Do informed investors manipulate markets using options prior to SEO?

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Abstract

This paper develops a model to investigate how the existence of options affects informed investors' incentives to manipulate markets prior to Seasoned Equity Offerings (SEOs). The model identifies a key variable influencing the manipulation incentives, intermarket liquidity, induced by the correlation of the uninformed orders of options and those of the underlying stock (ρ). The results show that manipulation is a dominant strategy only when ρ is low. Using a novel empirical proxy for ρ, the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock ($\hat{\rho}$), a significantly negative relation between $\hat{\rho}$ and SEO discounts is found, supporting the implications of the model. In addition, return reversals following SEOs are found only when $\hat{\rho}$ is low, being consistent with the presence of manipulation.

Keywords: Seasoned Equity Offerings, Manipulation, Option, Option leverage effect, Market Microstructure

JEL Classification: G13, G14, G23, G24, G32

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I. Introduction

"Does finance benefit society? Academics' view of the benefits of finance vastly exceeds societal perception" (Luigi Zingales, President of the American Finance Association 2014)

Do options always have positive impact on the market efficiency? I find that the options can be used as a manipulation device prior to seasoned equity offerings (SEOs).

SEOs are known to provide an incentive to manipulate the stock prices in order to get larger SEO discount. Previous studies show that SEO firms set offering prices below the market prices and these discounts are related to the information asymmetry (Altınkılıç and Hansen (2003); Beatty and Ritter (1986); Corwin (2003); Kim and Shin (2004); Mola and Loughran (2004); Rock (1986)). Other studies also show that manipulation prior to SEOs can lead to larger discounts when high information asymmetry is present (Gerard and Nanda (1993); Henry and Koski (2010)). High information asymmetry leads to greater SEO discounts since uninformed bidders are concerned about the Winner's Curse problem being present in such an environment (Beatty and Ritter (1986); Corwin (2003); Rock (1986)) and therefore, underwriters and issuing firms increase discounts to make sure that they raise enough capital. If informed investors even sell undervalued stocks to manipulate stock prices, which can lead to larger discounts, they can buy back shares at lower offering prices, which allows them to cover the costs involved with the manipulation and earn profits. Gerard and Nanda (1993) develop a model in which informed traders can make profits by manipulating the stock price (i.e., even selling undervalued stocks), which leads to greater discounts. They show that informed investors are more likely to engage in manipulation when the market is less liquid and the issuance size is larger. In a related study, Henry and Koski (2010) present the empirical evidence that abnormal short-sellings prior to the issuance increase issue discounts, which is consistent with the implication of Gerard and Nanda (1993).

In this paper, I develop a model to identify key variable that affects investors' manipulation decisions prior to SEOs and empirically test the implications of the model. Different from existing models, such as the one in Gerard and Nanda (1993), I allow options to be available to investors, and investigate how this changes investors' behavior. It turns out that the likelihood of trading both option and the underlying stock in the *same* direction by uninformed liquidity traders, ρ, is a critical variable that affects the optimal behavior of investors[1]. When ρ is lower, investors have more incentives to manipulate prior to SEOs and the prices of SEO stocks become less informative, since ρ affects the profit of investors' trading strategy. As in Kyle's model, liquidity is one of the most important parameter for the informed trading, since high liquidity guarantees better market price and profits. Liquidity for bid and ask, however, can be different, that is, there can be asymmetric demand for buying and selling the stock. High bid (ask) side liquidity means that there are enough uninformed investors who want to buy (sell) the stocks. If the likelihood of buy orders and those of sell orders are identical, the market has the highest and symmetric liquidity. With options listed, however, *intermarket liquidity* induced by the correlation of uninformed orders (ρ), which represents the easiness of the intermarket trading (i.e. trading in both stock and option), become important. In the markets with low intermarket liquidity, intermarket trading in both securities will generate price impact (demand shocks), even though each markets are liquid enough. For instances, in the markets with high ρ, buying or selling orders in both markets can be easily cleared. In the markets with low ρ, however, there will be demand shocks (price impact) in one of the markets, since the uninformed order pattern is different. Therefore, ρ determines the incentives of the informed trading, which affects price efficiency and SEO discount.

As ρ decreases, the manipulative (pooling) equilibrium become dominant over the informative (separating) equilibrium. The more informed investors actively engage in trading, the more efficient the prices are, since the new information is reflected to the price by informed trading. The market prices will be most efficient, therefore, when the informed traders participate in both stock and option markets. Then, the markets are in *fully informative equilibrium*, of which both markets are in the

[1] ρ can be expressed as the correlation of the uninformed orders of options and those of the underlying stock as in the abstract, since the correlation is a linear function of ρ as $2\rho - 1$

informative (separating) equilibrium[2]. This strategy, however, is attractive only when the informed investors have confidence of not generating demand shock (price impacts) in any markets. If there are price impacts (demand shock) in at least one market, the other market should immediately acknowledge (Muravyev (JF Forthcoming); Muravyev, Pearson and Paul Broussard (2013)). Therefore, high ρ is required for encouraging the informative trading in both markets, since the identical order pattern of informed investors in fully informative equilibrium can be only cleared by the identical order pattern of uninformed investors[3]. In other words, both markets should be liquid enough in the same direction, that is, high intermarket liquidity. As ρ decreases, however, due to the different order pattern of uninformed investors in two markets, the informed investors' orders cannot be fully executed, which causes demand shocks (price impacts) in at least one market. Therefore, informed traders have an incentive to manipulate in one market while trading according to their information in the other market, since they can avoid demand shock and get a better price. Then, the markets are in *partial manipulative equilibrium*. By shutting down one channel through which market makers abstract information from submitted orders, informed traders will have more opportunities to take advantage of their private information, leading to more manipulative equilibriums. Advantage of partial manipulative equilibrium is based on the uncertainty of order flows that both correlated and uncorrelated uninformed orders can clear the market, which means that the informed investors can avoid demand shock regardless of the correlation of uninformed orders. Also, information asymmetry remains at high level compared to fully informative equilibrium, which results in larger SEO discount. As ρ is close to 0, however, the markets can precisely deduce the price by Bayes' rule and the profit for partial manipulative equilibrium decreases, too. Extreme ρ makes it easier to estimate the stock

[2] Options are attractive in many aspects, such as the leverage effect. With budget constraints, participating only in the high levered option transaction can be profitable. Many of previous literatures focus on whether the informed traders participate in stock or option market; return predictability of the options (Ang, Hodrick, Xing and Zhang (2006); Blau, Nguyen and Whitby (2014); Pan and Poteshman (2006); Xing, Zhang and Zhao (2010)) and the information share approch (Chakravarty, Gulen and Mayhew (2004); Rourke (2014); Muravyev, Pearson and Paul Broussard (2013)). However, both market participation is also feasible even with budget constraints, since too much option orders can induce demand shock.

[3] For instances, in fully informative equilibrium, informed investors' strategy is buying (selling) both stock and options. There will not be price impact (demand shock) only when uninformed orders are both correlated selling (buying), which will clear the informed orders.

price. For extremely low ρ, however, SEOs make the strategy of manipulating both markets dominant, of which the markets are in the *fully manipulative equilibrium*. By sustaining high information asymmetry, price is least informative and SEO discount become largest. Although manipulating both markets is expensive, manipulators can reduce their total costs by taking advantage of largest SEO discounts. In short, small ρ makes hard for the informative trading to avoid price impacts (demand shock) and the informed traders rather do manipulation.

Since options provide enlarged trading strategies (Biais and Hillion (1994)) and leverage effects, they are perceived to encourage the informed traders to participate more in market transactions, which make the price of a stock become efficient (An, Ang, Bali and Cakici (2014); Chakravarty, Gulen and Mayhew (2004); Easley, O'Hara and Srinivas (1998); Hu (2014); Ni, Pan and Poteshman (2008); Pan and Poteshman (2006); Rourke (2013); Rourke (2014); Xing, Zhang and Zhao (2010); Yang and Zhang (2014)). As Biais and Hillion (1994) point out, however, options make the price discovery mechanisms more complicate to embody the possible interactions among securities (Back (1993); Jarrow (1994)). In a complete market, options are just redundant securities. However, Back (1993) posits that information asymmetry makes options no longer redundant and option markets can lead the stock market. Easley, O'Hara and Srinivas (1998) also argue that options are attractive to informed traders due to their characteristics of allowing highly levered positions and therefore, informed investors may prefer option trading rather then stock’s. In short, options provide informed traders with an additional channel to take advantage of their private information. However, they also allow market makers to have a better clue regarding the true value of the stock. For instances, even when informed traders succeed to camouflage their trading in the stock market, market makers might be able to abstract the information from the option market (Back (1993)). My model shows that how uninformed liquidity traders trade in both markets, which is captured by ρ, plays a critical role in determining whether informed investors can veil the information in both markets or not. Furthermore, this is the first paper to show that options also have a dark side in terms of market efficiency, especially prior to SEOs.

Using the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock as an empirical proxy for ρ, I find supporting empirical evidences that there is a negative relation between SEO discounts and $\hat{\rho}$, the empirical proxy for ρ. This supports the hypothesis that SEOs with low ρ are in the manipulative (pooling) equilibrium. Corwin (2003) finds the evidence that large pre-issue negative cumulative abnormal returns (CARs) are followed by larger discounts, supporting manipulation hypothesis. Henry and Koski (2010) find similar results. Unlike previous studies, results show that a large pre-issue market reaction, measured by |CAR|, lowers discounts and enhances efficiency. However, as ρ decreases, large |CAR| isn't followed by lower discounts, which supports the hypothesis that lower ρ leads the market more to the manipulative equilibrium. In addition, I find that SEOs with low ρ is followed by larger post-issue abnormal returns, being consistent with return reversals after manipulations.

Easley, O'Hara and Srinivas (1998) argue that high option leverage makes options attractive to informed traders. Furthermore, informed traders prefer to participate in option trasactions when the option market is more liquid than the stock market. Xing, Zhang and Zhao (2010) present the empirical evidences that option implied volatility losses its predictive power when the liqudity in the stock market is high. Using a novel methodology in Hasbrouck (1995), Chakravarty, Gulen and Mayhew (2004) find the similar results that the information share of options is larger for options with high option trading volume compared to the trading volume of the underlying stock. Given that the magnitude of ρ can affect the equibilirium, it is possible that the role of option leverage and liquidity on the price efficiency can depend on ρ. When ρ is high, the market is more likely to be in the informative (separating) eqiliubrium and therefore, the positive role of option leverage and liquidity can be diminished. Consistent with this conjecture, I find that option leverage and stock liquidity are not closely related to SEO discounts when ρ is high (and therefore, the market is more likely to be in the informative (separating) eqilibrium, limiting the role of opton leverage and stock liquidity). However, they become more closely related to SEO discounts as ρ decreases.

ρ is the parameter related to the cross-market lambda, which is the parameter in multi-security Kyle's model, explaining how the other market order imbalances affect the one market price. There are many papers studying cross-market trading (Back and Crotty (2015); Boulatov, Hendershott and Livdan (2013); Caballé and Krishnan (1994); Pasquariello and Vega (2015)). Back and Crotty (2015) posit that the cross-market lambda is large and each markets' return is largely explained by the others. Pasquariello and Vega (2015) finds that cross-price impact is significantly negative. However, the previous studies focus on the existence of cross-market lambda and their impact. Also, the market liquidity measured as the variance of the uninformed orders is thought to be important, but their correlation is neglected. This paper provides deep insights on how the correlation of the uninformed orders affects the informed trader's behavior and the market efficiency.

To the best of my knowledge, this is the first paper to show both theoretically and empirically that options and SEOs provide the incentive for the informed investors to manipulate the prices, to get a better price and larger SEO discount. This paper sheds light on understanding how the capital market is distorted and the tools expected to enhance market efficiency can ruin the markets. This paper is organized as follows. Section 2 develops the SEO manipulation model with options listed. Section 3 presents empirical results following the description of as well as describing the dataset and how we construct an empirical proxy for ρ. Section 4 concludes.

II. Theory

2.1. The model

SEO manipulation model with options is the extension to one-period Kyle's model with the concept of manipulation in Gerard and Nanda. Following Gerard and Nanda, there are 5 market participants; market makers, the informed trader, the uninformed (liquidity/noise) traders, the uninformed bidders, and the security issuer. All the market participants are risk neutral and trade both stock and call options. For simplicity, it is assumed that there are only European call options in the market. Market makers clear the market after observing the net order flow in both markets. Net order flow is the aggregate of the informed and the liquidity traders' orders. Market makers cannot distinguish where the orders come from, but should deduce the true value of the stock given the net order flow. The informed traders are given the true value of stock before the secondary market trading occurs. The ex-post true liquidation value of stock, $\tilde{V}$, has dichotomous values, V^+ or V^-. $X(\tilde{V}) = (x_s, x_o)$ are the informed trader's orders in stock and option market, respectively. For each states, X(V) can be $X(V^+)=(x_s^+, x_o^+)$ or $X(V^-)=(x_s^-, x_o^-)$. The liquidity traders' trading is independent of the true value. Their probability distribution of orders in two markets, $\tilde{U}=(\tilde{u}_s, \tilde{u}_o)$, is given as follows.

$$\tilde{U} \quad = \begin{bmatrix} (+u_s, +u_o) & with & \rho/2 \\ (-u_s, -u_o) & with & \rho/2 \\ (+u_s, -u_o) & with & (1-\rho)/2 \\ (-u_s, +u_o) & with & (1-\rho)/2 \end{bmatrix}$$

ρ is the probability of the identical direction between stock and option uninformed orders. ρ can be interpreted as the correlation of the uninformed orders between stock and options, since the cross-market uninformed order correlation is $2\rho - 1$. For high ρ, the liquidity traders tend to simultaneously buy (sell) both stock and options. That is, the trading pattern of two markets is correlated. Net order flow,$\tilde{Y}$, is $X(\tilde{V}) + \tilde{U}$. The security issuers set the offer price after monitoring the secondary market price. The informed bidders demand N_I shares and the uninformed bidders do N_U shares. Since the total number of shares newly issued, q, is more than N_I but less than N_U, the issuing firms have an incentive to discount in order for encouraging the uninformed bidders to participate in the issuance. The offer price, P^*, is set at the point where the uninformed bidders break even the profit. Therefore, the uninformed bidders will always participate in new issue allocation. However, the informed traders will avoid the issuance when the stock is overvalued. The number of new shares allocated to the informed bidders, α_I, and the number of new shares allocated to the uninformed bidders, α_U, are given as follows.

$$\alpha_I = \begin{cases} 0 & when\ \tilde{V} = V^- \\ q \times \frac{N_I}{N_I + N_U} & when\ \tilde{V} = V^+ \end{cases}, \qquad \alpha_U = \begin{cases} q & when\ \tilde{V} = V^- \\ q \times \frac{N_U}{N_I + N_U} = \frac{q}{\eta} & when\ \tilde{V} = V^+ \end{cases}$$

< *Insert* Figure 1>

Figure 1 presents timeline of the model. After the issuer announces SEO at t=ID−2, trading occurs at t=ID−1. At t=ID−2, initial price of the stock, P_s^0, is $V^- + \theta_0 \Delta V$ where θ_0 is the ex-ante unconditional probability of V^+ and ΔV is $V^+ - V^-$. Option price is also determined by the probability of V^+. For simplicity, it is assumed that there are only call options traded. Initial price of the option, P_o^0, is $\theta_0 \Delta V_K$ where ΔV_K is $V^+ - K$ and K is the option strikes price, of which the range is between V^+ and V^-. Without loss of generality, θ_0 is assumed to be 1/2 for simplicity. At t=ID−1, the liquidity traders and the informed traders participate in option and stock transaction and the market makers set the price at $P=E[\tilde{V}|\tilde{Y}]$, accordingly. The informed traders set the amount of orders for maximizing their expected profit. The security issuers specified the offer price before the issuance but after the secondary market price is set. At t=ID+1, the true value of the stock is revealed and options are expired.

2.2. Manipulative *vs.* Informative strategies

What is the manipulation? According to Kyle and Viswanathan (2008), manipulation is defined as "any activities undermining economic efficiency both by making prices less accurate and by making markets less liquid for risk transfer". Gerard and Nanda's concept of manipulation is also consistent with Kyle and Viswanathan. When the manipulation occurs, the market is incapable of judging anything. Manipulation indicates that the manipulators sell the stock even though the stock is undervalued. When the stock is overvalued, there is no incentive to manipulate, but anyway they sell the stock. Therefore, the trading pattern is identical regardless of the true value of the stock. Since the markets cannot get any information from order flows, information asymmetry is not resolved at all and the issuing firm should increase discount. In the model, it is described as pooling equilibrium. The informed traders' trading is expressed as x^+ when $\tilde{V}$ is V^+ and x^- when $\tilde{V}$ is V^-. In the pooling (manipulative) equilibrium, their trading pattern is identical, which means $x^+ = x^-$. In this equilibrium, although there are incoming sell orders, they cannot say that the sell orders are motivated by the overvaluation of the stock.

Without manipulation, the trading pattern of the informed traders is different, depending upon $\tilde{V}$; $x^+ \neq x^-$. It is well described in Kyle's model. In the equilibrium, the informed traders transaction is a linear function of $\tilde{V}$, which means that the trading pattern is mutually exclusive depending on $\tilde{V}$. It is plausible in the reality, since the informed traders naturally buy (sell) the securities when undervalued (overvalued). Also, if the securities are severely undervalued (overvalued), they will buy (sell) more. In my model, the trading pattern in the informative (separating) equilibrium is similar to Kyle's. The only difference is that unlike Kyle's model, the liquidation value of the stock is dichotomic. Due to the restrictive assumption, the transaction amounts in each states are bind each other. In Kyle model, since all the variables are continuous real number, the range of net order flow is real number, too. However, since $\tilde{V}$ is binary and the uninformed trader's orders are assumed to be discrete, the range of net order flows is also discrete. It is well described in Figure 2. Panel A of Figure 2 is the net order flows in the informative (separating) equilibrium and Panel B of Figure 2 is those in the manipulative (pooling) equilibrium, without options. Although x and u is real number, their levels are discrete depending on $\tilde{V}$. In the informative equilibrium, since there are two possible $X(\tilde{V})$ and two possible uninformed orders, there are 4 possible net order flows. If all the four net order flow values are different, market makers immediately track back the paths and identify the true value. Therefore, the informed traders should make some of the net orders identical in order for camouflaging their private information as $x^+=x^-+2u$. In the reality, the informed traders cannot infinitely buy (sell), since by doing so, they will generate demand shock (price impact). That is, their trading pattern in each states is bind. The gap between x^+ and x^- is widen as u increases, that is, the informed traders can buy (sell) more when undervalued (overvalued) as the uninformed investors trade enough. This is consistent with the previous literatures that the informed traders actively engage in trading if there is high liquidity and vigorous trading activities (Back (1992); Back (1993); Easley, O'Hara and Srinivas (1998); Kyle (1985)). In the informative strategy, there could be three different order flows. If

$\tilde{Y}=x^+ + u$ ($x^- - u$), there is positive (negative) demand shock and the market makers are immediately aware of the true value as V^+ (V^-). When $\tilde{Y}=x^+ - u = x^- + u$, there is no demand shock and market makers should deduce the price based on Bayes' rule. This is the case when the buy (sell) orders from the informed traders are offset by the sell (buy) orders from the uninformed traders.

