted spread, and the option Δ and ν. We find that for OTM options, the only $OSPIN$ measure that is significant and positive is the $OptVolPIN$ with an estimate of 0.0107 (se=0.0013). While the $OptDirPIN$ measure has significant positive effect for ATM option spreads with a coefficient of 0.0149 (se=0.0035). For ITM options, none of the $OSPIN$ measures are significant. We also find that the stock spread has significant and positive coefficient for OTM and ATM options quotes. Part of this can be attributed to the hedging costs as described in section 6.1.3 and the rest could be the indirect $StkDirPIN$ adverse selection cost. In table **??** we report the model estimates for proportional effective spread on options (OES). The results are similar to the option-quoted-spread results.

6.2.3 Stock Market Microstructure Measures

There is rich literature on the market microstructure of the stock market. The popular measures that are used to proxy for the adverse selection (information) cost in the stock market are: quoted spread, effective spread, AI_spread, and price impact

(λ.) In this section we use the equation **??** with stock microstructure variables as the dependent variable to study the relation between $OSPIN$ measures and adverse selection cost proxies in the stock market. The regression model results are reported in table 14. The estimates are significant only for the $StkDir$ PIN estimates, indicating that informed trading in options is not directly transmitted to the stock market spreads. The results suggests that informed trading in options markets do not directly affect the stock market microstructure measures. There is only a weak link through the option spread.

6.3 Relation between OSPIN Measures and Information Measures Based on Daily Data from OptionMetrics

The OptionMetrics provides daily data on all the options traded on the CBOE from 1996 to now. The data that is provided include end of day quotes, daily trading volume, open interest, implied volatility estimates, and option characteristics for each option contract.[12] Several studies have used $OptionMetrics$ data to estimate measures for informed trading (Kacperczyk, Emiliano, and Pagnotta, 2015)This data is readily available and easy to use compared to the transactions level data for options. In this study we look at how these measures are related to our $OSPIN$ measures.

6.4 Leverage Ratios: PCR

Pan and Poteshman (2006) define the put-call ratio as the number of put contracts divided by the sum of both put and call contracts.

$$PCR = \frac{NumberofPutContracts}{NumberofCallContracts + NumberofPutContracts} \tag{13}$$

The PCR can be calculated for each moneyness and maturity groups or for all the contracts.

In table 16 we report the regression results for the PCR measure on OSPIN measures and control variables. Since PCR is a ratio of put option trading relative to put plus call option trading, the intuition is that it measures negative information. Hence, in the regression model, we use $OSPIN$ measures that indicate whether informed trading is based on $bullish(H)$ or $bearish(L)$ information. We find that

[12] We obtain option price, option volume, and implied volatility information from the $OpprcdYEAR$ file of $OptionMetrics$, and stock closing quotes/prices and volume information from the $SecprcdYEAR$ file of $OptionMetrics$.

for $StkDir_H$ the PCR is significant and negative for ALL and for $LE30$ groups. The negative signs are consistent with less informed bullish trading. Also, for the $StkDir_L$ measure, the ATM_{PCR} is positive and significant. For the option market, the $OPTDir_L$ is significant and positive for ATM_{PCR} and ITM_{PCR}. The volatility measures are all positive and significant for all the PCR groups, except for the OTM_{PCR}.Overall the PCR measures, except for the PCR_{OTM} measure are related to bearish informed trading. But, they are also related to volatility and liquidity trading. The rlation to volatility trading is not surprising, give that negative stock returns are associated with increased volatility.

6.4.1 Option/Stock Volume Ratios- OSR

Roll, Schwartz, and Subrahmanyam (2010) conjecture that private information may increase the value of option volume relative to the volume in the underlying stock as options will provide more leverage or bang-for-the-buck. Also, when there are short selling constraints, options may provide a way to trade on negative information. Thus, episodes of information-motivated trades can display higher values of their option/stock volume (O/S) measure. Johnson and So (2012) compute the ratio of total option to stock trading volume as a measure of informed trading. The authors argue that a high option to stock volume ratio is especially informative around negative news, as informed investors have a greater incentive to express their view through trading put options in the presence of costly short-sale constraints. We consider following measures based on option to stock volume ratios.

$$\begin{aligned}
OSR_{O/S} &= \frac{All\,Option\,Volume}{Stock\,Volume} \\
OSR_{C/S} &= \frac{Call\,Option\,Volume}{Stock\,Volume} \\
OSR_{C/S} &= \frac{Put\,Option\,Volume}{Stock\,Volume}
\end{aligned} \tag{14}$$

Option volume includes the total volume in call and put options of all strikes and all maturities from OptionMetrics. We also consider a variation that is based on levered option volume.

Table reftable:lnosrreg shows the estimates based $LN(OSR)$ on $OSPIN$ estimates and controls. Interestingly, the $StkPin$ is significant for the *call* volume and for the ALL volume samples. Also, the $OptDirPin$ is significant for all three samples. The other $OSPIN$ measures are not significant. The significant directional pin measures for the option and stock markets suggest the this daily measure of $LN(OSR)$ would be "good" proxy for informed directional trading.

6.4.2 Levered Volume Ratio- LVR

Levered Volume Ratio is based on Black's (1975) insight that informed traders value leverage, and will trade OTM/ATM options for their leverage. We compute the ratio of volume in OTM and ATM options to ITM volume for all options on the same underlying stock.

$$LVR_{(OTM+ATM)} = \frac{(OptionVolume)_{(OTM+ATM)}}{(Option\ Volume)_{ITM}} \tag{15}$$

Table 18 gives the estimates for the $LVRvariableson$OSPIN$estimates.Theonlysignificantvariables$

6.4.3 Cross Market Price Impact (λ)

Easley et al. (1998) find that option volume has an informational role and can move stock prices. To capture this effect, they extend the the Kyle[1985] lambda used in estimating stock liquidity to the option and stock cross market liquidity. In particular, they propose a daily illiquidity measure that is analogous to the Amihud[2002] measure with the numerator being the absolute daily stock return and the denominator being the total option trading volume. which is defined as,

$$\lambda_{S|O,t} = \frac{\mid (StockReturn)_t \mid}{(OptionVolume)_t}. \tag{16}$$

A second measure, analogously, captures the interaction between stock volume and option returns. In particular, the daily illiquidity, $\lambda_{O|S}$, is the option return computed as the proportional daily change in the implied volatility of a particular contract divided by the stock volume. This is a reasonable approximation to option returns over a short period of one trading day. We summarize these measures for 6 different classes of options.

$$\lambda_{O|S,t} = \frac{\mid (OptionVolatilityReturn)_t \mid}{(StockVolume)_t}. \tag{17}$$

Table reftable:cmpireg describes the estimates for cross market price impact variable, $\lambda_{S|O}$, on OSPIN measures and control. The $OptDirPin$ is positive and significant for all the moneyeness groups and also for the two maturity groups. Also, If the measure is used as proxy for directional informed trading, then a researcher could use the OTM options that have short maturity. Table 20 gives the estimates for the $\lambda_{O|S}$ variable. We find that the cross-market $O \mid S$ variable is positively relate to OTM, and ATM $OptDir$ measures, and the liquidity measures. There is only a weak relation to the $OptVol$ measure.

6.5 Likelihood of Informed Trading Around Earnings Announcements

6.5.1 OSPIN Measures

Earnings announcement are information sensitive events and several studies have examined the changes in information measures on the stock market around earnings announcements (Maddala and Nimalendran 1995). Other studies have examined options trading around important events such as takeovers and find significant trading on options that are related to information about the outcomes (Cao, Chen, and Griffin 2005). NPP examine the changes in their volatility information measure around earnings announcements. In particular, they construct a measure of volatility price impact by creating securities from options that are sensitive to volatility but insensitive to directional information by using a straddle. Since a straddle will increase (decrease) in value when volatility increases (decreases) but is insensitive to small directional changes. NPP use the average of the call and put implied volatilises as the price of volatility, and examine the the volatility price impact with respect to non-market maker volume around earnings announcements. They find an increase in price impact prior to earnings announcement dates suggesting that market makers are reacting to informed traders. The NPP measure of volatility informed trading depends on using the Black-Scholes model to estimate the implied volatilities. In this section we examine the effect of earnings announcement on our $OSPIN$ measures. We estimate our $OSPIN$ measures for two (two-week) intervals before the announcement and for one (two-week) interval after the announcement. The two-weeks immediately preceding and the two-week interval following the earning announcement date are denoted as "pre-earnings" and "post-earnings". We then analyze the effects of earnings announcement by regressing $VolPIN$, $DirPIN$ and the relative bid-ask spread for options on dummy variables for each of the pre-earnings and post-earnings in addition to other control variables.

We find that our estimated PIN measures are consistent with higher levels of informed trading before an earnings announcement. Both $VolPIN$ and $DirPIN$ measures are significantly higher before the earnings announcements. The $VolPIN$ is higher by 4.2% and the $DirPIN$ is also higher by 4.45% compared to post-earnings period estimates. Similarly in the stock market, the $StockPIN$ is higher by 3.3%. We also find that the relative effective bid-ask spreads in option markets does not change significantly around the earning announcement. Finally, we also document a 2.1% decrease in *Implied Volatility* after the announcement and a very significant 13% increase in option volume after the announcement. The increase in option market volume is similar to what previous studies have documented for the stock market (Maddala and Nimalendran 1995).

These results suggest that, the probability of informed trading on volatility and directional information is higher prior to the announcement, and the higher volume of trading and lower volatility after the announcement is consistent with uninformed traders concentrating their trading after the announcement to avoid the information uncertainty about the earning.

6.5.2 High Frequency Posterior Likelihood of Informed Trading Around Earnings Announcements

The analysis of informed trading around earnings announcements based on OSPIN measures require a long window to estimate the parameters. However, informed traders' information around events are likely to be short-lived. Also, when trading options, time decay is an important factor, and this suggests that informed trading is likely to be concentrated close to the event. In section 3.5, we describe a model/methodology to estimate a high frequency measure of the posterior likelihood of informed trading based on the OSPIN model estimates as priors. This provides a way to examine informed trading close to earnings or other events. We first estimate the OSPIN parameters using data from 4-weeks before an earnings announcements to 2-week before an announcement. The estimates together with trade data during each day around earnings announcement is used to estimate the daily posterior likelihood of informed trading around earnings announcements. The figures 1-8 provide abnormal CAR and abnormal informed trading for different moneyness groups and for a placebo (non earnings announcement group). The charts give the cross sectional average relative to announcement date (day zero), and the +/- 2 Standard deviations around the the average estimates for the different posterior likelihoods.

Figure 1 provides the cumulative abnormal returns (CAR) around earnings announcements. For our sample,on average, the CAR is not different from zero. We then partition our sample based on whether AR(0) is in the top $75^{th.}$ percentile or the bottom $25^{th.}$ percentile. If there are traders with superior information about the forthcoming earnings, then they are likely to be in the top or bottom earnings AR(0) sample. Panels B and C of figure 1, give the *CARs* for these top and bottom groups. These two groups show clear drifts in the direction of the abnormal earnings, suggesting leakage of information before the announcement. One possible channel is trading in the options and or the stock market by informed traders.

Figure 2 panels (a) and (b) show the abnormal likelihood of informed trading in the stock market relative to day minus ten. We see that there is significant likelihood one day before and the day of the announcement. On day -1, there is .0134 (s.e of mean of 0.002) higher probability of informed bullish trading in stocks. On the other hand, the bullish likelihood of informed trading when $AR(0) < 25^{th.}$ percentile is 0.00097 (s.e of 0.0018) which not statistically different from zero at the 5% significance. Interestingly on day zero the probabilities of bullish trading is abnormally high for both top and bottom percentile of AR(0).The likelihood remains higher than normal for at least ten days after the announcement. Panel (b) shows bearish informed trading likelihood for the top and bottom quartiles of AR(0). We see significant abnormal trading from day -1 to +1 day around the after the announcement.

