Hedging by Options Market Makers: Theory and Evidence

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ABSTRACT

Market makers for financial derivative securities use a variety of hedging strategies to manage their exposure to unfavorable market movements. In this study, we develop a model to analyze the effects of hedging activities by options market makers (OMMs) facing informed trading. The model suggests that the OMMs' hedging activities motivated by adverse-selection risk lead to wider spreads in both stock and options markets. The hedging effect on spreads is more pronounced in the options market than in the stock market. The effect is larger when the OMMs hedge with the underlying asset than when they do with other options. In addition, hedging activities by the OMMs significantly alter the trading strategies of informed traders. Empirical tests provide evidence consistent with the model in the time-series and cross-sectional contexts.

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Thirty years ago, Ho and Stoll (1983) developed a model of competing stock market makers facing fundamental risk associated with inventory carrying. In their model, stock market makers adjust their quotes in response to transactions in other stocks to hedge their inventories. For derivative securities, market making raises some issues that are absent in the markets for the underlying assets. Given the no-arbitrage relation between a derivative and its underlying asset, liquidity in the underlying asset market is implicitly linked to that in the derivative market. Therefore, trading costs in derivative securities, measured by the bid-ask spreads, must be determined in conjunction with factors in the underlying asset market. Such is the conclusion of the work by Cho and Engle (1999), Fontnouvelle, Fishe, and Harris (2003) and Kaul, Nimalendran, and Zhang (2004).

One aspect that so far has been largely ignored in the market microstructure literature is how market makers' trades for *hedging* purposes, rather than *market-making* purposes, affect the behavior of traders and trading costs. For example, trading by an options market maker (OMM) who hedges his option position, given that his business is to make a market for other traders rather than to speculate, may necessarily exert some impact on the spreads and trading volume in the assets used to hedge his original position. Alternatively put, because hedging requires trading, the cost incurred by an options market maker to carry out his hedging activities must be reflected on the bid-ask prices of the assets involved. Similarly, considering that options market makers often make markets for multiple options, their cumulative hedging activities may affect the spreads of the associated assets in a non-trivial way.

To analyze these issues, we develop a model of an options market maker facing traders with varying degrees of information. Some of them are better informed and use this advantage to trade in the stock and options markets. If the OMM chooses to hedge his position using the stock out of concern about *adverse-selection* risk (as opposed to *fundamental* risk), the hedging trades have impacts on the bid-ask spreads in both markets. This, in turn, affects the trading strategies of informed traders. Given the replication condition, it is not surprising that liquidity in the options market interacts with that in the underlying asset market. Perhaps, more surprising is that in his role of market making, the OMM who hedges against adverse-selection risk inadvertently acts as a conduit of private information.

The existing literature documents that the options market is an important trading venue for informed traders. Theoretical work by Biais and Hillion (1994), Easley, O'Hara, and Srinivas (1998), and John, Koticha, Narayanan, and Subrahmanyam (2003) suggest that the degree of informed trading in the options market depends on the relative liquidity in the options market vis-à-vis the liquidity in underlying asset market. Several empirical studies also examine the role of hedging activities by options market makers. For example, Kaul et al. (2004) argue that spreads in the stock market have an impact on the spreads of options written on a stock due to OMMs' hedging activities. Fontnouvelle et al. (2003) find that option deltas are related to the level of option spreads, suggesting that hedging costs play an important part in setting the bid-ask spreads.

Despite the evidence that OMMs' hedging activities affect the level of the spreads in both stock and options markets, to date there is no theoretical framework that explicitly models how and why this is the case. This paper attempts to fill this gap. Our model builds upon the sequential trading scheme developed by Easley et al. (1998) and John et al. (2003).[1] A common feature of these models is that informed and uninformed traders interact through risk-neutral competitive market makers. What distinguishes our model is that, due to the OMM's concerns over information-driven risk, the OMM actively engages in hedging his option positions that result from market making. We consider several alternative cases, such as when the OMM hedges using the stock, as well as when using other options written on the same stock. Our model can be extended to other cases, such as when hedging is carried out with options in different assets. In any case, the OMM calculates the hedge ratio depending on his perception of the expected stock and options payoffs, upon observing the order flows. In equilibrium, market making competition drives the OMM to have zero expected profit.

The results of our study show that hedging by the OMM conveys information. First, we present the effects of the OMM's hedging activities using the stock when only one type of call option is available for trading in the options market. Whenever the OMM perceives potential information asymmetry from observing the order flow, he chooses to hedge his option position. This causes him additional transaction costs that must be recovered in the form of wider option spreads. At the same time, his hedging activities form an unintended channel of information asymmetry in the stock market. That is, the possibility of more informed trading originated by the OMM leads the stock market maker (SMM) to widen the stock spread. This in turn makes the OMM raise further the spread in the options market. In sum, the OMM's adverse-selection concern and his subsequent hedging activities are important drivers of the spreads in

[1] Several researchers have studied the issue of options market making with a sequential trading approach. For example, Biais and Hillion (1994) analyze the pricing of state contingent claims in options and stock markets, showing that options mitigate the market breakdown problem created by the combination of market incompleteness and asymmetric information; Easley, O'Hara, and Srinivas (1998) develop and test a model for the informational role played by signed option volume in predicting future stock prices; and John, Koticha, Narayanan, and Subrahmanyam (2003) analyze the impact of option trading and margin rules on the behavior of informed traders and the microstructure of stock and options markets.

both markets.

Second, we show how the mechanics of the OMM's hedging activities change if another call option (with a different strike price) is introduced. In general, the spread of the underlying stock narrows when several options co-exist. Also, with multiple options available, the spread for each option narrows. This is because information intensity is alleviated when informed traders have more trading alternatives, which in turn reduces the information content from the OMM's hedging activities. Furthermore, because options have a convex payoff structure, the hedge ratio drops when several options are available. These factors reduce the hedging costs of the OMM, which results in narrower option spreads, although the effect is not so strong as to offset the overall effect of the OMM's hedging activities. Interestingly, when each of the two different OMMs hedges his/her option position using the other option, the spread in the stock market is further reduced. However, the net effect of their hedging activities on the options spreads is complex and ambiguous.

Third, we provide empirical evidence on the impact of the OMMs' hedging activities. Following Roll, Schwartz, and Subrahmanyam (2010), we first calculate daily mean values across all call options available for option-related variables. We then compute the delta-hedging and rebalancing costs as proxies for hedging activities by the OMMs. To identify the specific role of information asymmetry in the OMMs' hedging activities, we employ the probability of informed trading (PIN) and its instrumental variables, such as price impact and institutional ownership, to construct the interaction terms. The data coverage is broad and long, spanning the 3,523 trading days from January 4, 1996 to December 31, 2009 for more than 980 NYSE/AMEX-listed stocks that have positive daily call volume. Consistent with our model, the test results strongly support the hypothesis that stock-based hedging activities by the OMMs lead to higher call option spreads in the time-series and cross-sectional contexts, even after controlling for liquidity trading and other firm characteristics. In particular, the wider call spreads are closely associated with their hedging activities motivated by informational risk, in addition to other considerations such as fundamental risk.

When there are multiple trading venues for traders, arbitrageurs act so that intermarket mispricing anomalies disappear. Interestingly, however, Kumar and Seppi (1994) show that while arbitrage would ultimately draw a futures market and its underlying asset market together, its immediate impact is to increase illiquidity in both markets, a result similar to ours. Our model looks into the issues in two related markets (options and stocks) in the presence of asymmetric information, but in a sense our study is also related to the literature on market fragmentation.[2] Thus, our model can be easily extended to an economy with multiple assets and imperfectly integrated markets.

The paper is organized as follows. Section I presents the basic model. Section II discusses the benchmark case, when an options market maker does not hedge his option position. In Section III, the model considers the OMM's hedging activities using the underlying asset. Section IV examines the detailed impacts of the OMM's hedging activities, comparing them to the non-hedging case. Section V extends the model by introducing another call option, with the OMM still hedging his positions using the underlying asset. In Section VI, we provide empirical evidence. Section VII concludes.

I. The Theoretical Framework

Consider an economy with two financial markets: an options market, where a European call option is traded, and a stock market, where the underlying asset of the call option is traded. The state of nature is denoted by θ, where $\theta \in \{H, L\}$ with an equal probability (1/2). H and L mean 'high' and 'low'. We denote the true value of the underlying asset by $\widetilde{v}$, where $\widetilde{v} \in \{v_H, v_L\}$, with $\widetilde{v}$ taking one of two values, depending on the states of nature. The exercise price of the call option is denoted by K, with $K \in [v_L, v_H]$. We assume there are two types of traders: informed and uninformed. Informed traders account for $\alpha\%$ of the trading population and the remaining $(1-\alpha)\%$ are uninformed traders. Uninformed traders trade in both stock and options markets for exogenous reasons, such as portfolio rebalancing and hedging. Specifically, $\beta\%$ of uninformed traders trade stocks while $(1-\beta)\%$ of them trade options. In our model, the presence of uninformed traders allows informed traders to camouflage their trading and also avoids the no-trade equilibrium described in Milgrom and Stokey (1982).

Informed traders privately observe an identical signal about the final value of the underlying asset. They randomize their trades in either the stock or the option to exploit their information advantage. The signal they receive is denoted by sig [$sig = G$ or B, where G (B) indicates a 'good' ('bad') signal]. The precision of the signal is measured by μ, a probability that the signal is accurate as to the state. That is, $Pr(sig = G|\theta = H) = Pr(sig = B|\theta = L) = \mu$ and $Pr(sig = B|\theta = H) = Pr(sig = G|\theta = L) = 1 - \mu$. For the signal to be informative, we assume that $0.5 < \mu < 1$. We also assume that μ is common knowledge.

[2] See, for example, Pagano (1989) for a model without information asymmetry, and Chowdhry and Nanda (1991) for a model with information asymmetry.

There is a representative, competitive market maker in the underlying market for the stock (the stock market maker, SMM) and a representative, competitive market maker in the options market (the options market maker, OMM). Market makers set prices rationally. Each market maker does not know, ex ante, the realized value of the underlying asset, but updates his beliefs according to the Bayes' rule. Market makers are risk neutral as in Easley, O'Hara, and Srinivas (1998), and John, Koticha, Narayanan, and Subrahmanyam (2003).[3] The risk-free discount rate is assumed to be zero.

There are five time points: $t = 0, 1, 2, 3$, and 4. At $t = 0$, informed traders observe a private signal. At $t = 1$, informed traders submit orders based on the signal they observe at $t = 0$. If the signal is good, an informed trader submits an order to buy either one share of the stock with probability ν, or one unit of a call option written on the stock with probability $(1 - \nu)$.[4] If the signal is bad, the informed trader submits an order to sell either one share of the stock with probability ω, or one unit of the call option with probability $(1 - \omega)$. Both ν and ω are endogenous and determined by the equilibrium conditions. At $t = 1$ uninformed traders also submit orders to buy or sell: the stock with an equal probability of $\beta/2$; and the call option with an equal probability of $(1 - \beta)/2$. Informed and uninformed traders can submit orders only once at $t = 1$.

Since the OMM and the SMM can observe order flows in the markets, the market makers collect information on the order imbalances. With this information, the OMM estimates what position in the call option he will end up with on his own account for market making purposes, and at the same time he updates his prior belief as to whether the option position comes from an informed or uninformed trader. At $t = 2$, the OMM may choose to submit an order in the stock market to hedge his option position.[5] At $t = 3$, the OMM and the SMM set bid and

[3]The risk-neutrality assumption for market makers is necessary to examine the effect of hedging against *informational* risk in trading, rather than that against more general *fundamental* risk of the inventories that marker makers incur from market-making activities. To distinguish between the two, the former risk is related to the fact that a trader (informed trader) does know, ex ante, the direction of price changes, while her counterparty (market maker) does not. Hedging against the latter risk involves transactions where neither party knows the direction of price or value changes in the assets. In our model, potential losses from informed trading is the primary concern of the market makers.

[4]With a certain amount of resources that can buy *one* share of the stock, the informed trader could, of course, buy *multiple* units of the call option. Without loss of generality, however, we assume throughout that the trader can buy *one* unit of the call option, which in turn carries the right to buy *one* share (not 100 shares) of the stock.

[5]For practical purposes, many books on options market making are available. See, for example, Baird (1992), Taleb (1997), and Bittman (2009). Especially, on pp. 280-298 Bittman (2009) nicely presents how an options market maker sets bid-ask prices and hedges his option positions using shares of the stock. However, it does not appear that stock market makers often hedge their stock positions using options. Instead, stock market makers tend to control risk by mean-reverting their inventory positions toward a target level [e.g., see Hansch, Naik, and Viswanathan (1998), Reiss and Werner (1998), and Naik and Yadav (2003)]. So, in our model, we do not consider the possibility that the SMM hedges his stock inventory position with options contracts.

ask quotes so that each of the two markets clears. Competition among market makers requires that, in equilibrium, each market maker makes zero expected profit from their market making activities. The OMM and the SMM observe the order flows in both markets before setting prices, as in Easley *et al.* (1998), which rules out the possibility of arbitrage across markets. The market clearing prices are regret-free quotes conditional on the order flows the market makers observe. Finally, at $t = 4$ the signal is publicly observed, and the call option expires.

Figure 1 exhibits the information and trading structure of the model. The probabilities of informed and uninformed trading in both markets are shown to the left of the vertical dashed line. This part of the figure corresponds to a scenario where the OMM does not hedge.

II. When the OMM Does Not Hedge: the Benchmark Case

As a benchmark case, we first derive the bid and ask prices in the stock and options markets when the OMM does not hedge his option position. In later sections, we consider the cases when the OMM hedges.

A. Bid and Ask Prices of the Stock

The zero expected profit of the market maker in the stock implies that the bid and ask quotes are the expected values of the asset, conditional on the order flow observed by the SMM. Denote S_a^* (S_b^*) as the ask (bid) price of the stock when the OMM does not hedge.[6] We have $S_b^* = E[\widetilde{v}|\text{Sell Stock}]$ and $S_a^* = E[\widetilde{v}|\text{Buy Stock}]$, where 'Buy Stock' means that traders (non-market makers) buy the stock. Using the Bayes' rule, we can show that the bid and ask prices of the stock are:[7]

$$S_b^* = \frac{v_H[\alpha(1-\mu)\omega + (1-\alpha)\beta\frac{1}{2}] + v_L[\alpha\mu\omega + (1-\alpha)\beta\frac{1}{2}]}{\alpha\omega + (1-\alpha)\beta}. \tag{1}$$

$$S_a^* = \frac{v_H[\alpha\mu\nu + (1-\alpha)\beta\frac{1}{2}] + v_L[\alpha(1-\mu)\nu + (1-\alpha)\beta\frac{1}{2}]}{\alpha\nu + (1-\alpha)\beta}. \tag{2}$$

[6] We use an asterisk (*) to denote the results for the benchmark case.

[7] Some of the statistical derivations and propositions are explained or proved in the Appendix. To save space, most of them are not reported in the text. Full derivations for the equations are available from the authors upon request.

B. Bid and Ask Prices of the Call Option

The zero expected profit of the market maker in the option implies that the bid and ask prices are the option's expected payoffs, conditional on the order flow observed by the OMM. Denote C_a^* (C_b^*) as the ask (bid) price of the call option and K as the exercise price of the option. Then, $C_b^* = E[(\widetilde{v} - K)^+|\text{Sell Call}]$ and $C_a^* = E[(\widetilde{v} - K)^+|\text{Buy Call}]$, where $(\widetilde{v} - K)^+$ indicates $max\{(\widetilde{v} - K), 0\}$. Similarly to the case for the stock, the Bayes' rule gives the bid and ask prices of the call option:

$$C_b^* = (v_H - K)\frac{\alpha(1-\mu)(1-\omega) + (1-\alpha)(1-\beta)\frac{1}{2}}{\alpha(1-\omega) + (1-\alpha)(1-\beta)}. \tag{3}$$

$$C_a^* = (v_H - K)\frac{\alpha\mu(1-\nu) + (1-\alpha)(1-\beta)\frac{1}{2}}{\alpha(1-\nu) + (1-\alpha)(1-\beta)}. \tag{4}$$

C. Informed Trading

Informed traders choose whether to trade the stock, the option, or both assets. If they trade in one particular market, they risk being spotted by the market maker in that market, who will adjust the spreads accordingly. Therefore, in equilibrium, informed traders prefer to use a mixed strategy by randomizing their trades in both markets, while the strategy of concentrating the trades in either of the markets is also feasible.