In the manipulative (pooling) equilibrium (Panel B of Figure 2), trading is restricted as $x^+=x^-$. Since net order flow is solely determined by the liquidity trader's orders, there is no direct information on the true stock value. This strategy is normally not profitable unless price momentum exists in multi-period model. However, if there is SEO or option, it could be attractive. Manipulative strategy has an advantage as they can camouflage their private information. Of course, there is a loss on secondary market trading, however, since they can make the market less efficient, there is more profit from the larger issue discount. Furthermore, even without SEO, they can manipulate the price with option while do informative trading in stock market and vice versa. Although there is a loss in the market in the manipulative equilibrium, they can earn more in the informative trading with preferable price. Therefore, the informed traders have an incentive to manipulate the market in the presence of SEO and options.

With options, the informed traders have two different choices in each markets; manipulating stock or option, or both or not. That is, the possible number of equilibria are 4, which are combinations of manipulating stock or not and manipulating options or not. In short, there are fully informative, partial stock/option manipulative, and fully manipulative equilibrium. S_i denotes each equilibrium.

Definition 1 (Definition of Manipulative and Informative strategies) There are two possible strategies for each securities; informative (separating) and manipulative (pooling) strategy. The informed orders are restricted as $\mathbf{x^+=x^-+2u}$ in the *informative strategy* and as $\mathbf{x^+=x^-}$ in the *manipulative strategy*. There are total four equilibria in the market; fully informative (S_1), partial Option/Stock manipulative (S_2/S_3), and fully manipulative (S_4) equilibrium. Each equilibria are defined as

S_1: Fully Informative Equilibrium

Stock Informative ($x_s^+=x_s^-+2u_s$) and Option informative ($x_o^+=x_o^-+2u_o$)

S_2: Partial Option Manipulative Equilibrium

Stock Informative ($x_s^+=x_s^-+2u_s$) and Option Manipulative ($x_o^+=x_o^-$)

S_3: Partial Stock Manipulative Equilibrium

Stock Manipulative ($x_s^+ = x_s^-$) and Option Informative ($x_o^+ = x_o^- + 2u_o$)

S_4: Fully Manipulative Equilibrium

Stock Manipulative ($x_s^+ = x_s^-$) and Option Manipulative ($x_o^+ = x_o^-$)

With options, there are 8 possible net order flows as in Figure 3. To camouflage their trading and private information, the informed traders bind some of the net order flows depending on the equilibrium. Therefore, the number of different net order flows diminishes as in Figure 4. The conditional distribution of net order flows and true stock value depends upon each equilibrium.

The model doesn't consider price momentum, but the previous studies focus on the manipulation based on price momentum. Jarrow (1992) proves that manipulation is possible when there is price momentum or positive feedback effect. When the firm size is small, information asymmetry is severe, and markets are suspicious about the firm, not so much amounts of sell orders can make the market panic and stock price plunges. Then, manipulators get the profits by purchasing the stock at a giveaway price with small cost. With price momentum, the manipulators can generate more profit besides SEOs. Therefore, there is two channel for the manipulation; SEO discount and price momentum. However, since price momentum makes manipulation possible regardless of SEOs, I focus on only SEOs and option. It is expected that manipulation would be more feasible with price momentum.

2.3.Market price and Discount

Market price and the offer price is efficiently specified conditional on net order flows under each equilibrium in Figure 4. If there is a demand shock at least one market, the true value is immediately unveiled and both prices are adjusted to the new information. For example, in Panel A of Figure 4, when $\widetilde{Y}=(x_s^+ - u_s,\ x_o^+ + u_o)$, although there is no demand shock in the stock market, the positive demand shock on option fully reveals the true value as V^+. After observing net order flow, market makers infer the price by estimating the conditional probability of V^+ which is a function of ρ. The Bayes' rule is applied to the price estimation process. The conditional probability of V^+ ,θ_1, is

$$\theta_1(\tilde{Y}, S_i) = \mathrm{Prob}(\tilde{V} = V^+ | \tilde{Y}, S_i) = \frac{\mathrm{Prob}(\tilde{V} = V^+) \cdot f(\tilde{Y} | \tilde{V} = V^+)}{\mathrm{Prob}(\tilde{V} = V^+) \cdot f(\tilde{Y} | \tilde{V} = V^+) + \mathrm{Prob}(\tilde{V} = V^-) \cdot f(\tilde{Y} | \tilde{V} = V^-)} \quad (1)$$

The conditional distribution of net order flow, $f(\tilde{Y}|\tilde{V})$, is estimated using order distribution in Figure 3 and Figure 4. Since $\tilde{V}$ is dichotomic, stock and option price are given as

$$P_s|\tilde{Y},S_i = E[\tilde{V}|\tilde{Y},S_i] = V^- + \theta_1 \Delta V, \quad P_o|\tilde{Y},S_i = E\,[(\tilde{V}-K)^+|\tilde{Y},S_i] = \theta_1 \Delta V_K \quad (2)$$

The price is identical to its conditional expected value since market makers are competitive[4]. The offer price and discount is calculated similarly. The expected profit of the uninformed bidders for participating in the issuance is $E[\alpha_U(\tilde{V} - P^*)|\tilde{Y}, S_i]$. The offer price is set at the break-even, that is,

$$P^*|S_i = \frac{E[\alpha_U \tilde{V} | \tilde{Y}, S_i]}{E[\alpha_U | \tilde{Y}, S_i]} = E[\tilde{V} | \tilde{Y}, S_i] + \frac{\mathrm{Cov}(\alpha_U, \tilde{V} | \tilde{Y}, S_i)}{E[\alpha_U | \tilde{Y}, S_i]} \quad (3)$$

The expected (offer) price conditional on the true value of the stock can be obtained accordingly.

$$E[P | \tilde{V}, S_i] = \sum_j P | Y_j, S_i \times f(\tilde{Y} = Y_j | \tilde{V}, S_i) \quad (4)$$

The expected prices have the form as

$$\begin{aligned} &E[P_s|V^+,S_i] = V^+ - \varepsilon(S_i)\Delta V, && E[P_s|V^-,S_i] = V^- + \varepsilon(S_i)\Delta V \\ &E[P_o|V^+,S_i] = (1-\varepsilon(S_i))\Delta V_K, && E[P_o|V^-,S_i] = \varepsilon(S_i)\Delta V_K \\ &E[P^*|V^+,S_i] = V^+ - \varepsilon'(S_i)\Delta V, && E[P^*|V^-,S_i] = V^- + \frac{\varepsilon'(S_i)}{\eta}\Delta V \end{aligned} \quad (5)$$

ε and ε' are specified later.

2.4. Equilibrium

Following Kyle (1985) and Kyle and Vila (1991), the equilibrium should satisfy profit maximization and market efficiency condition. Additionally, since there are more equilibria other than the informative equilibrium, beliefs off-the-equilibrium path should be specified (Gerard and Nanda (1993); Kreps and Wilson (1982)). This is similar to the dynamic game with incomplete information

[4] If there is only one market maker, it is required to solve the utility maximization problem to the market maker. However, I assume that the market makers are competitive and their expected profit is set to be zero, as seller's problem in the competitive market.

or signaling game. For a given equilibrium, the informed traders (senders) should optimize their trading choices to maximize the profit. After observing the net order flows, the market makers (receivers) will response to maximize their utility, that is, set the price based on their belief. However, since the market makers are competitive, their utility maximization problem is replaced by the zero profit condition. This indicates that the stock and option are priced at their fair (expected) value. Finally, there should be no incentives for the informed traders defecting to the information set off the equilibrium. These three processes are recursively interacted each other, and form a sequential Nash equilibrium.

Definition 2. (Definition of the equilibrium) The equilibrium is the sets of a pair X, P satisfying the three conditions: 1) *Profit maximization*; $E[\Pi(X,P)|\tilde{\mathbf{V}},S_i] \geq E[\Pi(X',P)|\tilde{\mathbf{V}},S_i]$, 2) *Market efficiency*; $P(\tilde{\mathbf{Y}})=E[\tilde{\mathbf{V}}|\tilde{\mathbf{Y}},S_i]$, and 3) *No defection*; $E[\Pi(S_i)|\tilde{\mathbf{V}},S_i] \geq E[\Pi(S_{-i})|\tilde{\mathbf{V}},S_i]$

The expected profit conditional on $\tilde{V}$ is

$$E[\Pi(X,P)|\tilde{V},S_i] = \begin{cases} \Pi^+ = \Pi^- & when\ \Pi^+ = \Pi^- \\ 0 & otherwise \end{cases}$$

where $\Pi^+=E[(V^+-P_s)x_s^+ + (V^+-K-P_o)x_o^+ + \alpha_I(V^+-P^*)|V^+,S_i]$

$\Pi^-=E[(V^- - P_s)x_s^- + (-P_o)x_o^-|V^-,S_i]$

Π^+ and Π^- are the profit function the informed traders try to maximize, however, the final expected profit is a Dirac delta function presented in Panel A, B of Figure 5 for one asset and a linear function in Panel C of Figure 5 for two assets. In Definition 1, the informed traders' trading pattern is bind not to reveal private information. By doing so, they can get the non-zero profit, otherwise cannot earn anything. However, this argument only imposes relative difference between x^+ and x^-. After calculating the expected price, the form of Π^+ and Π^- are given as

$$\Pi^+ = \varepsilon\,\Delta V\, x_s^+ + \varepsilon\,\Delta V_K\, x_o^+ + \alpha_I \varepsilon'$$

$$\Pi^- = -\varepsilon\,\Delta V\, x_s^- - \varepsilon\,\Delta V_K\, x_o^-$$

where ε and ε' are constants, which is proved in the Appendix B. Π^+ is monotonically increasing, while Π^- is decreasing with respect to X^+ and X^-, respectively. Therefore, the informed traders may make the unbounded profit by buying (selling) the infinite securities when the stock is undervalued (overvalued). Of course, the unbounded trading is not feasible. This is due to the fact that Definition 1 is not sufficient condition for camouflage. It indicates that no matter what values of x, the private information is not unveiled as long as the relative distance between x^+ and x^- is maintained, which is not true. In Panel A of Figure 5, x_s^* is negative and Π^* is positive. Since the informed traders' trading pattern is specified in the equilibrium, the set of net order flows, Y, is also known to the market makers. In this case, Y has two elements, $x_s^*-u_s$ and $x_s^*+u_s$. Let's suppose that the informed traders increase (decrease) x_s^* to x_s^{**}. Even in this situation, the relationship between x^+ and x^- is maintained as $x^+=x^-$, but the set, Y, has new values, $x_s^{**}-u_s$ and $x_s^{**}+u_s$. Although the market makers believe that the informed traders will do the same trading (x_s^{**}) regardless of the true value, they are notified that x_s^* changes to x_s^{**}. Increases (decreases) in x_s^* mean that the informed traders have an incentive to do so. That is, it is because they can increase Π^+ (Π^-) and $\tilde{V}$ is V^+ (V^-). Therefore, although the relation in Definition 1 is satisfied, the private information will be unveiled unless Π^+ and Π^- are identical. The analogous argument is applied to the informative equilibrium and the cases with options in Figure 5. An equilibrium exists when there is only a stock, and multiple equilibrium exists when the option is listed. This is consistent with the result in Back (1993), which shows that the uniqueness of the equilibrium is not necessarily achieved with derivatives.

The four equilibria are not compatible, since the profit off the equilibrium is no different to the profit for another equilibrium. It is assumed that the market makers can identify the strategy by observing the net order flow. The set of X is different for the different equilibrium and this makes the set of net order flows, Y, unique. Therefore, the net order flows itself reveals which strategy the informed traders follows and the deviation cannot generate the same net order flow as before. In short, $Y|S_i \neq Y|S_{-i}$. This is plausible not only in the model, but also in the reality. The market makers have the expectation of the net order flow and if it's suspicious, they will doubt that there is manipulation. Hence, without loss of generality, it is safe to assume that the net order flow reveals the strategy. This reduces the part of no defection condition as $E[\Pi(S_{-i})|\tilde{V},S_i]=E[\Pi(S_{-i})]$

The definition of the equilibrium is modified as Theorem 1.

Theorem 1 (Characteristics of the equilibrium) The equilibrium is the sets of a pair X, P satisfying the three conditions: 1) Profit maximization; Max $E[\Pi|\tilde{\mathbf{V}},S_i] = \Pi^+ = \Pi^-$, 2) Market efficiency; $P(\tilde{\mathbf{Y}}) = E[\tilde{\mathbf{V}}|\tilde{\mathbf{Y}},S_i]$, and 3) No defection; $E[\Pi(S_i)] \geq E[\Pi(S_{-i})]$ where

$$\Pi^+=E[(V^+-P_s)x_s^+ + (V^+-K-P_o)x_o^+ + \alpha_I(V^+-P^*)|V^+,S_i]$$

$$\Pi^- =E[(V^- -P_s)x_s^- + (-P_o)x_o^- |V^-,S_i]$$

2.5. Manipulation without options

First, I consider the case when there is no option, for understanding the basic mechanism of the manipulation. Some of the assumptions and parameters should be modified. Since only stock exists, there are two equilibria; the informative (separating) and the manipulative (pooling) equilibrium. Since options are not listed, the distribution of the liquidity order also different. The liquidity orders have dichotomic values, u_s and $-u_s$, with the probability of b_s and $1-b_s$, respectively. Since noise traders are considered not to have any intention for the direction of the prices, b_s is assumed to be 0.5. In the informative equilibrium, the true value is unveiled for some net order flows and the expected discount is low. In Panel A of Figure 2, net order flows inducing demand shock fully reveal true value and there is no discount. For the middle case, information asymmetry is not entirely resolved and there will be offer discount. On average, due to the informed traders' transaction, the clue for the true value of the stocks is given to the market and the issuing firm doesn't have to pay too much in the equity market. On the other hand, in the manipulative equilibrium, no information is leaked and new information is not updated. Therefore, the price remains at the initial value and the offer price should be discounted to attract the uninformed bidders. This argument requires the assumption of competitive market makers, who competitively pay the price at its fair value. If we loosen the assumption, manipulative sell orders will lower the price since there is nothing to lose for the market makers to pay at lower price. Even loosening the assumption, however, the price will not drop as in the informative equilibrium, since some investors will absorb the manipulative sell orders if the markets have a doubt on manipulation. In the manipulative equilibrium, the discount is enlarged, since the high level of the information asymmetry is maintained, which provides the very incentive to do manipulation. Following these arguments, the equilibrium are characterized as follows.

Theorem 2 (Manipulation condition without option) SS_1 denotes the informative equilibrium and SS_2 denotes the manipulative equilibrium. In each equilibria, the conditional expected prices have the form of $E[P|V^+]= V^+ - \varepsilon\Delta V$ and $E[P|V^-]=V^- + \varepsilon\Delta V$, where the price kernel, ε, is $b_s(1 - b_s)$ for SS_1, and 1/2 for SS_2. The conditional expected offer prices have the form of $E[P^*|V^+]= V^+ - \varepsilon'\Delta V$ and $E[P^*|V^-]= V^- + \varepsilon'/(\eta b_s)\Delta V$ for SS_1, and $E[P^*|V^+]= E[P^*|V^-]= V^+ - \varepsilon'\Delta V$ for SS_2. The offer price kernel, ε', is $\frac{\boldsymbol{\eta}}{\boldsymbol{\eta b_s}+(\mathbf{1}-\boldsymbol{b_s})}\boldsymbol{\epsilon}$ for SS_1, and $\frac{\boldsymbol{\eta}}{\boldsymbol{\eta}+\mathbf{1}}$ for SS_2. The equilibrium trading strategy is $x^+= x^-+2u_s$ $=\boldsymbol{u_s}-\frac{\boldsymbol{\alpha_I}}{\mathbf{2}}\cdot\frac{\boldsymbol{\eta}}{\boldsymbol{\eta b_s}+(\mathbf{1}-\boldsymbol{b_s})}$ for SS_1 and $x^+= x^-=-\boldsymbol{\alpha_I}\cdot\frac{\boldsymbol{\eta}}{\boldsymbol{\eta}+\mathbf{1}}$ for SS_2. The expected profit, $E[\Pi]$, has the form of $\left(\frac{\boldsymbol{\alpha_I}}{\mathbf{2}}\cdot\boldsymbol{\epsilon}'+\boldsymbol{u_s}\cdot\boldsymbol{\epsilon}\right)\boldsymbol{\Delta V}$ for SS_1 and $\frac{\boldsymbol{\alpha_I}}{\mathbf{2}}\cdot\boldsymbol{\epsilon}'\cdot\boldsymbol{\Delta V}$ for SS_2. With the assumption of b_s=0.5, there is manipulation when

$$\alpha_I \geq \left(1+\frac{1}{\eta}\right) u_s \tag{6}$$

Equation (6) is analogous to the equation (Ia) in Gerard and Nanda (1993), which states the condition for the existence of the manipulative equilibrium. They prove that the manipulation is profitable when the amount of shares issued is enough. For each equilibria, the profit to the informed traders is proportional to α_I. Interestingly, when there is no SEO, the profit for the manipulation becomes zero. That is, manipulation is not beneficial in the absence of SEO. This indicates that in the ordinary market, this kind of manipulation is not feasible. Also, when u_s is large enough, the profit for SS_1 increases, that is, it is less likely that the manipulation is dominant. u_s represents the liquidity or the trading activity. Consistent with Gerard and Nanda (1993), manipulation is more prominent when there is large SEO, low liquidity, and high information asymmetry.

2.6. Manipulation with options

Options provide the informed traders with additional channel to trade but also the market makers with the venue for gathering the information. Cross-market uninformed order correlation measured by ρ decides advantages and disadvantages to each player. ρ is the probability of the identical direction between stock and option uninformed orders. In the previous literatures such as Back (1993), the noise traders' order flows follow bivariate normal distribution with zero mean, since they trade independent of the true value of the stock. However, the distribution has non-zero variance and covariance. The uninformed distribution in the model is the simplified version of the conventional normal distribution, capturing the bottom line characteristics. When ρ is high, it is more probable for the noise traders to make same buy or sell orders in both markets. For example, if they buy the stock with high ρ, it is more likely to buy the options, too. On the other hand, when ρ is low, if they buy the stock, it is less likely to buy but probably sell the options. The noise traders trading pattern largely affects the informed traders' decision, since it's the core to camouflage their informed trading. Let's consider the undervaluation of the stocks (V^+) and its conditional price in Panel A of Figure 2. The informed traders make the x^+ market orders. When the uninformed traders simultaneously make the buy orders ($+u_s$), there are too much buy orders in the market and these positive demand shock immediately increases the price as V^+. However, if the uninformed traders sells the stocks ($-u_s$) and absorb the informed buy orders, there is not much left for the market makers to deal with. It depends on the market condition, but certainly, the price is less than or equal to V^+. Therefore, the informed traders can only camouflage when the uninformed orders offset theirs. Things become complicated when the options are listed. Now, the informed traders make another market orders of buying the options. Let's consider the fortune case when the uninformed traders sell the stocks and no positive demand shock presents in the stock market. If there are no options, this could be favorable situation for the informed traders. However, the existence of the options makes the informed traders think more. Although there is no positive demand shock in the stock market, the demand shock in the option market can unveil the true value and both markets will immediately appreciate the price. Options provide the informed traders with the additional channel to exploit their private information, but also the market makers with the place to get the new information. In order for succeeding the informative trading in both markets, the cross-market trading pattern of the uninformed orders should be identical. That is, ρ should be high enough to absorb both stock and option informed orders, simultaneously.

