Trading Mechanism, Ex-post Uncertainty and IPO Underpricing*

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Abstract

Falconieri et al. (2009) highlight that IPO underpricing does not only depend on ex-ante value uncertainty but is also affected by what they define as ex-post value uncertainty, i.e. uncertainty that persists in the beginning of the aftermarket. In this paper, we present a simple theoretical model that further develops their idea by showing that ex-post uncertainty depends on the specific trading platform used to open trade after the IPO. Specifically the model suggests that auction markets, such as the NYSE or AMEX, are more efficient in resolving ex post-uncertainty as opposed to dealership markets, such as the NASDAQ. The predictions of the model are then tested on as sample of US IPOs between 1993 and 1998 by using the proxy for ex-post uncertainty proposed by Falconieri et al. (2009). Consistently with the predictions of the theoretical model, our findings provide strong evidence that the level of the ex post uncertainty is influenced by the method used to open trading in the IPO aftermarket. Specifically, our results show that there is a larger level of uncertainty at the beginning of trading on NASDAQ than on exchange-listed IPOs, such as the NYSE or AMEX. This is in turn associated with larger levels of underpricing for NASDAQ IPOs. Additionally, we further test the robustness of our results by looking into the period following the introduction of the Nasdaq IPO opening cross in 2006. The opening cross effectively moved Nasdaq closer to the level of centralization at NYSE or AMEX and thus represents a natural experiment for us to test whether this change has resulted, as our model predicts, in a lower level of ex-post uncertainty and hence underpricing for Nasdaq IPOs. Our findings provide strong support to our hypothesis, thereby confirming the superior efficiency of auction markets.

Keywords: underpricing, ex post uncertainty, trading platforms.

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1 Introduction

Underpricing is a peculiar feature of initial public offerings (IPOs). While the traditional literature views underpricing as a premium for ex-ante uncertainty about the firm market value (Ritter (1984), Beatty and Ritter (1986)), more recent papers link underpricing to some kind of uncertainty in the aftermarket. Ellul and Pagano (2006), for instance, develop and test a model that shows that underpricing is also affected by uncertainty about the after-market liquidity. They find that the less liquid the after-market is expected to be the larger the IPO underpricing. Chen and Wilhelm (2008) propose a theoretical model that shows that asymmetric information among participants as well as uncertainty about the firm value is not fully resolved in the primary market but actually persists in the after-market. Falconieri et. al. (2009) label this type of uncertainty as "ex-post uncertainty" and develop proxies for it. They document a strong link between ex-post uncertainty and IPO underpricing consistent with Chen and Wilhelm's argument.

This paper builds on this recent literature and makes a step further in analysing the role of the after-market on the IPO underpricing. Specifically, we investigate, both theoretically and empirically, if different mechanisms to open secondary market trading affect the level of ex-post uncertainty and consequently of IPO underpricing.

In the US, till quite recently, there have traditionally been two alternative methods to open secondary market trading in equities. In order-driven environments like the NYSE, trading starts with a call auction where public orders are consolidated. In quote-driven markets like NASDAQ, the first trade is preceded by a period (pre-opening) during which dealers can display the prices at which they will buy and sell. These quotes however are non-binding and do not necessarily reflect information from public orders placed with dealers before the opening. The same processes are used to open secondary market trading after an IPO. If there is some ex-post uncertainty that persists in the secondary market, then the intuition suggests that the concentrated supply and demand structure provided by the call auction method of opening trading on the NYSE and the AMEX should allow for a quicker resolution of any residual value uncertainty than the fragmented supply and demand resulting from NASDAQ's method of opening trading. This would in turn results in less underpricing and narrower spreads on NYSE/AMEX IPOs than for IPOs that trade on NASDAQ.[1]

[1] While previous papers by Boehmer and Fishe (2000) and Ellis, Michaely, and O'Hara (2000) relate underpricing to market structure, they do not directly examine the relationship between the pricing of IPOs and the opening procedures in the secondary market.

In addition, very little has been done to compare IPOs on the two trading systems. Corwin and Harris (2001) and Affleck-Graves, Hegde, and Miller (1996) compare the size of underpricing on NYSE and NASDAQ IPOs reaching different results. However, neither study controls for industry effects, so that their results may be driven by differences in the types of firms on each market.

We develop a model that adapts and extends that by Ellul and Pagano (2006) to compare the two trading platforms. The model is able to capture the key differences between auction and dealership markets and clearly predicts that auction markets are superior in reducing information asymmetry and uncertainty and thus lead to less underpricing that dealership markets. The model's predictions are then tested on a sample of IPO data between 1993 and 1998. We find strong evidence that indeed ex-post uncertainty and thus underpricing are much lower on auction markets. We conduct a number of robustness check including looking at a sample of IPOs between June 2006 and May 2008. On May 30, 2006 in fact Nasdaq introduced a voluntary opening cross. This method resulted in an increased level of centralization of supply and demand on Nasdaq thereby making it closer to traditional auction markets such as NYSE and Amex. This represents a natural experiment to test the validity of our theory, as if our argument is correct we should observe less ex-post uncertainty and thus less underpricing on Nasdaq IPO following the start of the opening cross which is indeed what we find.

The reminder of the paper is organized as follows. The next section presents and solves the theoretical model. Section 3 describes the sample used for our empirical analysis while the results of the analysis are grouped in Section 4. Section 5 develops some robustness checks including testing our hypothesis on IPOs in the period following the introduction of the opening cross on Nasdaq. The last section concludes.

2 The Theoretical Model

Our model adapts and extends Ellul and Pagano's model (2006). We consider an IPO market for new shares with three periods. The primary market takes place at $t = 0$. We do not explicitly model the IPO process. Similarly to Ellul and Pagano (2006) we will assume that underpricing in this case is mainly associated to Rock's winner's curse effect. At $t = 1$, shares start trading on the secondary market.[2] Finally, at $t = 2$, all shares are liquidated.

Like in Ellul and Pagano (2006), our model captures the interactions between the primary and the secondary market by using the importance of asymmetric information in both markets. In some sense, we consider a double adverse selection effect that results from the existence of information asymmetries on both markets. However, the novelty of our model, in contrast with Ellul and Pagano (2006), is explicitely consider the impact of the market structure on the information links between the primary and the secondary market.

The information technology in our model is as follows: it is commonly known that the shares' fundamental value is $\widetilde{V} = V + \widetilde{s}_1 + \widetilde{s}_2$ where V is a positive constant that represents the non

[2] In line with our empirical analysis we have in mind the very first hours after trading opens.

conditional expected value of new shares and $\widetilde{s}_1$ and $\widetilde{s}_2$ are independently distributed random variables representing signals that will be observed by a fraction of the market participants at $t = 0$ and $t = 1$, respectively. Both variables represent simple binary signals about the quality of the issuer. The variable $\widetilde{s}_1$ is a private signal observed by a number of informed investors during the IPO process. It can take value η or $-\eta$ with probability 1/2. This signal becomes public before the opening of the secondary market. Some uncertainty about the shares' value however remains in the secondary market and is captured by the signal $\widetilde{s}$ which can take values $-\varepsilon$ or ε with probability 1/2. Given this information structure, the share value is then equal to $V + \widetilde{s}_1$ at $t = 1$ and to $V + \widetilde{s}_1 + \widetilde{s}_2$ at $t = 2$.