Figure 3 shows the abnormal likelihood for ATM options. Panel A give the abnormal likelihood of direction informed trading in options, and we see that the likelihood is significantly elevated two days before the announcement. More importantly, two days before, one day before, and the day of the announcement, the abnormal likelihood of high OptDir trading is .013, .039, and .039 respectively. The abnormal likelihood of .039 on day -1 is a 87% increase from the overall sample average of 045 (table 8, $OptDir_H$). We also see a significant abnormal likelihood of high OptDir trading when AR(0) is in the bottom quartile, though, the abnormal likelihood is 0.03 on day -1. We see similar patters of likelihoods for low OptDir trading (bearish information). The elevated likelihoods for the bottom quartile for $OptDir_H$ and the top quartile for $OPTDir_L$ is puzzling. A possible explanation may lie in the type of strategies that are used by traders that a re not captured by the model. For example, an informed trader may use a bull spread when trading on positive information. this require buying a call option of a particular strike price, and selling a call option with a higher strike price. But, this cannot explain why we see the same pattern in stock trading. The other possible explanation is that the private information is inherently very noisy and we see informed trading in both directions around earnings announcements.

Figure 3, panel (c) and (d) shows the volatility trading based on $\mid AR(0) \mid$ being in the top $75^{th.}$ percentile or the bottom $25^{th.}$ percentile. We see that there much higher abnormal likelihood of volatility trading when the volatility is expected to be higher compared to expectation of lower volatility.

Figure 3 panel(e) shows liquidity trading for the high AR(0) and low AR(0) groups. There is a very significant spike in liquidity trading 3 to 4 days before earnings and lasts up to to 3 days after the earnings. The liquidity trading pattern is consistent with differences in opinions about the earnings outcome.

Figures 4 describe the likelihood for OTM options. The patterns are show similar to to ATM option, though the abnormal likelihoods are much higher. For example, the $OPtDir_H$ has an abnormal likelihood of 0.075 compared to 0.039 one day before announcement. Panels (c) and (d) give the abnormal volatility trading, and these are also much higher than the ATM options for $OptVol_H$. Interestingly, the $OptVol_L$ is much lower at .04, one day before announcement. This is consistent with traders buying volatility and are less likely to sell volatility.

Figure 5 describes the patter of trading for ITM options. We would expect the patterns to be closer to the stock market trading. We see the the only significant abnormal direction, volatility , and liquidity trading is on the day of the announcement. We do not see any informed abnormal likelihood of trading before or after the announcement.

Finally, we also carry the same exercise for a placebo group around +25 days after an earnings announcement. Figures 7 and 8 show that abnormal likelihood of stock and option trading around the placebo date is not statistically different from zero.

The exercise around earnings announcements strongly indicate that the OSPIN model can be used to estimate high frequency measures of informed trading. However, the model does not discriminate well between high and low information events around earnings announcements. Further, the option markets indicate informed trading leading the stock markets a few days before the announcements. We believe that the model can be used at even higher frequencies to predict potential informed trading in the stock and options markets.

7 Conclusion

We propose a joint structural model to estimate separate measures for the probability of informed trading based on directional and volatility information in options and stock markets.The measures of informed trading are based on the signed trades and do not depend on the option prices. This has an advantage over using prices, as the option prices have to be adjusted for changes in the underlying Greeks of the options to obtain measures such as the price impact. Also, the implied volatility requires a model for option prices. Our objective is to use the $OSPIN$ measures to study the strategies of informed traders and how this leads to price discovery and liquidity in the option and stock markets. In particular, we examine the role of moneyness and maturity in informed directional and volatility trading. The model allows correlated directional informed trading in both markets, informed volatility trading in the options market, and correlated (buy/sell) liquidity trades in both markets. The model parameters and the probabilities of informed and liquidity trading in both markets are estimated using signed high-frequency stock and options trade data.

The study finds that moneyness and maturity play an important role in informed trading, and on the microstructure and price discovery in the stock and options markets. The findings are consistent with the trade off between leverage and liquidity, and the strategic behavior of market makers and traders. The arrival rates of informed directional, volatility, and liquidity traders are highest for the most liquid at-the-money short-term options, but these also have low probabilities of informed direction and volatility trading. Further, $OptPIN$ measures are related to both options and stock market microstructure (spread, AS-Spread, and price impact).While $StkPIN$ is related to only the stock market microstructure measures. Volatility informed trading is more likely in OTM options, and informed directional trading is concentrated in ATM options. In addition, several informed trading measures based on daily data (put-to-call volume, leverage ratio, cross market price impact) are correlated with both informed directional and volatility trading, and researchers must take this into account when using these measures. The $OSPIN$ estimates allow the estimation of high frequency conditional posterior probabilities of informed trading ($PPIT$) around earnings announcements. The high-frequency $PPIT$ measures in the options market spike several days before earnings announcements, and remain high for a few days after the announcement. In summary, options markets are very important in price discovery and provide more informative measures of informed trading relative to stock market measures alone.

We believe that analyzing the effect of informed trading on option markets will play a significant role as more information about both the future direction and volatility of stocks is revealed through trading on options, and we believe that the $VolPIN$ and $DirPIN$ measures, as proposed in this study, will help with this analysis.

References

[1] Walter Bagehot. "The only game in town". In: *Financial Analysts Journal* 27.2 (1971), pp. 12–14.

[2] Fischer Black. "Fact and fantasy in the use of options". In: *Financial Analysts Journal* (1975), pp. 36–72.

[3] Fischer Black and Myron Scholes. "The pricing of options and corporate liabilities". In: *The journal of political economy* (1973), pp. 637–654.

[4] Phelim P Boyle and Ton Vorst. "Option replication in discrete time with transaction costs". In: *The Journal of Finance* 47.1 (1992), pp. 271–293.

[5] M.J. Brennan, S. Huh, and A. Subrahmanyam. "High-Frequency Measures of Informed Trading and Corporate Announcements". In: *The Review of Financial Studies* 31.6 (June 2018), pp. 2326–2376.

[6] Charles Cao, Zhiwu Chen, and John M. Griffin. "Informational Content of Option Volume Prior to Takeovers". In: *The Journal of Business* 78.3 (May 2005), pp. 1073–1109. URL: http://ideas.repec.org/a/ucp/jnlbus/v78y2005i3p1073-1072.html.

[7] Sugato Chakravarty, Huseyin Gulen, and Stewart Mayhew. "Informed trading in stock and option markets". In: *The Journal of Finance* 59.3 (2004), pp. 1235–1258.

[8] Young-Hye Cho and Robert F Engle. *Modeling the impacts of market activity on bid-ask spreads in the option market*. Tech. rep. National Bureau of Economic Research, 1999.

[9] Thomas E Copeland and Dan Galai. "Information effects on the bid-ask spread". In: *the Journal of Finance* 38.5 (1983), pp. 1457–1469.

[10] Jefferson Duarte and Lance Young. "Why is {PIN} priced?" In: *Journal of Financial Economics* 91.2 (2009), pp. 119–138. ISSN: 0304-405X. DOI: https://doi.org/10.1016/j.jfineco.2007.10.008. URL: http://www.sciencedirect.com/science/article/pii/S0304405X08001827.

[11] David Easley, Soeren Hvidkjaer, and Maureen O'Hara. "Is Information Risk a Determinant of Asset Returns?" English. In: *The Journal of Finance* 57.5 (2002), pp. 2185–2221. ISSN: 00221082. URL: http://www.jstor.org/stable/3094509.

[12] David Easley, Nicholas M. Kiefer, and Maureen O'Hara. "Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow". English. In: *The Journal of Finance* 51.3 (1996), pp. 811–833. ISSN: 00221082. URL: http://www.jstor.org/stable/2329223.

[13] David Easley, Nicholas M. Kiefer, Maureen O'Hara, and Joseph B. Paperman. "Liquidity, Information, and Infrequently Traded Stocks". English. In: *The Journal of Finance* 51.4 (1996), pp. 1405–1436. ISSN: 00221082. URL: http://www.jstor.org/stable/2329399.

[14] David Easley and Maureen O'hara. "Price, trade size, and information in securities markets". In: *Journal of Financial economics* 19.1 (1987), pp. 69–90.

[15] David Easley, Maureen O'Hara, and Pulle Subrahmanya Srinivas. "Option volume and stock prices: Evidence on where informed traders trade". In: *The Journal of Finance* 53.2 (1998), pp. 431–465.

[16] David Easley and Maureen OHara. "Adverse selection and large trade volume: The implications for market efficiency". In: *Journal of Financial and Quantitative Analysis* 27.2 (1992), pp. 185–208.

[17] Lawrence R. Glosten and Paul R. Milgrom. "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders". In: *Journal of Financial Economics* 14.1 (Mar. 1985), pp. 71–100. URL: http://ideas.repec.org/a/eee/jfinec/v14y1985i1p71-100.html.

[18] Thomas Ho and Hans R Stoll. "Optimal dealer pricing under transactions and return uncertainty". In: *Journal of Financial economics* 9.1 (1981), pp. 47–73.

[19] Sahn-Wook Huh, Hao Lin, and Antonio Mello. "Hedging by Options Market Makers: Theory and Evidence". In: *Available at SSRN 2123965* (2012).

[20] Travis Johnson and Eric So. "A Simple Multimarket Measure of PIN". In: *Available at SSRN 2181038* (2013).

[21] Marcin T. Kacperczyk and Emiliano Pagnotta. "Chasing Private Information". In: *The Review of Financial Studies* (2018).

[22] Gautam Kaul, Mahendrarajah Nimalendran, and Donghang Zhang. "Informed trading and option spreads". In: *Available at SSRN 547462* (2004).

[23] Albert S Kyle. "Continuous Auctions and Insider Trading". In: *Econometrica* 53.6 (Nov. 1985), pp. 1315–35. URL: http://ideas.repec.org/a/ecm/emetrp/v53y1985i6p1315-35.html.

[24] Charles M. C. Lee and Mark J. Ready. "Inferring Trade Direction from Intraday Data". English. In: *The Journal of Finance* 46.2 (1991), pp. 733–746. ISSN: 00221082. URL: `http://www.jstor.org/stable/2328845`.

[25] Hayne E Leland. "Option pricing and replication with transactions costs". In: *The journal of finance* 40.5 (1985), pp. 1283–1301.

[26] GS Maddala and M Nimalendran. "An unobserved component panel data model to study the effect of earnings surprises on stock prices, trading volumes, and spreads". In: *Journal of Econometrics* 68.1 (1995), pp. 229–242.

[27] Ananth Madhavan and Seymour Smidt. "A Bayesian model of intraday specialist pricing". In: *Journal of Financial Economics* 30.1 (1991), pp. 99–134.

[28] Robert C Merton and Paul Anthony Samuelson. "Continuous-time finance". In: (1990).

[29] Sophie X Ni, Jun Pan, and Allen M Poteshman. "Volatility information trading in the option market". In: *The Journal of Finance* 63.3 (2008), pp. 1059–1091.

[30] Mahendrarajah Nimalendran. "Estimating the effects of information surprises and trading on stock returns using a mixed jump-diffusion model". In: *Review of Financial Studies* 7.3 (1994), pp. 451–473.

[31] Richard Roll. "A simple implicit measure of the effective bid-ask spread in an efficient market". In: *Journal of Financial Economics* 39.4 (Sept. 1984).

[32] Yusif E Simaan and Liuren Wu. "Price discovery in the US stock options market". In: *The Journal of Derivatives* 15.2 (2007), pp. 20–38.

[33] Hans R Stoll. "Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests". In: *The Journal of Finance* 44.1 (1989), pp. 115–134.

[34] Anand M Vijh. "Liquidity of the CBOE equity options". In: *The Journal of Finance* 45.4 (1990), pp. 1157–1179.