Given the ask and bid prices of the stock and the option, informed traders' expected profit ($E^*[\pi^{\text{Informed}}|sig = G \text{ or } B]$) from trading the stock alone or the call option alone is given by:

$$\begin{aligned} E^*[\pi^{\text{Informed}}|sig &= G] \\ &= \begin{cases} E^*[\pi^{\text{Informed}}_{Stock\ Market}|sig = G] & \\ \quad = E[\widetilde{v}|sig = G] - S_a^* & : \text{ if buying a stock} \\ E^*[\pi^{\text{Informed}}_{Options\ Market}|sig = G] & \\ \quad = E[(\widetilde{v} - K)^+|sig = G] - C_a^* & : \text{ if buying a call} \end{cases} \end{aligned} \tag{5}$$

and

$$E^*[\pi^{\text{Informed}}|sig = B] = \begin{cases} E^*[\pi^{\text{Informed}}_{Stock\ Market}|sig = B] = S_b^* - E[\widetilde{v}|sig = B] & : \text{ if selling a stock} \\ E^*[\pi^{\text{Informed}}_{Options\ Market}|sig = B] = C_b^* - E[(\widetilde{v} - K)^+|sig = B] & : \text{ if selling a call} \end{cases}, \quad (6)$$

Informed traders must be indifferent between the two single-market strategies. Therefore, we have:

$$E[\widetilde{v}|sig = G] - S_a^* = E[(\widetilde{v} - K)^+|sig = G] - C_a^* \quad (7)$$

$$\underbrace{S_b^* - E[\widetilde{v}|sig = B]}_{\text{Trading the Stock}} = \underbrace{C_b^* - E[(\widetilde{v} - K)^+|sig = B]}_{\text{Trading the Call Option}} \quad (8)$$

Let ν^* be the equilibrium probability that informed traders submit orders in the stock market, conditional on receiving a good signal (G), and ω^* be the equilibrium probability, conditional on receiving a bad signal (B). Expanding the conditional expectation operator using the Bayes' rule, and plugging Eqs. (1)-(4) into the above indifference condition, we can show that the equilibrium probabilities are given by:

$$\nu^* = \omega^* = \frac{\beta[\alpha(v_H - v_L) + (1 - \alpha)(1 - \beta)(K - v_L)]}{\alpha[v_H - K + \beta(K - v_L)]}. \quad (9)$$

III. When the OMM Hedges Using the Underlying Asset

Next we consider the case when the OMM hedges the option position incurred from his market-making activities. What distinguishes our model from other models such as those of Easley, O'Hara, and Srinivas (1998) and John, Koticha, Narayanan, and Subrahmanyam (2003) is that the OMM engages in hedging his option position against potential adverse-selection risk that he may face in market making. From the perspective of the SMM, stock orders can thus come from informed traders, uninformed traders, or the OMM. At t=3, the SMM sets market clearing prices in the stock market conditional on the order flow information. In Figure 1, the OMM's hedging activities are shown on the right-hand side of the vertical line. For now we assume that only one type of call option written on the stock is available in the options market. Later, we also consider the case of multiple options.

A. Bid and Ask Prices of the Stock and the Option

First, we derive the bid and ask prices of the stock when the OMM hedges. The bid price, S_b, and the ask price, S_a, are the expected values of the stock, conditional on the stock order flow observed by the SMM. That is, $S_b = E[\widetilde{v}|\text{Sell Stock}]$ and $S_a = E[\widetilde{v}|\text{Buy Stock}]$. Given the two possible states (H and L), we can expand the conditional expectations as follows:

$$S_b = E[\widetilde{v}|\text{Sell Stock}] = v_H Pr(\theta = H|\text{Sell Stock}) + v_L Pr(\theta = L|\text{Sell Stock}). \quad (10)$$

$$S_a = E[\widetilde{v}|\text{Buy Stock}] = v_H Pr(\theta = H|\text{Buy Stock}) + v_L Pr(\theta = L|\text{Buy Stock}). \quad (11)$$

Note from Eqs. (10) and (11) that hedging by the OMM affects the conditional probabilities, and hence the bid and ask prices of the stock. Proposition 1 below summarizes the bid and ask prices of the stock when the OMM hedges his call option position using the underlying asset.

Proposition 1. *When the options market maker (OMM) hedges his option trades using the underlying asset (i.e., the stock), the bid and ask prices of the stock are given by:*

$$S_b = \frac{v_H[\alpha(1-\mu)\omega + (1-\alpha)\beta\frac{1}{2}] + v_L[\alpha\mu + (1-\alpha)\frac{1}{2}]}{\alpha\mu + \alpha(1-\mu)\omega + (1-\alpha)(1+\beta)\frac{1}{2}}. \quad (12)$$

$$S_a = \frac{v_H[\alpha\mu + (1-\alpha)\frac{1}{2}] + v_L[\alpha(1-\mu)\nu + (1-\alpha)\beta\frac{1}{2}]}{\alpha\mu + \alpha(1-\mu)\nu + (1-\alpha)(1+\beta)\frac{1}{2}}. \quad (13)$$

Proof of Proposition 1: See the Appendix.

Informed traders maximize their total expected profit in both markets by choosing probabilities ν and ω of where to trade their signals. The maximization problem can be expressed as:

$$\max_{\nu,\omega}\{E[\pi^{\text{Informed}}|sig = G] + E[\pi^{\text{Informed}}|sig = B]\}. \quad (14)$$

Informed traders exploit their information advantage by randomizing their trades in the stock and/or options markets. In equilibrium they must be indifferent between the two single-market trading strategies. The indifference condition is given by expressions similar to Eq. (7) and Eq. (8). Substituting Eq. (12) and Eq. (13) into the equivalents of Eq. (7) and Eq. (8) leads to the bid and ask prices for the call option.

Proposition 2. *When the options market maker (OMM) hedges his option trades using the* *underlying asset, the bid price, C_b, and the ask price, C_a, of the call option are given by:*

$$C_b = S_b - v_L\mu - K(1-\mu). \tag{15}$$

$$C_a = S_a - K\mu - v_L(1-\mu). \tag{16}$$

Note from Eq. (15) and Eq. (16) that

$$(C_a - C_b) = (S_a - S_b) - (K - v_L)(2\mu - 1). \tag{17}$$

Since $\mu > 0.5$ and $K > v_L$, we have $(K - v_L)(2\mu - 1) > 0$. This indicates that the spread of the call option is positively related to the spread of the underlying asset.

B. Hedging Strategy of the OMM

The OMM may incur the option position from informed or uninformed traders. He sets the regret-free market clearing price at $t = 3$ before the true value of the underlying asset is revealed at $t = 4$. His observation of the options order flow at $t = 1$ provides some information, albeit noisy, which is not available to uninformed traders. Observing the order flow is useful in updating his prior in order to gauge possible information asymmetry and decide whether to hedge using the stock. Based on his inferences, the OMM estimates the delta-hedge ratio of the call option before submitting a hedging order at $t = 2$ as follows:

$$\Delta \equiv \frac{\partial C}{\partial S} = \frac{Pr(\text{Buy Call})E[(\widetilde{v} - K)^+|\text{Buy Call}] - Pr(\text{Sell Call})E[(\widetilde{v} - K)^+|\text{Sell Call}]}{Pr(\text{Buy Call})E[\widetilde{v}|\text{Buy Call}] - Pr(\text{Sell Call})E[\widetilde{v}|\text{Sell Call}]}, \tag{18}$$

where C and S are the prices of the call option and the stock, respectively.

Eq. (18) shows that the OMM estimates the payoffs of the stock and the call option by observing the order flow in the options market. He estimates the hedge ratio according to the amount by which the value of his option position changes, given a small, instantaneous change in the value of the stock. Expanding the conditional expectation function and applying Bayes' rule, we have the hedge ratio as follows:

$$\Delta = \frac{(v_H - K)[(2 - \nu - \omega)\mu - (1 - \omega)]}{(v_H - v_L)[(2 - \nu - \omega)\mu - 1] + v_H\omega - v_L\nu}. \tag{19}$$

Because of competition, the OMM earns a zero expected profit from making a market for the call option and trading the stock for hedging purposes. At $t = 3$, the OMM's profit/loss comes partly from making a market for the option as well as from his hedging activities in the stock market. Using Δ , S_a, S_b, C_b, and C_b defined above, we can express the profits from the two activities as:

$$E[\pi^{\text{OMM}}_{t=3,Options\ Market}] = -Pr(\text{Sell Call})C_b + Pr(\text{Buy Call})C_a \tag{20}$$

and

$$\begin{aligned} E[\pi^{\text{OMM}}_{t=3,Stock\ Market}] = & -Pr(\text{Buy Call})Pr(\theta = H|\text{Buy Call})S_a\Delta \\ & +Pr(\text{Sell Call})Pr(\theta = L|\text{Sell Call})S_b\Delta. \end{aligned} \tag{21}$$

At $t = 4$, when the signal is revealed and the option expires, the OMM's profit/loss comes from the value of the stock as well as from his option position. They are given by:

$$\begin{aligned} E[\pi^{\text{OMM}}_{t=4,Options\ Market}] = & -Pr(\text{Buy Call})E((\tilde{v} - K)^+|\text{Buy Call}) \\ & +Pr(\text{Sell Call})E((\tilde{v} - K)^+|\text{Sell Call}) \end{aligned} \tag{22}$$

and

$$E[\pi^{\text{OMM}}_{t=4,Stock\ Market}] = Pr(\text{Buy Call})E(\tilde{v}|\text{Buy Call})\Delta - Pr(\text{Sell Call})E(\tilde{v}|\text{Sell Call})\Delta. \tag{23}$$

Now, the condition for the OMM's expected profit (Π) implies that:[8]

$$\Pi = E[\pi^{\text{OMM}}_{t=3}] + E[\pi^{\text{OMM}}_{t=4}] = 0. \tag{24}$$

And the equilibrium is obtained by solving a system of equations described below:

i) Given the bid and ask prices of the stock and the call option, informed traders maximize their total expected profit by choosing the probabilities of trading in the stock market or in the options market. [see Eq. (14)]. Informed traders are indifferent between the two single-market strategies (trading the stock alone or the call option alone), conditional on receiving a signal ($sig = G$ or B) [the equivalents of Eq. (7) and Eq. (8)].

ii) Given the informed traders' strategy, the SMM and the OMM earn zero expected profits [see Eqs. (10), (11), and (24)].

[8] The competitive OMM has no incentive to experiment with quoted prices by widening the option spread as described by Leach and Madhavan (1993), since it is too costly for him to do that. Competition in options market making would drive the OMM who sets a wider spread out of the market.

IV. Comparative Statics: No Hedging vs. Hedging Using the Stock

When the OMM hedges his option trades resulting from making a market, it is not possible to obtain closed-form solutions to the problem, so we resort to numerical methods. We first compare the spreads in the stock and options markets when the OMM does not hedge versus the spreads when the OMM hedges with the underlying asset. We then show the effects of hedging on the trading strategy of the informed traders, and discuss how the spreads in the stock and options markets respond to changes in the exercise price of the call option (K), the fraction of informed traders (α), and the signal precision (μ). For our numerical computations, we use the parameter values and variable ranges shown in Table 1.[9]

A. Spreads in the Stock and Options Markets

Let's first look at how the spreads in the stock market [$(S_a - S_b)$ from Equations (12) and (13)] and in the options market [$(C_a - C_b)$ from Equation (17)] change when the OMM hedges using the underlying asset (stock), relative to the benchmark case when the OMM does not hedge [i.e., the benchmark spreads $(S_a^* - S_b^*)$ and $(C_a^* - C_b^*)$ computed in Section II]. The results are summarized in Figure 2. Figure 2 (A) exhibits how the level of the spread in the stock market changes in two different situations, as the signal precision (μ) increases. Figure 2 (B) does the same for the options market. As μ increases, the spreads in both markets tend to increase. Note that in both markets the absolute level of the spreads is *always* higher when the OMM hedges using the stock (dashed lines), regardless of the levels of μ.[10] This suggests that hedging by the OMM leads to higher transaction costs for traders in both markets. The effect of hedging is more pronounced in the options market than in the stock market, as seen in Figure 2.

Why do the spreads widen for the option and the stock when the OMM hedges? Trading the stock by the OMM for hedging purposes unintendedly conveys information. This information spillover occurs if the OMM hedges his option position using the stock. To see this, suppose that the OMM encounters a sell order, ending up taking a long position in the call option. The

[9] Given that $v_H = 50$, $v_L = 30$, and the probability that $\theta = H$ is 0.5, the unconditional expected value of the stock at $t = 4$ is 40. This implies that the call option with $K = 40$ will expire at the money (ATM) at $t = 4$.

[10] As seen in Figure 2, in this experiment the absolute level of stock spreads appears to be higher than what we would observe in real markets. Note, however, that the objective of our theoretical model is to illustrate our arguments qualitatively. Furthermore, option spreads of 100% or greater are not uncommon in the real world, especially for out-of-the-money options. According to Yahoo.com, for example, on October 3, 2011, the IBM \$205 October 2011 call option traded at (a daily closing price of) \$0.05, with its trading volume of one contract. Its daily closing ask and bid quotes were \$0.12 and \$0.04, respectively. This means that the proportional quoted spread of this IBM call option was 160% of its price!

OMM decides to hedge the long position given his estimation about the likelihood of trading being information-based.

On the one hand, if the OMM's inference is correct and the order indeed comes from an informed trader, the OMM's trade is in the same direction as that of an informed trader. That is, it turns out that the OMM sells the stock as an informed trader trading on private information in the stock market would do. While this trade allows the OMM to hedge the position against adverse selection from traders in the options market, it adds to informed trading in the stock market. The hedging trade also causes the OMM additional (round-trip) transaction costs in the stock market, which must be compensated by raising the spread in the options market.

On the other hand, if the sell order for the call option comes from an uninformed trader, the OMM unnecessarily hedges the long position in the call option, but nonetheless he faces additional transaction costs in the stock market. The additional transaction costs stems from the fact that the OMM's inference (from observing the order flows) about possible adverse selection in market making is not always correct. This means the OMM has to further adjust the spread upward in the options market to recoup the costs. Overall, the OMM's hedging, motivated by information-asymmetry concerns, results in wider spreads in the options market.

Consider next the effect of hedging by the OMM on the spread in the stock market. Although the OMM's inference from observing the order flows is not perfect, it is useful more often than not. Therefore, when the OMM chooses to hedge his option position by trading in the stock market, the likelihood that the resulting additional order flows in the stock market contain private information increases. The SMM perceives this risk and reacts by setting a wider spread in the stock market.

To summarize, potential information asymmetry leads the OMM to hedge the option position and his hedging activities using the stock consequently induce wider spreads in both markets, with a greater effect in the options market. This adversely affects the welfare of traders in the securities markets.

B. Where do Informed Traders Trade?

We have shown in Section II that when the OMM does not hedge, the probability that informed traders trade in the stock market upon receiving a bad signal (B), ω, and the probability that they trade in the stock market upon receiving a good signal (G), ν are equal [see Eq. (9)]. How does the trading intensity of informed traders change when the OMM hedges his option position?

We first examine where informed traders prefer to trade when the OMM does not hedge. In Panel A of Table 2, ω and ν are computed for different values of the exercise price of the call option (K) and the fraction of informed traders (α), as the signal precision (μ) increases. For a given value of K and α, we see that the probabilities ω and ν are the same regardless of the levels of μ. Note that $(1-\omega)$ and $(1-\nu)$ are less than 0.5. This suggests that, in general, informed traders prefer to trade in the stock market rather than in the options market. This is because the stock is more "information sensitive" than the option.[11] Contrary to the work in Danielsen and Sorescu (2001) and Ofek, Richardson, and Whitelaw (2004), our model does not impose short-selling constraints on stock trading, which allows informed traders to trade on information easily in the stock market. Interestingly, as the proportion of informed trading increases (with higher α), the probability that informed traders trade in the options market increases. The reason is that it is harder for informed traders to camouflage their trades in the stock market and, furthermore, the options can provide leverage.

When the OMM hedges using the stock, however, ω and ν take different values most of the time, as seen in Panel B of Table 2. That is, informed traders react differently to different signals. In particular, when the signal is bad, informed traders trade only in the stock market. The reason for this single-market strategy in this case is that trading (i.e., selling) the call option is not likely to be profitable. With a bad signal, informed traders' expected profits are determined by the level of the bid price of the call option set by the OMM. Without the OMM's hedging, the bid price is high enough, making it profitable to trade the option at the bid price. However, the OMM's hedging makes the call option spread significantly wider (see Section IV.A), which in turn causes the bid price down to the point where selling the option does not guarantee any profit for informed traders.

When the signal is good, informed traders trade more often in the stock market, and more so as the signal precision (μ) increases. Moreover, when the OMM hedges using the stock, the values of ω and ν tend to be higher than those in Panel A, except for some cases with lower α, indicating that more informed traders switch to the stock market in response to the OMM's hedging activities. The reason for this is related to the fact that the effect of the OMM's hedging on spreads is much higher in the options market, as we have shown before. In contrast to the results in Panel A, as the fraction of informed traders (α) increases, informed traders trade more often in the stock market when they receive a good signal. As the exercise price of

[11] As in John et al. (2003), since the variability of the stock $(v_H - v_L)$ exceeds that of the option $(v_H - K)$, informed traders prefer trading the stock to trading the option.

the option rises, the value of ν also rises. This is reasonable, given that the call option is more likely to be out of the money.