With small ρ, the informed traders prefer to do manipulation, since the market can easily identify their trading intention. Let's again assume that the stock is undervalued and the informed traders make buy orders in both markets. First, assuming that ρ is 1, there are only correlated buy or sell uninformed orders in both markets, equally likely. Therefore, the informed traders have fifty percent chances of getting profits and equal chances of nothing. The expected profit is definitely non-zero. Assuming that ρ is less than 1, there are non-zero probability of the uncorrelated uninformed orders between two markets, that is, if there are uninformed buy orders in one market, uninformed sell orders can be made in the other market. To avoid any demand shocks, there should be uninformed sell orders in both markets. However, if the cross-market uninformed orders are opposite, there is no way to hide, since positive demand shock occurs at least one market. Consequently, as ρ decreases, there is less incentive for the informed traders to do informative trading in both markets. On the contrary, small ρ is preferable condition for the manipulation. The problem for the informative trading with small ρ is that the market makers can get the information from the other market. If the informed traders manipulate at least one market, the market makers cannot obtain anything in that channel. Let's assume that the market believes that the informed traders manipulate the option market, but not the stock market. Therefore, the market makers have a doubt on the trading in the options market. Same situation that the informed traders make buy orders in stock market and the noise traders offset them happens, but the informed traders make the sell orders to confuse the market. The problem in this example was that the market makers can identify the true value through options even when no information is fully revealed in the stock market. However, in this modified case, the market makers cannot obtain anything in the option market and the informed traders are able to keep the secret. Prices is not appreciated to V^+. In short, with small ρ, since the true value can be easily unveiled in the informative trading, the informed traders have greater incentives to manipulate at least one market to block the channel for the market makers getting additional information. As ρ becomes real small, close to 0, even one market manipulation can reveal the information, since the market makers are easy to infer the price. In other words, although the informed traders avoid demand shock, the market makers can certainly identify the stock price using Bayes' rule. Therefore, for a extremely small ρ, it's better to manipulate both markets when SEOs present.

ρ is exogenously given to the model and its endogenous mechanism is beyond the scope of this paper. However, some of the considerations give the clues to the characteristics of ρ. Back (1993) comments that it is natural to have small ρ in the ordinary markets, since some investors only trade in the stock markets, options are used for the hedge, transaction costs are different, and the tax effect exists. That is, to understand how ρ forms, it is required to analyze the different types of the investors and their incentives. There are three different types of the uninformed investors; speculators, hedgers, and arbitrageurs. First, speculator's trading patterns are classified as delta and vega related trading. Delta trading is based on the direction of the stock. Delta speculators could be informed traders, uninformed manipulators (Allen and Gale (1992); Vitale (2000)), and sentiment investors (Baker and Wurgler (2006)). Unless they are informed, uninformed delta trading will increase ρ. Vega trading is based on the volatility of the stock (Ni, Pan and Poteshman (2008); Rourke (2014)). It is impossible to bet on the volatility of the stock without derivatives. Options provide unique instrument for volatility trading. Option value is an increasing function of underlying stocks' volatility. Vega trading strategy is purchasing both call and put options with same strike prices or options with delta hedged underlying stocks. The key element in the trading is that any directional movement of the stock should be eliminated. Therefore, whether informed or not, vega traders will decrease ρ. If small ρ is induced by vega trading, ρ may be a function of information asymmetry since high volatility has a positive correlation with asymmetric information. Finally, hedger and arbitrageur also lower ρ. As Back (1993) argues, the hedger trades in the opposite direction between two securities, that is, incurring small ρ. Therefore, there is the clientele effect, that is, ρ could be cross-sectionally variant depending on the characteristics of the investors. In short, due to the nature of the uninformed traders, it is natural to have small ρ.

Assumption 1 ρ, the probability of the identical direction of the uninformed orders between stock and option, is assumed to be less than or equal to 1/2.

ρ less than 1/2 means that the correlation of the uninformed traders orders between stock and options is negative, which is consistent with Back (1993). Similar to the manipulation without option, the equilibrium characteristics are specified in Theorem 3.

Theorem 3 (Equilibrium with options) In each equilibria, the conditional expected prices have the form of $E[P|V^+]= V^+ - \varepsilon\Delta V$ and $E[P|V^-]=V^- + \varepsilon\Delta V$. The conditional expected offer prices have the form of $E[P^*|V^+]= V^+ - \varepsilon'\Delta V$ and $E[P^*|V^-]= V^- + \varepsilon'/\eta\Delta V$. The price kernel (ε), the offer price kernel (ε'), equilibrium-trading strategy (x), and the expected profit are specified as follows.

S_1: Fully Informative Equilibrium

$$\varepsilon(S_1)=\rho/4,\ \ \varepsilon'(S_1)= 2\cdot\frac{\eta}{\eta+1}\cdot\varepsilon(S_1),$$

$$x_s^+ = -\frac{\Delta V_K}{\Delta V}x_o^+ + \left(u_s + u_o\frac{\Delta V_K}{\Delta V} - \frac{\alpha_I}{2}\cdot\frac{\varepsilon'}{\varepsilon}\right),$$

$$\Pi(S_1) = \left(\frac{\alpha_I}{2}\cdot\varepsilon' + \left(u_s + u_o\frac{\Delta V_K}{\Delta V}\right)\cdot\varepsilon\right)\Delta V = \frac{\rho}{4}[A + u_s + \delta u_o]\Delta V$$

S_2: Partial Option Manipulative Equilibrium

$$\varepsilon(S_2)=\rho(1-\rho),\ \varepsilon'(S_2)=\frac{\eta}{2}\cdot\frac{\eta+1}{(\eta-1)^2\varepsilon+\eta}\cdot\varepsilon(S_2),$$

$$x_s^+ = -\frac{\Delta V_K}{\Delta V}x_o^+ + \left(u_s - \frac{\alpha_I}{2}\cdot\frac{\varepsilon'}{\varepsilon}\right),$$

$$\Pi(S_2) = \left(\frac{\alpha_I}{2}\cdot\varepsilon' + u_s\cdot\varepsilon\right)\Delta V = \rho(1-\rho)[A' + u_s]\Delta V$$

S_3: Partial Stock Manipulative Equilibrium

$$\varepsilon(S_3)= \varepsilon(S_2),\ \ \varepsilon'(S_3)=\varepsilon'(S_2),$$

$$x_s^+ = -\frac{\Delta V_K}{\Delta V}x_o^+ + \left(u_o\frac{\Delta V_K}{\Delta V} - \frac{\alpha_I}{2}\cdot\frac{\varepsilon'}{\varepsilon}\right),$$

$$\Pi(S_3) = \left(\frac{\alpha_I}{2}\cdot\varepsilon' + u_o\frac{\Delta V_K}{\Delta V}\cdot\varepsilon\right)\Delta V = \rho(1-\rho)[A' + \delta u_o]$$

S_4: Fully Manipulative Equilibrium

$$\varepsilon(S_4)=1/2,\ \ \varepsilon'(S_4)= 2\cdot\frac{\eta}{\eta+1}\cdot\varepsilon(S_4),$$

$$x_s^+ = -\frac{\Delta V_K}{\Delta V}x_o^+ - \alpha_I\cdot\frac{\eta}{\eta+1},$$

$$\Pi(S_4) = \frac{\alpha_I}{2}\cdot\varepsilon'\cdot\Delta V = \frac{1}{2}\ A\,\Delta V$$

Where $A= \alpha_I\frac{\eta}{\eta+1}$, $A'=\frac{\eta\alpha_I}{4}\cdot\frac{\eta+1}{(\eta-1)^2\rho(1-\rho)+\eta}$, and $\delta = \frac{\Delta V_K}{\Delta V}$

Depending upon the equilibrium, the expected price is affected by ρ. Since ρ affects the (offer) price and the expected profit, it's the core parameter determining the equilibrium. As referred above, the price is linear function of ρ in S_1. However, it's the concave function in S_2 and S_3. In partial manipulative equilibrium, the informed traders can avoid the positive demand shock, but they should pay more since the market makers can extract the information. On the contrary, price kernel in S_4 is independent of any parameter, since no information is leaked. Similar to no options case, fully manipulative equilibrium is not feasible unless there is SEO. However, partial manipulative equilibrium can have non-zero profit even without SEO, since the manipulators can get the profit in the market where they do informative trading. Interestingly, the equilibrium trading amount of the stock is a function of the delta equivalent option trading. $\Delta V_K/\Delta V$ is a delta of the options. Therefore, the main drivers for the profit is each markets' liquidity and SEO discount. As stated in the previous literatures, the informative trading is beneficial when the liquidity is enough. Interesting point is that whether manipulating the options or stock in partial manipulative equilibrium depends on the other market's liquidity. That is, if the stock market is liquid, the option manipulation incentives is increased. According to Theorem 1, equilibrium and manipulation condition is specified as follows.

Theorem 4 (Infeasibility of S_1) Fully informative Equilibrium (S_1) is dominant if and only if the following conditions are satisfied. Under Assumption 1, S_1 is always inferior.

$$(S_2)\text{: } \rho > 1 - \frac{A+U}{4(A'+u_s)} \quad \text{and} \quad (S_3)\text{: } \rho > 1 - \frac{A+U}{4(A'+\delta u_o)} \quad \text{and} \quad (S_4)\text{: } \rho > 2 \cdot \frac{1}{1+U/A}$$

where $U=u_s+\delta u_o$, $\delta=\Delta V_K/\Delta V$, $A=\alpha_I \frac{\eta}{\eta+1}$, $A'=\frac{\eta\alpha_I}{4}\cdot\frac{\eta+1}{(\eta-1)^2\rho(1-\rho)+\eta}$

The proof to the Theorem 4 is trivial. A' is a function of ρ. Under Assumption 1, A' is monotonically decreasing function of ρ. Then, right-hand-side of inequalities decreases as ρ increases. Therefore, it is enough to check the condition at ρ=1/2. Since at least one condition is not satisfied at ρ=1/2, fully informative trading is not feasible when ρ is smaller than 1/2. The theorem provides novel intuition that in the ordinary market, the informed traders will not prefer to trade in both markets. It's too risky to trade, since it is easy to reveal their private information. Therefore, with or without SEO, the market is in the equilibrium with only one informative trading. Furthermore, A and A' is the term related to the amount of new shares issued. As A and A' become larger, the above inequalities become hard to be satisfied. That is, large SEO stimulates manipulation. These results are summarized in Corollary 1.

Corollary 1 S_1 is always inferior under Assumption 1, since at least one condition is not satisfied at $\rho=1/2$.

$$(S_2): \delta u_o - u_s > A \quad \text{or} \quad (S_3): u_s - \delta u_o > A \quad \text{or} \quad (S_4): (u_s+\delta u_o)/3 > A$$

For every sets of u_s, u_o, δ, and A, at least one of the first two conditions is not satisfied. Since the informed traders manipulate or don't engage in transaction in both markets, at least one market is absent of the new information. However, with SEOs, the more severe manipulation, S_4, become dominant over S_2 and S_3.

Theorem 5 (Manipulation condition) There is manipulation when the following conditions are satisfied. $\partial M_K/\partial \alpha_I > 0$ and $\partial M_K/\partial \tilde{\boldsymbol{u}}_{\boldsymbol{k}} < 0$ are always satisfied. When $\mathbf{M_k} > \frac{1}{4}$, regardless of ρ, there is always manipulation.

$$\rho < \frac{1}{2} \times \left[1 - \sqrt{1 - 4M_k}\right]$$

where $M_k(\alpha_I, \tilde{u}_k) = \left[f(\alpha_I, \tilde{u}_k) + \sqrt{f(\alpha_I, \tilde{u}_k)^2 + 32\eta^2(\eta-1)(\eta^2-1)\alpha_I \tilde{u}_k}\right] \Big/ 8(\eta-1)(\eta^2-1)\tilde{u}_k$,

$k = \{o, s\}$

$f(\alpha_I, \tilde{u}_k) = \eta(\eta^2 - 6\eta + 1)\alpha_I - 4\eta(\eta+1)\tilde{u}_k$

$\tilde{u}_s = u_s, \tilde{u}_o = \delta u_o$

<Insert Figure 6>

Theorem 5 implies that small ρ is the critical condition stimulating manipulation. In Panel A of Figure 6, as ρ decreases, the profits for S_2 and S_3 also decreases. When ρ is smaller than ρ^* which makes the inequality become identical, S_4 is dominant, that is, manipulation. As in Panel B of Figure 6, when M_K is greater than 1/4, no matter what values of ρ is, there is always manipulation. The profits for S_1 is always smaller than those for other equilibriums. As documented in Gerard and Nanda (1993), large SEO stimulates manipulation. In the above inequality, since $\partial M_K/\partial \alpha_I$ is positive, large α_I makes the RHS of inequality larger. Furthermore, the option leverage (δ) and liquidity suppress the manipulative trading and make the market more efficient. Since $\partial M_K / \partial \tilde{u}_k < 0$ is always satisfied, high option leverage and liquidity make RHS of inequality smaller. In the previous literatures, high option leverage encourages the informed traders to participate in the option transaction (Easley, O'Hara and Srinivas (1998); Xing, Zhang and Zhao (2010)), since it provides higher profit for a given amount of money invested. Option leverage can be defined as the elasticity of the option price to the stock price, that is, how much the option price moves as the stock price changes, which indicates how many stocks the options control. As the number of shares controlled by the option increases, the profit increases for a given traded option contract. The informed traders are better off by participating in the option transactions. If the informed traders manipulate the stock (options) price while doing informative trading in the option (stock) market with high leverage, they can generate more profit. Liquidity is also a critical parameter determining the informed traders' behavior. Highly liquid market is the venue for the informed traders to trade and has superior market efficiency (Back (1992); Gerard and Nanda (1993); Kyle (1985)). Similar logic can be applied to the liquidity.

The manipulators expect the profit in two channels. First, they can get a better price. Of course, in fully manipulative equilibrium, there is nothing to earn in secondary market trading and they should pay manipulation cost to get a higher discount. In the partial manipulative equilibrium, however, by paying manipulation cost only in one market, they don't have to pay too much in other market. Therefore, when they manipulate the option market, they can get a better price in stock market. For broader sense, when one market's informativeness is poor, the informed traders can get a preferable price in other market by at least not participating in poor informativeness market. Second, the manipulation returns greater SEO discount. SEO provides strong incentive to do manipulation, since it is well known that higher information asymmetry induces higher discount. Furthermore, manipulation not only worsen the information asymmetry, but also makes doubts on the intention of SEO, which reducing the demand for SEO. The demand for SEO is an important factor determining discount. That is, in terms of information asymmetry and demand based story, the model in this paper provides fare intuition. Consequently, it can be inferred that manipulation prior to SEO will return higher discount (Gerard and Nanda (1993)).

Theorem 6 (manipulation and SEO discount) The expected discount, which is given as follows, is greater for severe manipulation. That is, $E[DSCT|S_4] \geq E[DSCT|S_3] = E[DSCT|S_2] \geq E[DSCT|S_1]$. Since small ρ stimulates manipulation, there is negative relation between ρ and discount.

$$E[DSCT|S_1] = \frac{\rho}{4} \cdot \frac{\eta-1}{\eta+1} \Delta V$$

$$E[DSCT|S_2] = E[DSCT|S_3] = \frac{\rho(1-\rho)}{4} \cdot \frac{\eta^2-1}{(\eta-1)^2\rho(1-\rho)+\eta} \Delta V$$

$$E[DSCT|S_4] = \frac{1}{2} \cdot \frac{\eta-1}{\eta+1} \Delta V$$

<Insert Figure 7>

Figure 7 presents the relation between SEO discount and ρ for each equilibrium. No matter what values of ρ, S_4 has the biggest discount than others. Since small ρ makes S_4 dominant over any other equilibrium, it is expected that there is negative relation between ρ and SEO Discount.

After the true value of the stock is unveiled, it is expected that return reversal follows manipulation. As there is more severe manipulation, the information asymmetry is maintained at high level and price informativeness is poor. Therefore, conditional on the true value of the stock, price is appreciated or depreciated more in either direction.

Theorem 7 (Return reversal) Price movements after SEO are larger for more severe manipulation.

III. Empirical Analysis

In this section, I test the implication of the theoretical model. To do so, I develop the novel measure for ρ. Since small ρ indicates more manipulation, there is negative relation between ρ and discount. Large pre-issue market reaction measured by Cululative Abnormal Return (CAR) reduces discount but this effects dimish as ρ decreases. Manipulation is inevitably accompanied by the return reversal. In the post-issue performance analysis, I find the negative relation between ρ and post-issue return movement. Furthermore, low ρ is followed by good long-term performance. Since the option leverage and liquidity make the market efficient, the option leverage and liquidity make the discount smaller. However, this effect is marginal for high ρ, which indicates that the option leverage and liquidity is more important when ρ is small. Endogeneity concern and other robustness tests are also conducted.

3.1. Measurement of ρ

$\hat{\rho}$, empirical proxy for ρ, is defined as the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. It is possible to make a proxy directly using tick-level datasets. However, it requires heavy calculation and the complexity. Amihud provides a quite simple but novel methodology to measure order imbalances and liquidity. In a daily level, it is well documented that the net buy order imlance increases return and decreases liquidity (Chordia, Roll and Subrahmanyam (2002); Chordia and Subrahmanyam (2004)). High buyer demand and its presurre move price higher. This effect is also prominent in option market (Rourke (2014)). If the market is complete and option is redundant, there should not be dispersion of option price from theoretical value. However, with information asymmetry, option transaction have information (Back (1993)) and end-user demand pressure affects option price (Bollen and Whaley (2004); Garleanu, Pedersen and Poteshman (2009)). Furthermore, inventory risk of opion move price as much as information asymmetry (Muravyev (JF Forthcoming)). Therefore, on a day with higher net buy orders, stock and option return will be appreciated and the amount of return increase per voulme will be also higher. $\hat{\rho}$ is defined as

$$\hat{\rho} = Corr\left(\frac{r_s}{V_s}, \frac{r_o}{V_o}\right)$$

where r_s (r_o) is return on stock(option) and V_s (V_o) is trading volume normalized to shares outstanding (open interest). It is estimated in the period between 84 and 21 trading days prior to the issuance to be less affected by any informed tradings. In the model, the correlation of the uninformed order is calculated as 2ρ−1. However, it is expected for $\hat{\rho}$ to be close to one due to its definition. Options have two classes; call and put options. Since it is important to measure the direction of the option trading, return on option is defined as the return of a portfolio buying a call and selling a put option, which is synthetic futures. Since only ATM options are considered, the delta of the portfolio is 1 and comparable to purchase one stock. Return on call or put option is based on the mid point of the bid and ask price in Optionmetrics (Coval and Shumway (2001); Muravyev (JF Forthcoming)). Therefore, the return correlation should be close to one by definition. Although the signed Amihud illiquidity is not exactly same as the return, the characteristics should be similar. Signed Amihud illiquidity of the option is defined as

$$\frac{\mathrm{r_o}}{V_o} = \frac{r_c}{V_c} - \frac{r_p}{V_p}$$

where $r_c(r_p)$ is return on call(put) option and $V_c(V_p)$ is call(put) option trading volume normalized to open interest. For the robustness check, I also test the return correlation ($\hat{\rho}_{\mathrm{r}}$), the signed Amihud correlation using raw trading volume ($\hat{\rho}_{\mathrm{v}}$), the signed Amihud correlation with call options ($\hat{\rho}_{\mathrm{c}}$), and the signed Amihud correlation with put options ($\hat{\rho}_{\mathrm{p}}$). All other variables are defined in the Appendix A.