In the primary market , there are M uninformed traders who enter this market using only the public information and a group of N informed investors who instead observe the value of $\widetilde{s}_1$. Similarly, at $t = 1$ when trade opens in the secondary market, each trader has a probability Q to become informed and learn the signal $\widetilde{s}_2 = -\varepsilon$ or $\widetilde{s}_2 = \varepsilon$.[3]

Adverse selection in the secondary market arises as a consequence of the liquidity needs that agents may face. Specifically, we assume that each trader in the secondary market may become a *liquidity seller*, and thus be forced to sell the shares bought on the primary market, with probability z; with probability $1 - x$ he may become a *liquidity buyer* on the secondary market and with probability $1 - x - z$ he will hold his shares until the end of $t = 2$. This assumption differs from Ellul and Pagano (2006) who only allow an investor to be either a seller or a buyer. We think our way of modelling liquidity needs is more realistic particularly when we investigate order-driven markets. Dealers know the probability distribution of the incoming orders.

The primary market

The primary market in our set-up is organized à la Rock (1986). The underpricing occurs because of the winner's curse effect. When they receive new shares, uninformed agents infer that informed investors have learned negative information about the shares' value. Anticipating this, uninformed investors will revise downward their valuation of the new assets.

We further assume that the company sells an exogenous number, S, of shares in the IPO. The objective of the seller and of the underwriter is to maximize the IPO proceeds given by SP_0. Each investor can buy at most one share. Finally, in order to allow for the winner's curse story, we assume that uninformed agents are able to buy the whole quantity of shares, i.e. we assume that $M \geq S$. whereas informed investors cannot, i.e. $N < S$. Hence, the seller needs to attract bids from the uninformed investors in order to place all the shares.

[3] Like in Ellul and Pagano (2006), we assume that becoming informed in the secondary market is independent from having purchased shares on the primary market. *(is it correct this?!)*

The secondary market

The secondary market begins at $t = 1$. At this stage, all investors learn the signal $\widetilde{s}_1$. The prices determined on the secondary market will affect the investors' strategies on the primary markets. The price determination mechanism in the secondary market in turn depends on the specific market structure, i.e. whether it is a dealership or an order-book market. Below we spell out in details the differences between the two market structures and how these are reflected on the share prices.

Dealership markets

Our definition of the dealership market is similar to Ellul and Pagano (2006). Hence, we assume, with no loss of generality, that each liquidity trader is matched with one dealer and can place an order for at most 1 unit of shares. Dealers only observe whether the order is a "buy" or a "sell" order, but cannot know whether it comes from an informed or a liquidity trader. Thus the bid-ask spread is set based on their expectations of an order coming from an informed or a liquidity trader and taking into account that the market is assumed to be perfectly competitive. In other words, the bid and ask prices, denoted by P_1^{Db} and P_1^{Da} respectively, are given by

$$P_1^{Da} = E\left(\widetilde{V} \mid \widetilde{s}_1, \text{buy}\right) \text{ and } P_1^{Db} = E\left(\widetilde{V} \mid \widetilde{s}_1, \text{sell}\right)$$

Order-book market

Considering an order-book market structure along with the dealership one represents the innovative part of the model. The specificity of such market is that all the submitted orders are collected by the market maker who therefore has much more information about the demand than a dealer on a dealership market. This is for instance the case for exchanges such as the NYSE where the specialist have access to more information about the order process than other participants in the market. We assume however that the specialist is in competition with other liquidity providers through the market-order book process, this then implies that given the set of orders y_1, $y_2, ..., y_m$ the price pre share is then given by the following

$$P_1^A = E\left(\widetilde{V} \mid y_1, y_2, ..., y_m\right)$$

Note that in this market, informed agents will have an incentive to hide their orders behind the liquidity orders in order not to reveal their information. Since we know that uninformed traders will trade at most one unit, informed traders have no incentive to trade more than only one unit. So the set of strategies in the market would be to buy or sell one unit or to decide to remain out of the market. As specified above, uninformed agents submit orders for liquidity reasons while informed traders trade on the new piece of information they learn at this stage. Hence, an informed trader i will sell if and only if he expects to make a profit from trading, i.e. iff $\left(E\left(\widetilde{V}|s_2, P_1^O\right) - P_1^O\right) > 0$.

Going back to the primary market now, an investor will decide to bid for shares only if his expected revenues from selling the new share, conditional on his information, exceed the IPO offer price P_0^A with $A = \{D, O\}$ being the index for dealership and order-book market, respectively. Each potential buyer will sell the new share (for liquidity reasons) in the opening of the secondary market at the market bid price with probability z or hold them until the liquidation time $t = 2$ and sell it at price P_2. He can actually buy a new share in the secondary market because of liquidity reasons. With probabilty x (s)he will receive the liquidity shock and buy at the ask price. Investor j, where $j = \{i, u\}$ indexes for informed and uninformed investors will bid price P_0^A for a share in the IPO if

$$zE(P_1^{Ab} \mid \Phi_0^j) + (1 + x - z)E(P_2 \mid \Phi_0^j) - xE(P_1^{Aa} \mid \Phi_0^j) \geq P_0^A. \tag{1}$$

For $j = \{i, u\}$ and $A = \{D, O\}$. Note that P_2 does not depend on the structure of the market since it is equal to the expected liquidation value. Equilibria are derived below by backward induction in both market structures.

2.1 Market equilibrium in dealership markets

At $t = 2$ all information is public and the price $P_2 = \widetilde{V}$. At $t = 1$, traders submit orders to dealers who will then set a bid-ask spread conditional on the information revealed by the order flow. Order size cannot exceed 1 since uninformed traders cannot buy or sell more than one unit.[5] There is a probability Q that a trader observes the realization of s_2 which can be equal either to ε or $-\varepsilon$ with the same probability, 1/2. So from dealers' perspective $s_2 = \varepsilon$ with probability $Q/2 = q$. Because of the existence of liquidity traders, the conditional probability that a sell order is informed is $q/(q + z)$, and the probability that it is uninformed is $z/(q + z)$. Therefore, at $t = 1$, the bid price set by the competitive dealer is given by the expected value of the share conditional on the value of $\widetilde{s}_1$, which is public, and on receiving a sell order:

$$\begin{aligned} P_1^{Db} &= E\left(\widetilde{V} \mid \widetilde{s}_1, \text{sell}\right) \\ &= \frac{q}{q+z}(V + \widetilde{s}_1 - \varepsilon) + \frac{z}{q+z}(V + \widetilde{s}_1) \\ &= V + \widetilde{s}_1 - \frac{q}{q+z}\varepsilon. \end{aligned}$$

Similarly, conditionally upon receiving a buy order, the dealer will set the ask price as

$$\begin{aligned} P_1^{Da} &= E\left(\widetilde{V} \mid \widetilde{s}_1, \text{buy}\right) \\ &= V + \widetilde{s}_1 + \frac{q}{q+x}\varepsilon. \end{aligned}$$

[4] Note that we do not consider bid and ask prices for the order-book market since this will depend on the sum of orders.

[5] For informed traders is then never optimal to submit bigger orders in order not to disclose their type.