Table 3 summarizes the effects of μ, α, and K on the trading intensity of informed traders in the stock market for the two different cases.

C. *Effects of α, K, and μ on Spreads in the Stock and Options Markets*

Tables 4 and 5 compare the effects of changes in the signal precision (μ), the percentage of informed traders (α), and the exercise price of the call option (K) on the spreads in the stock and options markets, when the OMM does not hedge (Panel A) and hedges (Panel B). The two tables show that when the OMM does not hedge, the spread in the stock market widens with μ, α, and K (Panel A in Table 4). The spread in the options market also widens with μ and α, but narrows with K (Panel A in Table 5). When the OMM hedges his option position, the spread in the stock market increases with μ and α, but decreases with K (Panel B in Table 4). The spread in the options market becomes wider with α, narrower with K, and have no consistent pattern with respect to μ (Panel B in Table 5).

C.1. Effects of an Increase in α

Tables 4 and 5 show that the spreads in the stock and in the option always widen when the proportion of informed traders (α) increases, whether the OMM hedges his option position or not. This result is straightforward. On top of this effect, when the OMM hedges using the stock, his hedging activities induce more informed trading in the stock market. Therefore, the SMM responds by setting wider spreads in the stock market to protect himself against possible losses, as seen in Panel B of Table 4.

C.2. Effects of an Increase in K

When the OMM does not hedge, an increase in the exercise price (K) makes the call option less information-sensitive, causing informed traders to migrate to the stock market. This increases the spread in the stock, and narrows the spread in the options market, as shown in Panel A of Tables 4 and 5. With the OMM's hedging activities, however, informed traders trade less often in the options market, as K increases (see Panel B of Table 2). That is, there are proportionally more uninformed traders in the options market, which reduces the likelihood of information asymmetry for the OMM. This, in turn, diminishes the hedging demand of the OMM. In equilibrium, therefore, the spread in the stock falls, too, as the exercise price of the call option increases. This helps to explain why the difference in the stock spread when the OMM hedges versus when he does not hedge narrows as K increases.[12]

As seen in Table 5, as K increases, the spread in the call options market narrows, whether the OMM hedges or not, because the call option becomes further out of the money. This result is consistent with the findings in Kaul et al. (2004). For deeply out-of-the-money calls (i.e., as K becomes high), the spreads in the two different cases (the OMM's hedging versus no hedging) tend to converge.

C.3. Effects of an Increase in μ

A higher level of μ means a more accurate signal, hence a greater risk for the stock market maker. The SMM, therefore, protects himself by setting wider stock spread, whether the OMM hedges his option position or not (see Table 4).

Panel A in Table 5 shows that the effect of μ on the option spread when the OMM does not hedge is similar to that on the stock spread. However, when the OMM hedges, the effect depends on the proportion of informed traders (α) in the market (see Panel B in Table 5). A more precise information signal for informed traders increases the expected loss to the OMM, and the OMM responds by widening the option spread. This makes the absolute level of the option spread in Panel B higher than that in Panel A. On the other hand, higher μ allows the OMM to protect himself from the potential loss from trading with the informed by hedging his position in the stock market. This gives the OMM some leeway to set the option spread at a narrower level. In addition, as we have shown in Section IV and Panel B of Table 2, informed traders tend to migrate to the stock market as μ increases, which also helps the OMM to reduce the spread. Overall, when the risk of informed trading is less severe (measured by low levels of α), the spread in the options market decreases as μ increases. But when the risk of informed trading is more significant (higher levels of α), the option spread widens with μ.

All the effects examined above are briefly summarized in the two tables. Given that the effect of μ on the option spread when the OMM hedges is not consistent, we summarize the effect in Table 6 for the three different cases of moneyness. Also, the effects of the three variables

[12] With $\alpha = 0.50$, for example, when $K = 35$ the difference between the two values (7.88 and 11.26) at the top of the corresponding two columns in Panels A and B of Table 4 is 3.38, but when $K = 45$ the difference (between 9.33 and 10.86) is 1.53.

(α, K, and μ) on the spreads in both markets for the non-hedging versus hedging cases are tabulated in Table 7. In both tables, the + (-) sign denotes a positive (negative) relation of a variable with the spreads.

D. Informed Traders' Expected Returns from Trading

For informed traders, the expected returns from trading the stock and the option (relative to the quote mid-point) can be expressed as follows:

$$\text{Stock Return} = \frac{E[\pi^{\text{Informed}}_{Stock\ Market}|sig = G] + E[\pi^{\text{Informed}}_{Stock\ Market}|sig = B]}{(S_a + S_b)/2} \tag{25}$$

$$\text{Option Return} = \frac{E[\pi^{\text{Informed}}_{Options\ Market}|sig = G] + E[\pi^{\text{Informed}}_{Options\ Market}|sig = B]}{(C_a + C_b)/2}, \tag{26}$$

where the bid/ask prices and the expected values are available in Section II (when the OMM does not hedge) and Section III (when the OMM hedges his option position using the stock).

Based on the above equations, the returns computed are reported in Table 8, where "*Stk*" and "*Call*" denote the expected returns from trading the stock and the call option, respectively. Note that three columns in each of the two panels have all zero returns from trading the option. This is because informed traders in these cases pursue a single-market strategy, trading only in the stock market.

Panel A shows the expected returns when the OMM does not hedge his option position. In this case, the expected returns from trading both the stock and the option increase as the signal becomes more accurate (except for the columns with zero returns). Yet, informed traders' expected returns fall most of the time as the proportion of informed traders (α) in the market increases, because the OMM and the SMM respond by widening the spreads in the markets. Note also that when the OMM does not hedge, the return on the option is generally higher than the return on the stock. This is consistent with Black's (1975) intuition that informed traders prefer to trade in the options market because of the leverage effect.

With higher levels of K [i.e., at-the-money ($K = 40$) or out-of-the-money ($K = 45$) cases] in Panel A, why do informed traders opt out of the call option market when the level of α is lower, but start to trade the option as the level of α becomes higher? This has to do with the relative information sensitivity of the stock, as noted earlier. When the stock (relative to the option) is not very information-sensitive, informed traders choose a mixed strategy, trading both the stock and the call option. However, when the information sensitivity of the stock exceeds a certain threshold, informed traders switch to a single-market strategy, trading the stock only. The threshold increases with α. Consequently, informed traders are likely to trade the option only if the level of α is high. In Panel A, therefore, we see zero returns from trading the option when the level of α is lower (e.g., $\alpha = 0.25$ when $K = 40$) but positive returns when the level of α is higher (e.g., $\alpha = 0.50$ or 0.75 when $K = 40$).

In Panel B, we report the expected returns when the OMM hedges. Compared to the non-hedging case, informed traders' expected returns are lower in general. This is because the OMM's hedging activities raise the spreads in both markets. Perhaps more striking, however, is that the expected return from trading the stock now tends to be higher than the return from trading the option. Recall how the intensity of informed trading (ν and ω) changes when the OMM hedges (Panel B of Table 2). If informed traders receive a bad signal, they always trade (sell) the stocks but never trade the call option (i.e., $\omega = 1$). This explains why informed traders' expected returns from trading the option are significantly lower when the OMM hedges, than when the OMM does not hedge. In other words, because the trading profit comes from buying the call option (when the signal is good) but not from selling the call (when the signal is bad), the overall return from trading the option is lower. As described above, when the OMM hedges his option position, his hedging activities drive the bid price of the call option down to the point where selling (writing) the option is no longer profitable for informed traders.

V. The Case with Multiple Options: OMM's Hedging with the Stock

So far we have assumed only one type of call option written on the stock. In reality, multiple types of options are written on the same stock. Here, we extend the model by introducing another type of call option written on the same stock but with a different exercise price (and the same expiration date). The OMM makes markets for both options, and hedges his option positions using the stock.[13]

[13] We have also considered that a monopolistic OMM hedges in the stock market, rather than a competitive OMM. We calculate the stock and option spreads and analyze how informed traders would adjust their trading strategy. In the monopolistic setting, the option spread is generally wider, but the stock spread is wider or narrower depending on the parameter values. Also, informed traders trade both the stock and the options at a relatively low level of the signal precision (μ). But as μ increases, they leave the options market and trade only in the stock market. Intuitively, the monopolistic setting reduces the incentive for informed traders to trade the options. Although the OMM has his discretion to set wider option spreads, in doing so he loses order flows. Overall, our findings in this setting remain similar to the case of competitive options market making.

Denote (the prices of) the two call options by C^1 and C^2, with exercise prices K^1 and K^2 ($K^1 < K^2$), respectively. At $t = 1$, informed traders can submit orders to trade either or both of C^1 and C^2. If they receive a good signal, they will buy C^1 with probability p or buy C^2 with probability $(1 - p)$; if they receive a bad signal, they will sell C^1 with probability q or sell C^2 with probability $(1 - q)$. Probabilities p and q are determined by the equilibrium condition. Uninformed traders trade C^1 or C^2 with equal probabilities for exogenous reasons. When the OMM perceives possible information asymmetry, he hedges his positions using the stock. In this case, we have the following proposition for the bid and ask prices of the stock:

Proposition 3. *When another type of call option (written on the same stock but with a different exercise price) is available and the OMM hedges his option positions using the stock, the bid and ask prices of the stock have functional forms similar to Eqs. (12) and (13), whatever the number of types available in the market.*

Introducing more options does not change the probability structure for the OMM's hedging activities. It provides informed traders with more trading choices, but the probability at each node of the information structure when the OMM hedges (his positions of C^1 and C^2 combined) remains the same, regardless of the number of available options. Consequently, the bid and ask prices of the stock have similar forms.

Informed traders trying to disguise their trades choose a mixed strategy of trading the stock, option C^1, or option C^2.They are indifferent between trading either the stock or the options. Once informed traders choose to trade in the options market, they are also indifferent between trading option C^1 or option C^2. This gives the conditions:

$$E[\pi^{\text{Informed}}_{Stock}] = E[\pi^{\text{Informed}}_{C^1}] + E[\pi^{\text{Informed}}_{C^2}]. \tag{27}$$

$$E[\pi^{\text{Informed}}_{C^1}] = E[\pi^{\text{Informed}}_{C^2}]. \tag{28}$$

Let $Spr(C^1)$ and $Spr(C^2)$ denote the spreads in trading the call options. Collectively, the conditions given by Equations (27) and (28) lead to the following proposition:

Proposition 4. *The bid-ask spreads of the two call options, C^1 and C^2, written on the same underlying asset but with different exercise prices (with the same expiration date) satisfy the relation:*

$$Spr(C^1) - Spr(C^2) = (K^2 - K^1)(2\mu - 1).$$

Proof of Proposition 4: See the Appendix.

Proposition 4 states that the difference in the spreads of the two call options (written on the same stock) with different exercise prices is proportional to the difference in the exercise prices times a term related to the signal precision. Since $\mu > 0.5$ and $K^1 < K^2$, we have $Spr(C^1) > Spr(C^2)$: i.e., the call option with a lower exercise price has a wider spread. The difference in the exercise prices, $(K^2 - K^1)$, serves as compensation for the OMM's expected loss from trading with informed traders in the market. Intuitively, a call option with a lower exercise price is more sensitive to private information, and hence more attractive to informed traders. This is consistent with the findings in Kaul et al.(2004), but appears to contradict Black's intuition that informed traders prefer out-of-the-money options (Black, 1975).

Figure 3 shows the equilibrium spreads for the stock and the call options when two options are available for trading. Here we use $K^1 = 35$ (in the money) and $K^2 = 40$ (at the money). Figure 3 (A) compares the stock spread when both options are traded versus the stock spread when only one of the two options is traded. Figure 3 (B) compares the at-the-money option spread when both options are traded versus the at-the-money option spread when the at-the-money option only is available for trading.

In Figure 3 (A), we observe that for any level of μ (signal precision) the stock spread narrows when the two call options are traded (solid line) compared to when only one of the two options is traded. As discussed before, the OMM trades the stock in the same direction as informed traders do, and contributes to increase the risk of information asymmetry in the stock market. Yet, our numerical results show that there is less information content in his hedging trades when two options are traded. This allows the SMM to narrow the spread in the stock market.

We find a similar pattern in Figure 3 (B). The spread of the at-the-money call option is narrower when both options are traded (solid line with squares) than when only one of them is available for trading. This is because of the convexity property of the options' payoffs. The OMM's hedging costs are related to the hedge ratio. Let's denote a call delta (hedge ratio) for each of the two options by Δ^1 and Δ^2. When the OMM hedges his option positions (incurred by market making for the two options) using the stock, his effective hedge ratio (weighted by the probability of hedging each position), $\Delta^{\text{effective}}$, can be computed by

$$\Delta^{\text{effective}} = \Delta^1 Pr(Net\ Long\ \Delta^1) + \Delta^2 Pr(Net\ Long\ \Delta^2),$$

where $Pr(Net\ Long\ \Delta^i)$ is the probability that the OMM holds a net long position of Δ^i share(s) in the stock. By comparing this effective hedge ratio ($\Delta^{\text{effective}}$) with the call option delta when only one type of call option is traded (C^1 or C^2), we find that $\Delta^{\text{effective}}$ is smaller than in any of the latter cases. This suggests that the OMM needs to hold a smaller position in the stock to hedge when both options are traded. The lower hedging costs to the OMM translate into narrower option spreads when the OMM engages in market making for the two options.

In sum, introducing the second call option contributes to reducing the trading costs in both markets. However, note in Figure 3 that the declining effect (of more options becoming available) in the spreads is relatively modest when compared to the increasing effect in the spreads (caused by the OMM's hedging activities when only one type of call option is available). On balance, the overall effect of hedging activities by the OMM using the stock is that the spreads in both markets become wider.

We can further extend the model. Suppose that there are two (competitive) options market makers, OMM1 and OMM2, one for each option. OMM1 plays a role of market making for call option C^1 and hedges his option position using the other call option, C^2 (rather than the *stock*). Similarly, OMM2 makes a market for option C^2 and hedges her option position using the other call option, C^1. To save space, we briefly summarize only the main results of this extension.[14] In this setting, informed traders optimally trade two options at the same time (a long position in one option and a short position in the other), instead of trading only one of the two options. The result shows that the stock spread drops further, compared to the previous case where two types of the call options are available and the stock is used for hedging. For the option spreads, however, the effects are more complicated. The spread of the in-the-money option narrows, while that of the other option tends to widen, leaving the net effect unclear. This suggests that the overall effect of hedging is likely to be wider spreads in the options market.

VI. Empirical Tests

When the OMM hedges due to his concern about potential adverse-selection risk, our model suggests that his hedging activities have several effects on the spreads in securities, as well as on the behavior of market participants. In the model, the OMM's hedging causes the SMM to set wider spreads in the stock market. The OMM also widens the option spreads to cover the additional hedging costs. As a result, hedging activities by the OMM increase trading costs in both markets, with the widening effect being greater on the option spreads than on the stock spreads. A growing body of empirical studies appear to support several implications of our

[14] A full description of the extention is available from the authors.

model [e.g., see Fontnouvelle et al. (2003) and Kaul et al. (2004)].

In this section, we conduct empirical tests to verify the predictions of our model. Practically speaking, the issues we have discussed are difficult to test because of data availability. Although a thorough empirical analysis is impossible, however, some of the implications described in Sections IV and V are testable.[15] Therefore, we attempt to test the key implication of our model: i.e., the activities of options market makers who hedge their option positions against possible informational risk using the underlying assets lead to wider call option spreads.

A. Data and Variable Construction

One problem is that transaction-level (intradaily) data that follow the hedging activities by each of the individual OMMs are not available to us. This precludes us from separating out the effect of hedging activities originated purely by OMMs from that of hedging by other non-market makers [e.g., liquidity trading by portfolio managers may involve hedging their option (or stock) positions using stocks (or options)]. As a compromise, we test indirectly using a daily-frequency database, OptionMetrics, which provides information on quoted prices, volume, implied volatility, the 'Greeks,' and other relevant variables for all options available each trading day. Although OptionMetrics does not provide direct information for our empirical study, we can use the data to calculate at least some important proxies for the initial delta-hedging cost as well as the rebalancing cost required by OMMs for their hedging activities on a daily basis.

Roll, Schwartz, and Subrahmanyam (2010) examine the relative trading activities in options and stocks after calculating daily mean values for option-related variables, such as spreads, implied volatility, delta, etc., across all options available each day. Computing daily mean values averaged across all call (or put) options is useful in the sense that it effectively allows us to observe important characteristics of a *representative* call (or put) option for each firm each day. Following Roll et. al. (2010), for each trading day we calculate the daily mean values of spreads, delta, vega, implied volatility, and quote midpoints (as option prices) across all call options written on each stock. For daily trading volume, we also add volume of contracts across all call options available each day.[16] We then obtain the proxies for the initial delta-hedging cost and the rebalancing cost faced by OMMs for a representative call option as follows.