3.2. Characteristics of ρ

One of the critical assumption in the model is that the market makers can observe two markets' order flow. In practice, this could not be a true, since the market makers in one market may have a previllege to access private information contained in the order flow or the limit order book. However, post-trade transparency provides enough condition for the observability of order flow (Back and Crotty (2015)). Since the market makers can infer the order flow from the price movement, post-trade transparency is the sufficient assumption in the model setting. Equity markets are fairly transparent. Especially, in 1990s, NYSE allows the floor traders to view order book. On January 24, 2002, NYSE makes the public accessible to the real time depth of the limit order book (Baruch (2005); Boehmer, Saar and Yu (2005); Hasbrouck (2006)). Option markets also have fair level of transparency. In CBOE, under Rule 6.51, the seller and buyer should report the trading detail within 90 seconds of execution, such as price, transaction amount, broker, execution time, type, and maturity. Also, Plan for Reporting of Consolidated Options Last Sale Reports and Quotation Information has been approved under the Securities Exchange Act of 1934. This plan is for providing consolidated information on option quotes and trades. Recently, the Options Price Reporting Authority (OPRA) was founded as a limited liability company ("LLC") under the plan[5]. OPRA plan help the investors, broker-dealer, and market to get a better information and the best price (Battalio, Hatch and Jennings (2004); Battalio and Schultz (2006); Rourke (2013); Rourke (2014)). Even if there is reporting lag, since I use daily returns and volume, it is unlikely for the market makers to miss other market's order flow. Furthermore, 90 seconds reporting lag is short enough to assure that there is no reporting lag and enough transparency in daily level anaysis.

3.3. Data and Sample construction

My dataset is based on SDC New Issue database for Seasoned Equity Offerings (SEO) of U.S. Public Common Stock. The sample period starts in January 1996 and ends in December 2013. I exclude issues with missing offer date or CUSIP. Only the firm commitment and accelerated or block offer in SDC offer technique is included. These screening criteria yield a sample of 6,992 SEOs. To determine the effective offer date for offerings which take place after the close of day, I follows the volume-based offer date correction rule in Corwin (2003).

The stock price data is from Center for Research in Security Prices (CRSP). I only include common stock with share codes 10 and 11, listed on NYSE/AMEX or Nasdaq. Financial firms (SIC code between 6000 and 6999) and Utilities (SIC code between 4900 and 4999) are excluded. The CRSP data are merged with Compustat. Firms that do not have book equity value for the fiscal year prior to the issuance in Compustat are excluded. If the issue date is no later than 4 months after the last prior fiscal year, data in the fiscal year before the last are rather used. Firms with negative book equity are excluded. These data filters leave 3,010 SEOs.

Option data are from OptionMetrics providing numerous information such as price, implied volatilities, open interests, and volumes. I only include the at-the-money (ATM) options with positive

[5] http://www.opradata.com

open interest, the days to maturity between 30 and 60 ensuring enough liquidity. Options with |delta| between 0.375 and 0.625 are defined as ATM (Bollen and Whaley (2004)). Due to the restrictions on other variables, the final sample contains 1,155 SEOs.

< Insert Table 1>

Table 1 presents summary statistics. As predicted, all the correlation measures are close to 1. Average discount is 0.033[6], which is similar to the previous studies (Altınkılıç and Hansen (2003); Corwin (2003); Henry and Koski (2010)). On average, post-issue performance is negative. CAR[1,5] and CAR[6,10] are -0.8% and -1.2%, respectively. Consistent with previous literatures, the firms doing SEO show low long-run performance. 6 months Buy-and-Hold return (BHR), matching firm adjusted abnormal return (MBHAR), and Fama-French value-weighted portfolio adjusted abnormal return (VWBHAR) are -0.091, -0.031, and -0.104, respectively. Option leverage is 1.639, which means that ATM option return is 16.39% when the stock return is 1% (option leverage in the analysis is resized by 1/10). Since only ATM options with delta of 0.5 are analyzed, it indicates that the stock is 16 times expensive than the options. Average firm size is $4,890 M (7.395 in logarithm). Firm size is much larger compared to the previous studies, since the firms with options listed are usually large firms. When the SEO firms without options are included, average firm size is $2,016 M. Average Market-to-Book (MTB) is 12.04 (1.719 in logarithm). When the SEO firms without options are included, average MTB is 9.51 (1.533 in logarithm), which indicates that SEO firms with options are more close to the growth firm. Standard deviation of the stock return is 4%, which is higher than the sample including SEO without options. This is due to the fact that options make the volatility of underlying stocks stochastic (Back (1993); Jarrow (1994)). Amihud is 0.127, indicating that option listing provides liquidity to the stock. 39.7% of the sample is listed on New York Stock Exchange (NYSE). One-year prior abnormal stock return (ARPR) is 74.8% (0.352 in logarithm). That is, the

[6] Discount is defined in logarithm. The discount defined as offer price / stock close price one day prior to issuance is 3.15% (2.23%) on average (median).

firms issuing new shares outperform Fama-French value-weighted portfolio by 74.8%, one year prior to SEO. Pre-market reaction is on average negative. CAR[-5,-1] is -2.8%. 74.2% of the sample is primary offering and 25.2% of the sample use accelerated issuance. Relative offer size (RelOfrSize) is 13.5%. Since the firms with options are usually large, the offer size is relatively small. The stock close price one day prior to SEO is $34.93 (3.368 in logarithm). 73.4% of the sample do offer price clustering and 71.8% of the sample have lock-up provision. Lock-up provision helps the firms to resolve information asymmetry. However, since there is a selection bias that the firms with high information asymmetry choose to include the provision, there is positive correlation between information asymmetry and the provision (Karpoff, Lee and Masulis (2013)). On average, the firms conducting SEO previously issued shares 2.802 times. Tangible ratio is 47% and bid/ask spread (BA_Spread) is 5.2%. Overall, the sample analyzed in this paper has the firms with large size, high MTB (growth firm), and more efficient.

< Insert Table 2 & Table 3>

The characteristics of the sample and their relations are documented in Table 2 and Table 3. As predicted, $\hat{\rho}$ and SEO discount has negative relation. High $\hat{\rho}$ firms are larger, more liquid, and less information asymmetric. This is natural that the correlation measure doesn't only capture the order imbalance but also the price efficiency and information asymmetry. As Back (1993) documented, unless there is information asymmetry, options are redundant and there will not be dispersion in option price. Interestingly, $\hat{\rho}$ and market sentiments measured by r_{ipo} and n_{ipo} have positive correlation. This could be explained in various ways. In high sentiment market, it is more possible that irrational investors do uninformed speculative trading, which increases $\hat{\rho}$. Also, in that market, since many investors are optimistic about the future stock price, there will not be less heterogeneous opinion on valuation of the stock. For excluding these possibility, the signed Amihud correlation measure is better than the raw return correlation. In order to exclude the above concerns, I also control these issues by including control variables and endogeneity controlled analysis.

3.4. Results

In this section, I test the hypothesis about the manipulation and its relation with $\hat{\rho}$.

3.4.1. SEO discount and ρ

< Insert Table 4>

Since small $\hat{\rho}$ stimulates the manipulation and larger SEO discount, it is expected that there is negative relation between $\hat{\rho}$ and SEO discount. In Table 4, coloumn (1) to (3) present the results for the anlaysis of $\hat{\rho}$ and SEO discount. Coulmn (1) is the results of univariate regression. Coloumn (2) and (3) are the multivariate regression results with industry and year clustering (Petersen (2009)). All three results show that there is negative relation between $\hat{\rho}$ and SEO discount. Therefore, as $\hat{\rho}$ increases, the market is more likely to be in the less manipulative equilibrium and discount diminishes. It is economically significant, since as $\hat{\rho}$ increases one standard deviation (9.8%), SEO discount decreases about 0.52%. It's 11.54 percent of discount standard deviation (4.5%). The option leverage and Amihud have negtive and positive coefficient. Although they are insignificant, it's the evidence that they enhence the market efficiency. The degree of the option leverage and liquidity impacts is dependent on $\hat{\rho}$. In the later analysis, I show that their effect is much stronger in low $\hat{\rho}$ market. Consistent with previous literatures (Altınkılıç and Hansen (2003); Corwin (2003); Mola and Loughran (2004)), the level of price and offer price clustering have negative and positive impacts on SEO discount. The proxies for the information asymmetry such as LockUp, NumIssue, and BA_Spread have positive coefficients as predicted. Since Tangibility measures the inverse of information asymmetry, it has negative coefficients. Market inefficiency measured by $|AR_s|$ and $|AR_o|$ also have positive impacts on discount. Coloumn (4) to (7) are the regression with alternative correlation measures. All four alternatives also shows that there is negative relation.

Pre-issue market reaction is usually used as a tool to test manipulation. Corwin (2003) finds the evidence that positive reaction increases discount but negative reaction has no effect on SEO discount.

It supports the hypothesis that the issuing firm determine the offer price based on the expected price, not on recently dropped market price. Henry and Koski (2010) find, however, the contradicting evidences that negative CAR prior to the issuance is followed by larger discount. That is, poor market response will increases SEO discount, which is the evendence supporting manipulation hypothesis. Their arguments have a limitation in the sense that the manipulation doesn't always happen. It is required to control the sample with high manipulation possibility.

< Insert Table 5>

With option, pre-issue market reaction contains useful information only when ρ is high. If the market reaction is for resolving information asymmetry, higher return movement will lower the discount in either direction. Therefore, we can predict that there will be negative relation between absolute of pre-issue CAR and discount unless there is manipulation. Coloum (1) in Table 5 shows that the coefficient on |CAR[-5,-1]| is negative, which means that large market reaction is in general by the informative trading. The results in column (3) also supports this hypothesis. Negative CAR ($CAR[-5,-1]^{-}$) has positive but positive CAR ($CAR[-5,-1]^{+}$) has negative coefficients. However, the pre-issue reaction lose its power lowering discount as ρ decreases. In column (2), the coefficient on the interaction between |CAR[-5,-1]| and $\hat{\rho}$ is negative, which indicates that as $\hat{\rho}$ decreaes, high market reaction generate high discount. This results can be explained by manipulation hypothesis. In coloumn (4), the upper 50% sample with respect to $\hat{\rho}$ is tested. Negative and positive CAR has more significant coefficient than those in coloumn (3). On the other hand, lower 50% sample in coloumn (5) lose its significancy, which is consistent with the manipulation hypothesis when ρ is low. In short, I find the results supporting both hypothesis. There is manipulation only when $\hat{\rho}$ is low and pre-issue market reaction lose its power as $\hat{\rho}$ decreases.

3.4.2. Post-issue performance

< Insert Table 6>

The manipulation is accompanied by the return reversal, that is, there is negative relation bewteen post-issue market reaction and $\hat{\rho}$. In general, return reversal is considered as the case of the manipulators artificially dropping the price and then the price recovering to the fair level. However, if there is manipulation, there should be large price drop in negative direction, otherwise the market will not be decieved for the sell order. The manipulation is possible since the market should not know the intention of the order flow. Therefore, absolute of post-issue market reaction (|CAR|) is a proper measure to detect return reversal. Table 6 presents the results of the multivariate regression for |CAR| with respect to $\hat{\rho}$. In column (1), as $\hat{\rho}$ increases, |CAR[1,5]| decreases. For low $\hat{\rho}$ market, there is more chances of manipulation and information asymmetry sustains high. Therefore, the price should be move larger after the information asymmetry is resolved, in either directions. Interestingly, this effect lasts for up to 10 trading days. In column (2), the coefficient on $\hat{\rho}$ to |CAR[6,10]| is significantly negative. This raises the possibility that the true value is revealed not immediately after the issuance. I test the CAR^{+} and CAR^{-} after the issuance. For positive CAR, CAR^{+}, although they are both negative, the coefficient on $\hat{\rho}$ in coloumn (3) is insignificant, but one in coloumn (4) is significant. Therefore, for a good offer, it takes time for the true value to be unveiled. On the other hand, for negative CAR, CAR^{-}, the coefficient on $\hat{\rho}$ in coloumn (5) is significant, but one in coloumn (6) is insignificant. That is, for a bad offer, the true value is revealed faster than for a good offer. In short, the return reversal is accompanied by small $\hat{\rho}$.

< Insert Table 7>

The results in Table 6 raise a possibility that it can take longer to reveal the true value. Although the short-term post-issuance performance shows that there is large return movement for small $\hat{\rho}$, manipulation could make harder reveal the true value. In the model, there is a cost relating to the manipulation. However, if the manipulators can cover there short position with lower price, the mainpulation cost will be retrenched. Therefore, there is an incentive for the manipulators to slow down the information revealation process. Table 7 reports the long-run performance after the issuance. Coloumn (1) and (2) are the results for the size-and MTB matching firm adjusted buy-and-hold return. Coloumn (3) and (4) are the results for the Fama-French value-weighted portfolio adjusted buy-and-hold return. Coloumn (5) and (6) are the results for the raw buy-and-hold return. Unlike short-term performance results, low $\hat{\rho}$ perform much better than high $\hat{\rho}$ SEO. It lasts up to one year. This can be interpreted as low $\hat{\rho}$ SEO being manipulated and outperforming much compared to the bad offer with low $\hat{\rho}$. Consequently, it is evident that small $\hat{\rho}$ is an indication of the manipulation and outperforms SEO with high ρ.

3.4.3. Option leverage and liquidity

Option leverage and liquidity are known to enhance market efficiency. In Table 4, although they are both insignificant, OLev and and Amihud have negative and positive coefficient. Therefore, higher option leverage encourage the informed traders participate in the option market activities and high illiquidity measured by Amihud get the informed traders away from the market transaction. However, their roles are much more important when $\hat{\rho}$ is low. For the high $\hat{\rho}$ SEO, the market itself in the good condition for the informative trading. Therefore, although option leverage and liquidity is enhenced, their effects are marginal. Table 8 and Table 9 present the effects of option leverage and liquidity. In coloumn (1) of Table 8, the coefficient on the interaction term between Olev and $\hat{\rho}$ is positive while one on OLev is negative. As $\hat{\rho}$ decreases, option leverage lower more the discount. Coloumn (2) to (5) using alternative meausres also show similar results. Liquidity also have much more impacts when $\hat{\rho}$ is low. In coloumn (1) of Table 9, the coefficient on the interaction term between Amihud and $\hat{\rho}$ is negitive while one on Amihud is positive. As $\hat{\rho}$ decreases, illiquidity increases more the discount. That is, liquid SEO has smaller discount. Although the results in coloumn (1) are marginally significant, those in coloumn (2) to (5) using alternative measures show significant coefficients.

< Insert Table 8 and Table 9 >

3.5. Robustness test

Empirical proxy for ρ, $\hat{\rho}$, has issues that it doesn't only capture the order imbalance, but also does information asymmetry, market efficiency, and market sentiments. To alleviate these concerns, I run a first stage regression of $\hat{\rho}$ on engogineity proxies to get a residual, which is independent of those concerns. For proxies for information asymmetry, STD, LockUp, No_Issue, Tangible, and BA_Spread are used. For proxies for market efficiency, $|AR_s|$ and $|AR_o|$ are used. Finally, for proxies for market sentiments, r_{IPO} and n_{IPO} are used. Table 10 reports second stage results only. All the results are similar.

<Insert Table 10>

Another issue that can be arised is the measurement of long-run performance. Although Buy-and-hold return is widely used methodology, there is a statistical issue (Fama (1998); Loughran and Ritter (2000); Lyon, Barber and Tsai (1999)). For an additional check, I test the long-run performance after SEO by forming calandar-time portfolio. For a given month, firms issuing new shares for last six months are included in the portfolio. Also, there are two portfolio depending on ρ. If the firm's ρ is smaller than the median, it is designated to the small $\hat{\rho}$ portfolio. Otherwise, it goes to the high ρ portfolio. Table 11 reports the results. In coloumn (1), the high $\hat{\rho}$ group underperforms by 1.043% per month. However, the low ρ group in coloumn (2) has insignificance α. After the momentum factors are included in coloumn (3) and (4), the results are not changed. Coloumn (5) shows the results for the zero-investment porttolio analysis. High $\hat{\rho}$ group underperforms the low ρ group by 1.213% per month.

<Insert Table 11>

Table 12 presents the results using alternative correlation measures. All the results are consistents with the previous one, although some are marginally significant.

<Insert Table 12>

IV. Conclusion

I find the theoretical and empirical evidences that the existence of options can generate the incentives for informed investors to manipulate markets prior to SEOs. The primary parameter deciding manipulation is intermarket liquidity, induced by the likelihood of trading both option and the underlying stock in the *same* direction by uninformed liquidity traders (ρ). ρ can be expressed as the correlation of the uninformed orders between stock and options. As ρ decreases, the informed traders have more incentives to manipulate the market, since they cannot avoid demand shocks following the informative strategy. Interestingly, unless ρ is extremely high, the informed traders prefer to transact only in one of the two markets. However, in the normal condition, manipulating one market is dominant over informative (no manipulating) strategy. Similar to Gerard and Nanda (1993), SEOs make it even profitable to manipulate both markets, which is not feasible without SEOs. As ρ decreases more with SEOs, manipulating both markets requires costs in manipulative market trading, but generates enough SEO discount to cover all the costs. The model predicts that there will be larger SEOs discount when ρ is lower, since small ρ stimulates manipulation, which makes fully manipulative strategy is dominant.

To test the model, I develop the novel empirical proxy for ρ. $\hat{\rho}$ is defined as the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Since order imbalances move price and lower liquidity, singed Amihud can be a good measure for order imbalances. In the empirical analysis, I find that one standard devation increases of ρ (9.8%) lower the discount by 0.52%. This supports the hypothesis that SEOs with low ρ are in the manipulative equilibrium, which induce larger SEOs discount. The relation between pre-issue CAR and discount is usually used as an identification strategy for manipulation. I find that pre-issue CAR in either direction significantly reduce distount, which rejects the manipulation hypothesis. However, this effect is significantly reduces as ρ become smaller. Therefore, the informativeness of pre-issue stock movement weaken as ρ decreases, which supports the manipulation hypothesis with small ρ. Furthermore, SEOs with low ρ is followed by large post-issue return movement and higher long-run performance, being consistent with the return reversal followed by manipultion. This shows that small ρ induce manipulation and it takes time to reveal the true value of the stock. Finally, option leverage and liquidity insignificantly lower the discount. However, for SEOs with small ρ, their effects signify.