Appendices

Appendix A1: Likelihood Function - Probabilities and Arrival Rates

Likelihood Function - Probabilities and Arrival Rates

			Vol Up	Vol Down	Vol None
	Pr	Liq. Pr	p_V^u	p_V^d	$1 - p_V^u - p_V^d$
Dir Up	p_D^u	θ	$\gamma_{BC} = \epsilon_o + \lambda_o + \nu_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \lambda_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \lambda_o + \mu_o$
			$\gamma_{SC} = \epsilon_o + \lambda_o$	$\gamma_{SC} = \epsilon_o + \lambda_o + \nu_o$	$\gamma_{SC} = \epsilon_o + \lambda_o$
			$\gamma_{BP} = \epsilon_o + \lambda_o + \nu_o + \mu_o$	$\gamma_{BP} = \epsilon_o + \lambda_o$	$\gamma_{BP} = \epsilon_o + \lambda_o$
			$\gamma_{SP} = \epsilon_o + \lambda_o$	$\gamma_{SP} = \epsilon_o + \lambda_o + \nu_o$	$\gamma_{SP} = \epsilon_o + \lambda_o$
			$\gamma_{BS} = \epsilon_s + \lambda_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \lambda_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \lambda_s + \mu_s$
			$\gamma_{SS} = \epsilon_s + \lambda_s$	$\gamma_{SS} = \epsilon_s + \lambda_s$	$\gamma_{SS} = \epsilon_s + \lambda_s$
	p_D^u	$(1-\theta)$	$\gamma_{BC} = \epsilon_o + \nu_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \mu_o$
			$\gamma_{SC} = \epsilon_o$	$\gamma_{SC} = \epsilon_o + \nu_o$	$\gamma_{SC} = \epsilon_o$
			$\gamma_{BP} = \epsilon_o + \nu_o + \mu_o$	$\gamma_{BP} = \epsilon_o$	$\gamma_{BP} = \epsilon_o$
			$\gamma_{SP} = \epsilon_o$	$\gamma_{SP} = \epsilon_o + \nu_o$	$\gamma_{SP} = \epsilon_o$
			$\gamma_{BS} = \epsilon_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \mu_s$
			$\gamma_{SS} = \epsilon_s$	$\gamma_{SS} = \epsilon_s$	$\gamma_{SS} = \epsilon_s$
Dir Down	p_D^d	θ	$\gamma_{BC} = \epsilon_o + \lambda_o + \nu_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \lambda_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \lambda_o + \mu_o$
			$\gamma_{SC} = \epsilon_o + \lambda_o$	$\gamma_{SC} = \epsilon_o + \lambda_o + \nu_o$	$\gamma_{SC} = \epsilon_o + \lambda_o$
			$\gamma_{BP} = \epsilon_o + \lambda_o + \nu_o + \mu_o$	$\gamma_{BP} = \epsilon_o + \lambda_o$	$\gamma_{BP} = \epsilon_o + \lambda_o$
			$\gamma_{SP} = \epsilon_o + \lambda_o$	$\gamma_{SP} = \epsilon_o + \lambda_o + \nu_o$	$\gamma_{SP} = \epsilon_o + \lambda_o$
			$\gamma_{BS} = \epsilon_s + \lambda_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \lambda_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \lambda_s + \mu_s$
			$\gamma_{SS} = \epsilon_s + \lambda_s$	$\gamma_{SS} = \epsilon_s + \lambda_s$	$\gamma_{SS} = \epsilon_s + \lambda_s$
	p_D^d	$(1-\theta)$	$\gamma_{BC} = \epsilon_o + \nu_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \mu_o$	$\gamma_{BC} = \epsilon_o + \mu_o$
			$\gamma_{SC} = \epsilon_o$	$\gamma_{SC} = \epsilon_o + \nu_o$	$\gamma_{SC} = \epsilon_o$
			$\gamma_{BP} = \epsilon_o + \nu_o + \mu_o$	$\gamma_{BP} = \epsilon_o$	$\gamma_{BP} = \epsilon_o$
			$\gamma_{SP} = \epsilon_o$	$\gamma_{SP} = \epsilon_o + \nu_o$	$\gamma_{SP} = \epsilon_o$
			$\gamma_{BS} = \epsilon_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \mu_s$	$\gamma_{BS} = \epsilon_s + \mu_s$
			$\gamma_{SS} = \epsilon_s$	$\gamma_{SS} = \epsilon_s$	$\gamma_{SS} = \epsilon_s$

Appendix A1 (Cont.): Likelihood Function - Probabilities and Arrival Rates (Cont.)

			Vol Up	Vol Down	Vol None
	Pr	Liq. Pr	p_V^u	p_V^d	$1-p_V^u-p_V^d$
Dir None	$(1-p_D^u-p_D^d)$	θ	$\gamma_{BC}=\epsilon_o+\lambda_o+\nu_o$	$\gamma_{BC}=\epsilon_o+\lambda_o$	$\gamma_{BC}=\epsilon_o+\lambda_o$
			$\gamma_{SC}=\epsilon_o+\lambda_o$	$\gamma_{SC}=\epsilon_o+\lambda_o+\nu_o$	$\gamma_{SC}=\epsilon_o+\lambda_o$
			$\gamma_{BP}=\epsilon_o+\lambda_o+\nu_o$	$\gamma_{BP}=\epsilon_o+\lambda_o$	$\gamma_{BP}=\epsilon_o+\lambda_o$
			$\gamma_{SP}=\epsilon_o+\lambda_o$	$\gamma_{SP}=\epsilon_o+\lambda_o+\nu_o$	$\gamma_{SP}=\epsilon_o+\lambda_o$
			$\gamma_{BS}=\epsilon_s+\lambda_s$	$\gamma_{BS}=\epsilon_s+\lambda_s+\mu_s$	$\gamma_{BS}=\epsilon_s+\lambda_s$
			$\gamma_{SS}=\epsilon_s+\lambda_s$	$\gamma_{SS}=\epsilon_s+\lambda_s$	$\gamma_{SS}=\epsilon_s+\lambda_s$
	$(1-p_D^u-p_D^d)$	$(1-\theta)$	$\gamma_{BC}=\epsilon_o+\nu_o$	$\gamma_{BC}=\epsilon_o$	$\gamma_{BC}=\epsilon_o$
			$\gamma_{SC}=\epsilon_o$	$\gamma_{SC}=\epsilon_o+\nu_o$	$\gamma_{SC}=\epsilon_o$
			$\gamma_{BP}=\epsilon_o+\nu_o$	$\gamma_{BP}=\epsilon_o$	$\gamma_{BP}=\epsilon_o$
			$\gamma_{SP}=\epsilon_o$	$\gamma_{SP}=\epsilon_o+\nu_o$	$\gamma_{SP}=\epsilon_o$
			$\gamma_{BS}=\epsilon_s+\mu_s$	$\gamma_{BS}=\epsilon_s+\mu_s$	$\gamma_{BS}=\epsilon_s$
			$\gamma_{SS}=\epsilon_s$	$\gamma_{SS}=\epsilon_s$	$\gamma_{SS}=\epsilon_s$

Appendix A2: Log Likelihood Function

The marginal likelihood function for our model is derived from the state probabilities and the arrival rates, γ, given in table for each of the 18 states described in table A2. The equation (18) describes the first three states given in the first row of the table.

$$\begin{aligned} l(\Theta|\Omega) = & \frac{1}{BC!SC!BP!SP!BS!SS!}\{(1-p_D^u-p_D^d)\theta p_V^u(e^{-\gamma_{BC}}\epsilon^{BC}e^{-\gamma_{SC}}\epsilon^{SC}e^{-\gamma_{BP}}\epsilon^{BP}e^{-\gamma_{SP}}\epsilon^{SP}e^{-\gamma_{BS}}\epsilon^{BS}e^{-\gamma_{SS}}\epsilon^{SS} \\ & + (1-p_D^u-p_D^d)\theta p_V^d e^{-\gamma_{BC}}\epsilon^{BC}e^{-\gamma_{SC}}\epsilon^{SC}e^{-\gamma_{BP}}\epsilon^{BP}e^{-\gamma_{SP}}\epsilon^{SP}e^{-\gamma_{BS}}\epsilon^{BS}e^{-\gamma_{SS}}\epsilon^{SS} \\ & + (1-p_D^u-p_D^d)\theta(1-p_V^u-p_V^d)e^{-\gamma_{BC}}\epsilon^{BC}e^{-\gamma_{SC}}\epsilon^{SC}e^{-\gamma_{BP}}\epsilon^{BP}e^{-\gamma_{SP}}\epsilon^{SP}e^{-\gamma_{BS}}\epsilon^{BS}e^{-\gamma_{SS}}\epsilon^{SS} + ..\} \end{aligned} \tag{18}$$

The log likelihood function based on the likelihood for time period T is given by Equation (19).

$$\mathcal{L}(\Theta|Orders) = Log(\prod_{t=1}^{T} l_t). \tag{19}$$

A3: Model Implied Moments

In this section we provide the moments (expected values and the covariance matrix) for buy and sell orders in the option and stock markets based on the structural model parameters. the expected values are defined as $\mu_{x\in\Omega}$ and the variance and covariance terms are defined as $\sigma_{x,y\in\Omega}$, where, $\Omega = \{BC, SC, BP, SP, BS, SS\}$. The sample moments and the model implied moments provide an important check of our structural model estimates based on the ML method.$Means$

$\mu_{BC} = \epsilon_O + \lambda_O\theta + \mu_O p_V^u + \nu_O p_D^u$
$\mu_{SC} = \epsilon_O + \lambda_O\theta + \mu_O p_V^d + \nu_O p_D^d$
$\mu_{BP} = \epsilon_O + \lambda_O\theta + \mu_O p_V^u + \nu_O p_D^d$
$\mu_{SP} = \epsilon_O + \lambda_O\theta + \mu_O p_V^d + \nu_O p_D^u$
$\mu_{BS} = \epsilon_S + \lambda_S\theta + \nu_S p_D^u$
$\mu_{SS} = \epsilon_S + \lambda_S\theta + \nu_S p_D^d$

Variances

$\sigma_{BC,BC} = \epsilon_O + \lambda_O^2\theta(1-\theta) + \lambda_O\theta + \mu_O^2 p_V^u(1-p_V^u) + \mu_O p_V^u + \nu_O^2 p_D^u(1-p_D^u) + \nu_O p_D^u$
$\sigma_{SC,SC} = \epsilon_O + \lambda_O^2\theta(1-\theta) + \lambda_O\theta + \mu_O^2 p_V^d(1-p_V^d) + \mu_O p_V^d + \nu_O^2 p_D^d(1-p_D^d) + \nu_O p_D^d$
$\sigma_{BP,BP} = \epsilon_O + \lambda_O^2\theta(1-\theta) + \lambda_O\theta + \mu_O^2 p_V^u(1-p_V^u) + \mu_O p_V^u + \nu_O^2 p_D^d(1-p_D^d) + \nu_O p_D^d$
$\sigma_{SP,SP} = \epsilon_O + \lambda_O^2\theta(1-\theta) + \lambda_O\theta + \mu_O^2 p_V^d(1-p_V^d) + \mu_O p_V^d + \nu_O^2 p_D^u(1-p_D^u) + \nu_O p_D^u$
$\sigma_{BS,BS} = \epsilon_S + \lambda_S^2\theta(1-\theta) + \lambda_S\theta + \nu_S^2 p_D^u(1-p_D^u) + \nu_S p_D^u$
$\sigma_{SS,SS} = \epsilon_S + \lambda_S^2\theta(1-\theta) + \lambda_S\theta + \nu_S^2 p_D^d(1-p_D^d) + \nu_S p_D^d$