It follows that the bid-ask spread is given by

$$S^D = \underbrace{\frac{q}{q+x}\varepsilon}_{S_A^D} + \underbrace{\frac{q}{q+z}\varepsilon}_{S_B^D} = q\varepsilon\left(\frac{1}{q+x}+\frac{1}{q+z}\right)$$

with S_A^D denoting the ask-spread and S_B^D the bid-spread.

We use the expected prices derived above into Eq.(1) to determine the optimal trading strategies of informed and uninformed investors in dealership markets.

As far as informed traders are concerned, at $t=0$ they observe the value of $\widetilde{s}_1$ and, thus, they will be willing to buy shares in the IPO only if the offering price is lower than their expected selling revenues. In other words, given Eq.(1), prices should satisfy the following condition

$$\begin{aligned} zE(P_1^{Db} \quad &| \quad \widetilde{s}_1=\eta)+(1+x-z)E(\widetilde{P}_2 \mid \widetilde{s}_1=\eta)-xE(P_1^{Da} \mid \widetilde{s}_1=\eta) \geq P_0^D \geq \\ zE(P_1^{Db} \quad &| \quad \widetilde{s}_1=-\eta)+(1+x-z)E(\widetilde{P}_2 \mid \widetilde{s}_1=-\eta)-xE(P_1^{Aa} \mid \widetilde{s}_1=-\eta). \end{aligned} \tag{2}$$

which, after replacing into the random variables and P_1^{Db}, P_1^{Aa} can be rewritten as

$$V+\eta-q\left(\frac{z}{q+z}+\frac{x}{q+x}\right)\varepsilon \geq P_0^D \geq V-\eta-q\left(\frac{z}{q+z}+\frac{x}{q+x}\right)\varepsilon \tag{3}$$

This latter equation states that informed agents will bid only if they receive good information about the quality of the firm, i.e. if $\widetilde{s}_1=\eta$.. We will check ex post that the equilibrium offer price will indeed satisfy this condition.

Now we turn to the uninformed agents' strategy. Given, Eq.(1), their strategy is to buy shares if

$$zE(\widetilde{P}_1^{Db} \mid \Phi_0^u)+(1+x-z)E(P_2 \mid \Phi_0^u)-xE(P_1^{Da} \mid \Phi_0^u) \geq P_0^D \tag{4}$$

where Φ_0^u denotes their information set at $t=0$ which includes only publicly available information at $t=0$, i.e. distributions of random variables and the information inferred from the offer price P_0^D. Additionally, uninformed investors anticipate that there will be allocated more shares in the IPO when informed investors do not want to buy them, i.e. when they know they are low quality. Thus, let π^D be the probability that uninformed traders get high quality when they bid P_0^D and $(1-\pi^D)$ be the probability that they get low quality shares. Then we can write the expected bid and ask prices from their perspective as follows

$$\begin{aligned} E(\widetilde{P}_1^{Db} \left| \Phi_0^u, P_0^D\right.) &= \pi^D\left(V+\eta-\frac{q}{q+z}\varepsilon\right)+(1-\pi^D)\left(V-\eta-\frac{q}{q+z}\varepsilon\right) \\ &= V-\frac{q}{q+z}\varepsilon-(1-2\pi^D)\eta. \end{aligned} \tag{5}$$

Similarly

$$\begin{aligned} E(\widetilde{P}_1^{Da} \quad | \quad \Phi_0^u, P_0^D) &= \pi^D\left(V+\eta+\frac{q}{q+x}\varepsilon\right)+(1-\pi^D)\left(V-\eta+\frac{q}{q+x}\varepsilon\right) \\ = \quad V+\frac{q}{q+x}\varepsilon-(1-2\pi^D)\eta. \end{aligned}$$

$$E(P_2|\Phi_0^u, P_0^D) = \pi^D (V+\eta) + (1-\pi^D)(V-\eta)$$
$$= V - (1-2\pi^D)\eta. \quad (6)$$

Substitution into Eq.(4) finally gives

$$V - (1-2\pi^D)\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon \geq P_0^D. \quad (7)$$

As in Rock (1986), the company will set the highest price P_0^D that allows the participation of uninformed investors in the market in order to ensure that all the shares are placed. (since $N < S$). which implies that the above condition will hold as an equality in equilbrium. That is:

$$P_0^D = V - (1-2\pi^D)\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon \quad (8)$$

We can now state the next result about the size of underpricing in dealership markets:

Proposition 1 *In dealership markets, the level of underpricing is given by*

$$E(\widetilde{P}_1^D) - P_0^D = (\frac{1-\pi}{1+\pi})\eta + q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon = (\frac{1-\pi}{1+\pi})\eta + \left(zS_A^D + xS_B^D\right). \quad (9)$$

The above results highlights two main components of underpricing. The first one $(\frac{1-\pi}{1+\pi})\eta$ is related to the uncertainty on the primary market, so the traditional explanation of underpricing as a risk premium for the ex-ante value uncertainty about the firm (Ritter, 1984; Beatty and Ritter, 1986). The second component instead $q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon$ is related to the residual uncertainty about the firm's value that persists on the secondary market, which, following Falconieri et al. (2009), we will label as *ex-post (value) uncertainty.* Ex-post uncertainty is directly related to the expected bid-ask spread which depends on two distinct sources that interact together, the probability of informed trading measured by q on the one hand and the uncertainty about liquidity traders measured by x and z on the other. Note that if $q = 0$ the expected spread will be zero and the level of underpricing would be determined by the uncertainty on the primary market alone.

In the next section we look at firms going public on order-driven markets and derive the level of undepricing on these markets. We will then compare the results with those obtained in this section. The intuition suggests that due to the more concentrated supply and demand structure of order driven market which allows a more efficient information transmission, the second component of the underpricing due to ex-post value uncertainty should be smaller.

2.2 Market equilibrium in order-book markets

As for dealership markets, at $t = 2$ all information is public and the price $P_2 = \widetilde{V}$. To keep things tractable, we make the simplifying assumption that in $t = 1$, there is at most one trader that trades on information about the quality of the firm and one liquidity trader who, as before, trades depending on the shock received at $t = 1$. So, it will be a liquidity seller with probability z, a liquidity buyer with probability x and with the remaining probability $1 - z - x$, he will hold his shares till $t = 2$. Given this hypothesis, we compute the market prices as conditional expected values paid by the investors for all possible orders' vectors. Computations of these expected values is based on the trading strategies of investors in the secondary market. While uninformed agents do trade because of liquidity reasons, informed agents will decide to trade if their expected profits conditional on their information and the information transmitted by the market price is strictly positive. We will assume in the following that the informed agent will not trade more than only one share. Following a different strategy makes the signal valueless and we show later that this is indeed the optimal strategy for them.

The market maker observes only the aggregate demand which we denote by $A = \{-2; -1; 0; 1; 2\}$ and describe in details in the table below along with the relative probabilities. Note that the negative sign represents sell orders, the positive sign, buy orders and 0 stands for no order. The market maker will set a price $P_1^O(A) = E\left(\widetilde{V}|\widetilde{s}_1, A\right)$ for each possible value of A.