[15] In a broader sense, some trading strategies such as bear and bull spreads, butterfly spreads, and calendar spreads can be considered as the case where one option position is hedged using another option, as briefly mentioned in Section V. In this case, however, it seems more difficult to test empirically, because of data availability.

[16] OptionMetrics does not provide daily closing option prices, so we use the mid-points of daily closing ask and bid quotes as option prices.

Assuming that an options market maker hedges his option position on a daily basis using the underlying asset, the initial delta-hedging cost (termed DHG_Cost) is computed by (C_Delta) x ($S\_\%QSPR$) x (S_PRC), where C_Delta is the daily mean call option delta averaged across call options, $S\_\%QSPR$ is the (daily close) proportional quoted spread (relative to the quote midpoint) of the stock, and S_PRC is the (daily close) price of the stock on which the call options are written.

According to Leland (1985) and Boyle and Vorst (1992), the rebalancing cost can be computed by $2[(C\_Vega) \text{ x } (S\_\%QSPR)]/\sqrt{2\pi(\delta t)}$, where C_Vega is the daily mean vega averaged across call options available, and δt is the rebalancing interval. As the information about the rebalancing interval is not available, we assume that it is the same for all call options. Then we can think of the rebalancing cost as a function of (C_Vega) x ($S\_\%QSPR$). Therefore, we compute the rebalancing cost (termed REB_Cost) by (C_Vega) x ($S\_\%QSPR$) as part of the total hedging costs faced by the options market makers. If the OMMs use static hedging (with no rebalancing for volatility changes), REB_Cost may be of secondary importance. As we do not have this information, we include this cost proxy in the regression analyses.

Other option-related variables used for empirical analyses are the daily mean implied volatility averaged across call options (C_IVOLA), the daily mean call price averaged across call options (C_PRC), and the daily aggregated volume of contracts across call options (C_VOL).

We then combine option-related variables with other firm-specific variables, which include the probability of informed trading (PIN) and firm size ($SIZE$). $SIZE$ is the natural logarithm of daily market capitalization (obtained from the CRSP database). A proxy for informed trading (PIN) is a key variable for our empirical tests. PIN is estimated each quarter following Yan and Zhang (2010) [for details, see the Appendix]. The estimation requires first signing each trade in the Trade and Quote (TAQ) database via the Lee and Ready (1991) algorithm, and then counting the numbers of daily buys and sells.[17] To survive in the PIN sample, stocks must be listed on the NYSE/AMEX and have at least 40 positive-volume days in each quarter over the sample period. For daily regressions, the quarterly PIN data are converted to a daily series by filling the trading days in each quarter with the corresponding quarterly PIN estimate.[18]

We use NYSE/AMEX-listed stocks only, because the NASDAQ has different trading protocols. For our empirical tests, the data coverage is comprehensive and long, spanning the 3,523 trading days from January 4, 1996 through December 31, 2009 (14 years) for more than 980

[17] For details about the algorithm, see Brennan, Huh, and Subrahmanyam (2011), for instance.

[18] This method is often used when a variable is available only at a lower frequency. See, for example, Chordia, Huh, and Subrahmanyam (2007) and Asparouhova, Bessembinder, and Kalcheva (2009).

NYSE/AMEX-listed companies that have non-zero volume call options each day.

B. Time-Series Regressions

To examine the effect of the OMMs' initial hedging or rebalancing activities on the option spread seems no easy task. If we use the initial delta-hedging cost or the rebalancing cost as a main explanatory variable representing the OMM's hedging activities, each variable may also pick up the effect of hedging against more general, *fundamental* risk. In our model, the OMMs' hedging is motivated by potential losses from informed trading in the market-making process. We thus face another difficult question: how can we separate out the specific effect of the OMMs' hedging against *informational* risk coming from market making? For this purpose, we will employ an interaction term for regression analyses as described below (to examine the interactions between hedging costs and informed trading), in the spirit of Rajan and Zingales (1998 and 2003).[19]

We first consider time-series regressions. For a given underlying asset on which the (representative) call option is written, we wish to see what happens to the spread of the call option when the hedging activities by the OMM change over time. For this purpose, we specify the regression equation for each firm as follows:

$$C\_QSPR_{jd} = a + \theta\Omega_{jd} + \phi(\Omega_{jd} \text{ x } PIN_{jd}) + \sum_{n=1}^{N} c_n X_{njd} + \epsilon_{jd}, \tag{29}$$

where C_QSPR_{jd} is the quoted spread of a (representative) call option for firm j on day d, Ω_{jd} is either the initial delta hedging cost (DHG_Cost_{jd}) or the rebalancing cost (REB_Cost_{jd}) as part of the total hedging costs, (Ω_{jd} x PIN_{jd}) is an interaction term (Ω multiplied by PIN), and a set of control variables, X_{njd} (n = 1, 2,..., 4), includes implied volatility (C_IVOLA), firm size ($SIZE$), call option price (C_PRC), and trading volume of the call option (C_VOL).

In Eq. (29), the probability of informed trading (PIN) used for the interaction term is critical to further narrow down the effect of interest. Given that the partial derivative of C_QSPR with regard to Ω is $(\theta + \phi PIN)$ in Eq. (29), θ captures the general effects of the OMM's hedging for various reasons. Since PIN allows us to investigate whether the relationship between C_QSPR and Ω is different when information asymmetry exists vs. when it dose not,

[19]Rajan and Zingales (1998) document the importance of financial development for economic development by examining the interactions between financial development and dependency on external finance (e.g., see Table 4). Rajan and Zingales (2003) investigate the determinants of financial development by looking at the interactions between per-capita industrialization and openness (e.g., see Table 7).

we hope that ϕ can capture the specific effect of the OMM's hedging for informational reason, after controlling for liquidity trading and other firm characteristics. PIN is measured with stock trading data, because the corresponding measure for the call options requires intradaily trading data, which are not available. In the model, however, informed traders choose to trade on private information in both stock and options markets. Therefore, although PIN is estimated using stock transaction data, it is relevant to the options market as well.

We use four control variables. One is C_IVOLA, because some researchers (e.g., Roll et. al., 2010) suggest that higher implied volatility attracts more traders, which may affect the trading costs in the options market. $SIZE$ is often used to control for the firm-specific size effect (e.g., Battalio et. al., 2004). It is common in empirical studies to control for the price (C_PRC), because option spreads are likely to depend on its price levels. Call volume, C_VOL, is used to account for the effect of non-information-based trading in the call options market. Presumably, this variable may help control for liquidity trading initiated by non-OMMs who engage in hedging activities.

One implicit assumption in the above regression specification is that after controlling for non-information-based liquidity trading in the options market, the majority of hedging activities on a daily basis are originated by options market makers. To the extent that the hedging demand comes from sources other than OMMs, our empirical results should be interpreted with caution. Bittman (2009) suggests, however, that options market makers are major players in hedging activities [see Chapter 9 of Bittman (2009)].

For the time-series regressions, we select sample firms as follows. First, the aggregated volume across all call options for a firm each day should be positive for more than 2,000 trading days out of the total 3,523 trading days in our sample period (January 4, 1996 to December 31, 2009). Second, 15 types or more of calls on average should have positive volume each day. Third, PIN and other key variables should also be available for a reasonably long period. Based on the above criteria, 101 NYSE/AMEX-listed firms have been identified as shown in Table 9. The table shows that each day a typical firm has on average 59.2 types of call options available for trading, of which 23.5 types (on average) are actually traded (have positive volume) each day during the sample period. Biotech Holdrs Trust (SECID: 102186) has as many as 119.4 types of calls outstanding each day, while IBM (SECID: 106276) has as many as 52.9 types of calls traded each day.[20]

[20] The maximum number of call options written on a stock on a day can be much higher than the daily average numbers reported in Table 9. For example, Bank of America Corp. (SECID: 101966) had as many as 312 types of call options available on January 14, 2009 and 143 types of them were traded on that day.

For each of the 101 sample firms, we conduct time-series estimation using the regression specification in Eq. (29). The standard errors of the estimated coefficients in the time-series regressions are corrected for heteroskedasticity based on White (1980). Table 10 summarizes the results for two components of the hedging costs: one with the initial delta-hedging cost, DHG_Cost, in Panel A and the other with the rebalancing cost, REB_Cost, in Panel B. For time-series regressions, all the option-related variables used in Table 10 are volume-weighted, which means that zero-volume call options are excluded when we calculate daily average values for the option-related variables. The table shows that the regressions use 2,086.3 to 3,145.2 trading days on average for each firm. We also see that the average R^2 values are quite high (56.4%-59.0%).

Without the interaction term in Panel A, we find that out of the total 101 sample firms, 98 firms (97.0%) show positive coefficients on the initial delta-hedging cost (DHG_Cost), and the coefficients for 80 firms (79.2%) are statistically significant at the 5% level (based on the heteroskedasticity-consistent standard errors). The average t-value for the coefficients on DHG_Cost is 6.39, suggesting that when the OMMs actively hedge their call option positions using the stock, the call spread widens, after accounting for the effects of non-informed/liquidity trading and other firm characteristics. Among the control variables, firm size ($SIZE$), the price level of call options (C_PRC), and trading volume of call options (C_VOL) all play pivotal roles in explaining the call option spread. As one would expect, firm size and call volume are negatively related to the call spread. Notable is that the call option price (C_PRC) is positively and significantly related to the call spread for every sample firm used in the table. On the other hand, implied volatility (C_IVOLA) does not seem important in determining the option spread in the time-series context.

Although we see that the impact of hedging activities on the call spread is strong, it is not clear whether DHG_Cost picks up the effect of the OMMs' hedging against informational risk. To better capture this specific effect, we now include the interaction term using DHG_Cost and PIN in the right-hand part of Panel A. When the interaction term is added, the number of firms that have positive coefficients on DHG_Cost decreases substantially. Of more interest is, however, the role of the interaction term: 83 firms (82.2 %) show positive coefficients, out of which 65 firms have the coefficients significant at the 5% level. This confirms that the call spread indeed widens especially when the OMMs actively initiate hedging due to their adverse-selection concerns in market making. Adding the interaction term does not change the patterns of other variables very much, although the number of observations decreases by 34% because it is constrained by the availability of PIN.

In Panel B we use the rebalancing cost, REB_Cost, as another component of the total hedging costs, instead of the initial delta-hedging cost (DHG_Cost). It is interesting to see that the role of the rebalancing cost is also important. Without the interaction term, the coefficients of REB_Cost are statistically significant to a similar degree, with 82 firms having t-values greater than 1.96. When REB_Cost is interacted with PIN, 68 firms have significant coefficients on the interaction term, while more firms show negative loadings on REB_Cost itself. This again suggests that information asymmetry makes a difference in the relationship between the call option spread and the hedging activities of the options market makers.

C. Cross-Sectional Regressions

In the previous subsection, we have shown, using the 101 sample firms screened by the three criteria, that the spread of call options becomes wider when the hedging activities by the OMMs increase over time. Some issues in the above analysis could be that the sample is rather narrow and it does not provide any information about the effect of the OMMs' initial hedging or subsequent rebalancing on the option spread in the cross-sectional context. On a given trading day, the hedging demand of the OMMs holding options written on different stocks may be different across firms for various reasons. In this section, therefore, we use a more comprehensive data set and examine the cross-sectional behavior of the call option spread.

C.1. With PIN for the Interaction Term

For this purpose, we run a Fama and MacBeth (1973)-type cross-sectional regression each day (for 3,523 trading days) with the same equation specified in Eq. (29) using a broad cross-section of NYSE/AMEX-listed companies that have non-zero volume call options.[21] The number of component firms used for the regression ranges from 706 on January 4, 1996 to 1,274 on December 31, 2009. The results with PIN for the interaction term are reported in Table 11. We estimate the vector of coefficients, $\mathbf{c} = [a\ \theta\ \phi\ c_1\ c_2 ... c_N]'$, in Eq. (29) each day using the OLS method, and the reported estimator is the time-series average of the 3,523 daily coefficients. The standard error of this estimator is taken from the time series of the daily estimates. Given that the dependent variable is persistent, we provide the heteroskedasticity- and autocorrelation-consistent (HAC) t-statistics computed as in Newey and West (1987 and 1994).[22]

[21] Many option-written stocks can have zero-volume for every type of options available on a given trading day. Volume-weighting thus excludes a number of firms that have no trading in the call options.

[22] As suggested by Newey and West (NW) (1987, 1994), in choosing bandwidth parameter B (= L + 1) for the Bartlett kernel to compute the NW standard errors, we let lag length L be equal to the integer portion of

In addition to the average coefficients and t-statistics, we also compute the average of the adjusted R^2 values from the individual regressions (denoted by *Avg R-sqr*) and the average number of observations (*Avg #Firms*) used in the regression each day. As we believe that excluding zero-volume call options is more appropriate, we continue to volume-weight for the option-related variables. Panel A contains the results for DHG_Cost, while Panel B does the same for REB_Cost. The panels show that on average 982.1 firms are used each day when the interaction term is not used, but with the term the number decreases to 826.0. The average R^2 values from the cross-sectional regressions range from 31.2% to 32.2%.

First, let's look at the cross-sectional effect of the initial delta-hedging cost in Panel A. As can be seen in Specification 1a (without the interaction term), DHG_Cost is strongly positively related to the call option spread (C_QSPR), suggesting that firms with more active initial delta-hedging by the OMMs generally have wider call option spreads, after controlling for non-information-based trading and other firm characteristics. To capture the role of information asymmetry in the OMMs' hedging, we now include the interaction term (DHG_Cost x PIN) in Specification 2a. Intriguingly, the coefficient on DHG_Cost turns negative. On the other hand, the interaction term constructed with PIN emerges as a more important variable, exerting a positive and highly significant impact on the call option spread. This demonstrates that the OMMs' initial delta-hedging activities are closely related to their adverse-selection concerns in the market-making process.

Regardless of the interaction term, Panel A shows that the effects of the control variables on the call spread are generally consistent with previous studies as well as with our time-series results reported in Table 10. Firm size ($SIZE$) is negatively related to the call option spread, while the call price (C_PRC) is positively related. As the coefficient of C_VOL shows, a more actively traded call option is expected to have narrower spreads. This is contrary to the findings in Cho and Engle (1999), who document that option volume is irrelevant to the option spread. A noticeable difference from the time-series results is that implied volatility (C_IVOLA) is now strongly negatively related to the call option spread, indicating that higher volatility in the underlying asset improves the liquidity of call options written on it. This result is consistent with de Fontnouvelle et al. (2003).

Next, we examine whether the key features observed in Panel A change when the rebalancing cost is used as part of the total hedging costs. As Panel B shows, the pattern of the coefficient on REB_Cost and its impact on the call spread are by and large similar to those of DHG_Cost.

$4(T/100)^{2/9}$, where T is the number of observations in the estimated coefficient series.

Given that the value of high-vega options is vulnerable to changes in volatility, Specification 1b implies that the OMMs who hold such options in their inventories actively manage the initial hedging positions before the positions are liquidated, which in turn affects the call option spread. When REB_Cost is interacted with PIN in Specification 2b, the loading on the interaction term is again positive and highly significant, while the coefficient of REB_Cost itself becomes negative. The effects of the control variables are similar to those reported in Panel A.

C.2. Robustness Tests with Some Instrumental Variables

A potential issue in the above analysis is that PIN used to construct the interaction term might be endogenous: i.e., the probability of informed trading (PIN) and the call option spread (C_QSPR) could be simultaneously determined by some omitted variable. Therefore, along the lines of Rajan and Zingales (1998 and 2003), we instrument PIN with other variables. There seems no clear guidance on identifying proper instrumental variables for PIN in the literature. Using our judgement and discretion, we select two plausible candidates: one positively correlated with PIN and the other negatively correlated with it. As the first one, we use the price-impact parameter (LAM_GH) ("lambda") estimated with intradaily stock order flows based on Glosten and Harris (1988) [For details about estimating LAM_GH, see the Appendix]. This variable represents illiquidity caused by information asymmetry. The other is the proportion of shares in a firm owned by institutional investors, denoted by IO. Institutional investors are known to monitor managers and force them to disclose more information, thereby revealing and disseminating private information to the general public. So a firm with higher institutional ownership may be subject to less information asymmetry [e.g., see Chen, Harford, and Li (2007) and O'Neill and Swisher (2003)]. IO is obtained from the Thomson Reuters Institutional (13f) Holdings database. As before, the two lower-frequency variables (LAM_GH and IO) are converted to daily series.