This paper shed lights on understand how SEOs and options provide informed investors with the incentive to manipulate the markets, for getting better prices and larger SEO discount. Cross-market correlation of the uninformed traders, which is critical factors for intermarket liquidity and intermarket trading, is critical factor for manipulation and market efficiency.

Appendix

Appendix A. Variable Definition

Variables	Definition
Discount	log(closing stock price 1 day prior to the issuance/the offer price)
CAR[±t, ±s]	Cumulative abnormal return between I.D. ± t and I.D. ± s, using Fama-French model with momentum, where I.D. stands for issue date
|CAR[±t, ±s]|	Absolute value of CAR[±t, ±s]
$CAR[\pm t, \pm s]^{+}$	CAR[±t, ±s] when positive 0 otherwise
$CAR[\pm t, \pm s]^{-}$	CAR[±t, ±s] when negative 0 otherwise
PCR[±t, ±s]	Average Put to Call implied volatility ratio between I.D. ± t and I.D. ± s
OCAR[±t, ±s]	Cumulative abnormal option return between I.D. ± t and I.D. ± s, using delta-expected optioin return defined as the product of delta and stock return
BHR	Buy-and-hold return of the issuing firm (BHR = $\prod_{t=l}^{m}\left(1+r_{s,t}\right)-1$)
ARPR	log(1 year prior BHR)-log(1 year prior BHR of CRSP value-weighted return)
MBHAR	log(Event firm BHR) – log(Size/BTM matched firm BHR)
VWBHAR	log(Event firm BHR) – log(Fama-French Size/BTM 25 portfolio BHR)
OLev	Option leverage defined as $\frac{\partial C/C}{\partial S/S}-\frac{\partial P/P}{\partial S/S}=\delta_c\frac{S}{C}+\left(-\delta_p\right)\frac{S}{P}$ = CLev + Plev. OLev is divided by 10 for scailing
VOLM	log(average stock trading volumes normalized by shares outstanding between 84 days and 21 days prior to the issuance)
OVOLM	log(average call and put option trading volumes normalized by open interest between 84 days and 21 days prior to the issuance)
Size	log of Market equity value in Million dollars 21 trading days prior to the issuance (adjusted for inflation with purchasing power in 2005 dollar)
MTB	log(Market equity value to Book equity value). Book equity value is measured as Fama and French (1993)
STD	Standard deviation of the stock return between 84 days and 21 days prior to the issuance
AMIHUD	Amihud illiquidity between 84 days and 21 days prior to the issuance
NYSE	Dummy equals 1 if listed on NYSE and 0 otherwise
PRIM	Dummy equals 1 if primary offer and 0 otherwise. Primary offer is for the offer that more than 50% of the total offer is primary
ACCEL	Dummy equals 1 if accelerated or block offering and 0 otherwise
RELOFRSIZE	The average ratio of number of the shares issued to the share outstanding between 84 days and 21 days prior to the issuance
PRICE	log(closing stock price 1 day prior to the issuance)
PRICE_Cluster	Dummy equals 1 if the offer price is set at even such as 0, 0.25, 0.5, and 0.75
LOCKUP	Dummy equals 1 if lock-up provision exists and 0 otherwise
NUMISSUE	Number of preview issues by the issuing company
TANGIBILITY	(Property, Plant and Equipment)/(Total Asset)
BA_SPREAD	Average Stock Bid/Ask spread between 84 days and 21 days prior to the issuance
$\lvert AR_s \rvert$	absolute value of stock return autocorrelation between 84 days and 21 days prior to the issuance
$\lvert AR_o \rvert$	Absolute value of option return autocorrelation between 84 days and 21 days prior to the issuance
r_{IPO}	The average first-day return on the net IPOs from Jay Ritter
n_{IPO}	The gross number of IPOs from Jay Ritter

Appendix B. Proof

Proof for Theorem 2.

The sets of net order flows are $\Psi_1 = [x_s^+ + u_s,\ x_s^+ - u_s\ (= x_s^- + u_s),\ x_s^- - u_s] = [Y^1_1, Y^1_2, Y^1_3]$ for SS_1 and $\Psi_2 = [x_s^+ + u_s\ (= x_s^- + u_s),\ x_s^+ - u_s\ (= x_s^- - u_s)] = [Y^2_1, Y^2_2]$ for SS_2. The expected price conditional on $\tilde{V}$ is calculated as the product of the price conditional on $\tilde{Y}$ $(P|\tilde{Y})$ and the conditional distribution of $\tilde{Y}$ $(\mathrm{prob}(\tilde{Y}|\tilde{V}))$.

$$E[P|\tilde{V}] = \sum_{\tilde{Y}\in\Psi} P|\tilde{Y} \times \mathrm{prob}(\tilde{Y}|\tilde{V})$$

The price conditional on $\tilde{Y}$ is given as $P(Y^1_1) = V^+$, $P(Y^1_2) = V^- + (1-b_s)\Delta V$, $P(Y^1_3) = V^-$ for Ψ_1 and $P(Y^2_1) = P(Y^2_2) = P_0 = V^- + \Delta V/2$ for Ψ_2. The conditional distribution of $\tilde{Y}|V^+$ is given as $\mathrm{Prob}(Y^1_1|V^+) = b_s$, $\mathrm{Prob}(Y^1_2|V^+) = 1-b_s$, $\mathrm{Prob}(Y^1_3|V^+) = 0$ for Ψ_1 and $\mathrm{Prob}(Y^2_1|V^+) = \mathrm{Prob}(Y^2_2|V^+) = 1/2$ for Ψ_2. The conditional distribution of $\tilde{Y}|V^-$ is given as $\mathrm{Prob}(Y^1_1|V^-) = 0$, $\mathrm{Prob}(Y^1_2|V^-) = b_s$, $\mathrm{Prob}(Y^1_3|V^-) = 1-b_s$ for Ψ_1 and $\mathrm{Prob}(Y^2_1|V^-) = \mathrm{Prob}(Y^2_2|V^-) = 1/2$ for Ψ_2.

The expected offer price conditional on $\tilde{V}$ is calculated similarly. The offer price conditional on $\tilde{Y}$ is given as $P^*(Y^1_1) = V^+$, $P^*(Y^1_2) = V^+ - \frac{\eta b_s}{(\eta-1)b_s+1}\Delta V$, $P^*(Y^1_3) = V^-$ for Ψ_1 and $P^*(Y^2_1) = P^*(Y^2_2) = V^+ - \frac{\eta}{\eta+1}\Delta V$ for Ψ_2.

$E[P|V^+] = V^+ - \varepsilon\Delta V$ and $E[P|V^-] = V^- + \varepsilon\Delta V$ where the price kernel, ε, is $b_s(1-b_s)$ for SS_1, and 1/2 for SS_2. $E[P^*|V^+] = V^+ - \varepsilon'\Delta V$ and $E[P^*|V^-] = V^- + \varepsilon'/(\eta b_s)\Delta V$ for SS_1, and $E[P^*|V^+] = E[P^*|V^-] = V^+ - \varepsilon'\Delta V$ for SS_2. The offer price kernel, ε', is $\frac{\eta}{\eta b_s+(1-b_s)}\epsilon$ for SS_1, and $\frac{\eta}{\eta+1}$ for SS_2.

Therefore, the conditional expected profits for each equilibrium are

$$\Pi^+|SS_1 = \varepsilon\Delta V \cdot x_s^+ + \alpha_I\varepsilon'\Delta V$$

$$\Pi^-|SS_1 = -\varepsilon\Delta V \cdot x_s^- = -\varepsilon\Delta V \cdot (x_s^+ - 2u_s)$$

Following Theorem 1, the maximum profit, $\Pi|SS_1$, is $\left(\frac{\alpha_I}{2}\cdot\varepsilon' + u_s\cdot\varepsilon\right)\Delta V$. The trading schedule for the informed traders is $x_s^+ = x_s^- - 2u_s = u_s - \frac{\alpha_I}{2}\cdot\frac{\eta}{\eta b_s+(1-b_s)}$. The conditional expected profits for SS_2 are

$$\Pi^+|SS_2 = \varepsilon\Delta V \cdot x_s^+ + \alpha_I\varepsilon'\Delta V$$

$$\Pi^{-}|SS_2 = -\varepsilon\Delta V \cdot x_s^{-} = -\varepsilon\Delta V \cdot x_s^{+}$$

Following Theorem 1, the maximum profit, $\Pi|SS_2$, is $\frac{\alpha_I}{2} \cdot \varepsilon' \cdot \Delta V$. The trading schedule for the informed traders is $x_s^{+} = x_s^{-} = -\alpha_I \cdot \frac{\eta}{\eta+1}$.

Proof for Theorem 3.

Proof for Theorem 3 is similar to Theorem 2. The only difference is that the options are traded and the information leaked in one market is transmitted to the other, immediately. The price conditional on $\widetilde{Y}$ ($P|\widetilde{Y}$) and the conditional distribution of $\widetilde{Y}$ ($\mathrm{prob}(\widetilde{Y}|\widetilde{V})$) are given in Figure 4. For example, the conditional expected price in S_2 is given as follows.

$$\begin{aligned} E[P|V^{+},S_2] &= V^{+} \cdot \rho/2 + V^{+} \cdot (1-\rho)/2 + (V^{-}+(1-\rho)\,\Delta V) \cdot (1-\rho)/2 + (V^{-}+\rho\,\Delta V) \cdot \rho/2 + V^{-} \cdot 0 \\ &= V^{-} - \rho(1-\rho)\Delta V \\ &= V^{-} - \varepsilon\,\Delta V \end{aligned}$$

Other conditional expected prices are calculated similarly. The conditional profits for S_2 is given as follows. ε is $\rho(1-\rho)$ and ε' is $\frac{\eta}{2} \cdot \frac{\eta+1}{(\eta-1)^2\varepsilon+\eta} \cdot \varepsilon$ for S_2

$$\Pi^{+}|S_2 = \varepsilon\Delta V \cdot x_s^{+} + \varepsilon\Delta V_K \cdot x_o^{+} + \alpha_I\varepsilon'\Delta V$$

$$\Pi^{-}|S_2 = -\varepsilon\Delta V \cdot x_s^{-} - \varepsilon\Delta V_K \cdot x_o^{-} = -\varepsilon\Delta V \cdot (x_s^{+} - 2u_s) - \varepsilon\Delta V_K \cdot x_o^{+}$$

Following Theorem 1, the maximum profit, $\Pi|S_2$, is $\left(\frac{\alpha_I}{2} \cdot \varepsilon' + u_s \cdot \varepsilon\right)\Delta V$. The trading schedule for the informed traders is $x_s^{+} = x_s^{-} - 2u_s = -\frac{\Delta V_K}{\Delta V} x_o^{+} + \left(u_s - \frac{\alpha_I}{2} \cdot \frac{\varepsilon'}{\varepsilon}\right)$ and $x_o^{+} = x_o^{-}$. Other equilibrium can be similarly specified.

Proof for Theorem 5

Under Assumption 1, there is manipulation when $\Pi|S_4$ is the largest. Let $x = \rho(1-\rho)$, $\tilde{u}_s = u_s$, $\tilde{u}_o = \delta u_o$, and $k=(2,3)=(s,o)$. There is manipulation if and only if $\Pi|S_4 - \Pi|S_k > 0$.

$$\Pi|S_4 - \Pi|S_k = \frac{1}{2}A \cdot \Delta V - \rho(1-\rho)[A' + \tilde{u}_k] \cdot \Delta V > 0.$$

$\rightarrow 4\tilde{u}_k(\eta^2-1)(\eta-1)\, x^2 - [\alpha_I\eta(\eta^2-6\eta+1) - 4\eta(\eta+1)\tilde{u}_k]\, x - 2\eta^2\alpha_I < 0$

$\rightarrow 0 < x < M_k$

where $M_k = \frac{\left[f(\alpha_I,\tilde{u}_k) + \sqrt{f(\alpha_I,\tilde{u}_k)^2 + 32\eta^2(\eta-1)(\eta^2-1)\alpha_I\tilde{u}_k}\right]}{8(\eta-1)(\eta^2-1)\tilde{u}_k}$ and

$$f(\alpha_I,\tilde{u}_k) = \eta(\eta^2-6\eta+1)\alpha_I - 4\eta(\eta+1)\tilde{u}_k$$

Since $0 < \rho < 1/2$, $x > 0$. Therefore, the above ineqaulity is same as $\rho^2 - \rho + M_k > 0$.

$$\therefore \rho < \frac{1}{2} \times \left[1 - \sqrt{1 - 4M_k}\right]$$

$$\frac{\partial M_k}{\partial \alpha_I} = \frac{1}{8(\eta-1)(\eta^2-1)\tilde{u}_k}\left[\left(1 + \frac{f}{\sqrt{f^2 + \phi\alpha_I}}\right)\cdot \eta(\eta^2-6\eta+1) + \frac{\phi\tilde{u}_k}{2\sqrt{f^2+\phi\alpha_I\tilde{u}_k}}\right] > 0$$

$$\frac{\partial M_k}{\partial \tilde{u}_k} = -\frac{1}{\tilde{u}_k^2(\eta^2-1)(\eta-1)} \times \frac{1}{8\sqrt{f^2+\phi\alpha_I\tilde{u}_k}}\left[\frac{\phi\alpha_I\tilde{u}_k}{2} + \alpha_I\eta(\eta^2-6\eta+1)(f + \sqrt{f^2+\phi\alpha_I\tilde{u}_k})\right]$$

where $\phi = 32\eta^2(\eta-1)(\eta^2-1)$

The sign of $\frac{\partial M_k}{\partial \tilde{u}_k}$ depends on η. When $\eta^2-6\eta+1>0$, $\frac{\partial M_k}{\partial \tilde{u}_k}$ is always negative. When $\eta^2-6\eta+1<0$, $f<0$.

Let $g(u) = \frac{\phi\alpha_I\tilde{u}_k}{2} + \alpha_I\eta(\eta^2-6\eta+1)(f + \sqrt{f^2+\phi\alpha_I\tilde{u}_k}$. Since $M_k < 1/4$,

$$g(u) > \frac{\phi\alpha_I\tilde{u}_k}{2} + 2\alpha_I\eta(\eta-1)(\eta^2-1)(\eta^2-6\eta+1)\tilde{u}_k$$

$$= 2\alpha_I\eta(\eta-1)(\eta^2-1)(\eta+1)^2\tilde{u}_k$$

$$> 0$$

$$\therefore \frac{\partial M_k}{\partial \tilde{u}_k} < 0$$

Proof for Theorem 6

Under Assumption 1, E[DSCT|S_i] where i=(1,2,3) is an increasing function of ρ, since $E\left[\frac{\partial DSCT}{\partial \rho}\middle|S_1\right] = \frac{1}{4}\cdot\frac{\eta-1}{\eta+1}\Delta V$ and $E\left[\frac{\partial DSCT}{\partial \rho}\middle|S_2\right] = E\left[\frac{\partial DSCT}{\partial \rho}\middle|S_3\right] = \frac{1-2\rho}{4}\cdot\frac{\eta(\eta^2-1)}{[(\eta-1)^2\rho(1-\rho)+\eta]^2}\Delta V$. Therefore, if the discount at ρ = 1/2 is bigger than others, it's always larger regardless of ρ. Discounts at ρ = 1/2 are given as E[DSCT|S_1, ρ=1/2] = $\frac{1}{8}\cdot\frac{\eta-1}{\eta+1}\Delta V$, E[DSCT|$S_2$, ρ=1/2] = E[DSCT|$S_3$, ρ=1/2] = $\frac{1}{4}\cdot\frac{\eta-1}{\eta+1}\Delta V$, and E[DSCT|$S_4$, ρ=1/2] = $\frac{1}{2}\cdot\frac{\eta-1}{\eta+1}\Delta V$.

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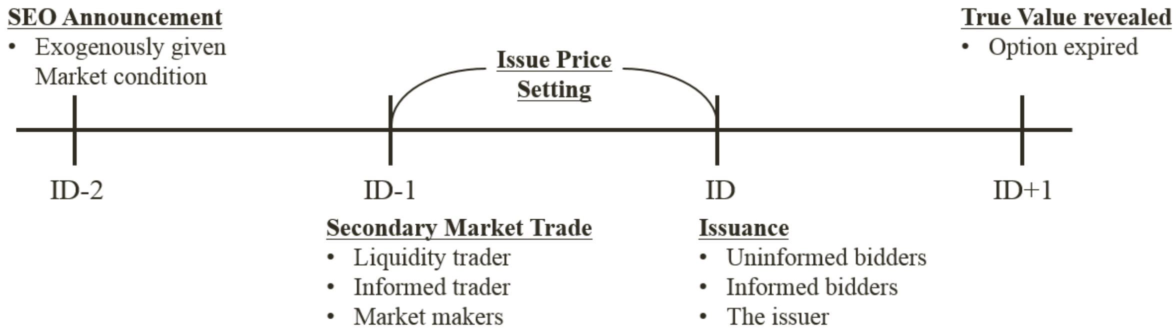

Figure 1 Timeline of option manipulation model

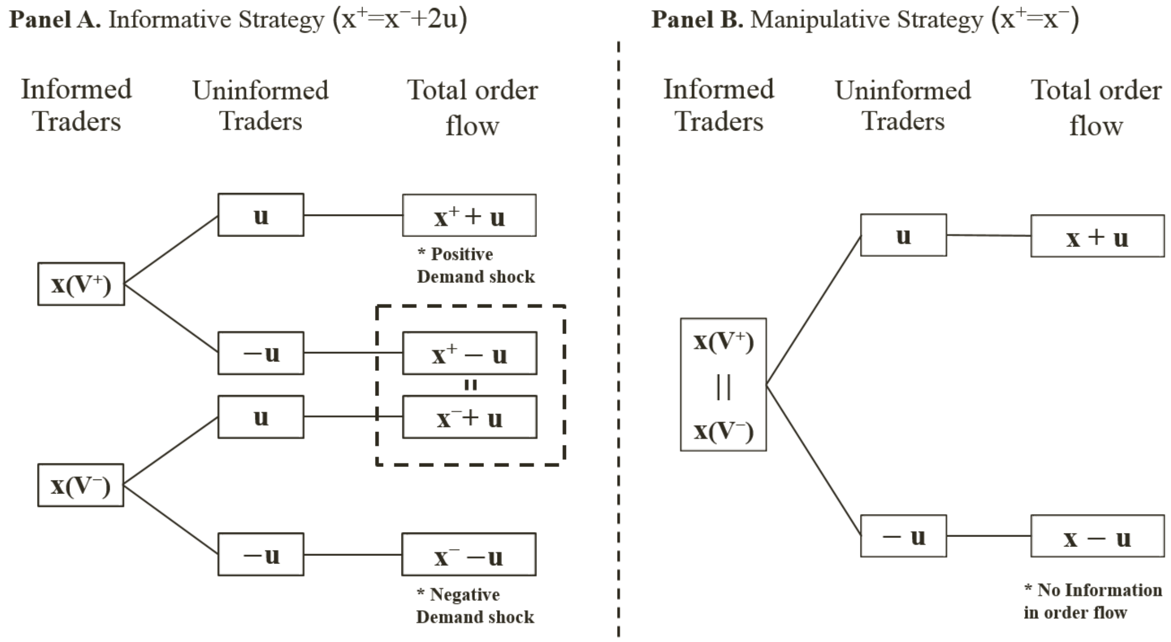

Figure 2 Net orders for Informative and Manipulative strategy

Panel A presents net orders in informative strategy and Panel B presents net orders in manluative strategy.