Covariances

$\sigma_{BC,SC} = \sigma_{BP,SP} = \lambda_O^2\theta(1-\theta) - \mu_O^2 p_V^d p_V^u - \nu_O^2 p_D^d p_D^u$
$\sigma_{BP,BC} = \lambda_O^2\theta(1-\theta) + \mu_O^2 p_V^u(1-p_V^u) - \nu_O^2 p_D^d p_D^u$
$\sigma_{SP,BC} = \lambda_O^2\theta(1-\theta) - \mu_O^2 p_V^d p_V^u + \nu_O^2 p_D^u(1-p_D^u)$
$\sigma_{BS,BC} = \sigma_{BS,SP} = \lambda_O\lambda_S\theta(1-\theta) + \nu_O\nu_S p_D^u(1-p_D^u)$
$\sigma_{SS,BC} = \sigma_{BS,SC} = \sigma_{BS,BP} = \sigma_{SS,SP} = \lambda_O\lambda_S\theta(1-\theta) - \nu_O\nu_S p_D^d p_D^u$
$\sigma_{BP,SC} = \lambda_O^2\theta(1-\theta) - \mu_O^2 p_V^d p_V^u + \nu_O^2 p_D^d(1-p_D^d)$
$\sigma_{SP,SC} = \lambda_O^2\theta(1-\theta) + \mu_O^2 p_V^d(1-p_V^d) - \nu_O^2 p_D^d p_D^u$
$\sigma_{SS,SC} = \sigma_{SS,BP} = \lambda_O\lambda_S\theta(1-\theta) + \nu_O\nu_S p_D^d(1-p_D^d)$
$\sigma_{SS,BS} = \lambda_S^2\theta(1-\theta) - \nu_S^2 p_D^d p_D^u$

Parameters:

ϵ_O: Uninformed noise rate for call options
ϵ_p: Uninformed noise rate for put options
ϵ_S: Uninformed rate for stocks
μ_O: Informed rate for volatility information for options
ν_O: Informed rate for directional information for options
ν_S: Informed rate for directional information for stocks

λ_O: Uninformed additional rate for any information for options
λ_S: Uninformed additional rate for any information for stocks
p_{Vu}: Probability of information that volatility will increase
p_{Vd}: Probability of information that volatility will decrease
p_{Du}: Probability of information that stock price will increase
p_{Dd}: Probability of information that stock price will decrease
θ: Probability of extra uninformed trading volume
Data Items:
BC: Count of call options bought
SC: Count of call options sold
BP: Count of put options bought
SP: Count of put options sold
BS: Count of shares bought
SS: Count of shares sold
p_{vu}: Probability of information that volatility will increase
p_{vd}: Probability of information that volatility will decrease
p_{du}: Probability of information that stock price will increase
p_{dd}: Probability of information that stock price will decrease

TABLES

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Table 1: MC Simulation: N(OBS)=250, FIRMS=200, Months =12

$SimorEst$	Par	$Mean$	se_{mean}	$P25$	$Median$	$P75$
Sim	p_V^u	0.118	0.0005	0.098	0.117	0.139
Est	p_V^u	0.120	0.0005	0.104	0.119	0.135
Sim	p_V^d	0.088	0.0004	0.071	0.086	0.104
Est	p_V^d	0.104	0.0005	0.088	0.103	0.118
Sim	p_D^u	0.089	0.0004	0.075	0.087	0.105
Est	p_D^u	0.083	0.0004	0.069	0.082	0.096
Sim	p_D^d	0.092	0.0003	0.079	0.093	0.104
Est	p_D^d	0.094	0.0004	0.080	0.094	0.108
Sim	θ	0.202	0.0006	0.180	0.203	0.227
Est	θ	0.187	0.0012	0.164	0.180	0.199
Sim	ϵ_s	1000	6.3	738	1023	1273
Est	ϵ_s	992	2.5	993	1006	1018
Sim	λ_s	1467	5.9	1228	1452	1709
Est	λ_s	1499	1.6	1462	1504	1544
Sim	ν_s	1103	4.4	910	1088	1286
Est	ν_s	1115	2.0	1054	1116	1176
Sim	ϵ_c	25	0.06	23	25	28
Est	ϵ_c	25	0.02	25	25	25
Sim	ϵ_p	15	0.06	13	15	18
Est	ϵ_p	15	0.02	15	15	15
Sim	λ_o	62	0.44	43	60	80
Est	λ_o	59	0.09	57	59	61
Sim	ν_o	40	0.12	36	40	46
Est	ν_o	40	0.04	39	40	41
Sim	μ_o	30	0.06	28	30	32
Est	μ_o	30	0.03	30	30	31

The table gives the summary of simulated (Sim) parameters and the estimated (Est) parameters based on the MLE method. There were 2378 firm months out of 2400 that converged.

Table 2: MC Simulation- Simulated and Estimated PIN Measures

Sim/Est	PIN	$Mean$	se_{mean}	$P25$	$Median$	$P75$
Sim	π_S^D	0.075	0.0005	0.055	0.071	0.089
Est	π_S^D	0.073	0.0003	0.064	0.071	0.079
Sim	π_S^L	0.222	0.0014	0.170	0.218	0.266
Est	π_S^L	0.206	0.0016	0.181	0.196	0.213
Sim	π_O^D	0.094	0.0004	0.080	0.092	0.105
Est	π_O^D	0.094	0.0003	0.085	0.093	0.103
Sim	π_O^V	0.080	0.0003	0.066	0.078	0.092
Est	π_O^V	0.090	0.0003	0.081	0.090	0.099
Sim	π_O^L	0.308	0.0016	0.238	0.311	0.377
fEst	π_O^L	0.285	0.0008	0.262	0.283	0.305

The table gives the summary of simulated (Sim) and estimated (Est) PIN measures and liquidity for the options and stock markets.based on the MLE method. There were 2378 firm months out of 2400 that converged. The subscripts S and O represent stock and options respectively. The superscripts D, V, and L represent direction, volatility and correlated liquidity measures.

Table 3: Stock Descriptive Summary

Variable	Units	Mean	STD	25p	50P	75p
Market Cap (MCAP)	$ Billion	45	55	13	26	169
Price (PRC)	$	66	74	31	47	72
Volume (VOL)	Millions/D	2.55	5.89	0.71	1.25	2.26
Number of Trades (TRD)	Millions/M	1.06	0.87	0.47	0.8	1.35
Intra day Volatility (STD)	%	0.181	0.073	0.127	0.168	0.221
Quoted Spread (QS)	%	0.041	0.031	0.025	0.032	0.046
Realized Spread (RS)	%	0.032	.055	0.014	0.023	0.038
Effective Spread (ES)	%	0.032	0.024	0.02	0.026	0.036
Price Impact(λ)	$\times 10^6$	19.77	314.92	0.64	1.16	2.01
Adverse Selection Spread (AS)	%	0.012	0.025	0.003	0.007	0.014

The table reports probabilities associated with informed and correlated liquidity trading based on the the OSPIN model estimates. The summary statistics are averaged within market value quintile and by moneyness.

Table 4: Panel A - Options Quoted Spread (%)

	Mean	STD	p25	Median	p75
ITM	2.69	1.45	1.76	2.28	3.15
ATM	5.39	2.67	3.68	4.52	6.10
OTM	10.43	3.98	7.56	9.50	12.42
$\leq$ 30 days	8.10	3.19	5.88	7.16	9.34
$>$ 30 days	4.32	2.45	2.82	3.51	4.80

Panel B - Options Effective Spread (%)

	Mean	STD	p25	Median	p75
ITM	1.94	1.00	1.32	1.68	2.24
ATM	4.62	2.13	3.22	4.00	5.29
OTM	9.10	3.40	6.63	8.35	10.87
$\leq$ 30 days	7.00	2.56	5.22	6.32	8.17
$>$ 30 days	3.65	1.97	2.43	3.08	4.13

The table reports probabilities associated with informed and correlated liquidity trading based on the the OSPIN model estimates. The summary statistics are averaged within market value quintile and by moneyness.

Table 5: Options Spread by MV Quintile (%), N=2389

Panel A - Quoted Spread

	ATM		ITM		OTM	
	Mean	STD	Mean	STD	Mean	STD
MVQ 1(S)	6.98	3.40	3.80	1.80	12.52	4.81
MVQ 2	6.11	2.99	3.18	1.45	11.39	4.38
MVQ 3	4.90	2.15	2.58	1.21	9.83	3.29
MVQ 4	4.35	1.60	2.19	0.89	9.16	2.82
MVQ 5(L)	4.58	1.63	1.68	0.55	9.19	2.97

Panel B - Effective Spread

	ATM		ITM		OTM	
	Mean	STD	Mean	STD	Mean	STD
MVQ 1	5.73	2.69	2.63	1.22	10.50	3.94
MVQ 2	5.17	2.43	2.30	1.05	9.77	3.75
MVQ 3	4.21	1.78	1.86	0.85	8.57	2.93
MVQ 4	3.82	1.34	1.62	0.65	8.15	2.62
MVQ 5	4.16	1.40	1.29	0.42	8.49	2.91

The table reports option spreads by market value quintiles. The summary statistics are averaged within market value quintile and by moneyness.

Table 6: Stock and Option Trade Summary (All)

Panel A: Number of Trades

Variable	Mean	STD	p25	Median	p75
BS	1593	1911	569	1030	1893
SS	1604	1931	571	1034	1905
BC	41	165	4	11	32
BP	28	112	2	7	21
SC	37	148	4	11	30
SP	24	98	2	6	18

Correlations (ALL)

	BS	SS	BC	BP	SC	SP
BS	1.00					
SS	0.87	1.00				
BC	0.46	0.40	1.00			
BP	0.37	0.42	0.46	1.00		
SC	0.45	0.44	0.62	0.46	1.00	
SP	0.40	0.38	0.46	0.56	0.48	1.00

Table 7: Panel B - Stock and Option Trade Summary by Moneyness

	ATM		OTM		ITM		≤ 30		> 30	
Variable	Mean	STD	Mean	STD	Mean	STD	Mean	STD		
BC	35	149	5	18	2	8	24	120	18	56
BP	23	98	4	17	1	6	18	89	10	32
SC	31	132	4	17	2	8	21	105	16	51
SP	20	86	4	14	1	6	16	78	9	28

Correlations (ATM)

	BS	SS	BC	BP	SC	SP
BS	1.00					
SS	0.87	1.00				
BC	0.45	0.38	1.00			
BP	0.36	0.40	0.44	1.00		
SC	0.40	0.41	0.61	0.42	1.00	
SP	0.38	0.37	0.42	0.55	0.46	1.00

Correlations (OTM)

	BS	SS	BC	BP	SC	SP
BS	1.00					
SS	0.87	1.00				
BC	0.25	0.23	1.00			
BP	0.23	0.25	0.18	1.00		
SC	0.21	0.23	0.36	0.17	1.00	
SP	0.23	0.21	0.16	0.36	0.15	1.00

Correlations (ITM)

	BS	SS	BC	BP	SC	SP
BS	1.00					
SS	0.87	1.00				
BC	0.22	0.19	1.00			
BP	0.15	0.18	0.58	1.00		
SC	0.20	0.22	0.36	0.08	1.00	
SP	0.16	0.15	0.07	0.32	0.05	1.00

The table reports summary statistics and correlations for the number of stock and option trades during thirteen intraday half-hour intervals from 9:30AM - 4:00 PM. The data is based on 200 large firms' trading characteristics in 2011 over 251 days. The statistics are based on 651,560 half-hour observations. The correlations are calculated for each firm-month and then averaged across the firm months (2376 obs.)

Correlations - Maturity $\leq$ 30 days

	BS	SS	BC	BP	SC	SP
BS	1.00					
SS	0.87	1.00				
BC	0.39	0.34	1.00			
BP	0.33	0.36	0.42	1.00		
SC	0.35	0.37	0.58	0.41	1.00	
SP	0.35	0.33	0.41	0.54	0.44	1.00

Correlations - Maturity $\geq$ 30 days

	BS	SS	BC	BP	SC	SP
BS	1.00					
SS	0.87	1.00				
BC	0.37	0.33	1.00			
BP	0.28	0.32	0.42	1.00		
SC	0.33	0.34	0.55	0.38	1.00	
SP	0.30	0.28	0.38	0.47	0.42	1.00

The table reports summary statistics and correlations for the number of stock and option trades during thirteen intraday half-hour intervals from 9:30AM - 4:00 PM. The data is based on 200 large firms' trading characteristics in 2011 over 251 days. The statistics are based on 651,560 half-hour observations. The correlations are calculated for each firm-month and then averaged across the firm months (2376 obs.)