The results for the two different interacting variables are reported in Table 12. As we see in Specification 3a of Panel A, when the interaction term is constructed by price impact (LAM_GH) instead of PIN, the coefficient on DHG_Cost remains positive and significant, unlike that in Specification 2a of Table 11. This indicates that hedging demand not motivated by information asymmetry also commands higher call option spreads. We note however that adverse-selection concerns strongly dictate the relationship between the call option spread and the initial hedging cost, as we observe a positive and more significant coefficient on the interaction term (DGH_Cost x LAM_GH). When PIN is instrumented with IO for the interaction term in Specification 4a, the coefficient on DHG_Cost continues to be positive and significant. The coefficient on the interaction term (DHG_Cost x IO) is highly negative and statistically significant. Considering that IO is an instrument negatively correlated with PIN, observing the negative coefficient is reasonable.

In Panel B, we conduct similar experiments with the rebalancing cost. Although the magnitude of the coefficients on REB_Cost and the two interaction terms [(REB_Cost x LAM_GH) and (REB_Cost x IO)] in Specifications 3b and 4b is larger than that of the corresponding specifications in Panel A, their statistical significance is about the same. The effects of the control variables are also similar to those in Panel A.

To summarize, our empirical tests are consistent with the model, strongly supporting the idea that stock-based hedging activities by the OMMs lead to higher call option spreads, after accounting for the effect of liquidity trading and other firm characteristics. Especially, the higher call spreads are associated with their hedging activities motivated by informational risk in market making, in addition to other considerations.

VII. Conclusion

In this paper, we develop a model of market making to evaluate the effects of hedging by an options market maker. Informed traders strategically randomize their trading in the stock and options markets to take advantage of their private information. The OMM updates his estimates about future states by observing the order flows and hedges his option position using the underlying asset (or call options). Competition drives that the OMM's expected profit from market-making and hedging activities is zero.

Our results provide new insights into the hedging activities of the options market makers. With a single type of call option available, the OMM chooses to hedge his option position incurred from market making whenever he perceives any potential risk of informed trading. This causes the OMM additional transaction costs, which is to be recovered by raising the option spread. His hedging activities also form an unintended source of information asymmetry in the stock market. The possibility of increased informed trading from the OMM in turn leads the stock market maker to widen the spread in the stock market. This eventually makes the OMM widen further the call option spread. Therefore, the OMM's adverse-selection concern and his ensuing hedging activities are important driving forces of the spreads in both markets.

With the introduction of another call option, informed traders have more choices to exploit their information advantage. When the OMM hedges the two different call positions still using the underlying asset, the hedging trades contain less information and thus both stock and option spreads narrow, although this dampening effect is relatively minor. In the extended model, when the two different OMMs hedge their positions using each other's option, the stock spread narrows further, but the net effect on the call spreads is not clear.

We empirically test the key implication of our model. To provide reliable results, we use a data set covering the 3,523 trading days for a broad cross-section of NYSE/AMEX-listed stocks. The test results strongly support the notion that stock-based hedging activities by the OMMs lead to higher call option spreads, even after controlling for liquidity trading and other firm characteristics. In particular, the wider call spreads are tightly linked to their hedging activities motivated by adverse-selection risk in market making, in addition to other considerations such as fundamental risk.

Appendix

A. Proof of Proposition 1

Here we solve for the *bid* price of the stock quoted by the SMM when the OMM hedges his option position using the stock. The *ask* price can be obtained similarly.

Consider the $Pr(\theta = L|\text{Sell Stock})$ part in Eq. (10), which is the probability that the state of nature is low (L), given SMM's observation of a stock sale. Using Bay's rule, the probability (from the perspective of the SMM) can be expressed as:

$$
\begin{aligned}
Pr(\theta &= L|\text{Sell Stock}) \\
&= \frac{Pr(\theta = L)Pr(\text{Sell Stock}|\theta = L)}{Pr(\theta = L)Pr(\text{Sell Stock}|\theta = L) + Pr(\theta = H)Pr(\text{Sell Stock}|\theta = H)}
\end{aligned}
$$

where $Pr(\text{Sell Stock}|\theta = L)$ is the probability that traders sell (short) the stock when the state of nature is low (L). Orders to sell (short) the stock come from three sources: informed and uninformed traders at $t = 1$; and the OMM (for hedging) at $t = 2$. We see in Figure 1 that the probability of an informed stock sale is $\alpha\mu\omega$, and that of an uninformed stock sale is $\frac{1}{2}(1-\alpha)\beta$.

Now we focus on the probability of a hedging sale by the OMM. Since the SMM can estimate the probability of a hedging trade from the OMM, this probability is equivalent to the probability of OMM's hedging when the state is low, which depends on how the OMM perceives the moneyness of his option position given his observation of the options order flow. When the state is low and the OMM receives a sell order for the call option, his long position in the call option incurred by market making is likely to be out of the money and hedging is needed, which requires the OMM to sell the underlying asset. Note in Figure 1 that the probability of the OMM's hedging (by selling the stock) is equivalent to the probability that the OMM ends up with a long call position (there are two cases where the nodes are indicated "Sell Call").[23] This equals the sum of the probabilities of a call sale from informed traders ($\alpha\mu(1 - \omega)$) and that from uninformed traders ($\frac{1}{2}(1 - \alpha)(1 - \beta)$).

[23] We consider only the *probability* of the OMM's hedging (by selling the stock). The exact number of shares that the OMM sells depends on the hedge ratio.

Therefore, we have:

$$\begin{aligned}
Pr(\text{Sell Stock}|\theta = L) &= Pr(\text{Informed Sell Stock}|\theta = L) \\
&\quad + Pr(\text{Uninformed Sell Stock}|\theta = L) \\
&\quad + Pr(\text{OMM Hedging Sell Stock}|\theta = L) \\
&= \alpha\mu\omega + \frac{1}{2}(1-\alpha)\beta + Pr(\text{Informed Sell Call}|\theta = L) \\
&\quad + Pr(\text{Uninformed Sell Call}|\theta = L) \\
&= \alpha\mu\omega + \frac{1}{2}(1-\alpha)\beta + \alpha\mu(1-\omega) + \frac{1}{2}(1-\alpha)(1-\beta) \\
&= \alpha\mu + \frac{1}{2}(1-\alpha) \qquad (30)
\end{aligned}$$

When the state is high ($\theta = H$) and the OMM observes a sell order for the call option, his long call position incurred by market making is likely to be in the money and need not be hedged. Hence, the probability of the OMM's hedging is zero. We thus have:

$$\begin{aligned}
Pr(\text{Sell Stock}|\theta = H) &= Pr(\text{Informed Sell Stock}|\theta = H) \\
&\quad + Pr(\text{Uninformed Sell Stock}|\theta = H) \\
&\quad + Pr(\text{OMM Hedging Sell Stock}|\theta = H) \\
&= \alpha(1-\mu)\omega + \frac{1}{2}(1-\alpha)\beta + 0 \\
&= \alpha(1-\mu)\omega + \frac{1}{2}(1-\alpha)\beta \qquad (31)
\end{aligned}$$

As the OMM hedges only when he perceives that he might lose money on the option position, the probabilities of the OMM's hedging (by selling the stock) in the two different states ($\theta = L$ vs. H) are different. This difference directly affects the bid and ask prices of the stock. Given Eqs. (30) and (31), we have:

$$\begin{aligned}
Pr(\theta &= L|\text{Sell Stock}) = \frac{\alpha\mu + (1-\alpha)\frac{1}{2}}{\alpha\mu + \alpha(1-\mu)\omega + (1-\alpha)(1+\beta)\frac{1}{2}} \\
Pr(\theta &= H|\text{Sell Stock}) = \frac{\alpha(1-\mu)\omega + (1-\alpha)\beta\frac{1}{2}}{\alpha\mu + \alpha(1-\mu)\omega + (1-\alpha)(1+\beta)\frac{1}{2}}
\end{aligned}$$

Using these results and the definitions of the bid and ask prices for the stock shown in Eqs. (10) and (11), we obtain Proposition 1.

B. Proof of Proposition 4

Let C_a^i and C_b^i (i =1 or 2) denote the ask and bid prices of the two options (C^1 and C^2). Informed traders are indifferent between trading the stock and trading the options (C^1 and/or C^2). This gives the indifference conditions:

$$\underbrace{E[\tilde{v}|sig = G] - S_a}_{} = p\{E[(\tilde{v} - K^1)^+|sig = G] - C_a^1\} + (1-p)\{E[(\tilde{v} - K^2)^+|sig = G] - C_a^2\} \quad (32)$$

$$\underbrace{S_b - E[\tilde{v}|sig = B]}_{\text{Trading Stocks}} = \underbrace{q\{C_b^1 - E[(\tilde{v} - K^1)^+|sig = B]\} + (1-q)\{C_b^2 - E[(\tilde{v} - K^2)^+|sig = B]\}}_{\text{Trading Options}} \quad (33)$$

In addition, informed traders are indifferent between trading option C^1 and option C^2:

$$E[(\tilde{v} - K^1)^+|sig = G] - C_a^1 = E[(\tilde{v} - K^2)^+|sig = G] - C_a^2 \quad (34)$$

$$\underbrace{C_b^1 - E[(\tilde{v} - K^1)^+|sig = B]}_{\text{Trading Option } C^1} = \underbrace{C_b^2 - E[(\tilde{v} - K^2)^+|sig = B]}_{\text{Trading Option } C^2} \quad (35)$$

Combining the above indifference conditions gives Proposition 4.

C. Estimation of PIN

To estimate the PIN measure developed by Easley, Hvidkjaer, and O'Hara (2002), we denote B_j and S_j as the daily number of buyer- and seller-initiated trades for trading day j, respectively. On day j, a private information event occurs with probability ϕ, or no information event occurs with probability $(1-\phi)$. If the event occurs on that day, it conveys bad news with probability δ or good news with probability $(1-\delta)$. Now trade orders from uninformed buyers (sellers) arrive randomly at rate ε_b (ε_s) on that day. Also, orders from informed traders arrive randomly at rate γ, but only if the information event occurs on day j (i.e., informed traders buy on good news and sell on bad news). Then, the likelihood of observing B_j buys and S_j sells on trading day j is given by:

$$\begin{aligned} L(B_j, S_j|\theta) &= \phi(1-\delta)e^{-(\gamma+\varepsilon_b)}\frac{(\gamma+\varepsilon_b)^{B_j}}{B_j!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_j}}{S_j!} \\ &\quad +\phi\delta e^{-\varepsilon_b}\frac{\varepsilon_b^{B_j}}{B_j!}e^{-(\gamma+\varepsilon_s)}\frac{(\gamma+\varepsilon_s)^{S_j}}{S_j!} + (1-\phi)e^{-\varepsilon_b}\frac{\varepsilon_b^{B_j}}{B_j!}e^{-\varepsilon_s}\frac{\varepsilon_s^{S_j}}{S_j!}, \end{aligned} \quad (36)$$

where $\theta = (\phi, \delta, \gamma, \varepsilon_b, \varepsilon_s)$ is a vector of the parameters defined above. Assuming that trading days are independent, the joint likelihood of observing a series of daily buys and sells over trading days $j = 1, 2, ..., J$ is the product of the daily likelihoods:

$$L(M|\theta) = \prod_{j=1}^{J} L(\theta|B_j, S_j), \tag{37}$$

where $M = ((B_1, S_1), ..., (B_J, S_J))$ is the data set. The parameter vector θ can be estimated by maximizing the joint likelihood defined in Eq. (37). Using the parameters estimated above, we then calculate the PIN measure as follows:

$$PIN = \frac{\phi\gamma}{\phi\gamma + \varepsilon_b + \varepsilon_s}. \tag{38}$$

Some concerns have been expressed about estimating the parameter vector θ (and hence PIN) by maximizing Eq. (37) [see Brown *et al.* (2004), Vega (2005), and Yan and Zhang (2010)]. For example, an estimate may vary with initial values chosen by a computer, which means that the θ estimate may not reach the global maximum for the objective function. Sometimes the parameter values chosen by the computer in the last iteration step may be corner solutions. Other times the computer cannot even compute PIN because of numerical 'overflow.'

To alleviate these problems, we estimate PIN using the Yan and Zhang (2010) algorithm on a quarterly basis. This approach involves running the optimization procedure up to *125 times* for each stock-quarter using pre-specified 125 sets of initial parameter values. Among the estimated candidates up to 125 sets, the algorithm chooses the θ estimate that does not include any corner solution and, at the same time, maximizes the objective function [Eq. (37)]. This algorithm therefore makes computations much more burdensome. Although this method cannot address all the problems mentioned above, Yan and Zhang (2010) show that it reduces corner solutions, increases the probability of delivering the PIN estimate, and makes the estimate more reliable in terms of achieving the global maximum. Moreover, our *quarterly* estimation has an advantage over *annual* estimation for empirical analyses as well as for reducing the overflow problem [e.g., Easley, Hvidkjaer, and O'Hara (2002) and Duarte and Young (2009) estimate PIN on an annual basis].

D. Estimation of Price Impact (LAM_GH)

Glosten and Harris (1988) decompose trading costs into four components: i) a transitory fixed cost (denoted as $\overline{\varphi}$), ii) a transitory variable cost ($\overline{\lambda}$), iii) a permanent fixed cost (φ), and iv) a permanent variable cost (λ). The first two components are due to specialist rents, inventory maintenance, and order processing fees, while the last two components are due to adverse selection or information asymmetry.

Let μ_t denote the expected value of a security for a market maker who observes only the order flows ($S_t V_t$) and the public information signal (ξ_t). Models of price formation such as Kyle (1985) and Admati and Pfleiderer (1988) then imply that μ_t evolves as $\mu_t = \mu_{t-1} + \lambda S_t V_t + \xi_t$. Glosten and Harris (1988) find evidence that the permanent fixed cost and the transitory variable cost are negligible in their sample, i.e., $\varphi = \overline{\lambda} = 0$. In the estimation, we reflect their finding and assume risk-neutral, competitive market makers. Given the sign ($S_t = +1$ if the trade is buyer-initiated and $S_t = -1$ if it is seller-initiated) of each trade, we can write the observed security price as $P_t = \mu_t + \overline{\varphi} S_t$. Plugging the first equation to the second, we have $P_t = \mu_{t-1} + \lambda S_t V_t + \overline{\varphi} S_t + \xi_t$. We also know that $P_{t-1} = \mu_{t-1} + \overline{\varphi} S_{t-1}$. If we subtract the last equation from the third and use the notations in a more specific way, the price change, ΔP_t, is given by

$$\Delta P_{i,t,m} = \lambda_{i,m}^{GH} S_{i,t,m} V_{i,t,m} + \overline{\varphi}_{i,m}^{GH} (S_{i,t,m} - S_{i,t-1,m}) + \xi_{i,t,m}, \qquad (39)$$

where $\lambda_{i,m}^{GH}$ (Glosten-Harris 'lambda') is the price-impact parameter (for stock i at trade t in month m) used in our study, $\overline{\varphi}_{i,m}^{GH}$ denotes the transitory fixed cost, and $\xi_{i,t,m}$ is the unobservable error term. To estimate $\lambda_{i,m}^{GH}$ each month for each stock, we run the time-series regressions as in Eq.(39) (with a constant term) using all the intradaily order flows (processed from TAQ) available within month m.

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Table 1: Parameter Values and Variable Ranges for Numerical Computations

This table reports the parameter values and variable ranges to be used for numerical calculations. The high and low prices of the stock are denoted by v_H and v_L, respectively. β denotes the percentage of the uninformed traders who trade in the stock market. μ is the probability that the private signal is accurate for the informed traders. α is the percentage of the informed traders in the trading population. *K* is the exercise price the call option.

Parameters	Values	Variables	Values/Ranges
v_H	50	μ	0.85-0.99
v_L	30	α	0.25, 0.50, 0.75
β	0.5	*K*	35, 40, 45

Table 2: Informed Trading Intensity in the Stock Market When the OMM Does Not Hedge vs. When the OMM Hedges Using the Stock

Panel A reports the informed trading intensity in the stock market (ω and ν) when the OMM does not hedge. Panel B does the same for the case where the OMM hedges his options position using the stock. ω is the probability that informed traders trade in the stock market when they receive a bad signal (B), while ν is defined similarly when they receive a good signal (G). Three cases are reported in each panel for three different values of *K* (the exercise price of the call option). For a given value of *K*, the values of ν and ω are computed for three different values of α (the percentage of the informed traders in the trading population), as μ (the probability that the private signal is accurate) increases.