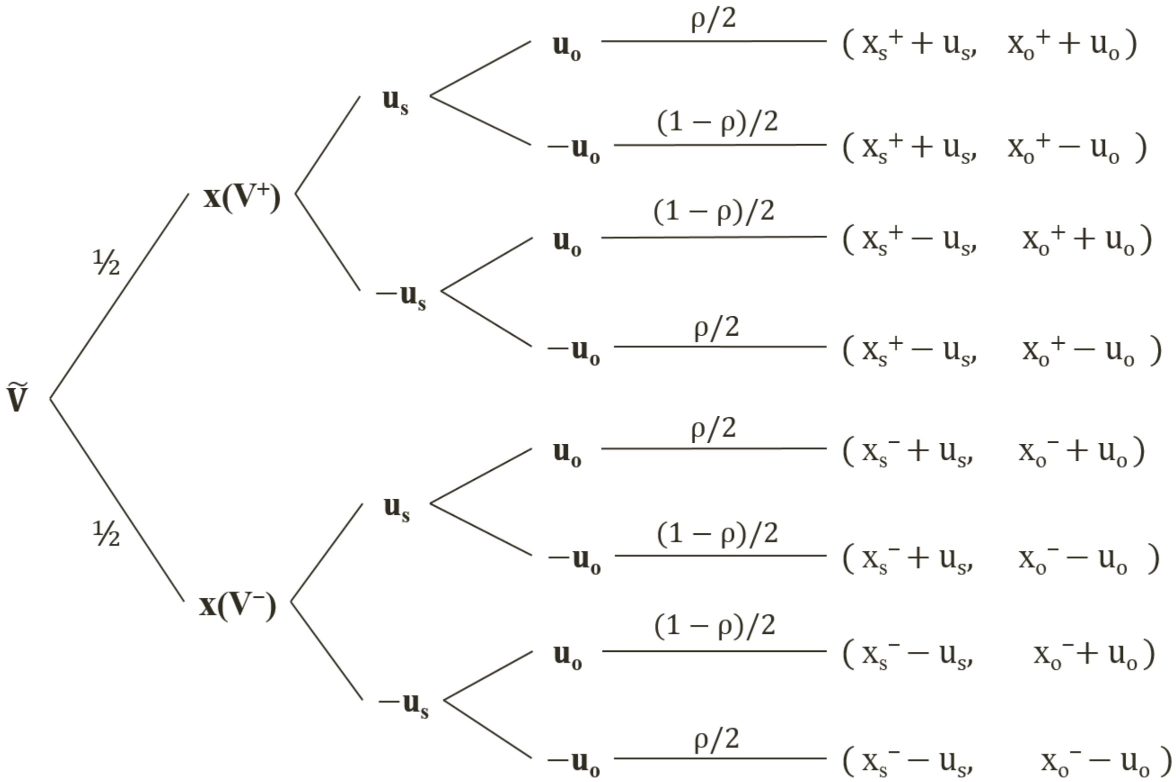

Figure 3 Net order flow diagram

Since $\tilde{V}$ is dichotomic, there are two informed order. Therefore, net order flows can have maximum 8 different values, since there are 2 assets with 2 uninformed orders.

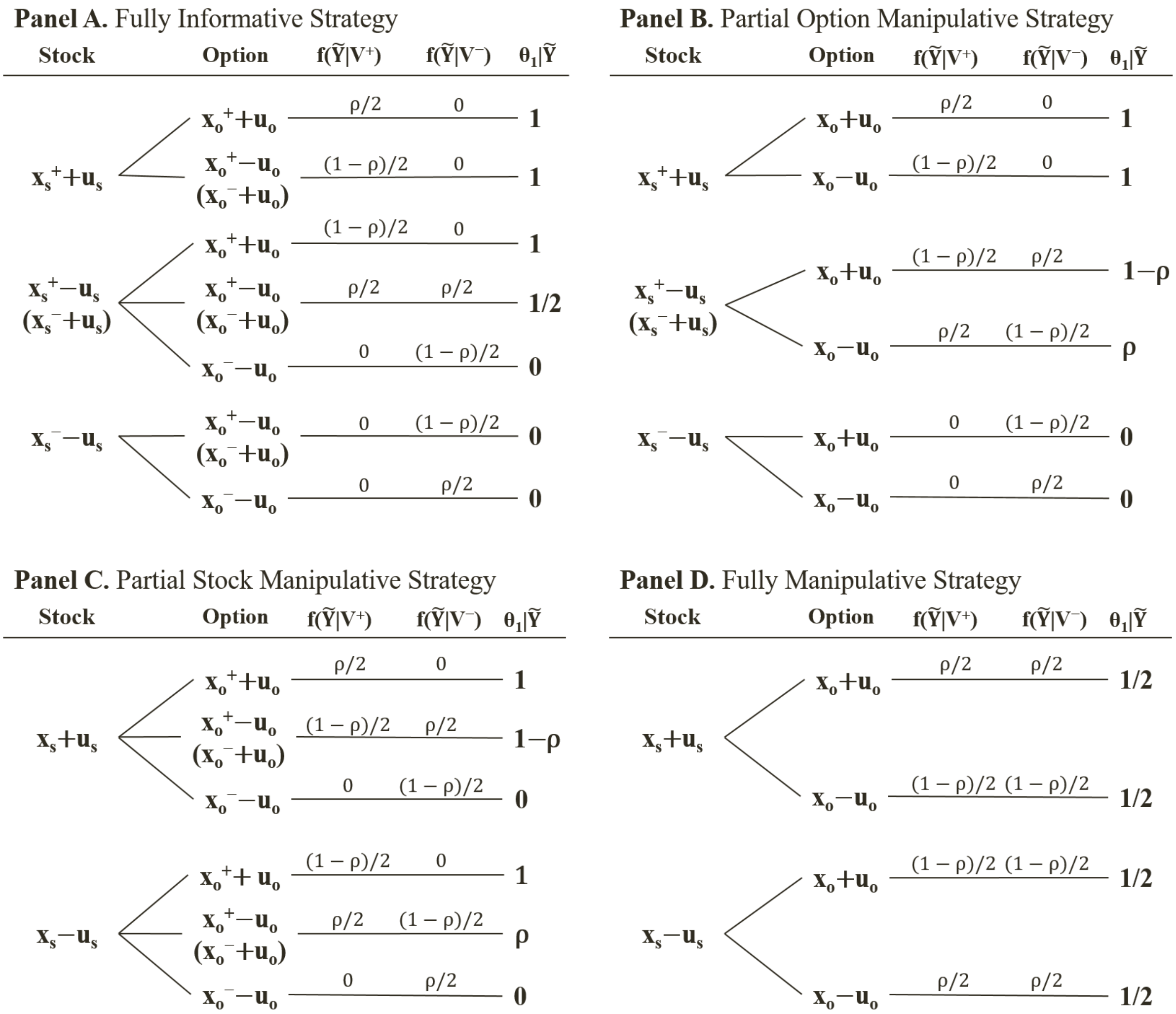

Figure 4 Conditional expected price for each strategy

Panel A is fully informative strategy, Panel B is partial option manipulative strategy, Panel C is partial stock manipulative stratey, and Panel D is fully manipulative strategy. Conditional on equilibrium and observed net orders, the conditional expected prices are changed.

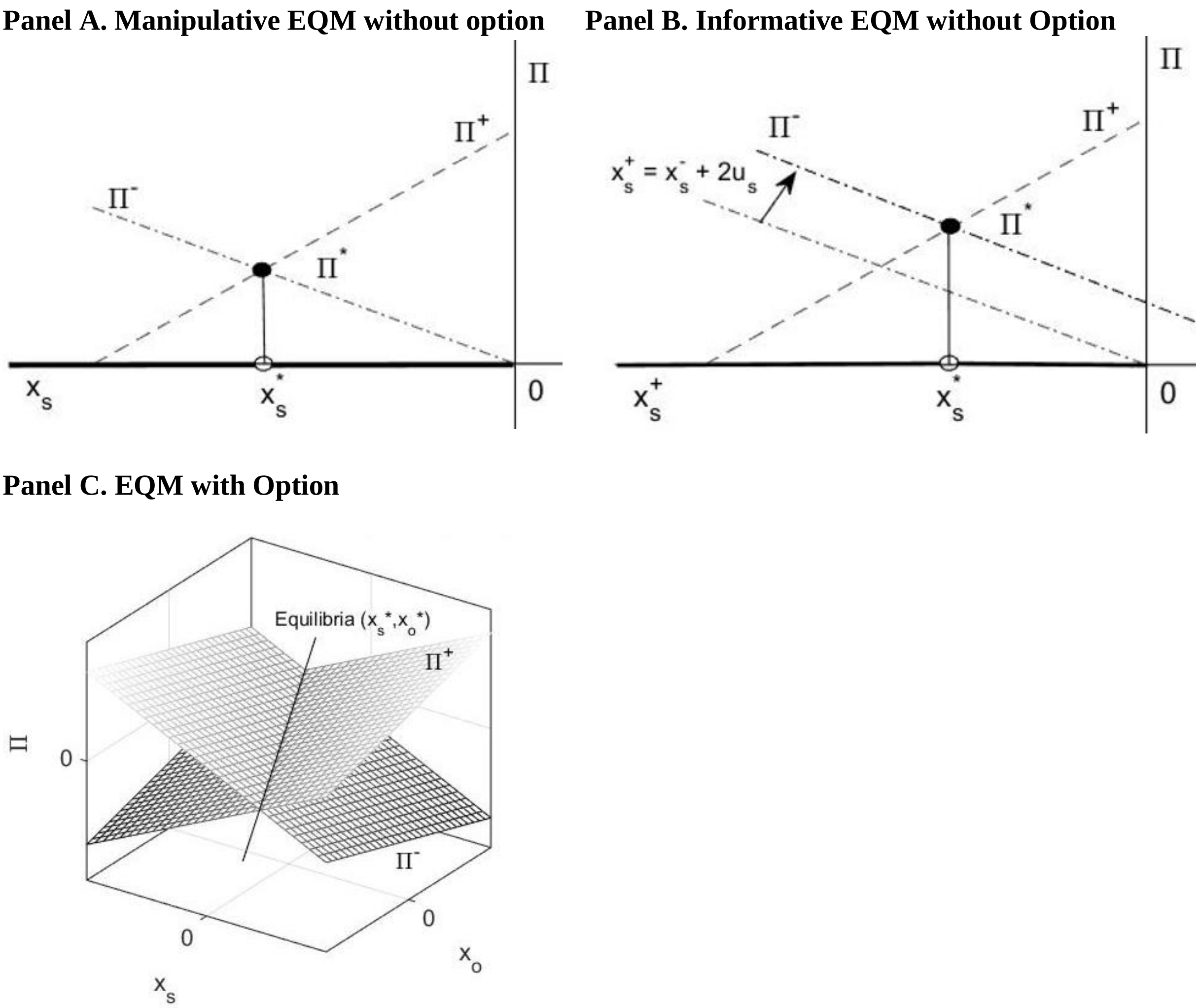

Figure 5 Profit function and Equilibrium

Panel A and B are the profit functions with respect to informed orders (x) for a single asset case. Panel A is manipulative equilibrium and Panel B is informative equilibrium profit graph. Panel C is the profit functions with respect to informed orders (x) for two assets case, which has multiple equilibriums.

Panel A. $M_K < 1/4$ **Panel B.** $M_K > 1/4$

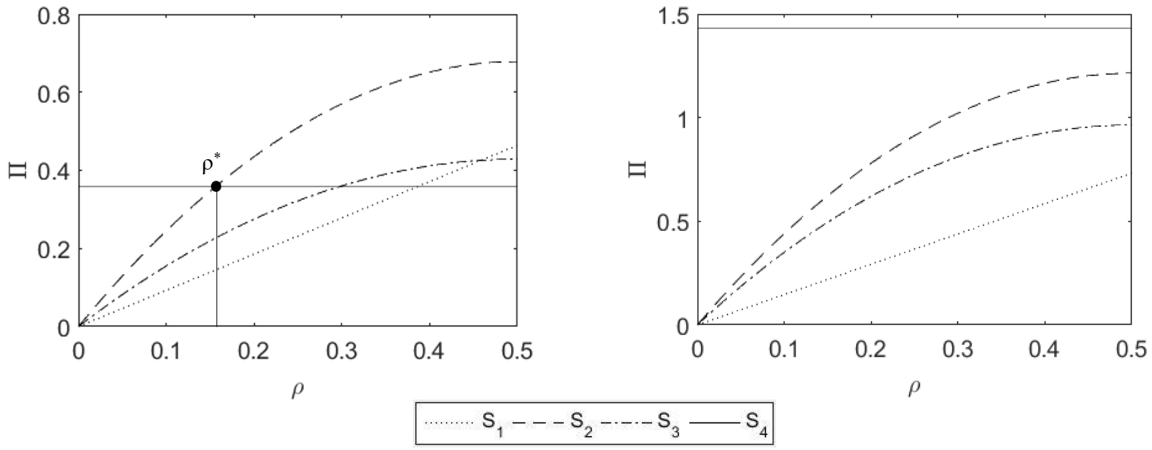

Figure 6 Equilibrium Condition with respect to ρ.

Graph for profits with respect to ρ. Equilibrium with higher profits dominates others. S_1 is fully informative equilibrium. S_2 is partial option manipulative equilibrium. S_3 is partial stock manipulative equilibrium. S_4 is fully manipulative equilibrium.

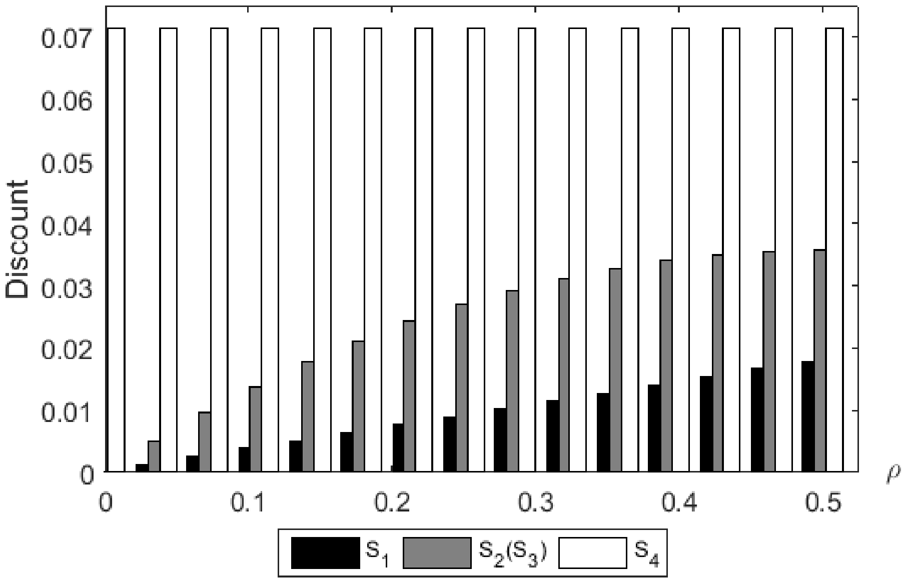

Figure 7 SEO Discount and ρ

S_1 is fully informative equilibrium. S_2 is partial option manipulative equilibrium. S_3 is partial stock manipulative equilibrium. S_4 is fully manipulative equilibrium.

Table 1 Summary statistics

This table presents the descriptive statistics for a sample of the firms listed in NYSE, AMEX, and NASDAQ, conducting SEOs between 1996 and 2013 with options listed. The sample contains 1,155 observations. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Other correlation measures are similarly defined; the return correlation ($\hat{\rho}_r$), the signed Amihud correlation using raw trading volume ($\hat{\rho}_v$), the signed Amihud correlation with call options ($\hat{\rho}_c$), and the signed Amihud correlation with put options ($\hat{\rho}_p$). All the other variables are defined in Appendix A.

	Mean	Median	STD	Skewness
$\hat{\rho}$	0.928	0.953	0.098	-6.605
$\hat{\rho}_r$	0.938	0.962	0.091	-6.878
$\hat{\rho}_v$	0.713	0.752	0.171	-2.690
$\hat{\rho}_c$	0.878	0.903	0.102	-4.205
$\hat{\rho}_p$	0.870	0.899	0.112	-5.257
Discount	0.033	0.023	0.045	1.076
CAR[1,5]	-0.008	-0.005	0.074	-0.198
CAR[6,10]	-0.012	-0.008	0.081	-0.348
PCR[1,5]	1.024	1.015	0.064	1.657
PCR[6,10]	1.027	1.017	0.061	2.062
OCAR[1,5]	0.012	-0.004	0.325	1.853
OCAR[6,10]	-0.000	-0.007	0.313	0.544
MBHAR	-0.031	-0.023	0.584	0.085
VWBHAR	-0.104	-0.042	0.457	-1.336
BHR	-0.091	-0.021	0.516	-1.304
OLev	1.639	1.511	0.689	1.367
Volm	0.015	0.011	0.015	3.319
OVolm	0.562	0.451	0.429	2.314
Size	7.395	7.251	1.296	0.648
MTB	1.719	1.669	1.114	0.442
STD	0.040	0.035	0.024	3.189
Amihud	0.127	0.051	0.213	4.744
NYSE	0.397	0.000	0.490	0.419
ARPR	0.352	0.311	0.616	0.020
CAR[-5,-1]	-0.028	-0.021	0.096	0.580
OCAR[-5,-1]	0.025	-0.000	0.388	0.404
PRIM	0.742	1.000	0.438	-1.106
ACCEL	0.252	0.000	0.434	1.143
RelOfrSize	0.135	0.117	0.091	2.174
Price	3.368	3.402	0.716	-0.123
Price_Cluster	0.734	1.000	0.442	-1.060
LockUp	0.718	1.000	0.450	-0.968
NumIssue	2.802	2.000	1.842	1.543
Tangibility	0.470	0.328	0.427	1.618
BA_Spread	0.052	0.046	0.025	1.251
$\lvert AR_s \rvert$	0.105	0.088	0.080	0.886
$\lvert AR_o \rvert$	0.170	0.124	0.172	2.429
r_{IPO}	0.218	0.148	0.241	2.079
n_{IPO}	0.234	0.170	0.201	1.434

Table 2 Correlation

This table presents the Pearson correlation coefficients among variables for a sample of the firms listed in NYSE, AMEX, and NASDAQ, conducting SEOs between 1996 and 2013 with options listed. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Other correlation measures are similarly defined; the return correlation ($\hat{\rho}_r$), the signed Amihud correlation using raw trading volume ($\hat{\rho}_v$), the signed Amihud correlation with call options ($\hat{\rho}_c$), and the signed Amihud correlation with put options ($\hat{\rho}_p$). All the other variables are defined in Appendix A. The symbols, *, **, and ***, indicates that the correlation coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively.