Table 8: OSPIN Estimates by Moneyness and Maturity

	ALL		OTM		ATM		ITM		≤30 Days		>30 Days	
Par	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
p_V^u	0.18	0.20	0.08	0.08	0.06	0.07	0.06	0.07	0.25	0.22	0.18	0.16
p_V^d	0.07	0.10	0.05	0.06	0.03	0.04	0.04	0.05	0.11	0.12	0.12	0.13
p_D^u	0.06	0.05	0.07	0.05	0.05	0.04	0.09	0.07	0.07	0.05	0.07	0.05
p_D^d	0.07	0.05	0.08	0.06	0.06	0.05	0.09	0.07	0.08	0.06	0.08	0.06
θ	0.21	0.07	0.22	0.09	0.23	0.08	0.22	0.11	0.21	0.07	0.21	0.07
ϵ_S	1134	891	1075	863	1091	862	1006	887	1131	889	1132	887
λ_S	1748	1366	1696	1418	1698	1349	1510	1491	1755	1379	1759	1378
ν_S	1597	1536	2009	2580	2377	2751	1653	2427	1549	1523	1541	1483
ϵ_O	46.52	117.47	2.27	5.81	21.40	77.63	1.01	3.56	29.81	83.23	23.09	48.44
λ_O	61.75	139.17	7.57	15.44	34.26	95.59	3.64	10.04	44.70	105.05	29.22	64.84
ν_O	69.85	128.45	14.98	26.52	64.50	109.58	5.87	12.26	46.00	83.13	33.03	42.13
μ_O	61.45	105.63	18.62	32.49	71.36	130.01	8.41	16.76	38.59	70.74	30.37	37.96

The table reports summary statistics and correlations for the number of stock and option trades during thirteen intraday half-hour intervals from 9:30AM - 4:00 PM. The data is based on 200 large firms' trading characteristics in 2011 over 251 days. The statistics are based on 651,560 half-hour observations. The correlations are calculated for each firm-month and then averaged across the firm months (2376 obs.)

Table 9: OSPIN Estimates by Moneyness and Maturity

	ALL		OTM		ATM		ITM		≤30 Days		>30 Days	
Par	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
$StkDir$	0.052	0.023	0.060	0.028	0.049	0.024	0.065	0.040	0.055	0.022	0.055	0.022
$StkDirHigh$	0.025	0.015	0.029	0.017	0.023	0.014	0.032	0.023	0.027	0.015	0.025	0.01
$StkDirLow$	0.027	0.016	0.031	0.017	0.026	0.016	0.033	0.024	0.028	0.016	0.030	0.016
$StkLiq$	0.230	0.044	0.230	0.068	0.250	0.054	0.210	0.088	0.230	0.042	0.230	0.042
$StkNoise$	0.720	0.041	0.710	0.071	0.700	0.053	0.730	0.100	0.720	0.041	0.720	0.041
$OptDir$	0.069	0.043	0.180	0.099	0.096	0.054	0.220	0.130	0.087	0.057	0.083	0.052
$OptDirHigh$	0.033	0.023	0.090	0.055	0.045	0.031	0.110	0.072	0.042	0.031	0.038	0.029
$OptDirLow$n	0.037	0.028	0.095	0.060	0.045	0.031	0.110	0.075	0.046	0.039	0.058	0.056
$OptVol$	0.100	0.070	0.170	0.092	0.095	0.050	0.130	0.098	0.150	0.100	0.142	0.091
$OptVolHigh$	0.067	0.045	0.100	0.064	0.061	0.034	0.078	0.067	0.099	0.069	0.084	0.056
$OptVolLow$	0.034	0.040	0.070	0.057	0.035	0.033	0.051	0.055	0.050	0.054	0.058	0.056
$OptLiq$	0.200	0.075	0.320	0.130	0.300	0.060	0.410	0.180	0.220	0.089	0.200	0.078
$OptNoise$	0.620	0.110	0.330	0.180	0.510	0.110	0.240	0.220	0.550	0.150	0.580	0.130

The table reports summary statistics for the OSPIN model estimates. The estimates are based on stock and option trades during thirteen intra-day half-hour intervals from 9:30AM - 4:00 PM over each month. The data is based on 200 large firms' trading characteristics in 2011 over 251 days.

Table 10: OSPIN Model Probabilities by Market Value Quintile and Moneyness

Quintile	Desc.	OSPIN	ATM		ITM		OTM	
			Mean	Std	Mean	Std	Mean	Std
1(Small)	*StkDir*	π_S^D	0.062	0.027	0.072	0.046	0.072	0.033
	StkLiq	π_S^L	0.236	0.052	0.191	0.091	0.214	0.066
	OptDir	π_O^D	0.137	0.053	0.263	0.127	0.232	0.102
	OptVol	π_O^V	0.121	0.054	0.136	0.106	0.196	0.102
	OptLiq	π_O^L	0.303	0.074	0.460	0.190	0.351	0.153
2	*StkDir*	π_S^D	0.055	0.022	0.068	0.044	0.064	0.028
	StkLiq	π_S^L	0.234	0.054	0.203	0.092	0.215	0.067
	OptDir	π_O^D	0.118	0.049	0.243	0.136	0.222	0.097
	OptVol	π_O^V	0.113	0.053	0.132	0.108	0.195	0.097
	OptLiq	π_O^L	0.305	0.068	0.449	0.194	0.344	0.135
3	*StkDir*	π_S^D	0.048	0.022	0.066	0.035	0.060	0.028
	StkLiq	π_S^L	0.248	0.049	0.201	0.083	0.228	0.061
	OptDir	π_O^D	0.096	0.047	0.223	0.122	0.192	0.090
	OptVol	π_O^V	0.097	0.051	0.127	0.098	0.169	0.089
	OptLiq	π_O^L	0.295	0.058	0.420	0.180	0.311	0.124
4	*StkDir*	π_S^D	0.042	0.021	0.066	0.040	0.050	0.021
	Stkliq	π_S^L	0.250	0.050	0.209	0.081	0.232	0.059
	OptDir	π_O^D	0.077	0.042	0.203	0.116	0.162	0.085
	OptVol	π_O^V	0.089	0.049	0.129	0.092	0.158	0.077
	OptLiq	π_O^L	0.294	0.057	0.389	0.161	0.295	0.111
5 (Large)	*StkDir*	π_S^D	0.037	0.020	0.054	0.030	0.048	0.021
	StkLiq	π_S^L	0.264	0.048	0.228	0.073	0.247	0.057
	OptDir	π_O^D	0.051	0.029	0.158	0.100	0.114	0.067
	OptVol	π_O^V	0.056	0.035	0.117	0.084	0.128	0.073
	OptLiq	π_O^L	0.285	0.050	0.336	0.146	0.283	0.095

The table reports probabilities associated with informed and correlated liquidity trading based on the the OSPIN model estimates. The summary statistics are averaged within market value quintile and by moneyness.

Table 11: Multivariate Regression Model of Stock Quoted Spread (SQS) on OSPIN and Controls

VARIABLES	OTM	ATM	ITM	30	> 30	ALL_
Stkdirpin	0.000381**	3.67e-05	0.000160**	5.65e-05**	0.000438**	0.000268*
	(0.000135)	(4.97e-05)	(5.59e-05)	(2.50e-05)	(0.000177)	(0.000122)
StkLiq	-2.39e-05	-3.69e-05	-7.15e-05	-1.85e-05	-2.91e-05	-2.34e-05
	(5.79e-05)	(4.18e-05)	(6.30e-05)	(1.28e-05)	(5.54e-05)	(5.53e-05)
Optdirpin	3.25e-05	7.97e-05*	-1.40e-05	1.50e-05	-3.48e-05	7.86e-05
	(6.99e-05)	(4.06e-05)	(5.95e-05)	(1.79e-05)	(4.94e-05)	(7.12e-05)
Optvolpin	-3.44e-05	1.04e-05	5.86e-06	-7.44e-06	-1.34e-06	-1.06e-05
	(4.09e-05)	(2.17e-05)	(3.76e-05)	(1.80e-05)	(2.44e-05)	(2.75e-05)
OptLiq	-8.20e-06	2.39e-05	-3.95e-05	-1.24e-05	1.04e-05	8.45e-06
	(1.91e-05)	(2.18e-05)	(5.25e-05)	(1.26e-05)	(1.50e-05)	(2.22e-05)
OQS	0.00194*	0.00194*	0.00197*	0.00205*	0.00195*	0.00188*
	(0.000882)	(0.000887)	(0.000906)	(0.000935)	(0.000900)	(0.000897)
Observations	2,387	2,393	2,317	2,379	2,393	2,368
R-squared	0.858	0.934	0.881	0.867	0.925	0.929
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month CSE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The control variables include log(STKVOLUME), log(OPTVOLUME$_{A}LL), PINV, andIV$

Table 12: Multivariate Regression Model of Option Quoted Spread (OQS) on OSPIN and Controls

VARIABLES	OTM	ATM	ITM	30	> 30	ALL_
StkDirPIN	0.000260	0.0124	-0.00424	0.00853	0.0220**	0.0121
	(0.00844)	(0.00758)	(0.00490)	(0.0111)	(0.00934)	(0.00941)
StkLiq	-0.00253	0.00242	-6.26e-06	0.0115**	0.00703	0.00918**
	(0.00298)	(0.00347)	(0.00114)	(0.00396)	(0.00436)	(0.00327)
OptDirPIN	0.000582	**0.0149*****	-0.000544	-0.00564	0.00310	0.00578
	(0.00213)	(0.00351)	(0.00195)	(0.00523)	(0.00385)	(0.00501)
OptVolPIN	***0.0107******	0.00532	0.000707	0.00332	-0.00305	0.00211
	(0.00129)	(0.00416)	(0.00152)	(0.00227)	(0.00301)	(0.00391)
OptLiq	-0.000207	0.00854*	0.00178**	-0.00177	-0.000388	0.00224
	(0.00205)	(0.00397)	(0.000673)	(0.00267)	(0.00123)	(0.00253)
Stk_QS	12.46***	17.40***	4.259	16.81***	7.499**	12.42***
	(3.471)	(3.307)	(3.295)	(3.569)	(3.260)	(2.787)
Observations	2,387	2,393	2,317	2,379	2,393	2,368
R-squared	0.858	0.934	0.881	0.867	0.925	0.929
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month CSE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The control variables include log(STKVOLUME), log(OPTVOLUME$_{A}LL$)$, PINV, andIV$

Table 13: Regression Model Estimates of Option Effective Spread (OES) on OSPIN Measures

VARIABLES	OTM	ATM	ITM	30	> 30	ALL
StkDirPIN	0.00838	0.0185*	0.000547	0.0134	0.0320***	0.0103
	(0.0201)	(0.00951)	(0.00423)	(0.0158)	(0.00752)	(0.0114)
StkLiq	-0.00621	0.00201	-0.000172	0.0245***	0.00323	0.0104*
	(0.0116)	(0.00330)	(0.00196)	(0.00757)	(0.00365)	(0.00579)
OptDirPIN	0.00818	0.0173**	0.000185	0.00871	0.00753	0.0131
	(0.00897)	(0.00632)	(0.00101)	(0.00960)	(0.00519)	(0.00776)
OptVolPIN	0.0188**	0.00757	0.000612	-0.00387	0.00142	-0.00403
	(0.00817)	(0.00482)	(0.00172)	(0.00699)	(0.00298)	(0.00439)
OptLiq	0.00628	0.00815	0.00107	0.000938	-6.68e-05	0.00174
	(0.00529)	(0.00667)	(0.000714)	(0.00642)	(0.00228)	(0.00330)
Stk-ES	52.85***	31.16***	-0.429	34.56***	26.89***	27.38***
	(10.01)	(4.216)	(2.766)	(10.51)	(4.828)	(5.603)
Observations	2,388	2,393	2,317	2,379	2,393	2,368
R-squared	0.800	0.937	0.760	0.712	0.912	0.881
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month CSE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Stock Microstructure Variables (OSPIN-ALL)