Panel A: Informed Trading Intensity in the Stock Market When the OMM Does Not Hedge

	K = 35						K = 40						K = 45					
	α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75	
μ	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν
0.85	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.86	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.87	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.88	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.89	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.90	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.91	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.92	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.93	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.94	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.95	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.96	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.97	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.98	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90
0.99	0.79	0.79	0.64	0.64	0.60	0.60	1.00	1.00	0.83	0.83	0.72	0.72	1.00	1.00	1.00	1.00	0.90	0.90

Panel B: Informed Trading Intensity in the Stock Market When the OMM Hedges

	K = 35						K = 40						K = 45					
	α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75	
μ	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν	ω	ν
0.85	1.00	0.33	1.00	0.71	1.00	0.88	1.00	0.72	1.00	0.78	1.00	0.89	1.00	1.00	1.00	1.00	1.00	1.00
0.86	1.00	0.35	1.00	0.71	1.00	0.88	1.00	0.75	1.00	0.78	1.00	0.88	1.00	1.00	1.00	1.00	1.00	1.00
0.87	1.00	0.37	1.00	0.71	1.00	0.88	1.00	0.78	1.00	0.79	1.00	0.89	1.00	1.00	1.00	1.00	1.00	1.00
0.88	1.00	0.39	1.00	0.71	1.00	0.88	1.00	0.81	1.00	0.79	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.89	1.00	0.40	1.00	0.72	1.00	0.88	1.00	0.84	1.00	0.80	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.90	1.00	0.42	1.00	0.72	1.00	0.88	1.00	0.86	1.00	0.81	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.91	1.00	0.43	1.00	0.72	1.00	0.88	1.00	0.88	1.00	0.81	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.92	1.00	0.45	1.00	0.73	1.00	0.89	1.00	0.91	1.00	0.82	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.93	1.00	0.46	1.00	0.73	1.00	0.89	1.00	1.00	1.00	0.82	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.94	1.00	0.47	1.00	0.73	1.00	0.89	1.00	1.00	1.00	0.82	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.95	1.00	0.49	1.00	0.73	1.00	0.89	1.00	1.00	1.00	0.83	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.96	1.00	0.50	1.00	0.74	1.00	0.89	1.00	1.00	1.00	0.83	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.97	1.00	0.51	1.00	0.74	1.00	0.89	1.00	1.00	1.00	0.84	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.98	1.00	0.52	1.00	0.74	1.00	0.89	1.00	1.00	1.00	0.84	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00
0.99	1.00	0.53	1.00	0.75	1.00	0.89	1.00	1.00	1.00	0.84	1.00	0.90	1.00	1.00	1.00	1.00	1.00	1.00

Table 3: The Effects of μ, α and *K* on the Trading Strategy of Informed Traders

This table summarizes the effects of μ, α, and *K* on the trading intensity of informed traders in the stock market (ω and ν) in the two different settings: when the OMM hedges his options position incurred by market making; and when the OMM does not hedge. ω is the probability that informed traders trade in the stock market when they receive a bad signal (B), while ν is defined similarly when they receive a good signal (G). The other variables are defined as follows: μ: the probability that the private signal is accurate for the informed traders; α: the percentage of the informed traders in the trading population; *K*: the exercise price of the call option. The + (-) sign indicates a positive (negative) relationship of ω and ν with μ, α and *K*.

Variable	Intensity of Informed Trading in the Stock Market (ω and *v*)	
	With the OMM's Hedging (ω ≠ *v*)	Without the OMM's Hedging (ω = *v*)
μ	+	Independent
α	+	-
K	+	+

Table 4: The Spreads in the Stock Market When the OMM Does Not Hedge vs. When the OMM Hedges Using the Stock

Panel A reports the spreads in the stock market when the OMM does not hedge. Panel B does the same for the case where the OMM hedges his options position using the stock. Three cases are reported in each panel for three different values of *K* (the exercise price of the call option). For a given value of *K*, the spreads in the stock market are computed for three different values of α (the percentage of the informed traders in the trading population), as μ (the probability that the private signal is accurate) increases.

Panel A: Spreads in the Stock Market When the OMM Does Not Hedge

	K = 35			K = 40			K = 45		
μ	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75
0.85	4.81	7.88	10.94	5.60	8.75	11.38	5.60	9.33	11.82
0.86	4.95	8.10	11.25	5.76	9.00	11.70	5.76	9.60	12.15
0.87	5.09	8.33	11.56	5.92	9.25	12.03	5.92	9.87	12.49
0.88	5.23	8.55	11.88	6.08	9.50	12.35	6.08	10.13	12.83
0.89	5.36	8.78	12.19	6.24	9.75	12.68	6.24	10.40	13.16
0.90	5.50	9.00	12.50	6.40	10.00	13.00	6.40	10.67	13.50
0.91	5.64	9.23	12.81	6.56	10.25	13.33	6.56	10.93	13.84
0.92	5.78	9.45	13.13	6.72	10.50	13.65	6.72	11.20	14.18
0.93	5.91	9.68	13.44	6.88	10.75	13.98	6.88	11.47	14.51
0.94	6.05	9.90	13.75	7.04	11.00	14.30	7.04	11.73	15.85
0.95	6.19	10.13	14.06	7.20	11.25	14.63	7.20	12.00	15.19
0.96	6.33	10.35	14.38	7.36	11.50	14.95	7.36	12.27	15.53
0.97	6.46	10.58	16.69	7.52	11.75	15.28	7.52	12.53	15.86
0.98	6.60	10.80	15.00	7.68	12.00	15.60	7.68	12.80	16.20
0.99	6.74	11.03	15.31	7.84	12.25	15.93	7.84	13.07	16.54

Panel B: Spreads in the Stock Market When the OMM Hedges

	K = 35			K = 40			K = 45		
μ	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75
0.85	9.38	11.26	12.77	9.11	11.16	12.75	8.92	10.86	12.53
0.86	9.46	11.46	13.07	9.20	11.36	13.05	9.05	11.09	12.85
0.87	9.55	11.66	13.38	9.30	11.56	13.36	9.17	11.31	13.17
0.88	9.63	11.86	13.68	9.40	11.77	13.66	9.29	11.54	13.49
0.89	9.72	12.06	13.99	9.50	11.97	13.97	9.42	11.77	13.81
0.90	9.81	12.26	14.29	9.60	12.18	14.28	9.54	12.00	14.13
0.91	9.90	12.46	14.60	9.71	12.39	14.58	9.66	12.23	14.45
0.92	9.99	12.66	14.90	9.82	12.60	14.89	9.78	12.46	14.77
0.93	10.08	12.86	15.21	9.91	12.80	15.19	9.91	12.69	15.09
0.94	10.18	13.07	15.51	10.03	13.01	15.50	10.03	12.91	15.41
0.95	10.27	13.27	15.81	10.15	13.22	15.80	10.15	13.14	15.73
0.96	10.37	13.47	16.12	10.28	13.44	16.11	10.28	13.37	16.05
0.97	10.47	13.68	16.42	10.40	13.65	16.42	10.42	13.60	16.37
0.98	10.57	13.88	16.73	10.52	13.86	16.72	10.55	13.83	16.69
0.99	10.67	14.08	17.03	10.65	14.07	17.03	10.66	14.06	17.01

Table 5: The Spreads in the Options Market When the OMM Does Not Hedge vs. When the OMM Hedges Using the Stock

Panel A reports the spreads in the (call) options market when the OMM does not hedge. Panel B does the same for the case where the OMM hedges his options position using the stock. Three cases are reported in each panel for three different values of *K* (the exercise price of the call option). For a given value of *K*, the spreads in the options market are computed for three different values of α (the percentage of the informed traders in the trading population), as μ (the probability that the private signal is accurate) increases.

Panel A: Spreads in the Options Market When the OMM Does Not Hedge

	K = 35			K = 40			K = 45		
μ	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75
0.85	1.31	4.38	7.44	0.00	1.75	4.38	0.00	0.00	1.31
0.86	1.35	4.50	4.65	0.00	1.80	4.50	0.00	0.00	1.35
0.87	1.39	4.63	8.86	0.00	1.85	4.63	0.00	0.00	1.39
0.88	1.43	4.75	8.08	0.00	1.90	4.75	0.00	0.00	1.43
0.89	1.56	4.88	8.29	0.00	1.95	4.88	0.00	0.00	1.46
0.90	1.50	5.00	8.50	0.00	2.00	5.00	0.00	0.00	1.50
0.91	1.54	5.13	8.71	0.00	2.05	5.13	0.00	0.00	1.54
0.92	1.58	5.25	8.93	0.00	2.10	5.25	0.00	0.00	1.58
0.93	1.61	5.38	9.14	0.00	2.15	5.38	0.00	0.00	1.61
0.94	1.65	5.50	9.35	0.00	2.20	5.50	0.00	0.00	1.65
0.95	1.69	5.63	9.56	0.00	2.25	5.63	0.00	0.00	1.69
0.96	1.73	5.75	9.78	0.00	2.30	5.75	0.00	0.00	1.73
0.97	1.76	5.88	9.99	0.00	2.35	5.88	0.00	0.00	1.76
0.98	1.80	6.00	10.20	0.00	2.40	6.00	0.00	0.00	1.80
0.99	1.84	6.13	10.41	0.00	2.45	6.13	0.00	0.00	1.84

Panel B: Spreads in the Options Market When the OMM Hedges

	K = 35			K = 40			K = 45		
μ	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75	α = 0.25	α = 0.50	α = 0.75
0.85	5.88	7.76	9.27	2.11	4.16	5.75	0.02	0.36	2.03
0.86	5.86	7.86	9.47	2.00	4.16	5.85	0.01	0.29	2.05
0.87	5.85	7.96	9.68	1.90	4.16	5.96	0.01	0.21	2.07
0.88	5.83	8.06	9.88	1.80	4.17	6.06	0.01	0.14	2.09
0.89	5.82	8.16	10.09	1.70	4.17	6.17	0.01	0.07	2.11
0.90	5.81	8.26	10.29	1.60	4.18	6.28	0.01	0.02	2.13
0.91	5.80	8.36	10.50	1.51	4.19	6.38	0.01	0.01	2.15
0.92	5.79	8.46	10.70	1.42	4.20	6.49	0.01	0.01	2.17
0.93	5.78	8.56	10.91	1.61	4.20	6.59	0.01	0.01	2.19
0.94	5.78	8.67	11.11	1.23	4.21	6.70	0.01	0.01	2.21
0.95	5.77	8.77	11.31	1.15	4.22	6.80	0.01	0.01	2.23
0.96	5.77	8.87	11.52	1.08	4.24	6.91	0.01	0.01	2.25
0.97	5.77	8.98	11.72	1.00	4.25	7.02	0.01	0.01	2.27
0.98	5.77	9.08	11.93	0.92	4.26	7.12	0.01	0.01	2.29
0.99	5.77	9.18	12.13	0.84	4.27	7.23	0.01	0.01	2.31

Table 6: The Effect of μ on the Spreads in the Options Market When the OMM Hedges

This table provides a summary of the effect of μ (the probability that the private signal is accurate) on the spreads in the options market. The effects are reported for three levels of α (the percentage of the informed traders in the trading population) in each of the three types of moneyness for the call option: in the money (ITM), at the money (ATM), and out of the money (OTM). The + (-) sign indicates a positive (negative) relationship of μ with the options spreads.

The Effect of μ on the Options Spread								
ITM (K = 35)			ATM (K = 40)			OTM (K = 45)		
α = 0.25	α = 0.5	α = 0.75	α = 0.25	α = 0.5	α = 0.75	α = 0.25	α = 0.5	α = 0.75
-	+	+	-	+	+	-	-	+

Table 7: Summary of the Effects of μ, α and *K* on the Spreads in the Stock and Options Markets When the OMM Does Not Hedge vs. When the OMM Hedges

This table summarizes the effects of μ, α and *K* on the spreads in the stock and options markets when the OMM does not hedge his options position and when he hedges. The variables are defined as follows: μ: the probability that the private signal is accurate for the informed traders; α: the percentage of the informed traders in the trading population; *K*: the exercise price of the call option. The + (-) sign indicates a positive (negative) relationship of a variable with the spreads. The inconsistent relationship between μ and the option spreads when the OMM hedges (summarized in Table 6) is indicated by "?".

	Spreads in the Stock Market		**Spreads in the Options Market**	
Variable	OMM Not Hedge	OMM Hedges	OMM Not Hedge	OMM Hedges
μ	+	+	+	?
α	+	+	+	+
K	+	-	-	-

Table 8: Informed Traders' Returns from Trading in the Stock and/or Options markets

This table reports informed traders' expected returns from trading in the stock and/or options markets, computed based on Eqs. (25) and (26). Panel A reports the results when the OMM does not hedge, while Panel B does the same when the OMM hedges his options position using the stock. Three cases are reported in each panel for three different values of *K* (the exercise price of the call option). For a given value of *K*, the expected returns are computed for three different values of α (the percentage of the informed traders in the trading population), as μ (the probability that the private signal is accurate) increases. The expected return from trading the stock is denoted by "*Stk*" and that from trading the call option by "*Call*".

Panel A: Returns When the OMM Does Not Hedge

	K = 35						K = 40						K = 45					
	α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75	
μ	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call
0.85	0.18	0.26	0.10	0.29	0.05	0.17	0.21	0.00	0.11	0.18	0.05	0.15	0.21	0.00	0.12	0.00	0.05	0.09
0.86	0.19	0.27	0.10	0.30	0.05	0.17	0.22	0.00	0.11	0.18	0.05	0.15	0.22	0.00	0.12	0.00	0.05	0.09
0.87	0.19	0.28	0.10	0.31	0.05	0.17	0.22	0.00	0.12	0.19	0.05	0.15	0.22	0.00	0.12	0.00	0.05	0.09
0.88	0.20	0.29	0.11	0.32	0.05	0.18	0.23	0.00	0.12	0.19	0.05	0.16	0.23	0.00	0.13	0.00	0.05	0.10
0.89	0.20	0.29	0.11	0.32	0.05	0.18	0.23	0.00	0.12	0.20	0.05	0.16	0.23	0.00	0.13	0.00	0.05	0.10
0.90	0.21	0.30	0.11	0.33	0.05	0.19	0.24	0.00	0.12	0.20	0.05	0.17	0.24	0.00	0.13	0.00	0.06	0.10
0.91	0.21	0.31	0.12	0.34	0.05	0.19	0.25	0.00	0.13	0.21	0.06	0.17	0.25	0.00	0.14	0.00	0.06	0.10
0.92	0.22	0.32	0.12	0.35	0.05	0.20	0.25	0.00	0.13	0.21	0.06	0.18	0.25	0.00	0.14	0.00	0.06	0.11
0.93	0.22	0.32	0.12	0.36	0.06	0.20	0.26	0.00	0.13	0.22	0.06	0.18	0.26	0.00	0.14	0.00	0.06	0.11
0.94	0.23	0.33	0.12	0.37	0.06	0.21	0.26	0.00	0.14	0.22	0.06	0.18	0.26	0.00	0.15	0.00	0.06	0.11
0.95	0.22	0.34	0.13	0.37	0.06	0.21	0.27	0.00	0.14	0.23	0.06	0.19	0.27	0.00	0.15	0.00	0.06	0.11
0.96	0.24	0.35	0.13	0.38	0.06	0.22	0.28	0.00	0.14	0.23	0.06	0.19	0.28	0.00	0.15	0.00	0.06	0.12
0.97	0.24	0.35	0.13	0.39	0.06	0.22	0.28	0.00	0.15	0.24	0.06	0.20	0.28	0.00	0.16	0.00	0.06	0.12
0.98	0.25	0.36	0.14	0.40	0.06	0.23	0.29	0.00	0.15	0.24	0.06	0.20	0.29	0.00	0.16	0.00	0.06	0.12
0.99	0.25	0.37	0.14	0.41	0.06	0.23	0.29	0.00	0.15	0.25	0.07	0.20	0.29	0.00	0.16	0.00	0.07	0.12

Panel B: Returns When the OMM Hedges

	K = 35						K = 40						K = 45					
	α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75		α = 0.25		α = 0.50		α = 0.75	
μ	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call	Stk	Call
0.85	0.08	0.18	0.06	0.04	0.03	0.01	0.11	0.13	0.06	0.05	0.03	0.01	0.13	0.00	0.08	0.00	0.03	0.00
0.86	0.09	0.19	0.06	0.05	0.03	0.01	0.11	0.12	0.07	0.06	0.03	0.01	0.13	0.00	0.08	0.00	0.03	0.00
0.87	0.09	0.20	0.07	0.05	0.03	0.01	0.12	0.12	0.07	0.06	0.03	0.01	0.14	0.00	0.09	0.00	0.04	0.00
0.88	0.10	0.21	0.07	0.06	0.04	0.01	0.13	0.11	0.08	0.07	0.04	0.01	0.15	0.00	0.09	0.00	0.04	0.00
0.89	0.10	0.22	0.08	0.06	0.04	0.01	0.14	0.10	0.08	0.07	0.04	0.01	0.15	0.00	0.10	0.00	0.04	0.00
0.90	0.11	0.22	0.08	0.06	0.04	0.01	0.15	0.09	0.09	0.07	0.04	0.02	0.16	0.00	0.10	0.00	0.04	0.00
0.91	0.12	0.23	0.09	0.07	0.04	0.01	0.16	0.08	0.09	0.07	0.04	0.02	0.17	0.00	0.10	0.00	0.05	0.00
0.92	0.12	0.24	0.09	0.07	0.04	0.01	0.17	0.06	0.10	0.07	0.05	0.02	0.18	0.00	0.11	0.00	0.05	0.00
0.93	0.13	0.25	0.09	0.07	0.05	0.01	0.18	0.00	0.10	0.08	0.05	0.02	0.18	0.00	0.11	0.00	0.05	0.00
0.94	0.14	0.25	0.10	0.08	0.05	0.01	0.19	0.00	0.10	0.08	0.05	0.02	0.19	0.00	0.12	0.00	0.05	0.00
0.95	0.14	0.26	0.10	0.08	0.05	0.02	0.20	0.00	0.11	0.08	0.05	0.02	0.20	0.00	0.12	0.00	0.05	0.00
0.96	0.15	0.26	0.11	0.08	0.05	0.02	0.20	0.00	0.11	0.08	0.05	0.02	0.20	0.00	0.13	0.00	0.06	0.00
0.97	0.16	0.27	0.11	0.09	0.06	0.02	0.21	0.00	0.12	0.08	0.06	0.02	0.20	0.00	0.13	0.00	0.06	0.00
0.98	0.16	0.27	0.12	0.09	0.06	0.02	0.22	0.00	0.12	0.08	0.06	0.02	0.20	0.00	0.13	0.00	0.06	0.00
0.99	0.17	0.28	0.12	0.09	0.06	0.02	0.22	0.00	0.13	0.09	0.06	0.03	0.20	0.00	0.14	0.00	0.06	0.00

Table 9: Sample Firms for Time-Series Regressions

This table reports the list of selected firms for time-series regressions. To survive in the sample, the call option volume (across all call options) each day for a firm should be positive for 2,000 trading days or more out of the total 3,523 trading days in the sample period (01/04/1996 to 12/31/2009), and also on average 15 calls or more should be traded each day. Out of those firms, PIN and other key variables should also be available for a reasonably long period of time. Based on these criteria, the following 101 NYSE/AMEX-listed firms have been identified. In the table, the information about the security identification codes in OptionMetrics (*SECID*), the company name (*Issuer*), the average number of call options available each day (*Avg. #Calls Per Day*), and the average number of positive-volume call options each day (*Avg. #Posi-Vol. Calls Per Day*) is included.