	$\hat{\rho}$	Discount	MBHAR	OLev	Volm	OVolm
$\hat{\rho}$	1.000					
Discount	-0.175***	1.000				
MBHAR	-0.077***	0.004	1.000			
OLev	0.039	-0.236***	0.016	1.000		
Volm	0.057*	0.136***	-0.028	-0.218***	1.000	
OVolm	0.057*	0.031	-0.020	0.016	0.387***	1.000
CAR[1,5]	0.014	-0.007	0.062**	0.069**	-0.138***	-0.061**
CAR[6,10]	-0.008	-0.042	0.044	0.058*	-0.075**	-0.013
PCR[1,5]	-0.070**	0.060**	0.008	-0.046	0.042	-0.023
PCR[6,10]	-0.002	0.072**	0.014	-0.090***	0.021	-0.055*
OCAR[1,5]	0.000	-0.043	0.041	-0.010	0.070**	-0.030
OCAR[6,10]	-0.046	-0.022	0.041	-0.005	0.001	0.016
VWBHAR	-0.070**	-0.022	0.748***	0.148***	-0.029	0.006
BHR	-0.070**	-0.027	0.685***	0.164***	-0.017	0.007
Size	0.195***	-0.230***	-0.004	0.406***	-0.096***	0.108***
MTB	0.023	-0.056*	-0.007	-0.240***	-0.079***	-0.066**
STD	-0.008	0.235***	0.001	-0.620***	0.333***	0.041
Amihud	-0.072**	0.096***	0.030	-0.289***	-0.239***	-0.230***
NYSE	0.101***	-0.104***	0.050*	0.419***	-0.027	0.069**
ARPR	0.081***	-0.108***	0.035	-0.139***	0.017	0.056*
CAR[-5,-1]	-0.004	-0.050*	0.010	0.164***	-0.041	-0.029
OCAR[-5,-1]	0.002	-0.016	-0.025	-0.018	0.076***	0.049*
PRIM	-0.007	0.139***	0.011	-0.270***	0.211***	0.003
ACCEL	-0.008	0.040	-0.028	0.264***	0.002	0.053*
RelOfrSize	-0.064**	0.148***	0.014	-0.217***	0.139***	-0.015
Price	0.195***	-0.278***	0.006	0.296***	-0.101***	0.027
Price_Cluster	-0.024	0.133***	-0.035	-0.125***	0.037	-0.012
LockUp	-0.096***	0.109***	0.021	0.147***	0.212***	0.141***
NumIssue	0.015	0.017	-0.013	0.139***	0.030	0.090***
Tangibility	0.062**	-0.038	0.037	0.082***	0.053*	0.000
BA_Spread	0.009	0.285***	-0.015	-0.728***	0.273***	0.001
$\lvert AR_s \rvert$	-0.014	0.061**	-0.023	0.013	-0.026	0.012
$\lvert AR_o \rvert$	-0.192***	0.076***	0.041	-0.018	-0.096***	-0.091***
r_{IPO}	0.088***	-0.109***	0.075**	-0.205***	-0.128***	-0.158***
n_{IPO}	0.051*	-0.124***	0.043	-0.079***	-0.238***	-0.276***

Table 3 Univariate Analysis

This table presents the univariate analysis for a sample of the firms listed in NYSE, AMEX, and NASDAQ, conducting SEOs between 1996 and 2013 with options listed. The sample contains 1,155 observations. The sample is divided into quintile. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Other correlation measures are similarly defined; the return correlation ($\hat{\rho}_{\mathrm{r}}$), the signed Amihud correlation using raw trading volume ($\hat{\rho}_{\mathrm{v}}$), the signed Amihud correlation with call options ($\hat{\rho}_{\mathrm{c}}$), and the signed Amihud correlation with put options ($\hat{\rho}_{\mathrm{p}}$). All the other variables are defined in Appendix A. The symbols, *, **, and ***, indicates that difference of means between high and low quintile are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses.

	Low 1	2	3	4	High 5	High-Low
$\hat{\rho}$	0.810	0.927	0.953	0.968	0.982	0.172***
						(15.37)
OLev	1.580	1.634	1.744	1.582	1.655	0.075
						(1.21)
Volm	0.013	0.016	0.016	0.015	0.015	0.002
						(1.28)
OVolm	0.551	0.617	0.568	0.550	0.522	-0.029
						(-0.75)
Size	6.910	7.311	7.297	7.577	7.882	0.972***
						(8.22)
MTB	1.720	1.619	1.647	1.739	1.871	0.150
						(1.42)
STD	0.041	0.039	0.039	0.041	0.040	-0.001
						(-0.38)
Amihud	0.173	0.123	0.126	0.109	0.103	-0.070***
						(-3.26)
NYSE	0.294	0.403	0.385	0.420	0.485	0.190***
						(4.27)
ARPR	0.247	0.372	0.376	0.341	0.424	0.176***
						(3.21)
PRIM	0.736	0.714	0.732	0.784	0.745	0.009
						(0.21)
ACCEL	0.277	0.260	0.225	0.268	0.229	-0.048
						(-1.18)
RelOfrSize	0.146	0.135	0.147	0.130	0.116	-0.030***
						(-3.84)
Price	3.043	3.311	3.409	3.468	3.608	0.566***
						(8.75)
LockUp	0.810	0.727	0.758	0.662	0.632	-0.177***
						(-4.33)
NumIssue	2.861	2.853	2.874	2.680	2.740	-0.121
						(-0.72)
Tangibility	0.429	0.477	0.468	0.436	0.542	0.113***
						(2.65)
BA_Spread	0.052	0.051	0.051	0.053	0.053	0.001
						(0.58)
$\lvert AR_s \rvert$	0.108	0.107	0.110	0.102	0.100	-0.008
						(-1.10)
$\lvert AR_o \rvert$	0.205	0.175	0.156	0.140	0.177	-0.028
						(-1.51)
r_{IPO}	0.168	0.208	0.212	0.224	0.280	0.111***
						(4.88)
n_{IPO}	0.210	0.242	0.225	0.239	0.255	0.045**
						(2.41)

Table 4 Discount and $\hat{\rho}$

This table presents the results of Ordinary Least Squares (OLS) regression for SEO discount on $\hat{\rho}$. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variable is *Discount*, defined as the logarithm of the ratio of closing stock price 1 day prior to the issuance to the offer price. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Other correlation measures are similarly defined; the return correlation ($\hat{\rho}_r$) for column (4), the signed Amihud correlation using raw trading volume ($\hat{\rho}_v$) for column (5), the signed Amihud correlation with call options ($\hat{\rho}_c$) for column (6), and the signed Amihud correlation with put options ($\hat{\rho}_p$) for column (7). All the other variables are defined in Appendix A. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level, except for the column (3) which is clustered at the year.

	(1)	(2)	(3)	(4) $\hat{\rho}_r$	(5) $\hat{\rho}_v$	(6) $\hat{\rho}_c$	(7) $\hat{\rho}_p$
$\hat{\rho}$	**-0.067***** **(-13.89)**	**-0.053***** **(-7.32)**	**-0.053***** **(-3.51)**	**-0.033***** **(-2.97)**	**-0.014**** **(-2.08)**	**-0.033**** **(-2.68)**	**-0.034***** **(-2.72)**
OLev		-0.001 (-0.26)	-0.001 (-0.30)	-0.001 (-0.31)	-0.001 (-0.20)	0.001 (0.22)	-0.005 (-0.82)
Volm		0.119 (0.91)	0.119 (1.33)	0.105 (0.83)	0.051 (0.39)	0.117 (0.88)	0.088 (0.69)
OVolm		0.000 (0.06)	0.000 (0.05)	-0.000 (-0.00)	-0.001 (-0.26)	-0.001 (-0.22)	-0.001 (-0.22)
Size		0.001 (0.42)	0.001 (0.37)	0.001 (0.30)	-0.000 (-0.13)	0.000 (0.24)	0.001 (0.43)
MTB		0.001 (0.46)	0.001 (0.50)	0.001 (0.44)	0.001 (0.51)	0.001 (0.47)	0.001 (0.33)
STD		-0.105 (-1.00)	-0.105 (-1.26)	-0.102 (-0.93)	-0.087 (-0.80)	-0.105 (-0.96)	-0.109 (-1.02)
Amihud		0.015 (1.34)	0.015 (1.69)	0.016 (1.30)	0.015 (1.14)	0.015 (1.28)	0.016 (1.37)
NYSE		0.003 (0.95)	0.003 (0.85)	0.003 (0.93)	0.003 (1.00)	0.003 (0.77)	0.004 (1.00)
ARPR		-0.003 (-1.02)	-0.003 (-1.69)	-0.003 (-1.03)	-0.003 (-1.04)	-0.003 (-1.10)	-0.003 (-1.04)
CAR[-5,-1]		0.019 (0.82)	0.019 (0.86)	0.020 (0.84)	0.020 (0.86)	0.019 (0.78)	0.018 (0.81)
OCAR[-5,-1]		-0.004 (-1.45)	-0.004 (-0.97)	-0.004 (-1.53)	-0.004 (-1.66)	-0.004 (-1.56)	-0.003 (-1.33)
PRIM		0.005 (1.54)	0.005* (2.04)	0.006 (1.58)	0.006 (1.62)	0.006 (1.61)	0.006 (1.62)
ACCEL		0.016*** (4.93)	0.016*** (5.30)	0.016*** (4.97)	0.016*** (5.10)	0.016*** (4.96)	0.016*** (4.94)
RelOfrSize		0.028 (1.05)	0.028 (1.11)	0.027 (1.00)	0.028 (1.06)	0.028 (1.02)	0.028 (1.07)
Price		-0.008*** (-3.47)	-0.008*** (-3.70)	-0.008*** (-3.72)	-0.008*** (-3.66)	-0.009*** (-3.79)	-0.008*** (-3.73)
Price_Cluster		0.012*** (5.53)	0.012*** (5.64)	0.012*** (5.54)	0.012*** (5.61)	0.012*** (5.50)	0.012*** (5.44)
LockUp		0.006 (1.52)	0.006* (1.77)	0.006 (1.51)	0.005 (1.49)	0.005 (1.48)	0.006 (1.65)
NumIssue		0.001 (1.38)	0.001 (1.51)	0.001 (1.34)	0.001 (1.37)	0.001 (1.32)	0.001 (1.25)
Tangibility		-0.007*** (-3.66)	-0.007* (-1.77)	-0.007*** (-3.65)	-0.007*** (-3.52)	-0.007*** (-3.54)	-0.007*** (-3.50)
BA_Spread		0.457**	0.457***	0.452**	0.447**	0.472***	0.439**

		(2.62)	(5.57)	(2.57)	(2.56)	(2.75)	(2.50)
$\mid AR_s \mid$		0.034***	0.034**	0.033***	0.032***	0.032***	0.034***
		(3.15)	(2.42)	(3.02)	(2.95)	(3.02)	(3.15)
$\mid AR_o \mid$		-0.001	-0.001	0.001	0.002	0.002	0.002
		(-0.17)	(-0.15)	(0.14)	(0.25)	(0.25)	(0.24)
r_{IPO}		-0.010	-0.010**	-0.010	-0.010	-0.010	-0.009
		(-1.65)	(-2.31)	(-1.46)	(-1.46)	(-1.48)	(-1.40)
n_{IPO}		0.001	0.001	0.000	0.001	0.000	0.002
		(0.09)	(0.08)	(0.04)	(0.16)	(0.06)	(0.22)
Constant	0.096***	0.075***	0.075**	0.062**	0.048**	0.060**	0.059***
	(11.68)	(3.24)	(2.78)	(2.47)	(2.12)	(2.35)	(2.95)
Observations	1,155	1,155	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.092	0.194	0.194	0.187	0.185	0.188	0.190
S.E. Cluster	Industry	Industry	Year	Industry	Industry	Industry	Industry

Table 5 Discount and pre-issue market reaction

This table presents the results of Ordinary Least Squares (OLS) regression for SEO discount on $\hat{\rho}$. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variable is *Discount*, defined as the logarithm of the ratio of closing stock price 1 day prior to the issuance to the offer price. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Column (4) is the subsample analysis for the group of upper 50% $\hat{\rho}$ and column (5) is those for the group of lower 50% $\hat{\rho}$. All the other variables are defined in Appendix A. Control variables are included in the analysis, but not reported. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

	(1)	(2)	(3)	(4) High $\hat{\rho}$	(5) Low $\hat{\rho}$
$\hat{\rho}$	-0.053***	0.026	-0.053***	0.040	-0.057***
	(-7.44)	(1.07)	(-7.31)	(0.24)	(-3.91)
|CAR[-5,-1]|	**-0.050****	0.692***			
	(-2.17)	(3.71)			
x $\hat{\rho}$		**-0.797*****			
		(-3.84)			
$CAR[-5,-1]^+$			**-0.034**	**-0.042**	**-0.018**
			(-1.15)	**(-1.61)**	**(-0.24)**
$CAR[-5,-1]^-$			**0.060***	**0.083****	**0.043**
			(1.92)	**(2.56)**	**(1.04)**
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	577	578
Adj. R^2	0.198	0.211	0.198	0.153	0.198

Table 6 Return-reversal and short-term performance after SEOs

This table presents the results of Ordinary Least Squares (OLS) regression for short-term performance after SEOs on $\hat{\rho}$. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variable is Cumulative Abnormal Return (CAR) after SEOs; |CAR[1,5]|, the absolute value of CAR 1 day and 5 days after the issue date, for column (1); |CAR[6,10]|, the absolute value of CAR 6 days and 10 days after the issue date, for column (2); $CAR[1,5]^+$, CAR 1 day and 5 days after the issue date when positive 0 otherwise, for column (3); $CAR[6,10]^+$, CAR 6 day and 10 days after the issue date when positive 0 otherwise, for column (4); $CAR[1,5]^-$, CAR 1 day and 5 days after the issue date when negative 0 otherwise, for column (5); $CAR[6,10]^-$, CAR 6 day and 10 days after the issue date when negative 0 otherwise, for column (6). $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. All the other variables are defined in Appendix A. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

Dependent Variables	(1) |CAR[1,5]|	(2) |CAR[6,10]|	(3) $CAR[1,5]^+$	(4) $CAR[6,10]^+$	(5) $CAR[1,5]^-$	(6) $CAR[6,10]^-$
$\hat{\rho}$	**-0.046^{***}**	**-0.048^{***}**	**-0.012**	**-0.029^{*}**	**0.034^{***}**	**0.019**
	(-4.13)	**(-3.44)**	**(-1.33)**	**(-1.84)**	**(3.39)**	**(1.47)**
Discount	0.006	0.005	0.025	-0.030	0.019	-0.035
	(0.17)	(0.08)	(0.78)	(-0.84)	(0.47)	(-0.43)
OLev	-0.004	-0.009^{***}	-0.000	-0.004	0.003	0.005
	(-0.94)	(-3.15)	(-0.10)	(-1.64)	(1.25)	(1.54)
Volm	0.491^{*}	0.288	0.037	0.263^{*}	-0.455^{***}	-0.025
	(1.90)	(1.30)	(0.17)	(1.76)	(-3.16)	(-0.11)
OVolm	0.005^{*}	0.005	0.003	0.006	-0.002	0.001
	(1.98)	(1.07)	(0.84)	(1.21)	(-0.69)	(0.19)
Size	-0.002	-0.002	0.002	-0.003	0.004^{**}	-0.000
	(-0.97)	(-1.10)	(1.14)	(-1.67)	(2.34)	(-0.09)
MTB	0.001	0.001	-0.000	0.001	-0.002	-0.001
	(0.77)	(1.14)	(-0.31)	(0.31)	(-0.92)	(-0.64)
STD	0.483^{***}	0.491^{***}	-0.044	-0.196^{**}	-0.527^{***}	-0.687^{***}
	(3.73)	(3.53)	(-0.79)	(-2.71)	(-4.10)	(-4.07)
Amihud	0.002	0.005	0.002	0.010	0.001	0.005
	(0.19)	(0.34)	(0.26)	(1.11)	(0.10)	(0.55)
NYSE	0.002	0.010^{**}	0.000	0.000	-0.001	-0.010^{**}
	(0.44)	(2.54)	(0.11)	(0.07)	(-0.40)	(-2.26)
ARPR	0.008^{***}	0.003	-0.001	-0.009^{***}	-0.009^{**}	-0.012^{***}
	(3.06)	(0.70)	(-0.45)	(-4.45)	(-2.53)	(-3.72)
CAR[-5,-1]	-0.004	-0.019	0.018	0.055^{***}	0.022	0.073^{**}
	(-0.16)	(-0.53)	(1.48)	(3.46)	(1.31)	(2.35)
OCAR[-5,-1]	-0.001	0.003	-0.004	-0.003	-0.003	-0.006
	(-0.23)	(0.80)	(-1.24)	(-1.20)	(-1.08)	(-1.32)
PRIM	0.002	-0.002	-0.001	-0.009^{***}	-0.002	-0.007
	(0.40)	(-0.33)	(-0.19)	(-2.86)	(-0.86)	(-1.64)
ACCEL	0.002	0.001	-0.006^{**}	-0.003	-0.007^{**}	-0.004
	(0.44)	(0.27)	(-2.39)	(-0.83)	(-2.65)	(-1.10)
RelOfrSize	0.009	0.005	0.033	-0.007	0.024^{**}	-0.012
	(0.50)	(0.23)	(1.65)	(-0.68)	(2.53)	(-0.48)
Price	-0.003	0.004	-0.008^{***}	-0.001	-0.006^{**}	-0.006
	(-0.83)	(1.53)	(-4.04)	(-0.36)	(-2.18)	(-1.60)
Price_Cluster	0.003	-0.003	0.004^{*}	-0.001	0.002	0.002
	(1.02)	(-0.52)	(1.96)	(-0.24)	(1.06)	(0.58)
LockUp	-0.001	-0.000	0.001	0.005	0.002	0.005
	(-0.21)	(-0.02)	(0.18)	(1.13)	(0.36)	(0.85)
NumIssue	0.000	0.000	0.000	-0.000	-0.000	-0.000