VARIABLES	Stk-QS	Stk-ES	Stk-AIS	Stk-PI (λ)
StkDirPIN	0.000362**	0.000284**	0.000255**	8.76e-07***
	(0.000124)	(9.15e-05)	(9.16e-05)	(2.74e-07)
StkLiq	-4.13e-05	-3.56e-05	-2.61e-05	3.14e-07***
	(5.47e-05)	(3.81e-05)	(4.36e-05)	(9.55e-08)
OptDirPIN	4.36e-05	3.45e-05	1.86e-05	-3.57e-07*
	(6.74e-05)	(4.12e-05)	(3.97e-05)	(1.99e-07)
OptVolPIN	-2.38e-05	-2.95e-05	-5.86e-06	-1.67e-08
	(4.07e-05)	(3.06e-05)	(3.11e-05)	(1.08e-07)
OptLiq	-1.08e-05	-1.72e-05	2.56e-06	-3.14e-08
	(2.00e-05)	(1.57e-05)	(9.28e-06)	(5.72e-08)
OQS	0.00211**	0.00167**	0.00121**	4.08e-06
	(0.000908)	(0.000639)	(0.000469)	(2.62e-06)
Observations	2,370	2,370	2,370	2,370
R-squared	0.974	0.979	0.957	0.961
Controls	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes
Stock/Month CSE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Options Microstructure Measures (OptionMetrics-Daily Data)

Variable Description	Stat	OTM $\geq$ 30D	OTM $<$ 30D	ATM $\geq$ 30D	ATM $<$ 30D	ITM $\geq$ 30D	ITM $<$ 30D
Implied Volatility- Calls (IV_C)(%)	Mean	35.98	31.69	33.88	33.46	41.39	36.58
	Std	11.84	10.76	12.9	11.53	13.45	11.39
Implied Volatility-Puts (IV_P)(%)	Mean	44.87	37.48	35.03	34.17	35.15	32.04
	Std	13.35	11.45	12.96	11.4	13	10.79
Quoted Spread-Calls (OQS_C)(%)	Mean	8.81	5.17	5.55	3.3	3.46	2.59
	Std	2.14	2.08	1.93	1.76	1.66	1.38
Quoted Spread - Puts (OQS_P) (%)	Mean	8.44	4.47	5.65	3.09	3.81	2.52
	Std	2.07	2.03	2.04	1.71	1.85	1.34
$OSR_C = \frac{CallVolume}{StockVolume} \times 10^4$	Mean	1.61	2.26	5.42	3.02	0.85	0.58
	Std	2.71	1.8	11.01	2.56	3.67	0.84
$OSR_P = \frac{PutVolume}{StockVolume} \times 10^4$	Mean	1.68	1.85	3.77	1.87	0.25	0.25
	Std	3.17	1.53	8.53	1.53	0.45	0.28
$PCR_{Volume} = \frac{Put}{Put+call}$	Mean	0.52	0.45	0.40	0.40	0.35	0.35
	Std	0.20	0.13	0.12	0.11	0.27	0.21
$ILLIQ_{S\|C} = \frac{\|StockReturn\|}{CallVolume} \times 10^6$	Mean	4.70	0.63	0.50	0.57	11.12	6.04
	Std	6.84	1.12	1.36	1.36	16.84	10.32
$ILLIQ_{S\|P} = \frac{\|StockReturn\|}{PutVolume} \times 10^6$	Mean	3.65	1,00	0.99	1.05	16.63	11.42
	Std	5.60	2.10	2.18	2.68	20.52	13.81
$ILLIQ_{O\|S} = \frac{\|IVReturn\|}{StockVolume} \times 10^{?}$?	Mean						
	Std						

The table reports mean and standard deviation by option moneyness and maturity of options market microstructure measures based on daily option metrics data. The summary statistics are averaged by moneyness.

Table 16: Multivariate Regression of $PCR = (\frac{Put}{(Put+call)})$ and OSPIN Measures by Moneyness and Maturity

OSPIN	PCR_{OTM}	PCR_{ATM}	PCR_{ITM}	PCR_{LE30}	PCR_{GT30}	PCR_{ALL}
StkDir_H	-0.0744	-0.175	-0.0451	-0.845***	-0.410	-0.599**
	(0.244)	(0.248)	(0.246)	(0.257)	(0.260)	(0.230)
StkDir_L	-0.369*	0.746***	0.568*	0.438	0.276	0.439
	(0.178)	(0.137)	(0.285)	(0.289)	(0.273)	(0.280)
StkLiq	-0.154***	0.151**	0.186***	-0.0204	-0.0661**	-0.0403
	(0.0433)	(0.0537)	(0.0536)	(0.0498)	(0.0300)	(0.0273)
OptDir_H	-0.0736	0.189*	0.000690	0.278	0.288	0.276
	(0.0947)	(0.104)	(0.0642)	(0.166)	(0.189)	(0.174)
OptDir_L	0.0684	0.365**	0.437***	-0.0555	0.254	0.0634
	(0.0833)	(0.119)	(0.0785)	(0.183)	(0.170)	(0.176)
OptVol_H	-0.212***	0.275***	0.192**	0.219***	0.225***	0.152**
	(0.0578)	(0.0820)	(0.0697)	(0.0462)	(0.0434)	(0.0614)
OptVol_L	-0.109	0.545***	0.422***	0.337***	0.244***	0.322***
	(0.0642)	(0.0768)	(0.0936)	(0.0631)	(0.0569)	(0.0716)
OptLiq	-0.105**	0.297***	0.162***	0.163***	0.157***	0.124***
	(0.0418)	(0.0464)	(0.0310)	(0.0380)	(0.0215)	(0.0306)
SQS	37.54	-66.95**	30.07	-85.62**	-6.805	-47.21
	(58.04)	(29.14)	(81.78)	(33.13)	(37.88)	(30.01)
$\text{OQS}_{M/Mat}$	0.0482	-0.0224	1.399**	0.623**	0.121	0.478**
	(0.291)	(0.360)	(0.622)	(0.267)	(0.291)	(0.188)
Observations	2,385	2,393	2,315	2,378	2,386	2,361
R-squared	0.450	0.479	0.485	0.380	0.475	0.481
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month CSE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Multivariate Regression of Log(OSR) on OSPIN by Option Type (call/Put)

VARIABLE	$Log(OSR_{PUT})$	$Log(OSR_{CALL})$	Log(OSR$_{ALL}$)$ref[table:lnosrregshowsthe$
stkdirpin	0.491	0.912***	0.741***
	(0.287)	(0.207)	(0.233)
stkliqpin	-0.169*	0.0123	-0.0588
	(0.0876)	(0.0594)	(0.0691)
optdirpin	0.214***	0.181***	0.182***
	(0.0287)	(0.0413)	(0.0327)
optvolpin	-0.0666	0.348***	0.182***
	(0.0616)	(0.0561)	(0.0438)
optliqpin	-0.139***	-0.0119	-0.0585*
	(0.0340)	(0.0311)	(0.0284)
sqs	-293.3**	-596.4**	-526.2**
	(130.9)	(217.2)	(179.6)
oqs_put	9.342***		
	(2.381)		
oqs_call		8.997***	
		(2.867)	
oqs_all			10.71***
			(3.207)
Observations	14,279	14,279	14,279
R-squared	0.856	0.854	0.878
Controls	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes
Stock/Month CSE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, *

Table 18: Multivariate Regression of Levered Option Volume on OSPIN Measures

VARIABLE	$LN(\frac{OTMOptionVolume}{ITMOptionVolume})$	$LN(\frac{ATMOptionVolume}{ITMOptionVolume})$
StkDir	-0.213	-0.0345
	(0.338)	(0.373)
StkLiq	0.405**	0.323***
	(0.146)	(0.0830)
OptDir	0.0399	0.0457
	(0.0751)	(0.0639)
OptVol	0.173	0.125
	(0.0992)	(0.0941)
OptLiq	0.155***	0.118**
	(0.0447)	(0.0407)
OQS_{OTM}	0.230	
	(2.135)	
SQS	-369.8***	-286.1**
	(113.7)	(110.1)
OQS_{ATM}		5.027**
		(2.143)
Observations	14,220	14,226
R-squared	0.318	0.399
Controls	Yes	Yes
Stock/Month FE	Yes	Yes
Stock/Month CSE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Multivariate Regression Model of Cross Market Price Impact ($ILLIQ_{S|O}$) on OSPIN Measures

cmpireg OSPIN	OTM	ATM	ITM	LE 30D	GT30 D	All
StkDir	0.206	-0.450	0.386	0.364	0.158	0.360
	(0.584)	(0.523)	(0.255)	(0.738)	(0.862)	(0.654)
StkLiq	-0.709	-0.586*	-0.323**	-0.266	-0.221	-0.363
	(0.408)	(0.307)	(0.121)	(0.386)	(0.326)	(0.284)
OptDir	1.286***	3.048***	0.222**	0.641**	0.664*	0.105
	(0.318)	(0.299)	(0.0868)	(0.249)	(0.354)	(0.326)
OptVol	0.303	1.447***	-0.204	0.446	0.938***	0.328
	(0.320)	(0.413)	(0.116)	(0.256)	(0.216)	(0.278)
OptLiq	0.386	0.480*	0.0306	0.0178	0.211	-0.352
	(0.239)	(0.248)	(0.0756)	(0.173)	(0.203)	(0.238)
SQS	504.3	-418.2	-604.9**	-174.5	-671.1	-176.0
	(405.1)	(294.1)	(271.2)	(260.3)	(439.4)	(203.8)
OQS_{OTM}	5.608*					
	(2.803)					
OQS_{ATM}		14.97***				
		(4.026)				
OQS_{ITM}			13.37***			
			(3.670)			
$OQS_{\leq 30D}$				12.65***		
				(3.027)		
$OQS_{>30D}$					9.344***	
					(2.779)	
OQS_{ALL}						15.63***
						(2.995)
Observations	2,388	2,397	2,318	2,397	2,397	2,371
R-squared	0.799	0.925	0.864	0.834	0.879	0.879
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Multivariate Regression Model of Cross Market Price Impact ($ILLIQ_{O|S}$) on OSPIN Measures

OSPIN	OTM	ATM	ITM	$\leq 30D$	GT 30D	All
StkDir	-0.163	-0.467	0.0232	-0.114	0.669	0.269
	(0.254)	(0.350)	(0.169)	(0.441)	(0.436)	(0.328)
StkLiq	0.0453	0.00640	-0.0267	0.131	0.116	0.223
	(0.138)	(0.112)	(0.126)	(0.177)	(0.173)	(0.178)
OptDir	0.417***	0.489**	0.113	0.280**	-0.0114	0.299
	(0.0769)	(0.180)	(0.0719)	(0.110)	(0.147)	(0.221)
OptVol	0.104	0.301*	-0.00301	0.0495	0.0301	-0.00934
	(0.0878)	(0.163)	(0.0635)	(0.0811)	(0.107)	(0.168)
OptLiq	0.291***	0.411***	0.0588	0.0109	0.0273	-0.0620
	(0.0731)	(0.0949)	(0.0579)	(0.0546)	(0.0497)	(0.0659)
SQS	145.0	180.3	119.8	136.9	102.8	95.19
	(181.0)	(190.4)	(185.8)	(177.1)	(214.6)	(196.1)
OQS$_{OTM}$	2.220**					
	(0.877)					
OQS$_{ATM}$		6.819***				
		(1.467)				
OQS$_{ITM}$			6.836***			
			(1.815)			
OQS$_{\leq 30D}$				3.902**		
				(1.582)		
OQS$_{>30D)}$					12.38***	
					(1.785)	
OQS$_{ALL}$						6.523***
						(1.869)
Observations	2,387	2,396	2,317	2,396	2,396	2,370
R-squared	0.954	0.957	0.923	0.948	0.957	0.956
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock/Month Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