Informed order	Liquidity trader	Total demand	Probability	Expected alue
-1	-1	-2	qz	$V + \widetilde{s}_1 - \varepsilon$
-1	+1	0	qx	$V + \widetilde{s}_1 - \varepsilon$
-1	0	-1	$q(1 - x - z)$	$V + \widetilde{s}_1 - \varepsilon$
0	-1	-1	$(1 - 2q)z$	$V + \widetilde{s}_1$
0	+1	+1	$(1 - 2q)x$	$V + \widetilde{s}_1$
0	0	0	$(1 - 2q)(1 - x - z)$	—-
1	-1	0	qz	$V + \widetilde{s}_1 + \varepsilon$
1	+1	+2	qx	$V + \widetilde{s}_1 + \varepsilon$
1	0	+1	$q(1 - x - z)$	$V + \widetilde{s}_1 + \varepsilon$

Before turning to the calculation of the market prices for each possible value of the aggregate demand A, we introduce the following piece of notation: let α_A be the probability of having an aggregate order equal to A, then we have

$$\alpha_{-2} = \Pr(A = -2) = qz \tag{10}$$

$$\alpha_{-1} = \Pr(A = -1) = q(1 - x - z) + (1 - 2q)z \tag{11}$$

$$\alpha_0 = \Pr(A = 0) = q(x + z) + (1 - 2q)(1 - x - z) \tag{12}$$

$$\alpha_1 = \Pr(A = 1) = q(1 - x - z) + (1 - 2q)x \tag{13}$$

$$\alpha_2 = \Pr(A = 2) = qx \tag{14}$$

Given the above probabilities, we can now define the market prices. For $A = -2$, the market maker can infer the informed investor's information and so we have

$$P_1^O(-2) = E\left(\widetilde{V} \mid \widetilde{s}_1, -2\right) = V + \widetilde{s}_1 - \varepsilon$$

Symmetrically, we have for $A = 2$

$$P_1^O(2) = E\left(\widetilde{V} \mid \widetilde{s}_1, 2\right) = V + \widetilde{s}_1 + \varepsilon.$$

If instead, the market maker observes an excess offer of one unit, i.e., $A = -1$, the information is not fully revealed. The market maker knows that this level of demand may be the result of different orders' combination. The price in that case is

$$\begin{aligned} P_1^O(-1) &= E\left(\widetilde{V} \mid \widetilde{s}_1, -1\right) \\ &= \frac{q(1-x-z)}{q(1-x-z)+(1-2q)z}\left(V+\widetilde{s}_1-\varepsilon\right) + \frac{(1-2q)z}{q(1-x-z)+(1-2q)z}\left(V+\widetilde{s}_1\right) \\ &= V+\widetilde{s}_1 - \left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon \end{aligned}$$

And symmetrically, for $A = 1$ we have

$$\begin{aligned} P_1^O(1) &= E\left(\widetilde{V} \mid \widetilde{s}_1, 1\right) \\ &= \frac{q(1-x-z)}{q(1-x-z)+(1-2q)x}\left(V+\widetilde{s}_1+\varepsilon\right) + \frac{(1-2q)x}{q(1-x-z)+(1-2q)x}\left(V+\widetilde{s}_1\right) \\ &= V+\widetilde{s}_1 + \left(\frac{q(1-x-z)}{\alpha_{1}}\right)\varepsilon \end{aligned}$$

Finally, the seller should also set the market price when $A = 0$. This occurs when the marker maker receives two market clearing orders (one buy and one sell) or when there is no order at all.

$$\begin{aligned} P_1^O(0) &= E\left(\widetilde{V} \mid \widetilde{s}_1, 0\right) \\ &= \frac{qx}{q\,(x+z)+(1-2q)(1-x-z)}\left(V+\widetilde{s}_1-\varepsilon\right) + \\ &\quad \frac{(1-2q)(1-x-z)}{q\,(x+z)+(1-2q)(1-x-z)}\left(V+\widetilde{s}_1\right) + \frac{qz}{q\,(x+z)+(1-2q)(1-x-z)}\left(V+\widetilde{s}_1+\varepsilon\right) \\ &= V+\widetilde{s}_1+\frac{q\,(z-x)}{\alpha_0}\varepsilon \end{aligned}$$

Note that even when the aggregate demand is $A = 0$ some information about the share value is conveyed as the expected value is different from $V + \widetilde{s}_1$. Moreover, this information will depend on the relative values of z and x, respectively. If selling needs are more likely, *i.e.*, $z > x$, the occurrence of $A = 0$ transmits a higher likelihood of having a good signal and so increases the price, viceversa if buying needs are more likely, i.e $x > z$.

Given the above prices, we now have to show that informed agents behave consistently with the information they receive. This requires that, conditionally on receiving a bad signal, an informed investor will submit a sell order if his expected profit conditional on his information is positive. That is if the following holds:

$$E(P_1^O \mid \widetilde{s}_1, u_i = -\varepsilon) = zP_1^O(-2) + (1-x-z)\, P_1^O(-1) + xP_1^O(0) \geq V + \widetilde{s}_1 - \varepsilon$$

with

$$\begin{aligned} E(P_1^O \quad &\mid \quad \widetilde{s}_1, u_i = -\varepsilon) = z\,(V + \widetilde{s}_1 - \varepsilon) + (1-x-z)\left(V + \widetilde{s}_1 - \left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon\right) + x\left(V + \widetilde{s}_1 + \frac{q\,(z-x)}{\alpha_0}\varepsilon\right) \\ &= \quad V + \widetilde{s}_1 - \left(z + \frac{q(1-x-z)^2}{q(1-x-z) + (1-2q)z} - \frac{qx\,(z-x)}{q\,(x+z) + (1-2q)(1-x-z)}\right)\varepsilon \end{aligned}$$

which can be shown to be larger than $V + \widetilde{s}_1 - \varepsilon$ [6]

Simmetrically, we also require that an informed agent with a good signal submits a buy order if his conditional expected profit is positive. That is if . Note that the expected price to pay for a buy order is

$$E(P_1^O \mid \widetilde{s}_1, u_i = \varepsilon) = xP_1^O(2) + (1-x-z)\, P_1^O(1) + zP_1^O(0) \geq V + \widetilde{s}_1 + \varepsilon$$

with

$$\begin{aligned} E(P_1^O \quad &\mid \quad \widetilde{s}_1, u_i = \varepsilon) = x\,(V + \widetilde{s}_1 + \varepsilon) + (1-x-z)\left(V + \widetilde{s}_1 + \left(\frac{q(1-x-z)}{\alpha_1}\right)\varepsilon\right) + z\left(V + \widetilde{s}_1 + \frac{q\,(z-x)}{\alpha_0}\varepsilon\right) \\ &= \quad V + \widetilde{s}_1 + \left(x + \frac{q(1-x-z)^2}{q(1-x-z) + (1-2q)x} + \frac{qz\,(z-x)}{q\,(x+z) + (1-2q)(1-x-z)}\right)\varepsilon \end{aligned}$$

which again can be shown to be smaller than $V + \widetilde{s}_1 + \varepsilon$, i.e. the final value of the stock.[7]

We can now turn to the primary market and analyze the bidding strategies of the investors. Note that both types of investors will use Eq.(1) in order to choose their strategies. We start by looking at the informed investors' strategies.