	(0.52)	(0.02)	(0.13)	(-0.47)	(-0.37)	(-0.37)
Tangibility	-0.001	-0.007	0.008*	0.005*	0.008**	0.012**
	(-0.23)	(-1.28)	(1.84)	(1.83)	(2.38)	(2.58)
BA_Spread	0.128	0.289	0.128	0.199	-0.000	-0.090
	(0.87)	(1.49)	(0.89)	(1.10)	(-0.00)	(-0.32)
$\| AR_s \|$	-0.028	-0.021	-0.024	-0.006	0.005	0.015
	(-0.90)	(-1.44)	(-0.83)	(-0.33)	(0.45)	(1.13)
$\| AR_o \|$	0.007	0.006	-0.000	-0.004	-0.008	-0.011*
	(0.78)	(1.37)	(-0.07)	(-0.72)	(-0.81)	(-1.73)
r_{IPO}	0.011	0.016	-0.003	0.002	-0.014*	-0.013
	(1.37)	(1.06)	(-0.59)	(0.18)	(-1.82)	(-0.69)
n_{IPO}	-0.016	-0.013	-0.016	-0.009	0.000	0.005
	(-1.14)	(-0.66)	(-1.24)	(-0.91)	(0.01)	(0.22)
Constant	0.135***	0.066**	0.067***	0.097***	-0.068**	0.031
	(6.11)	(2.59)	(3.05)	(3.01)	(-2.12)	(1.21)
Observations	1,155	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.225	0.223	0.047	0.094	0.147	0.145

Table 7 Long-term performance after SEOs

This table presents the results of Ordinary Least Squares (OLS) regression for long-term performance after SEOs on $\hat{\rho}$. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variable is Buy-and-hold return (BHR) after SEOs; MBHAR, 6 months and 1 year BHR adjusted to Size-and-BTM matched firm for column (1) and (2), respectively; VWBHAR, 6 months and 1 year BHR adjusted to Fama-French 25 Size-and-BTM portfolio for column (3) and (4), respectively; BHR, 6 months and 1 year for column (5) and (6), respectively. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. All the other variables are defined in Appendix A. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

Dependent Variables	(1) MBHAR 0.5 Year	(2) MBHAR 1 Year	(3) VWBHAR 0.5 Year	(4) VWBHAR 1 Year	(5) BHR 0.5 Year	(6) BHR 1 Year
$\hat{\rho}$	**-0.553****	**-0.690*****	**-0.330*****	**-0.236***	**-0.318*****	**-0.213***
	(-2.46)	**(-3.57)**	**(-3.39)**	**(-1.73)**	**(-3.41)**	**(-1.71)**
Discount	0.456	0.254	0.246	0.206	0.165	0.104
	(1.02)	(0.40)	(0.53)	(0.33)	(0.34)	(0.16)
OLev	0.029	0.108**	0.072**	0.140***	0.066*	0.130***
	(0.81)	(2.15)	(2.30)	(3.98)	(1.90)	(3.36)
Volm	-0.618	-0.697	0.180	0.540	-0.388	0.437
	(-0.43)	(-0.39)	(0.14)	(0.31)	(-0.28)	(0.22)
OVolm	0.025	-0.044	0.032	0.012	0.033	0.008
	(0.57)	(-0.70)	(1.01)	(0.27)	(0.97)	(0.16)
Size	-0.003	0.005	0.015	0.011	0.032	0.026
	(-0.11)	(0.13)	(0.72)	(0.32)	(1.46)	(0.76)
MTB	-0.004	-0.006	-0.030*	-0.061**	-0.044**	-0.075***
	(-0.24)	(-0.18)	(-1.93)	(-2.50)	(-2.67)	(-3.02)
STD	0.991	0.606	1.752*	0.173	2.774***	0.036
	(1.08)	(0.60)	(1.74)	(0.12)	(3.90)	(0.02)
Amihud	0.051	0.052	0.177	0.112	0.117	0.054
	(0.34)	(0.31)	(1.53)	(0.61)	(0.98)	(0.28)
NYSE	0.068	0.111*	0.007	0.061	0.004	0.073
	(1.55)	(1.93)	(0.21)	(1.30)	(0.12)	(1.46)
ARPR	0.045	0.104	0.063	0.079*	0.058	0.060
	(0.83)	(1.58)	(1.62)	(1.90)	(1.59)	(1.37)
CAR[-5,-1]	0.013	-0.255	-0.173	-0.558***	-0.208	-0.578***
	(0.07)	(-1.21)	(-1.43)	(-3.20)	(-1.61)	(-2.96)
OCAR[-5,-1]	-0.045	-0.034	-0.003	0.003	-0.006	-0.016
	(-1.12)	(-0.75)	(-0.09)	(0.10)	(-0.17)	(-0.45)
PRIM	0.007	0.004	0.024	-0.008	0.013	-0.019
	(0.14)	(0.06)	(0.73)	(-0.17)	(0.39)	(-0.37)
ACCEL	-0.042	-0.048	-0.027	-0.026	-0.037	-0.024
	(-0.92)	(-1.06)	(-0.81)	(-0.62)	(-0.94)	(-0.54)
RelOfrSize	0.073	-0.025	0.139	0.043	0.174	0.100
	(0.35)	(-0.09)	(0.89)	(0.16)	(0.97)	(0.35)
Price	-0.005	0.038	-0.066**	-0.040	-0.076**	-0.025
	(-0.13)	(0.78)	(-2.30)	(-1.19)	(-2.43)	(-0.61)
Price_Cluster	-0.068***	-0.081	-0.063*	-0.077	-0.072*	-0.080
	(-2.95)	(-1.39)	(-1.85)	(-1.30)	(-1.99)	(-1.41)
LockUp	0.051	0.011	0.060	0.042	0.082*	0.051
	(0.92)	(0.10)	(1.26)	(0.55)	(1.72)	(0.63)
NumIssue	-0.002	-0.001	0.004	0.016	0.006	0.017
	(-0.16)	(-0.08)	(0.61)	(1.50)	(0.79)	(1.45)
Tangibility	0.048	0.096	0.050	0.122***	0.058*	0.137***

	(0.87)	(1.25)	(1.48)	(3.04)	(1.69)	(3.66)
BA_Spread	-1.019	-1.116	-4.083***	-3.911*	-4.286***	-3.200
	(-0.68)	(-0.30)	(-4.11)	(-1.96)	(-4.06)	(-1.59)
$\lvert AR_s \rvert$	-0.220	-0.045	-0.245	-0.247	-0.261	-0.234
	(-0.95)	(-0.13)	(-1.61)	(-1.04)	(-1.61)	(-0.95)
$\lvert AR_o \rvert$	0.052	-0.048	-0.086*	-0.128	-0.100	-0.138
	(0.65)	(-0.36)	(-1.69)	(-1.56)	(-1.64)	(-1.65)
r_{IPO}	0.025	-0.152	0.101	-0.090	0.172	-0.208
	(0.13)	(-0.68)	(0.75)	(-0.75)	(1.05)	(-1.50)
n_{IPO}	-0.113	-0.394	0.092	-0.205	0.005	-0.716***
	(-0.85)	(-1.07)	(0.98)	(-1.09)	(0.06)	(-3.64)
Constant	0.248	0.383	0.184	0.366	0.369	0.815**
	(0.80)	(0.66)	(0.87)	(1.09)	(1.64)	(2.22)
Observations	1,155	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.004	0.021	0.079	0.115	0.201	0.251

Table 8 Leverage effect

This table presents the results of Ordinary Least Squares (OLS) regression for SEO discount on $\hat{\rho}$ and its interaction with option leverage (OLev). The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variable is *Discount*, defined as the logarithm of the ratio of closing stock price 1 day prior to the issuance to the offer price. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Other correlation measures are similarly defined; the return correlation ($\hat{\rho}_r$) for column (2), the signed Amihud correlation using raw trading volume ($\hat{\rho}_v$) for column (3), the signed Amihud correlation with call options ($\hat{\rho}_c$) for column (4), and the signed Amihud correlation with put options ($\hat{\rho}_p$) for column (5). All the other variables are defined in Appendix A. Control variables are included in the analysis, but not reported. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

	(1)	(2) $\hat{\rho}_r$	(3) $\hat{\rho}_v$	(4) $\hat{\rho}_c$	(5) $\hat{\rho}_p$
$\hat{\rho}$	-0.171***	-0.143***	-0.066***	-0.137***	-0.100***
	(-5.99)	(-4.69)	(-3.11)	(-3.00)	(-3.43)
OLev	**-0.073*****	**-0.065*****	**-0.027****	**-0.113****	**-0.101*****
	(-3.80)	**(-3.57)**	**(-2.22)**	**(-2.17)**	**(-3.06)**
x $\hat{\rho}$	**0.077*****	**0.067*****	**0.034****	**0.129****	**0.108*****
	(3.88)	**(3.52)**	**(2.42)**	**(2.26)**	**(2.88)**
Amihud	0.014	0.014	0.015	0.014	0.016
	(1.31)	(1.26)	(1.20)	(1.31)	(1.42)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.205	0.192	0.191	0.194	0.198

Table 9 Liquidity

This table presents the results of Ordinary Least Squares (OLS) regression for SEO discount on $\hat{\rho}$ and its interaction with Amihud. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variable is *Discount*, defined as the logarithm of the ratio of closing stock price 1 day prior to the issuance to the offer price. $\hat{\rho}$, empirical proxy for ρ, is the correlation of signed Amihud (2002)'s illiquidity measures of options and those of the underlying stock. Other correlation measures are similarly defined; the return correlation ($\hat{\rho}_{\mathrm{r}}$) for column (2), the signed Amihud correlation using raw trading volume ($\hat{\rho}_{\mathrm{v}}$) for column (3), the signed Amihud correlation with call options ($\hat{\rho}_{\mathrm{c}}$) for column (4), and the signed Amihud correlation with put options ($\hat{\rho}_{\mathrm{p}}$) for column (5). All the other variables are defined in Appendix A. Control variables are included in the analysis, but not reported. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

	(1)	(2) $\hat{\boldsymbol{\rho}}_{\mathbf{r}}$	(3) $\hat{\boldsymbol{\rho}}_{\mathbf{v}}$	(4) $\hat{\boldsymbol{\rho}}_{\mathbf{c}}$	(5) $\hat{\boldsymbol{\rho}}_{\mathbf{p}}$
$\hat{\rho}$	-0.015	0.001	-0.008	-0.007	-0.003
	(-0.53)	(0.02)	(-0.89)	(-0.25)	(-0.13)
Amihud	**0.205***	**0.211***	**0.038**	**0.140***	**0.180**
	(1.71)	**(1.81)**	**(1.61)**	**(1.83)**	**(1.48)**
x $\hat{\boldsymbol{\rho}}$	**-0.209**	**-0.214***	**-0.031***	**-0.144***	**-0.187**
	(-1.65)	**(-1.78)**	**(-1.76)**	**(-1.79)**	**(-1.46)**
OLev	-0.001	-0.001	-0.001	0.001	-0.006
	(-0.34)	(-0.35)	(-0.24)	(0.18)	(-0.89)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.202	0.193	0.186	0.193	0.196

Table 10 Robustness test (Endogeneity control)

This table presents the results of Ordinary Least Squares (OLS) regression for SEO discount and post-issue performance, after controlling endogeneity of the variables. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variables are defined in top of each columns. All the other variables are defined in Appendix A. First-stage regression results are not reported. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

	(1) Discount	(2) |CAR[1,5]|	(3) |CAR[6,10]|	(4) MBHAR 0.5 Year	(5) VWBHAR 0.5 Year	(6) BHR 0.5 Year
$\hat{\rho}_e$	**-0.048***** **(-6.82)**	**-0.044***** **(-4.12)**	**-0.043***** **(-2.99)**	**-0.558**** **(-2.42)**	**-0.375*** **(-1.90)**	**-0.362***** **(-3.40)**
Discount		0.015 (0.44)	0.028 (0.37)	0.387 (0.86)	0.024 (0.07)	-0.044 (-0.09)
OLev	-0.005* (-1.74)	-0.011*** (-2.83)	-0.019*** (-5.56)	0.031 (1.02)	0.107*** (2.94)	0.094*** (2.96)
Volm	0.224* (2.01)	0.799*** (2.73)	0.647** (2.60)	-0.345 (-0.24)	-0.208 (-0.24)	-0.254 (-0.22)
OVolm	0.000 (0.15)	0.006** (2.35)	0.006 (1.18)	0.025 (0.54)	0.038 (0.97)	0.039 (1.10)
Size	0.001 (0.55)	-0.002 (-1.43)	-0.003 (-1.32)	-0.010 (-0.35)	0.008 (0.59)	0.025 (1.07)
MTB	0.001 (0.30)	0.004** (2.28)	0.003*** (2.92)	0.005 (0.30)	-0.018 (-0.83)	-0.034** (-2.33)
Amihud	0.024** (2.05)	0.012 (1.23)	0.020 (1.54)	0.053 (0.35)	0.122 (1.49)	0.078 (0.68)
NYSE	0.000 (0.10)	0.000 (0.09)	0.007* (1.80)	0.079* (1.97)	0.027 (0.91)	0.022 (0.71)
PreCAR[-5,-1]	0.015 (0.69)	-0.010 (-0.44)	-0.024 (-0.66)	-0.008 (-0.04)	-0.143 (-1.40)	-0.178 (-1.66)
PreOCAR[-5,-1]	-0.005* (-1.93)	-0.000 (-0.12)	0.003 (0.80)	-0.041 (-1.01)	0.003 (0.10)	0.002 (0.05)
PRIM	0.006* (1.70)	0.002 (0.44)	-0.001 (-0.19)	0.006 (0.13)	0.028 (0.56)	0.021 (0.60)
ACCEL	0.017*** (5.32)	0.001 (0.14)	-0.000 (-0.01)	-0.051 (-1.09)	-0.033 (-1.58)	-0.044 (-1.12)
RelOfrSize	0.031 (1.15)	0.012 (0.66)	0.007 (0.34)	0.097 (0.48)	0.129 (0.71)	0.153 (0.76)
Price	-0.012*** (-4.40)	-0.003 (-0.97)	0.003 (0.88)	0.001 (0.03)	-0.039 (-1.01)	-0.052 (-1.62)
Price_Cluster	0.013*** (7.00)	0.004 (1.48)	-0.001 (-0.30)	-0.066** (-2.71)	-0.065 (-1.27)	-0.072* (-1.81)
Constant	0.073*** (3.27)	0.114*** (9.72)	0.056*** (3.47)	-0.237 (-1.04)	-0.189 (-1.20)	-0.009 (-0.03)
Observations	1,155	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.175	0.191	0.189	0.007	0.065	0.187

Table 11 Calendar Time portfolio

This table presents the results of calander-time portfolio (Fama (1998)) analysis. The sample period is 1996 to 2013, containing 1,155 SEOs. For each monthly portfolio, the firms issuing new shares prior to 6 months are included. r_{high} includes the firms in the upper 50% $\hat{\rho}$ group and r_{low} includes the firms in the lower 50% $\hat{\rho}$ group. The dependent variables are defined in top of each columns. MKTRT is market-portfolio return, SMB is small-minus-big size portfolio, HML is high-minus-low BTM portfolio, and UMD is up minus down portfoilo return from Kenneth R. French's website. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
	r_{high}	r_{low}	r_{high}	r_{low}	r_{high} - r_{low}
α	**-1.043*****	**-0.046**	**-1.171*****	**0.042**	**-1.213*****
	(-3.13)	**(-0.12)**	**(-3.54)**	**(0.11)**	**(-2.75)**
MKTRT	1.359***	1.499***	1.435***	1.447***	-0.011
	(18.49)	(17.27)	(18.65)	(15.72)	(-0.11)
SMB	0.758***	0.897***	0.728***	0.918***	-0.190
	(7.56)	(7.58)	(7.34)	(7.74)	(-1.44)
HML	-0.477***	-0.079	-0.419***	-0.118	-0.300**
	(-4.53)	(-0.64)	(-3.97)	(-0.94)	(-2.14)
UMD			0.182***	-0.124	0.306***
			(2.88)	(-1.64)	(3.63)
Observations	218	218	218	218	218
Adj. R^2	0.741	0.688	0.749	0.691	0.079

Table 12 Robustness test

This table presents the results of Ordinary Least Squares (OLS) regression for SEO discount and post-issue performance, for other correlation measures. The sample period is 1996 to 2013, containing 1,155 SEOs. The dependent variables are defined in top of each columns. All the other variables are defined in Appendix A. Control variables are included in the analysis, but not reported. The symbols, *, **, and ***, indicates that the regression coefficients are significantly different from zero at the 10%, 5%, and 1% confidence level, respectively. t-statictics are reported in parentheses. Year and industry fixed effects are included in all the analyses. Standard errors are clustered at the industry level.

Panel A. Discount and pre-issue market reaction

	(1) Discount $\hat{\rho}_r$	(2) Discount $\hat{\rho}_v$	(3) Discount $\hat{\rho}_c$	(4) Discount $\hat{\rho}_p$
Correlation	0.046**	0.016	0.008	0.032
	(2.17)	(0.93)	(0.29)	(1.54)
|CAR[-5,-1]|	**0.758*** **	**0.228***	**0.374**	**0.478*** **
	(5.13)	**(1.78)**	**(1.68)**	**(2.72)**
x *Correlation*	**-0.859*** **	**-0.394** **	**-0.487***	**-0.622*** **
	(-5.26)	**(-2.20)**	**(-1.86)**	**(-3.01)**
Controls	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	1,155
Adj. R^2	0.203	0.200	0.197	0.207

Panel B. Short-term performance

	(1) |CAR[1,5]| $\hat{\rho}_r$	(2) |CAR[1,5]| $\hat{\rho}_v$	(3) |CAR[1,5]| $\hat{\rho}_c$	(4) |CAR[1,5]| $\hat{\rho}_p$	(5) |CAR[6,10]| $\hat{\rho}_r$	(6) |CAR[6,10]| $\hat{\rho}_v$	(7) |CAR[6,10]| $\hat{\rho}_c$	(8) |CAR[6,10]| $\hat{\rho}_p$
Correlation	**-0.040*** **	**-0.013**	**-0.041** **	**-0.022**	**-0.040** **	**-0.010**	**-0.045**	**-0.029** **
	(-4.64)	**(-1.69)**	**(-2.64)**	**(-1.13)**	**(-2.36)**	**(-1.11)**	**(-1.50)**	**(-2.68)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.223	0.220	0.224	0.220	0.221	0.219	0.222	0.221

Panel C. Long-run performance

	(1) MBHAR 0.5 Year $\hat{\rho}_r$	(2) MBHAR 0.5 Year $\hat{\rho}_v$	(3) MBHAR 0.5 Year $\hat{\rho}_c$	(4) MBHAR 0.5 Year $\hat{\rho}_p$	(5) VWBHAR 0.5 Year $\hat{\rho}_r$	(6) VWBHAR 0.5 Year $\hat{\rho}_v$	(7) VWBHAR 0.5 Year $\hat{\rho}_c$	(8) VWBHAR 0.5 Year $\hat{\rho}_p$
Correlation	**-0.602** **	**-0.139**	**-0.391***	**-0.171**	**-0.393*** **	**-0.130** **	**-0.288*** **	**-0.152** **
	(-2.38)	**(-1.00)**	**(-1.91)**	**(-0.95)**	**(-2.91)**	**(-2.03)**	**(-2.80)**	**(-2.69)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,155	1,155	1,155	1,155	1,155	1,155	1,155	1,155
Adj. R^2	0.005	-0.002	0.001	-0.002	0.080	0.077	0.078	0.076