SECID	Issuer	Avg. #Calls per Day	Avg. #Posi-Vol. Calls per Day	SECID	Issuer	Avg. #Calls per Day	Avg. #Posi-Vol. Calls per Day
107616	3M CO	57.02	23.19	102963	CHESAPEAKE ENERGY CORP	44.86	25.08
100974	ABERCROMBIE & FITCH CO	64.25	19.25	102968	CHEVRON CORP NEW	59.84	26.83
101121	ADVANCED MICRO DEVICES INC	68.88	37.09	103049	CITIGROUP INC	92.75	45.08
112507	AETNA INC NEW	62.94	17.97	108969	CONOCOPHILLIPS	58.00	25.35
101149	AGILENT TECHNOLOGIES INC	61.63	21.19	103380	CONTINENTAL AIRLS INC	50.42	18.04
101204	ALCOA INC	48.36	22.61	103434	CORNING INC	74.44	27.07
101273	ALLSTATE CORP	53.97	16.77	103617	CYPRESS SEMICONDUCTOR CORP	53.25	17.51
114722	AMERICA MOVIL SAB DE CV	54.29	15.16	103736	DEERE & CO	55.22	20.17
100917	AMR CORP	59.73	24.62	103802	DEVON ENERGY CORP NEW	55.12	22.08
101533	ANADARKO PETE CORP	51.50	18.88	103821	DIAMOND OFFSHORE DRILLING IN	68.57	17.76
101535	ANALOG DEVICES INC	64.13	15.59	103879	DISNEY WALT CO	55.72	26.04
101580	APACHE CORP	50.79	20.16	103936	DOW CHEM CO	47.84	17.59
109775	AT&T INC	56.31	23.19	103969	DU PONT E I DE NEMOURS & CO	51.99	23.13
102833	AVIS BUDGET GROUP	49.53	16.87	104207	ELAN PLC	55.21	24.25
101920	BAKER HUGHES INC	58.88	18.01	104232	ELECTRONIC DATA SYS NEW	54.71	15.52
101966	BANK OF AMERICA CORPORATION	83.39	38.90	104635	FEDEX CORP	52.83	20.85
101988	BANK ONE CORP	51.63	18.04	112487	FLUOR CORP NEW	49.87	16.92
102021	BARRICK GOLD CORP	50.64	24.96	105003	FREEPORT-MCMORAN COPPER & GO	61.75	26.54
102061	BEAR STEARNS COS INC	49.99	16.89	105155	GENENTECH INC	70.56	31.12
102113	BEST BUY INC	81.90	31.40	105175	GENERAL MTRS CORP	68.96	34.47
102186	BIOTECH HOLDRS TR	119.37	25.72	105244	GILLETTE CO	39.52	17.09
102265	BOEING CO	69.51	34.24	105316	GOLDCORP INC NEW	55.63	32.90
102296	BOSTON SCIENTIFIC CORP	55.61	19.76	105512	HALLIBURTON CO	55.41	26.63
101893	BP PLC	48.76	17.29	105558	HARLEY DAVIDSON INC	43.71	16.69
102349	BRISTOL MYERS SQUIBB CO	57.87	27.30	101322	HESS CORP	58.15	15.79
103296	CA INC	57.47	16.17	105785	HONEYWELL INTL INC	55.90	20.69
102702	CAPITAL ONE FINL CORP	60.42	21.92	105816	HOVNANIAN ENTERPRISES INC	47.03	16.17
102796	CATERPILLAR INC DEL	63.10	31.37	106276	INTERNATIONAL BUSINESS MACHS	90.81	52.94

(Table 9: continued)

SECID	Issuer	Avg. #Calls per Day	Avg. #Posi-Vol. Calls per Day	SECID	Issuer	Avg. #Calls per Day	Avg. #Posi-Vol. Calls per Day
106295	INTL PAPER CO	44.75	16.18	110433	SPRINT NEXTEL CORP	57.35	16.57
106521	JABIL CIRCUIT INC	48.95	15.29	110810	TARGET CORP	55.49	22.44
106566	JOHNSON & JOHNSON	60.41	27.63	110972	TEXAS INSTRS INC	75.15	37.81
102936	JPMORGAN CHASE & CO	86.10	40.87	111434	UNITED PARCEL SERVICE INC	55.84	23.02
106893	LEHMAN BROS HLDGS INC	68.48	26.22	111337	UNITED STATES STL CORP NEW	59.40	24.24
106967	LILLY ELI & CO	56.88	22.29	111459	UNITED TECHNOLOGIES CORP	54.99	18.71
107045	LOWES COS INC	54.01	20.43	111469	UNITEDHEALTH GROUP INC	69.64	22.54
106776	LSI CORPORATION	53.73	18.75	111560	VALERO ENERGY CORP NEW	68.42	33.12
107050	LUCENT TECHNOLOGIES INC	65.18	32.53	111668	VERIZON COMMUNICATIONS	58.18	24.67
111296	MARATHON OIL CORP	45.90	17.00	104847	WACHOVIA CORP NEW	55.26	19.84
107455	MERRILL LYNCH & CO INC	83.28	34.81	111860	WAL MART STORES INC	67.50	35.31
107544	MICRON TECHNOLOGY INC	82.34	36.58	111861	WALGREEN CO	41.74	17.18
107885	NABORS INDUSTRIES LTD	49.13	17.75	111884	WASHINGTON MUT INC	56.95	23.53
107939	NATIONAL OILWELL VARCO INC	42.40	15.91	112042	WILLIAMS COS INC DEL	41.60	15.41
107951	NATIONAL SEMICONDUCTOR CORP	56.19	17.82	101387	WYETH	50.68	19.11
108130	NEWMONT MINING CORP	62.40	33.24	112169	XEROX CORP	50.46	16.96
108174	NOKIA CORP	78.59	36.25	103533	XTO ENERGY INC	42.82	15.12
108196	NORTEL NETWORKS CORP NEW	56.60	19.37		Grand Average	59.22	23.52
108279	NUCOR CORP	51.20	17.15				
108385	OCCIDENTAL PETE CORP DEL	48.55	18.00				
108849	PENNEY J C INC	48.76	15.88				
108962	PHELPS DODGE CORP	53.19	17.00				
109117	POTASH CORP SASK INC	72.91	26.23				
109224	PROCTER & GAMBLE CO	65.69	28.76				
109954	SCHERING PLOUGH CORP	52.00	22.11				
109956	SCHLUMBERGER LTD	68.90	31.10				
109965	SCHWAB CHARLES CORP NEW	59.26	22.33				
110046	SEMICONDUCTOR HLDRS TR	64.27	27.53				

Table 10: Time-Series Regression Results for the Call Option Spread

This table reports the results of the time-series regressions using the spreads of call options written on the 101 NYSE/AMEX-listed stocks shown in Table 9 for the sample period from January 4, 1996 to December 31, 2009 (14 years). The dependent variable is C_QSPR. The definitions of the variables are as follows: *C_QSPR*: the daily mean quoted spread of call options averaged across call options available on each trading day; *DHG_Cost*: the initial delta-hedging cost required to hedge a call option position, which is computed by (C_Delta) x (S_%QSPR) x (S_PRC), where C_Delta is the daily mean call option delta averaged across call options available each day, S_%QSPR is the (daily close) proportional (relative to the quote midpoint) quoted spread of the underlying asset (stock), and S_PRC is the (daily close) price of the underlying asset (stock) on which the call options are written; *REB_Cost*: the rebalancing cost computed by (C_Vega) x (S_%QSPR), where C_Vega is the daily mean call option vega averaged across call options available each day; *PIN*: the probability of informed trading estimated based on Yan and Zhang (2010); *C_IVOLA*: the daily mean implied volatility averaged across call options available each day; *SIZE*: the firm size variable, computed by the natural logarithm of market capitalization (the daily close stock price times the total number of shares outstanding on that day); *C_PRC*: the daily mean call option price, which is computed by averaging the quote midpoints [i.e., (daily close ask + daily close bid)/2] of call options available on each trading day; *C_VOL*: the daily call volume of contracts aggregated across call options available each trading day. "x" is used to indicate multiplication between variables to construct interaction terms. The daily mean values for the option-related variables (C_QSPR, C_Delta, C_Vega, C_IVOLA, and C_PRC) are all contract-volume weighted (hence zero-volume call options are *excluded* in the calculations). Panel A reports the 101 time-series regression results using the initial delta-hedging cost (DHG_Cost), while Panel B does the same using the rebalancing cost (REB_Cost). Each panel contains the average coefficients (*Avg. Coeff.*), the average *t*-values (*Avg. t-Value*), the number of firms with the coefficients being positive or negative, and the number of firms with the coefficients being statistically significant or not at the 5% level. The standard errors of the estimated coefficients in the time-series regressions are corrected for heteroskedasticity based on White (1980). *Avg R-sqr* is the average of adjusted R-squared values. *Avg #Days* is the average number of trading days used for the time-series regressions. The average number of trading days (observations) used in the regressions is 2,086.3 to 3,145.2.

(Table 10: continued)

	Panel A: With the Initial Delta-Hedging Cost: Dep Var = C_QSPR					
	Without the Interaction Term			With the Interaction Term		
Expla. Variables	Avg. Coeff. (Avg. *t*-Value)	#Firms with Coeff. > 0 (Coeff. < 0)	#Firms with *t*-Value ≥ 1.96 (*t*-Value ≤ -1.96)	Avg. Coeff. (Avg. *t*-Value)	#Firms with Coeff. > 0 (Coeff. < 0)	#Firms with *t*-Value ≥ 1.96 (*t*-Value ≤ -1.96)
Intercept	0.868	82	80	0.941	80	78
	(16.45)	(19)		*(12.57)*	(21)	
DHG_Cost	0.129	98	80	-0.056	38	23
	(6.39)	(3)		*(-0.99)*	(63)	
DHG_Cost x PIN				1.684	83	65
				(3.81)	(18)	
C_IVOLA	-0.004	50		-0.037	35	
	(-0.65)	(51)	(40)	*(-1.88)*	(66)	(50)
SIZE	-0.045	21		-0.049	22	
	(-14.71)	(80)	(78)	*(-10.92)*	(79)	(75)
C_PRC	0.026	101	101	0.027	101	101
	(18.44)	(0)		*(18.20)*	(0)	
C_VOL	-0.001	16		-0.003	3	
	(-2.89)	(85)	(59)	*(-3.92)*	(98)	(74)
Avg R-sqr		0.564			0.590	
Avg #Days		3145.2			2086.3	

(Table 10: continued)

	Panel B: With the Rebalancing Cost: Dep Var = C_QSPR					
	Without the Interaction Term			With the Interaction Term		
Expla. Variables	Avg. Coeff. (Avg. *t*-Value)	#Firms with Coeff. > 0 (Coeff. < 0)	#Firms with *t*-Value ≥ 1.96 (*t*-Value ≤ -1.96)	Avg. Coeff. (Avg. *t*-Value)	#Firms with Coeff. > 0 (Coeff. < 0)	#Firms with *t*-Value ≥ 1.96 (*t*-Value ≤ -1.96)
Intercept	0.874	81	80	0.929	81	77
	(17.35)	(20)		*(12.60)*	(20)	
REB_Cost	0.368	96	82	-0.264	34	20
	(6.17)	(5)		*(-1.82)*	(67)	
REB_Cost x PIN				5.829	86	68
				(4.12)	(15)	
C_IVOLA	-0.001	51		-0.027	40	
	(-0.28)	(50)	(38)	*(-1.34)*	(61)	(45)
SIZE	-0.046	21		-0.048	23	
	(-15.71)	(80)	(78)	*(-11.05)*	(78)	(73)
C_PRC	0.027	101	101	0.028	101	101
	(19.52)	(0)		*(19.30)*	(0)	
C_VOL	-0.001	16		-0.003	4	
	(-2.93)	(85)	(61)	*(-3.95)*	(97)	(76)
Avg R-sqr		0.559			0.585	
Avg #Days		3145.2			2086.3	

Table 11: Cross-Sectional Regression Results with PIN for the Interaction Term

This table reports the results of the daily Fama-MacBeth (1973)-type cross-sectional regressions (with PIN for the interaction term) using the spreads of call options written on the NYSE/AMEX-listed stocks over the 3,523 trading days from January 4, 1996 to December 31, 2009 (14 years). The dependent variable is C_QSPR. The definitions of the variables are as follows: *C_QSPR*: the daily mean quoted spread of call options averaged across call options available on each trading day; *DHG_Cost*: the initial delta-hedging cost required to hedge a call option position, which is computed by (C_Delta) x (S_%QSPR) x (S_PRC), where C_Delta is the daily mean call option delta averaged across call options available each day, S_%QSPR is the (daily close) proportional (relative to the quote midpoint) quoted spread of the underlying asset (stock), and S_PRC is the (daily close) price of the underlying asset (stock) on which the call options are written; *REB_Cost*: the rebalancing cost computed by (C_Vega) x (S_%QSPR), where C_Vega is the daily mean call option vega averaged across call options available each day; *PIN*: the probability of informed trading estimated based on Yan and Zhang (2010); *C_IVOLA*: the daily mean implied volatility averaged across call options available each day; *SIZE*: the firm size variable, computed by the natural logarithm of market capitalization (the daily close stock price times the total number of shares outstanding on that day); *C_PRC*: the daily mean call option price, which is computed by averaging the quote midpoints [i.e., (daily close ask + daily close bid)/2] of call options available on each trading day; *C_VOL*: the daily call volume of contracts aggregated across call options available each trading day. "x" is used to indicate multiplication between variables to construct interaction terms. The daily mean values for the option-related variables (C_QSPR, C_Delta, C_Vega, C_IVOLA, and C_PRC) are contract-volume-weighted averages (hence zero-volume call options are *excluded* in calculations). Panel A reports the results using the initial delta-hedging cost (DHG_Cost), while Panel B does the same using the rebalancing cost (REB_Cost). The values in the first row for each explanatory variable are the time-series averages of coefficients obtained from the day-by-day cross-sectional regressions. The values italicized in the second row of each variable are *heteroskedasticity*- and *autocorrelation-consistent (HAC) t*-statistics computed based on Newey and West (1987, 1994). *Avg R-sqr* is the average of adjusted R-squared values. *Avg #Firms* is the average number of companies (observations) used each day in the cross-sectional regressions, which ranges from 826.0 to 982.1. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 11: continued)