Specifically, informed investors, who observe the value of $\widetilde{s}_1$ at $t = 0$, will bid for shares in the primary market only if the offering price is lower than their expected profit from trading in the

[6] We just to need to show that

$$z + \frac{q(1-x-z)^2}{q(1-x-z) + (1-2q)z} - \frac{qx\,(z-x)}{q\,(x+z) + (1-2q)(1-x-z)} \leq 1$$

after some manipulation, we can show that it is equal to

$$z + \frac{q(1-x-z)^2}{q(1-x-z) + (1-2q)z} - \frac{qx\,(z-x)}{q\,(x+z) + (1-2q)(1-x-z)} = 1 - \frac{(1-2q)z(1-x-z)}{q(1-x-z) + (1-2q)z} - \frac{2qxz + x(1-2q)(1-x-z)}{q\,(x+z) + (1-2q)(1-x-z)}$$

which is clearly lower than 1.

[7] The proof is similar to the previous one for the case of a sell order (see Footnote 6).

secondary given their private signal. In other words, their participation constraint requires the following,

$$\begin{aligned} zE(\widetilde{P}_1^O & \mid sell, \widetilde{s}_1 = \eta) + (1+x-z)E(\widetilde{P}_2 \mid \widetilde{s}_1 = \eta) - xE(P_1^O \mid buy, \widetilde{s}_1 = \eta) \geq P_0^O \\ & \geq zE(\widetilde{P}_1^O \mid sell, \widetilde{s}_1 = -\eta) + (1+x-z)E(\widetilde{P}_2 \mid \widetilde{s}_1 = -\eta) - xE(P_1^O \mid buy, \widetilde{s}_1 = -\eta) \end{aligned} \tag{15}$$

The expected value of $\widetilde{P}_2$ conditional on the value of $\widetilde{s}_1$ is equal to $V+\eta$ or $V-\eta$ depending on whether the signal is good or bad, respectively. At $t=0$, the price the investor expects to pay at $t=1$ conditional on submitting a sell order is instead given by

$$E(\widetilde{P}_1^O \mid sell, \widetilde{s}_1 = \eta) = qE(\widetilde{P}_1^O(-2) \mid \widetilde{s}_1 = \eta) + (1-2q)E(\widetilde{P}_1^O(-1) \mid \widetilde{s}_1 = \eta) \\ +qE(\widetilde{P}_1^O(0) \mid \widetilde{s}_1 = \eta)$$

Substitution of the values of expected prices at $t=1$ gives

$$\begin{aligned} E(\widetilde{P}_1^O & \mid sell, \widetilde{s}_1 = \eta) = q\left(V+\eta-\varepsilon\right) + q\left(V+\eta+\frac{q\left(z-x\right)}{\alpha_0}\varepsilon\right) + (1-2q)\left(V+\eta-\left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon\right) \\ &= V+\eta+q\left(-1+\frac{q\left(z-x\right)}{\alpha_0}-\frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right)\varepsilon \\ &= V+\eta-\varphi_1\varepsilon = V+\eta-S_B^O \end{aligned}$$

where

$$\varphi_1 = q\left(1-\frac{q\left(z-x\right)}{\alpha_0}+\frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right)$$

and where $S_B^O = \varphi_1\varepsilon$ define the bid spread in this market.

Similarily, we have that

$$\begin{aligned} E(\widetilde{P}_1^O \mid buy, \widetilde{s}_1 = \eta) &= qE(\widetilde{P}_1^O(2) \mid \widetilde{s}_1 = \eta) + (1-2q)E(\widetilde{P}_1^O(1) \mid \widetilde{s}_1 = \eta) \\ &\quad +qE(\widetilde{P}_1^O(0) \mid \widetilde{s}_1 = \eta) \\ &= q\left(V+\eta+\varepsilon\right) + (1-2q)\left(V+\eta+\left(\frac{q(1-x-z)}{\alpha_1}\right)\varepsilon\right) + q\left(V+\eta+\frac{q\left(z-x\right)}{\alpha_0}\varepsilon\right) \\ &= V+\eta+\varphi_2\varepsilon = V+\eta+S_A^O \end{aligned}$$

where

$$\varphi_2 = q\left(1+\frac{(1-2q)(1-x-z)}{\alpha_1}+\frac{q\left(z-x\right)}{\alpha_0}\right)$$

and $S_A^O = \varphi_2\varepsilon$ defining the ask spread. Hence the bid-ask spread on order driven market is given by $S_A^O + S_B^O = q\left[2+\frac{(1-2q)(1-x-z)}{\alpha_1}+\frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right]$.

By replacing into 15 it is immediate to see that the informed investors' participation contraint is then satisfied.

Finally, we need to consider the participation constraint of uninformed investors at $t = 0$, which is similar to that in dealership markets. That is

$$zE(\widetilde{P}_1^O \mid sell, \Phi_0^u) + (1 + x - z)E(\widetilde{P}_2 \mid \Phi_0^u) - xE(P_1^O \mid \text{buy}, \Phi_0^u) \geq P_0^O \qquad (16)$$

where Φ_0^u contains only public information at $t = 0$, i.e. distributions of random variables and the information inferred from the selling price P_0^O.

We formalize the result about the underpricing in order-driven markets in the next proposition:

Proposition 2 *In order driven markets the level of underpricing is given by*

$$E(\widetilde{P}_1^O) - P_0^O = (\frac{1-\pi}{1+\pi})\eta + (z\varphi_1 + x\varphi_2)\,\varepsilon = (\frac{1-\pi}{1+\pi})\eta + \left(zS_A^O + xS_B^O\right) \qquad (17)$$

where $\varphi_1 = q\left(1 - \frac{q(z-x)}{\alpha_0} + \frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right)$ *and* $\varphi_2 = q\left(1 + \frac{(1-2q)(1-x-z)}{\alpha_1} + \frac{q(z-x)}{\alpha_0}\right)$.

Proof: See the Appendix.

The interesting thing to notice is that the underpricing on auction markets has exactly the same structure as in dealership markets and, as in the latter case, it depends on two different effects a *firm-specific effect* $(\frac{1-\pi}{1+\pi})\eta$ which is intuitively common to the two market structures, and a *market structure effect,* $\left(zS_A^O + xS_B^O\right)$, which is essentially measured by the bid-ask spread on the two markets and captures the extent to which ex-post uncertainty about the firm's value persists on the secondary market.

Consequently, comparing the two trading platforms effectively reduces to see which of them is more effective in reducing this ex-post uncertainty which ultimately means which of the two generates the lowest bid-ask spread.

Corollary 3 *The underpricing in order-driven markets is lower than the underpricing in dealership markets if and only if the ex-post uncertainty on the order-driven markets is smaller than that on dealership markets; i.e. if and only if :*

$$z\varphi_1 + x\varphi_2 \leq q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)$$

with

$$z\varphi_1 + x\varphi_2 = q\left(z\left(1 - \frac{q\,(z-x)}{\alpha_0} + \frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right) + x\left(1 + \frac{(1-2q)(1-x-z)}{\alpha_1} + \frac{q\,(z-x)}{\alpha_0}\right)\right)$$

Corollary 4 *Or equivalently*

$$z(S_A^O - S_A^D) + x(S_B^O - S_B^D) \leq 0$$

The above result cannot be proved analytically, or rather we can find a necessary but not sufficient condition for the above result to hold[8]. Therefore we simulate the results under several sets of parameters and we consistently find that the above relationship is satisfied. The results of the simulations are collected in Appendix 2.