FIGURES

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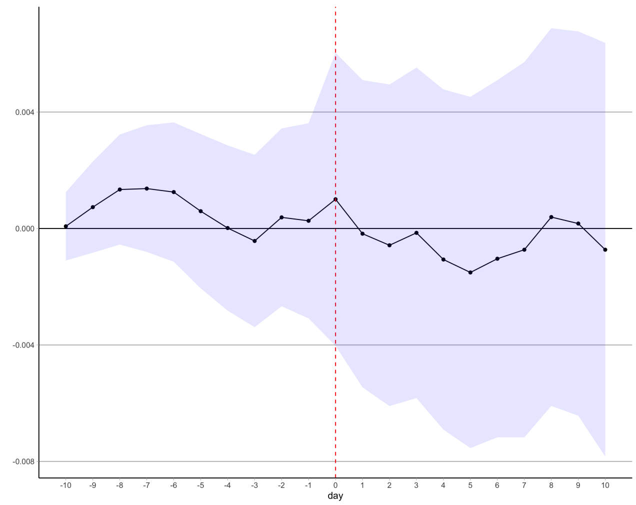
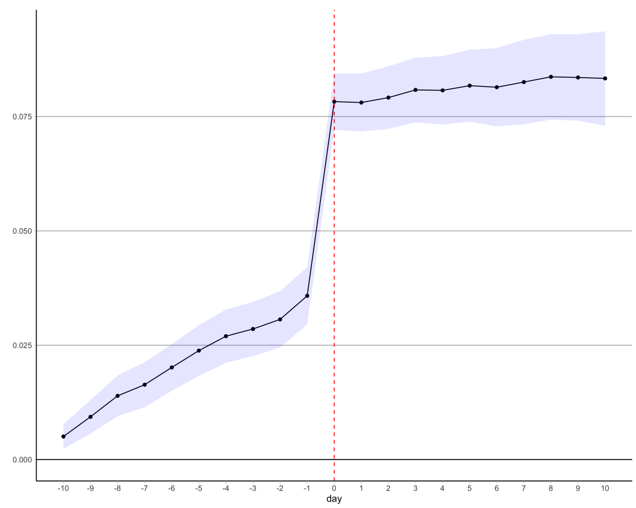
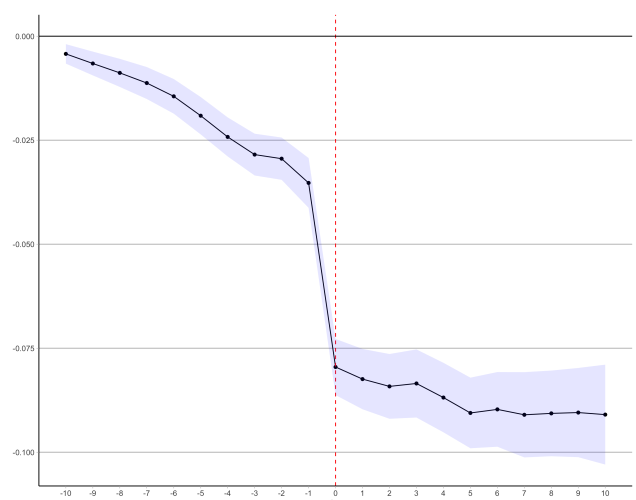


(a) CAR

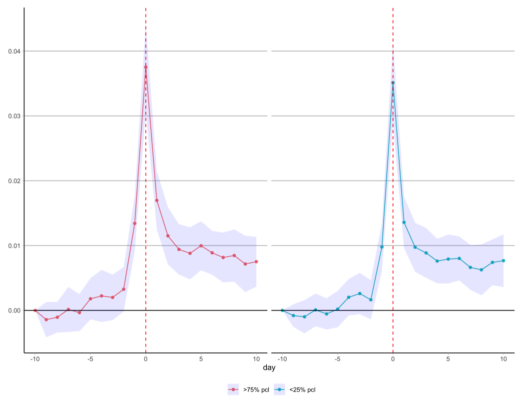


(b) CAR | $AR(0) > 75^{th} Pcl.$

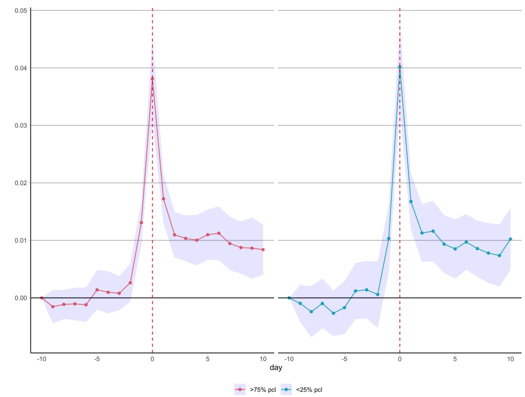


(c) CAR | $AR(0) < 25^{th} Pcl.$

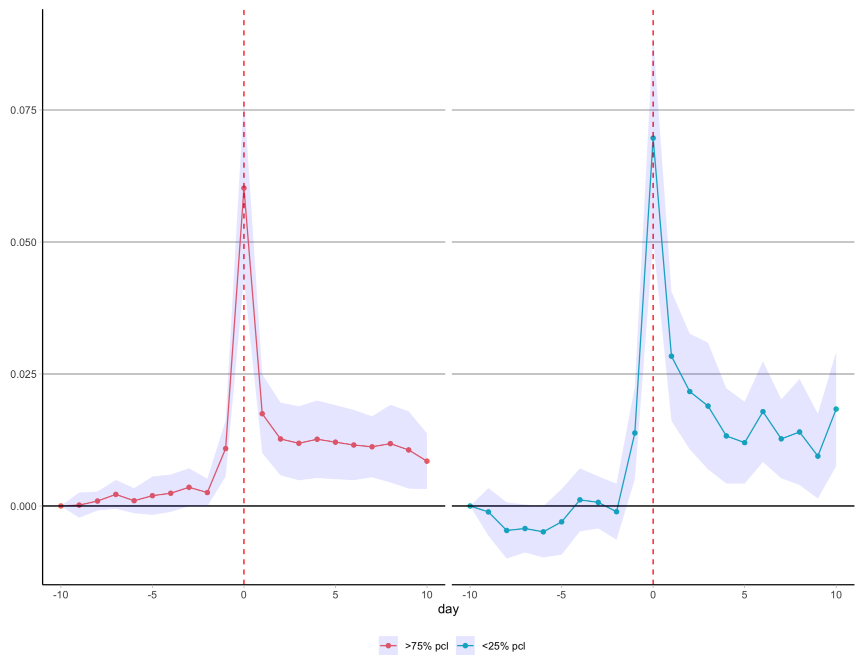
Figure 1: CAR Around Earnings Announcements Day(=0)



(a) StkDir_H

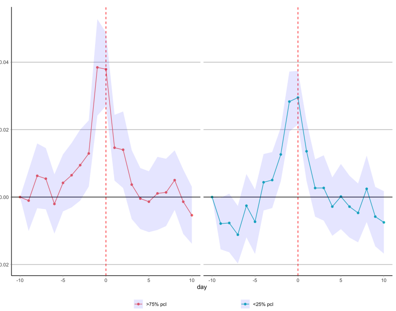


(b) StkDir_L

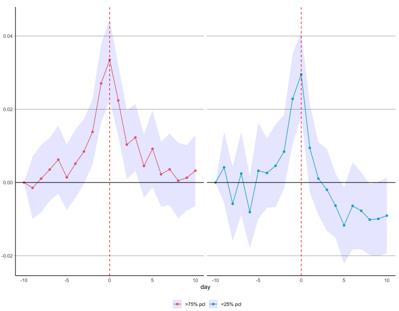


(c) StkLiq

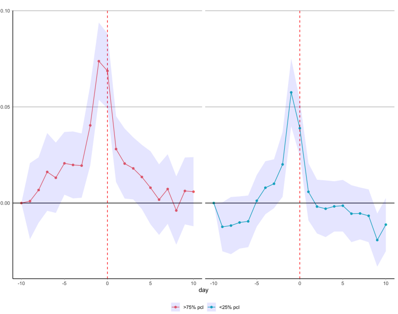
Figure 2: Abnormal Posterior Likelihood of Stock Trading (Relative to Day=-10) $(a) StkDiR_{High} \mid AR(0) > 75thPcl.(b) StkDiR_{Low} \mid AR(0) < 25thPcl.$



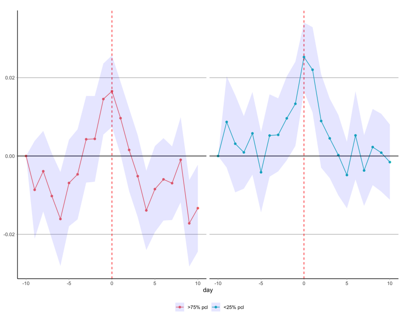
(a) $OptDir_H$



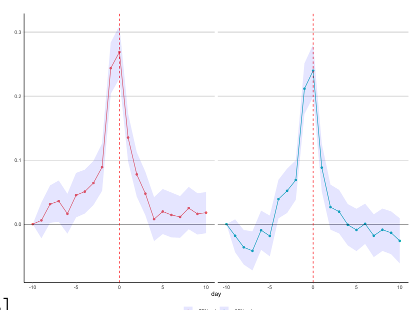
(b) $OptDir_L$



[$OptVol_H$]

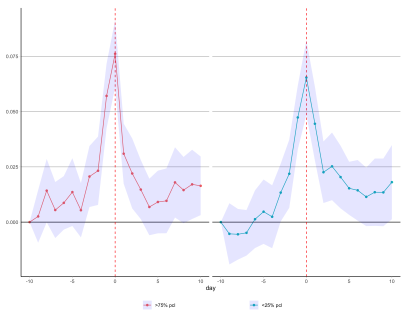


[(d) $OptVol_L$]

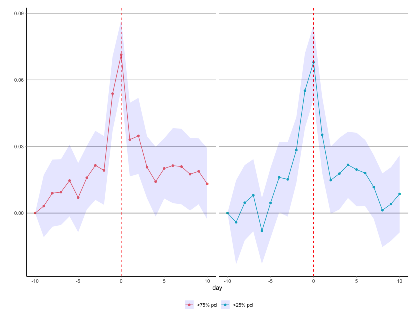


[(e) OptLiq]

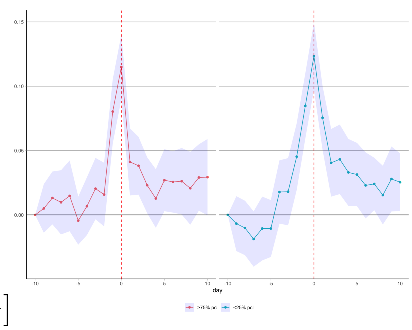
Figure 3: ATM Options
Posterior Likelihood of Abnormal (Relative to AR(-10)) Option Trading Around Earnings Announcements Day(=0)



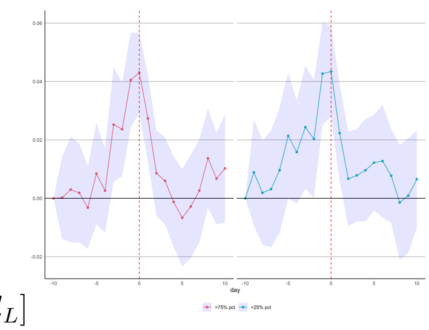
(a) $OptDir_H$



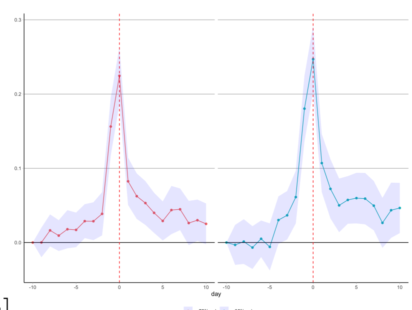
(b) $OptDir_L$



[$OptVol_H$]