With PIN for the Interaction Term (Dep. Var. = C_QSPR)									
Panel A: With the Initial Delta-Hedging Cost					Panel B: With the Rebalancing Cost				
Expla. Variables	1a		2a		Expla. Variables	1b		2b	
Intercept	0.580	**	0.457	**	Intercept	0.577	**	0.459	**
	33.87		*40.33*			*33.76*		*39.66*	
DHG_Cost	0.585	**	-0.250	**	REB_Cost	1.812	**	-0.621	**
	12.05		*-5.24*			*12.22*		*-5.00*	
DHG_Cost x PIN			7.237	**	REB_Cost x PIN			21.658	**
			15.14					*14.94*	
C_IVOLA	-0.177	**	-0.160	**	C_IVOLA	-0.170	**	-0.156	**
	-22.94		*-22.08*			*-22.34*		*-21.46*	
SIZE	-0.024	**	-0.016	**	SIZE	-0.024	**	-0.016	**
	-23.57		*-23.01*			*-23.39*		*-22.66*	
C_PRC	0.040	**	0.045	**	C_PRC	0.041	**	0.045	**
	31.46		*30.10*			*32.58*		*31.25*	
C_VOL	-0.004	**	-0.007	**	C_VOL	-0.004	**	-0.007	**
	-25.95		*-12.79*			*-26.08*		*-13.11*	
Avg R-sqr	0.312		0.322		Avg R-sqr	0.312		0.320	
Avg #Firms	982.1		826.0		Avg #Firms	982.1		826.0	

Table 12: Cross-Sectional Regression Results with Some Instrumental Variables for the Interaction Term

This table reports the results of the daily Fama-MacBeth (1973)-type cross-sectional regressions (with some instrumental variables for the interaction term) using the spreads of call options written on the NYSE/AMEX-listed stocks over the 3,523 trading days from January 4, 1996 to December 31, 2009 (14 years). The dependent variable is C_QSPR. The definitions of the variables are as follows: *C_QSPR*: the daily mean quoted spread of call options averaged across call options available on each trading day; *DHG_Cost*: the initial delta-hedging cost required to hedge a call option position, which is computed by (C_Delta) x (S_%QSPR) x (S_PRC), where C_Delta is the daily mean call option delta averaged across call options available each day, S_%QSPR is the (daily close) proportional (relative to the quote midpoint) quoted spread of the underlying asset (stock), and S_PRC is the (daily close) price of the underlying asset (stock) on which the call options are written; *REB_Cost*: the rebalancing cost computed by (C_Vega) x (S_%QSPR), where C_Vega is the daily mean call option vega averaged across call options available each day; *LAM_GH*: the price-impact parameter ("lambda") estimated with intradaily stock order flows (in dollars) based on Glosten and Harris (1988) (multiplied by 10^5); *IO*: institutional ownership (proportion of shares owned by institutional investors); *C_IVOLA*: the daily mean implied volatility averaged across call options available each day; *SIZE*: the firm size variable, computed by the natural logarithm of market capitalization (the daily close stock price times the total number of shares outstanding on that day); *C_PRC*: the daily mean call option price, which is computed by averaging the quote midpoints [i.e., (daily close ask + daily close bid)/2] of call options available on each trading day; *C_VOL*: the daily call volume of contracts aggregated across call options available each trading day. "x" is used to indicate multiplication between variables to construct interaction terms. The daily mean values for the option-related variables (C_QSPR, C_Delta, C_Vega, C_IVOLA, and C_PRC) are contract-volume-weighted averages (hence zero-volume call options are *excluded* in calculations). Panel A reports the results using the initial delta-hedging cost (DHG_Cost), while Panel B does the same using the rebalancing cost (REB_Cost). In each panel, PIN for the interaction term is instrumented with LAM_GH or IO. The values in the first row for each explanatory variable are the time-series averages of coefficients obtained from the day-by-day cross-sectional regressions. The values italicized in the second row of each variable are *heteroskedasticity*- and *autocorrelation-consistent (HAC) t*-statistics computed based on Newey and West (1987, 1994). *Avg R-sqr* is the average of adjusted R-squared values. *Avg #Firms* is the average number of companies (observations) used each day in the cross-sectional regressions, which ranges from 910.5 to 982.1. Coefficients significantly different from zero at the significance levels of 1% and 5% are indicated by ** and *, respectively.

(Table 12: continued)

With Some Instrumental Variables for the Interaction Term (Dep. Var. = C_QSPR)									
Panel A: With the Initial Delta-Hedging Cost					Panel B: With the Rebalancing Cost				
Expla. Variables	3a		4a		Expla. Variables	3b		4b	
Intercept	0.569	**	0.605	**	Intercept	0.567	**	0.600	**
	33.40		*32.48*			*33.51*		*32.38*	
DHG_Cost	0.444	**	1.230	**	REB_Cost	1.489	**	3.650	**
	9.41		*14.12*			*9.76*		*14.36*	
DHG_Cost x LAM_GH	16.088	**			REB_Cost x LAM_GH	46.641	**		
	13.05					*12.93*			
DHG_Cost x IO			-0.988	**	REB_Cost x IO			-2.745	**
			-14.52					*-14.12*	
C_IVOLA	-0.183	**	-0.177	**	C_IVOLA	-0.176	**	-0.170	**
	-23.23		*-21.79*			*-22.60*		*-21.26*	
SIZE	-0.023	**	-0.026	**	SIZE	-0.023	**	-0.026	**
	-22.77		*-22.99*			*-22.79*		*-22.78*	
C_PRC	0.040	**	0.041	**	C_PRC	0.041	**	0.042	**
	31.26		*32.20*			*32.41*		*33.18*	
C_VOL	-0.004	**	-0.004	**	C_VOL	-0.004	**	-0.004	**
	-25.96		*-24.71*			*-26.06*		*-24.75*	
Avg R-sqr	0.319		0.336		Avg R-sqr	0.318		0.335	
Avg #Firms	982.1		910.5		Avg #Firms	982.1		910.5	

Figure 1: The Information Structure of the Model: with a Choice of Hedging Using the Stock
The information tree shows the probabilities of informed and uninformed trading in the stock and options markets. The information shown on the left-hand side of the vertical line corresponds to the case where the options market maker (OMM) does not hedge. The information shown on the right-hand side of the vertical line denotes the cases where the OMM hedges his call options position (incurred by his market making activities) using underlying asset (the stock).

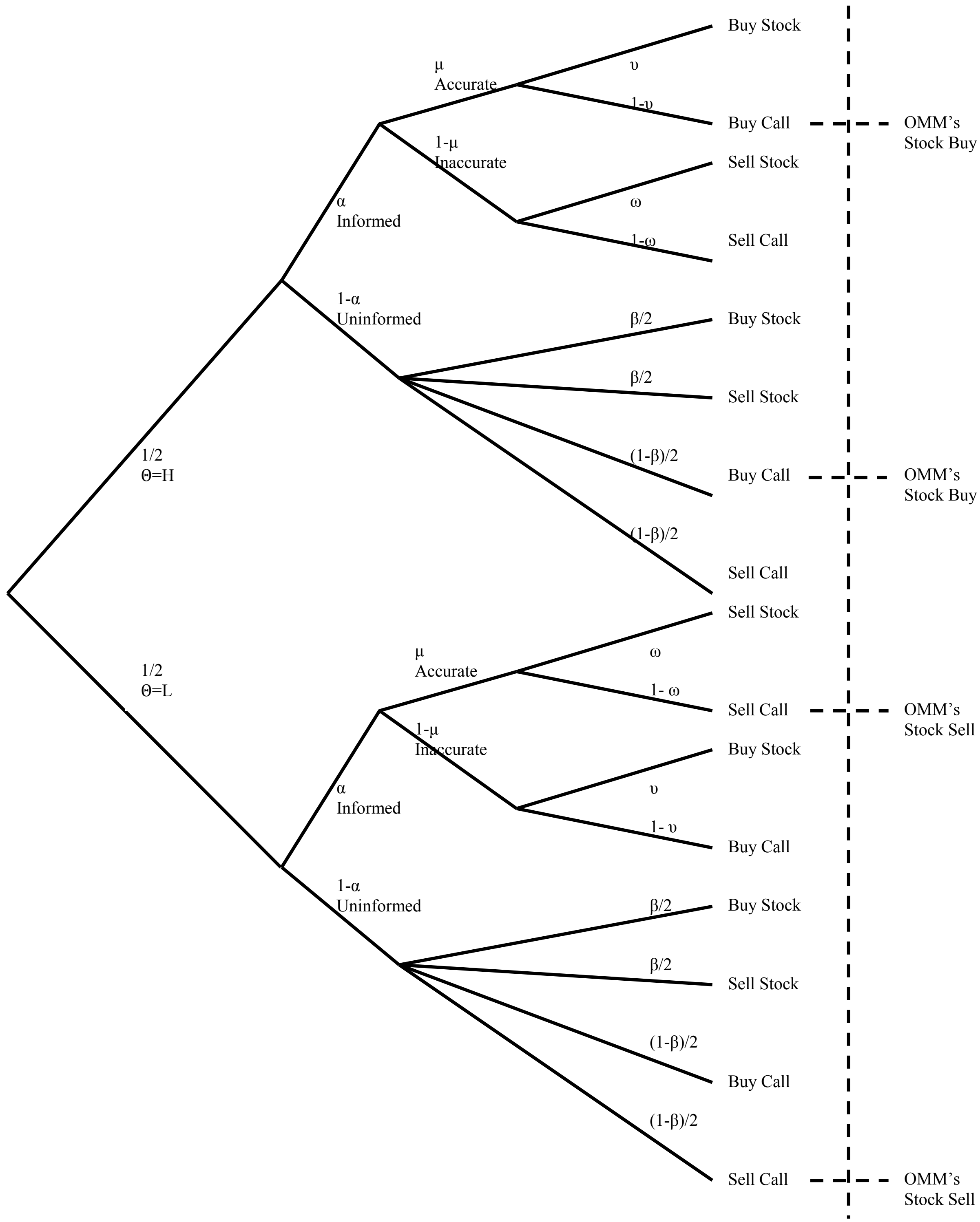
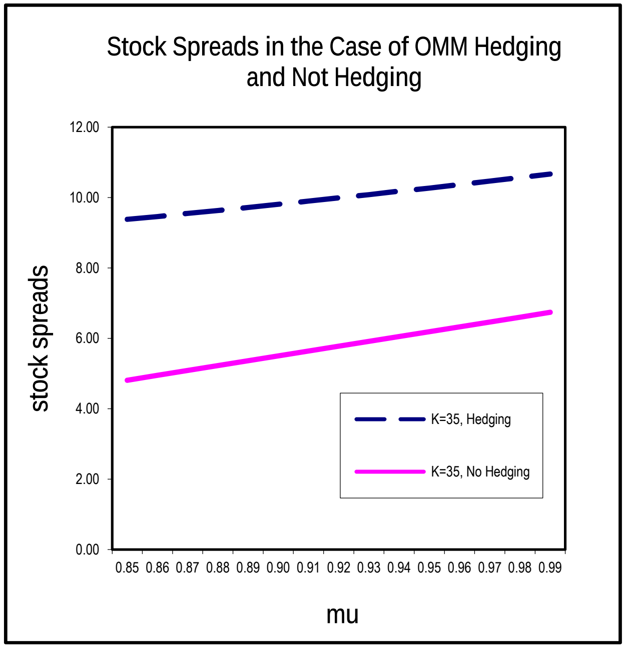
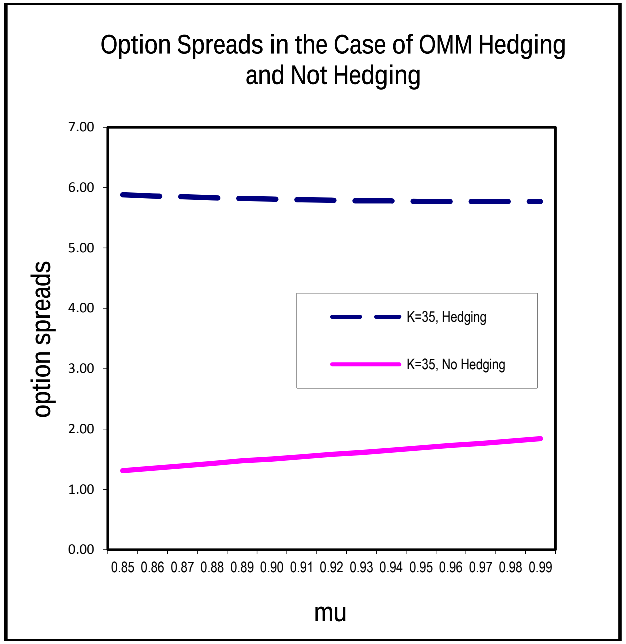


Figure 2: Spreads in the Stock and Options Markets: When the OMM Does not Hedge vs. When the OMM Hedges Using the Stock

Figure 2 (A) plots the level of spreads in the stock market when the OMM does not hedge his options position (the solid line) vs. when the OMM hedges the position using the underlying asset (the dashed line), as the signal precision (μ: *mu*) increases. Figure 2 (B) does the same for the options market. For the computations in the panels, K = 35 (for the exercise price of the call option) and α = 0.25 (for the percentage of the informed traders) are used.



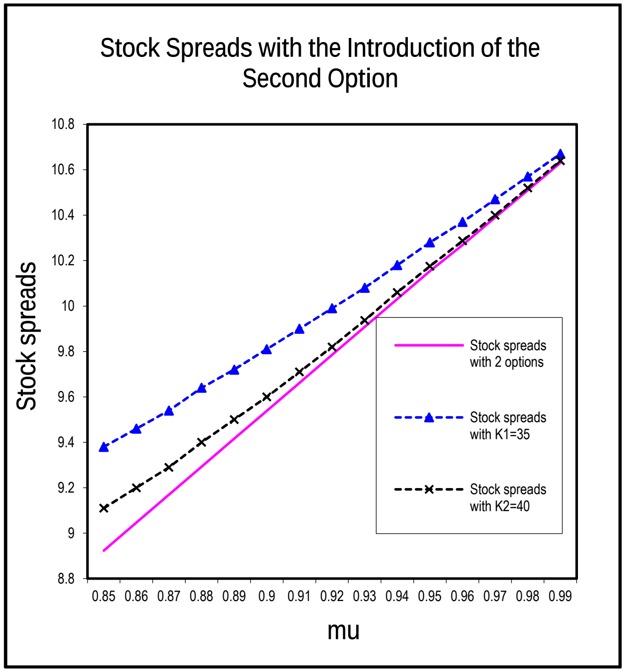
(A) Spreads in the Stock Market



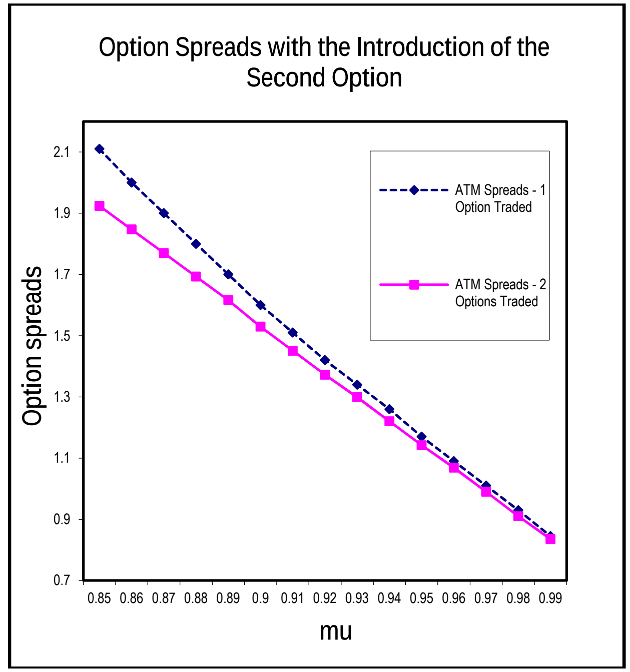
(B) Spreads in the Options Market

Figure 3: Spreads in the Stock and Options Markets When Two Call Options Exist and the OMM Hedges Using the Stock

Figure 3 (A) shows the spreads in the stock market [as the signal precision, μ (*mu*), increases] when the second call option (written on the same stock but with a different exercise price) becomes available. Here the solid line plots the stock spread when the two options (with the two different exercise prices of $K^1 = 35$ and $K^2 = 40$) are both traded in the market. The dotted line with triangles plots the stock spread when only the in-the-money call option (with $K^1 = 35$) is traded in the market, while the dotted line with crosses plots the stock spread when only the at-the-money call option (with $K^1 = 45$) is traded. Figure 3 (B) shows the spreads in the options market (as the signal precision, μ, increases) when the second call option (written on the same stock but with a different exercise price) becomes available. The solid line with squares plots the spread of the at-the-money call option ($K^2 = 40$) when both options are traded in the market. The dotted line with diamonds plots the spread of the at-the-money call option when the at-the-money call option is the only one traded in the market.



(A) Spreads in the Stock Market



(B) Spreads in the Options Market