In the next Section we describe the data set we use to test the predictions of the model.

3 Data

Our first step is to compile a list of all IPOs between January 1993 and December 1998 from the Securities Data Corporation (SDC) New Issues Database. Since we are concerned with the opening of trading in an IPO, we set the beginning of our sample period to coincide with the availability of intraday data on the NYSE TAQ database, 1993. We end our sample period in 1998 to avoid influences from the NASDAQ technology bubble and its subsequent bursting. Barry and Jennings (1993) find that the returns of operating companies and closed-end-funds behave very differently. Therefore, consistent with Corwin and Harris (2001), we exclude investment funds (including mortgage securities), REITs, and real estate firms from our sample. Also excluded are ADRs and firms incorporated outside the United States since they are most likely cross-listed firms with established stock values on other exchanges.

We cross-check the offering date and market on both the TAQ and CRSP data bases. CRSP standard industry classifications (SIC) are used for our data rather than SDC's designation since they are found to be more accurate. Corrections are made to issue dates by confirming the first trade date on the TAQ data base. Since our hypothesis is that the method of opening trading in IPOs on exchanges will lead to lower value uncertainty than on NASDAQ, we group NYSE and AMEX IPOs together for comparison with NASDAQ IPOs. The resulting sample consists of 361 exchange listed stocks and 1,668 NASDAQ stocks.

Table 1 contains descriptive statistics for our sample. Examining Table 1 reveals that the average exchange-listed IPO is over five times larger than the average NASDAQ IPO. Also, the average exchange-listed IPO offering price is about 5 times larger than the average NASDAQ IPO.

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Please insert Table 1 here

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The listing requirements for NYSE stocks are higher than those on the AMEX and NASDAQ. Therefore, a number of NASDAQ firms are not eligible for listing on the NYSE and any observed

[8] The necessary condition requires the following: $2q > z + x$. We omit the proof for the sake of brevity but it is available from the authors upon requests.

differences in ex-post value uncertainty (and underpricing) may be due to firm specific differences and not the method of opening trading. To control for listing choice we create a sub-sample of NASDAQ stocks that are eligible to list on any exchange at the time of going public. We define this as any firm with an offering of at least $40,000,000. There are 444 such NASDAQ firms. Examining the last column of Table 1 reveals that these NASDAQ firms have an offering price closer to the NYSE/AMEX sample, but that the offering size is still less than half that of the typical NYSE/AMEX IPO.

4 Empirical Results

The first variable we examine is the amount of underpricing for our sample. For this portion of the study. Consistent with previous studies, we define the amount of underpricing as the offer to close return on the first day of trading. The results are contained in Table 1. The amount of underpricing for NASDAQ IPOs is greater than for NYSE/AMEX IPOs. Overall the average NASDAQ first day return is nearly 80% larger than exchange listed underpricing (9.9% versus 17.7%). The last column of Table 1 shows that the exchange eligible NASDAQ sub-sample has an even larger (23%) level of underpricing.

We find that NASDAQ firms are about the same volume of trading as NYSE/AMEX firms despite the fact that NYSE/AMEX offerings are more than three times as large as the typical NASDAQ offering (in shares.) Consistent with prior studies, we find that NASDAQ firms are younger and have higher daily volatility that exchange listed firms. We next compare spread patterns for our samples.

4.1 Opening and Closing Spreads

Saar (2001) develops a model of demand uncertainty that suggests that a specialist system of trading (as on the NYSE and AMEX) is better able to ascertain demand (therefore lower demand uncertainty) and will thus have narrower spreads than a multiple market maker system. Our data provide a good test of this hypothesis. The results for the opening spreads for IPOs are contained in Table 1. Opening spreads are defined as the spread (ask minus bid) in effect at the time of the first trade or the first quote after the first trade. NASDAQ spreads are significantly larger than NYSE/AMEX spreads. In particular, NASDAQ opening spreads are on average two and one half times larger than exchange listed spreads.

Wide opening spreads are consistent with the uncertain demand hypothesis of Saar (2001). The fact that we find much wider opening spreads on NASDAQ suggests that the method used by NASDAQ to open trading in IPOs leads to a lower amount of information concerning demand –

vis a vis the opening call auction on exchanges. However, the difference in opening spreads may merely be a reflection of the wider spreads on NASDAQ documented by many studies.

McInish and Wood (1992) and Chan, Christie, and Schultz (1995) examine the intraday pattern of spreads on the NYSE and NASDAQ, respectively. Wood and McInish find a reverse J pattern of spreads for NYSE stocks where closing spreads are about 10% less than opening spreads. Chan, Christie, and Schultz find evidence of a declining spread pattern on NASDAQ stocks with closing spreads about 5% less than opening spreads. If the difference in opening spreads, between markets, is due to general market structure rather than to different levels of demand uncertainty, we would expect the same difference in closing spreads adjusted by the average intraday decline observed by other authors. Therefore, we next examine average closing spread on the first trading day, for our sample.

The results, listed just below the results for opening spreads in Table 1, show that the difference between NYSE/AMEX and NASDAQ closing spreads for underpriced IPOs is less than half of what it is at the open – $0.15. Comparing closing spreads to opening spreads, for our under-priced sample, reveals that exchange listed closing spreads are 23% less than opening spreads ($0.16 versus $0.21), which is consistent with the general pattern for NYSE stocks documented by McInish and Wood (1992). In contrast NASDAQ closing spreads decline by more than 40% from opening levels. The NASDAQ decline is far greater than that found in Chan, Christie, and Schultz (1995). This suggests that the pattern of NASDAQ spreads is different on IPO days than on other days. It also provides support for the hypothesis that NASDAQ's method of opening IPOs is associated with more uncertainty as to demand than the exchange-listed method.

To complete our analysis of spreads, we return to Figure 1 to examine the intraday spread pattern for our IPO sample to determine how long it takes for the differences in spread width to reduce. We find that while average exchanged-listed spreads (ask minus bid) exhibit an almost flat pattern over the first 10 minutes, the pattern of NASDAQ spreads exhibits a much more dramatic decline within the first 4 minutes of trading. In particular spreads decline by $0.17 in the first few minutes. This is in contrast with Chan, Christie, and Schultz (1995) who find spreads are fairly stable on NASDAQ stocks over the first 2 hours of trading. The decline in NASDAQ spreads is consistent with the uncertainty hypothesis suggesting that uncertainty is resolved within the first few minutes of trading. To the extent that underpricing is associated with ex-post value uncertainty (examined in more depth later) these findings suggest that at least part of the difference in underpricing between stocks in our NASDAQ and exchange-listed samples may be due to differences in opening procedures.

Four minutes is a slightly more than 1% of the 390 minutes in a full trading day. It could therefore be argued that resolving uncertainty in the first 4 minutes of trading is of little consequence. To examine this issue, we calculate the proportion of total first day share volume traded in the first 4 minutes of trading.

. Examining the percentage of shares traded in the first four minutes by listing market type (Table 1), we find that almost 40% of the total daily trading volume in exchange-listed stocks occurs in the first 4 minutes of trading. We further find that 15% of NASDAQ first day volume occurs in the first 4 minutes. Two observations are warranted. First, it is clear that a large amount of trading occurs in the first few minutes of trading, suggesting that this short time span is important for a large group of investors. Second the fact that exchanged listed volume in the first few minutes of trading is much greater than NASDAQ volume suggests that it may be related to the greater uncertainty as to firm value imparted by that market's method of opening trading.