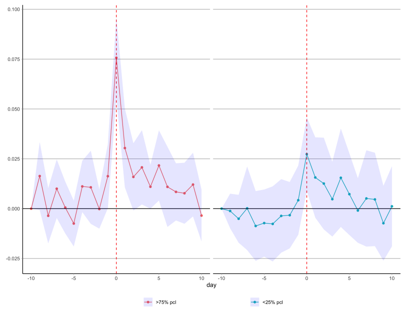


[(d) $OptVol_L$]

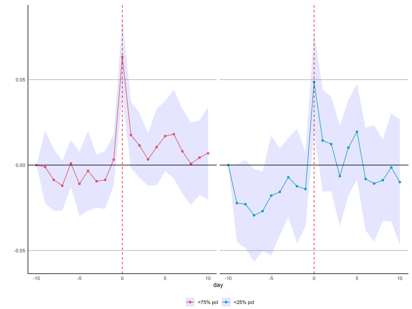


[(e) OptLiq]

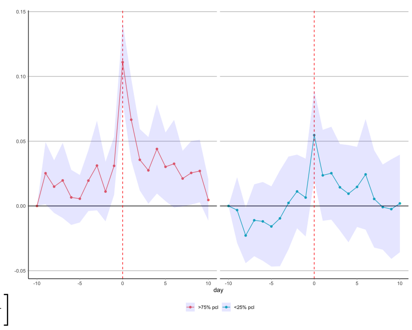
Figure 4: OTM Options
Posterior Likelihood of Abnormal (Relative to AR(-10)) Option Trading Around Earnings Announcements Day(=0)



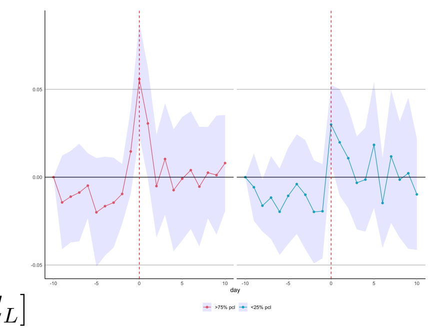
(a) $OptDir_H$



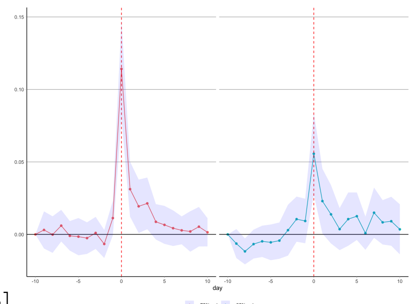
(b) $OptDir_L$



[$OptVol_H$]

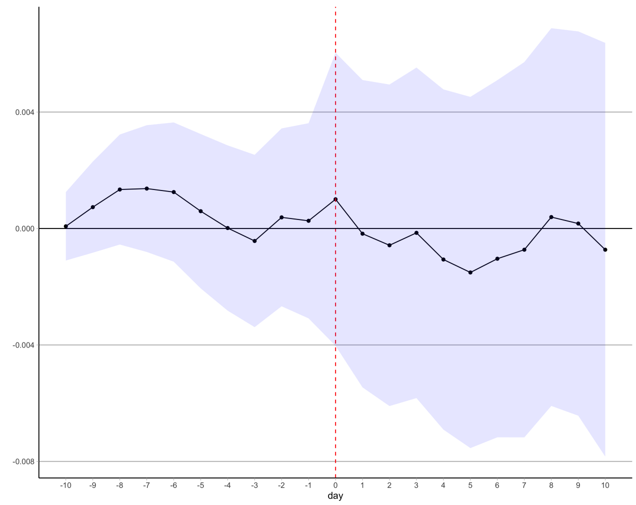


[(d) $OptVol_L$]

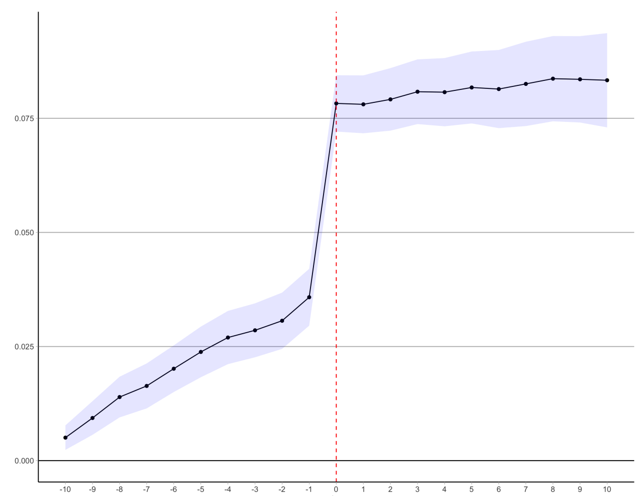


[(e) OptLiq]

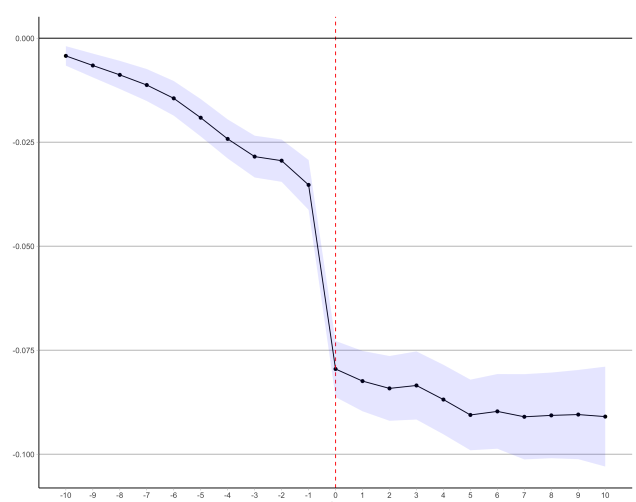
Figure 5: ITM Options
Posterior Likelihood of Abnormal (Relative to AR(-10)) Option Trading Around Earnings Announcements Day(=0)



(a) CAR

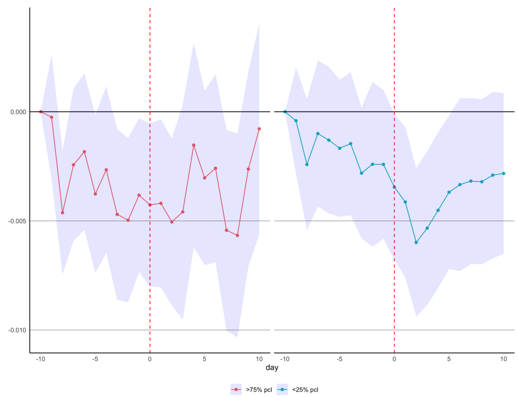


(b) CAR | $AR(0) > 75^{th} Pcl.$

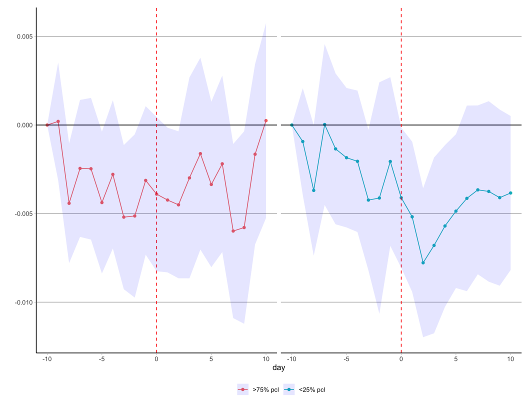


(c) CAR | $AR(0) < 25^{th} Pcl.$

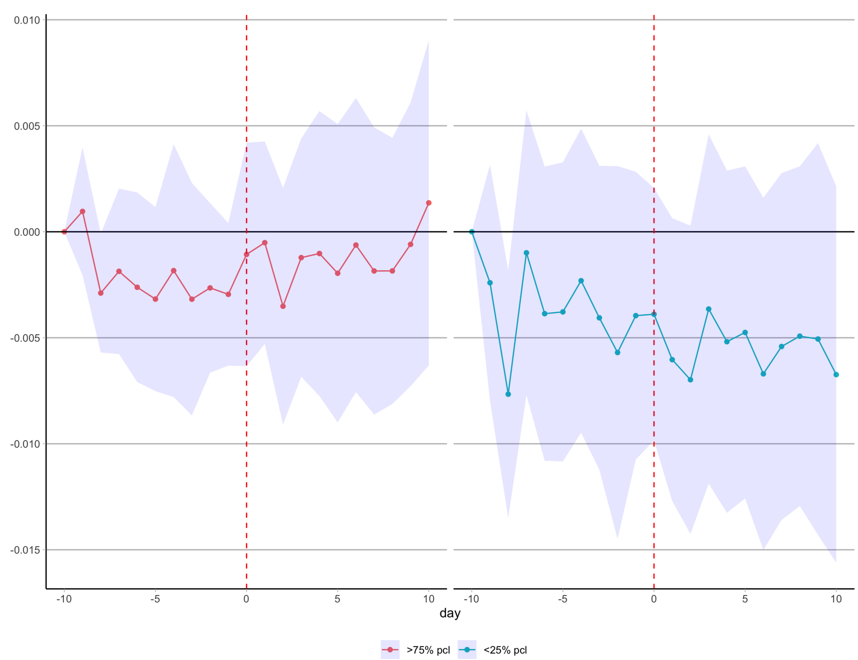
Figure 6: PLACEBO: CAR Around Earnings Announcements Day(+25) is event day 0



(a) StkDir_H

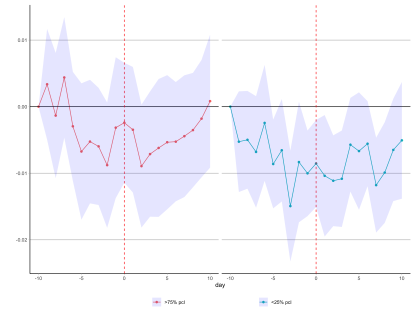


(b) StkDir_L

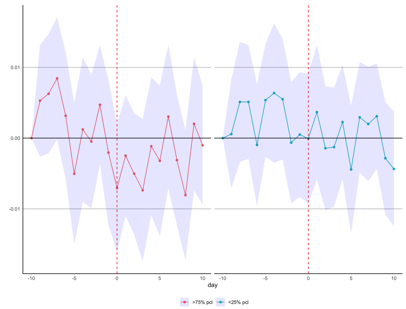


(c) StkLiq

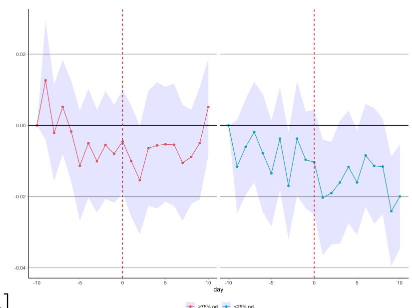
Figure 7: PLACEBO: Abnormal Likelihood of Stock Trading Around Earnings Announcements Day(=+15 to +35)Relative to Day=-10)



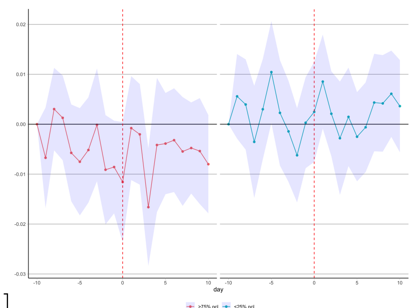
(a) $OptDir_H$



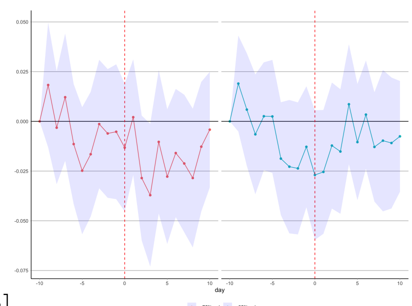
(b) $OptDir_L$



[$OptVol_H$]



[(d) $OptVol_L$]



[(e) OptLiq]

Figure 8: ATM Placebo
Likelihood of Abnormal (Relative to AR(-10)) Option Trading Around Earnings Announcements Day(=+15 to +35)