4.2 Ex-post Value Uncertainty

Chen and Wilhelm (2005) and Draho (2001) develop a theoretical model that asserts that uncertainty as to an IPO's value has is not completely resolved prior to the start of secondary market trading. Falconieri, Murphy, and Weaver (2009) develop empirical proxies for what they term ex-post value uncertainty. They show that their proxies greatly improve the explanatory power of previous models of underpricing. The predictions of our theoretical model suggest that the method for opening trading in an IPO across markets results in higher levels for the ex-post uncertainty measure and hence underpricing.

Falconieri, Murphy, and Weaver (2009) suggest using the standard deviation of quote midpoints for the first two hours of trading as a proxy for ex-post value uncertainty. They suggest dividing the standard deviation of quote midpoints by the offering price to employ a relative measure. They also examine the persistence of uncertainty by calculating standard deviations for additional periods after the initial two hour period. We adopt that methodology here as well.

Examining Table 1, we find that consistent with our model's predictions, our NASDAQ sample exhibits a larger ex-post uncertainty measure than the exchange-listed IPO sample. This suggests that the fragmented trading structure of the NASDAQ open leads to more value uncertainty as compared to the more concentrated trading structure of the exchange-listed. The results for the relative value uncertainty measure exhibits the same pattern. As with the level of underpricing, the NYSE eligible NASDAQ sample exhibits even stronger differences than the full NASDAQ sample.

Examining the standard deviation of quote midpoints for the remainder of the day as well as the first two hours in the following day, we find that for all samples the first two hours of trading appears to have a much higher volatility level, suggesting that a resolution of uncertainty during that period. Having established that NASDAQ firms exhibit a higher level of uncertainty at the beginning of trading, we next examine the relationship of the uncertainty with the observed differences in underpricing between the different market types.

4.3 Relationship Between ex-post Value Uncertainty and Under-Pricing

For our next step we investigate whether the amount of underpricing is related to the uncertainty of demand (as measured by the volatility ratios). Given that we find that the larger underpricing on NASDAQ is as well associated with a higher ex-post value uncertainty proxy as compared to the exchange-listed, this would suggest the existence of a link between the two variables. We test for evidence of this relationship.

For each market, we regress the amount of underpricing on our ex-post uncertainty proxy, while controlling for other variables known to be associated with underpricing, including the offering size as measured by the IPO proceeds as well as the riskiness of the issue as measured by the volatility of inter-daily returns over the first 20 days of trading. We need to introduce these two controls because, as we have seen, NASDAQ offering sizes are much smaller than exchange-listed offering sizes. We need therefore to be sure that the offering size is not the driving force of the differences in the level of underpricing we observe in our sample. Similarly, we need to control for volatility since residual volatility – after the demand uncertainty is resolved – is higher on NASDAQ than on the exchange-listed. It may be that the higher underpricing for NASDAQ IPOs is due to their higher riskiness. Note, that equally priced and over priced IPOs are also included in the sample for these tests.

We also control for other deal-specific characteristics. This includes an indicator of whether the issue is oversubscribed (hot issues) since there is evidence in the literature (Cornelli and Goldreich (2001)) that oversubscription is positively related to underpricing. We also control for the reputation of the IPO lead underwriter which the literature documents to be positively related to the degree of underpricing during our sample period. In addition, we also incorporate firm specific characteristics such as the age of the firm and whether the firm is technology based or a dot com, which previous studies have shown to be related to underpricing (see Loughran and Ritter (2004) among others). Consequently, we perform the following regression

$$\begin{aligned} \%Under_i &= \alpha + \beta_1 ExPostUncert_i + \beta_2 Offering_i + \beta_3 Volatility_i + \beta_4 Hot_i + \\ &\quad \beta_5 Ln(1 + age) + \beta_6 Internet_i + \beta_7 Tech_i + \beta_8 Rank_i \end{aligned} \tag{18}$$

where $\%Under_i$ is defined as *(First Day Closing Price – Offering Price) / First Day Closing Price*; $ExPostUncert_i$ is the standard deviation of spread midpoints for the first 2 hours as constructed by Falconieri et al. (2009); $Offering_i$ is the log of firm i's offering size (in millions of dollars) computed as the total number of shares issued at the offering times the offering price; $Volatility_i$ is the standard deviation of daily returns. Hot_i is defined as *(Offering Price – Mid Range)/Mid Range*; where *Mid Range* is the midpoint of the originally filed price range[9]. $Ln(1 + age)$is the measure used in Loughran and Ritter (2004) where age is the number of years since the company was founded.[10] $Internet$ and $Tech$are dummy variables assigned the value of 1 if the IPO is an internet or technology IPO, respectively.[11] $Rank_i$ is the lead underwriter rank obtained from Loughran and Ritter's (2004) classification which is based on Carter and Manaster (1990) and Carter, Dark and Singh (1998) rankings. Underwriters are ranked from 1 to 9 with higher numbers indicating higher reputation and quality. Regressions are performed both overall and by market. The results for the absolute measure are contained in Table 2. The results for the relative measure are qualitatively similar and hence not reported here.

4.4 Ex-post Uncertainty and Trading Location

Thus far we have observed that our ex-post uncertainty proxy, is directly related to the amount of underpricing. We also observe that firms listing on an exchange have lower ex-post uncertainty proxies than those that trade on NASDAQ. Our model predicts that this is due to the fact that the consolidated method of opening trading on exchanges leads to lower uncertainty and hence lower underpricing. To test this prediction, we model our ex-post uncertainty proxy, as a function of an exchange listing dummy, $ExchDum$, and a series of control variables. A significant negative relationship between our ex-post uncertainty proxy and the exchange dummy would support our conjecture.

First among the control variables is the volatility of daily return, $Volatility$. We expect a direct relationship between the ex-post uncertainty proxy and overall volatility. The next control variable we consider is whether the issue price is significantly higher than the original filing range. Hot is defined as *(Offering Price – Mid Range)/Mid Range*; where Mid Range is the midpoint of the original filed price range. The price revisions associated with large values of Hot are indicative of uncertainty as to the value of the firm. Therefore we predict a direct relationship.

Note that we would not consider size to be related to our measure of value uncertainty. As proof of this we call attention to the fact that internet firms have been among the largest IPOs, yet also

[9] Cornelli and Goldreich (2002) show that hot issues are more likely to be priced close to the upper bound of the originally filed price range.

[10] The source of founding dates is the Field-Ritter dataset of company founding dates, as used in Laura C. Field and Jonathon Karpoff "Takeover Defenses of IPO Firms" in the October 2002 Journal of Finance Vol. 57. No. 5, pp. 1857-1889, and Tim Loughran and Jay R. Ritter, "Why Has IPO Underpricing Changed Over Time?" in the Autumn 2004 Financial Management Vol. 33, No. 3, pp. 5-37.

[11] Both are obtained from Jay Ritter's website and constitute Appendix C and D of Loughran and Ritter (2004).

have the most value uncertainty. It is sometimes argued that larger firms have more information available about them. This argument seems better applied to the age of the firm. That is, the longer a firm has been in business the more information is available about the operations of the firm. This in turn should lead to less uncertainty as evidenced by a smaller volatility ratio. Accordingly, we include the log of 1 plus the age of the firm, $Ln(1 + age)$, as a control variable and predict an inverse relationship between it and our volatility ratio.

By their nature, stocks of technology firms and internet based firms may be harder to value than firms in more established industries. $Internet$ and $Tech$ are as before dummy variables assigned the value of 1 if the IPO is an internet or technology IPO, respectively. We expect a direct relationship between these dummies and our ex-post uncertainty measure. The final control variable we consider is the rank of the lead underwriter. More prestigious underwriters may be better at determining firms value than less experienced underwriters. The variable $Rank$ varies from 1 to 9. Since higher ranked underwriters have larger values of Rank, we predict an inverse relationship. We model the relationship between our ex-post uncertainty measure and the above variables as:

$$\begin{aligned} ExPostUncert_i &= \alpha + \beta_1 Volatility_i + \beta_2 Hot_i + \beta_3 Ln(1+age) + \\ &\quad \beta_4 Internet_i + \beta_5 Tech_i + \beta_6 Rank_i + \beta_7 ExchDum \end{aligned} \tag{19}$$

Firms large enough to list on an exchange or trade on NASDAQ have a choice of trading locations, Therefore, the variable ExchDum is endogenous. That is firms with lower levels of uncertainty may choose to list on an exchange rather than trade on NASDAQ. Thus the above equation may reflect the choice of firms going public rather than be a function of exchange structure. To control for the endogeneity of $ExchDum$ we first determine a model of exchange choice and then solve the equations simultaneously using two-stage least squares. The model of exchange choice is below.

$$\begin{aligned} ExchDum_i &= \alpha + \beta_1 ExPostUncert_i + \beta_2 Offering_i + \beta_3 Volatility_i + \beta_5 Ln(1+age) + \\ &\quad \beta_6 Internet_i + \beta_7 Tech_i \end{aligned} \tag{20}$$

Including our volatility ratio on the right hand side controls for the possibility that firms with lower levels of uncertainty choose to list on an exchange. Larger firms may choose to list on an exchange since size is one of the main criteria for obtaining an exchange listing. We accordingly include the log of the size of the offering, $Offering$, as proxy for total firm value at the time of the

IPO. We predict a direct relationship. $Volatility$, $Ln(1+age)$, $Internet$, and $Tech$ are all defined as before.

We solve the above two equations simultaneously using two-stage least squares which controls for the endogeneity of exchange listing choice. In the first stage we estimate the parameters for equation (3) using a logit regression. We then use the parameter estimates to determine a predicted value of $ExchDum$, denoted $ExchPred$, which is then used to estimate parameters for Equation (2) using OLS. The second stage parameter estimates are listed below (t statistics in italics below the estimates):

$$\begin{aligned} ExPostUncert_i \quad = \quad & \underset{2.61^{***}}{0.093} + \underset{7.65^{***}}{4.135} Volatility_i + \underset{13.88^{***}}{0.722}\, Hot_i + \underset{0.5}{0.004} Ln(1+age) \\ & -\underset{-0.41}{0.025} Internet_i + \underset{7.80^{***}}{0.407} Tech_i - \underset{-1.03}{0.004} Rank_i - \underset{-2.34^{**}}{0.012}\, Exch\Pr ed \end{aligned} \qquad (21)$$

Our prediction is that the structure of the opening of IPO trading on exchanges leads to lower uncertainty and hence a lower ex-post uncertainty measure. Therefore the variable of interest is $ExchPred$ in Equation 4. We find that the estimate of this parameter, after controlling for the endogeneity of choice of trading location, is of the predicted sign and statistically significant. This supports our model's prediction, that the structure of the opening procedure on exchanges leads to lower value uncertainty relative to NASDAQ.

To further control for the endogeneity of the ExchDum variable and make sure that our empirical results are truly due to different market structures and not instead to a self-selection bias we partition our NASDAQ sample into those firms that are large enough to list on the NYSE and those not large enough. Firms too small to list on the NYSE have no choice but to trade on NASDAQ, so the distribution of volatility ratio cannot be contaminated by a self-selection bias. In contrast if firms can choose between an exchange listing and trading on NASDAQ (and the observed differences are due to a self selection bias) then larger firms with less value uncertainty will choose the NYSE. This self-selection will truncate the distribution of volatility ratios for firms that chose to go public on NASDAQ instead of the NYSE.

For our sample of NASDAQ offerings, we round ex-post uncertainty measures by 1.00 and then examine the percentage frequency at each rounded ratio. If our reported differences between exchanges and NASDAQ are due to a self selection bias, then we would expect the group of firms large enough to list on the NYSE to exhibit fewer percentages of firms with low volatility ratios than those firms who cannot list. Figure 2 graphs the percentage frequencies of rounded volatility ratios for the groups that can list (had a choice) and those that cannot list (had no choice). Examining Figure 2 reveals remarkably similar patterns. This leads us to conclude that the observed differences in volatility ratios between exchanges and NASDAQ are not due to a self selection bias.

5 Robustness Tests

5.1 Matched Sample

The first robustness check we conduct consists in creating a matched sample of firms that listed on each market type and compare variables of interest employing paired-difference t tests. Creating a matched sample controls for industry effects and market conditions. For each NYSE firm, we find all NASDAQ firms with the same Fama-French industry that went public within 12 months of the NYSE IPO. This latter condition attempts to correct for biases related to overall market conditions. In the case of multiple NASDAQ matches we choose the NASDAQ IPO that is closest in value to the NYSE IPO. This results in a final sample of 128 NYSE IPOs and a matched sample of 128 NASDAQ IPOs. Our sample of 256 IPOs is much smaller than the actual number of IPOs that occurred during our sample period but is similar in size to the 220 IPOs examined in Corwin, Harris, and Lipson (2004). Our matching methodology allows us to control for overall market conditions as well as industry effects. Therefore, we are not subject to the criticism that NASDAQ IPOs have a larger amount of underpricing due to the fact that more technology stocks list there. We thus feel that our design will allow us to draw inferences about the impact of differing market designs on the level of underpricing.

Notwithstanding the reduction in sample size, we compute the difference for each pair for variables of interest and compute a paired difference t test. The results are contained in Table 3. Turning first to the differences in offering size, we observe that our matching procedure produced NASDAQ firms that are less than one third the size of their NYSE match and are 40% riskier. The NASDAQ matches, consistent with our full sample results, have wider spreads both at the open and close on the first trading day. Also consistent is the fact that the change in spread over the course of the first trading day is significantly larger for NASDAQ firms.

The variable of highest interest is our ex-post uncertainty measure. We find that the measure is nearly one third larger for the NASDAQ matches. This supports the idea that differences in the ex-post uncertainty measure between the market types is not driven by differences in industry types or market conditions at the time of the IPO.

5.2 The Nasdaq Opening Cross

On May 30, 2006, NASDAQ implemented a voluntary opening cross as a supplement to the process it uses to open trading in IPOs. Investors can either have their orders submitted as part of the cross or allow dealers to display their orders in the dealer's quote. Recall that our hypothesis is that the centralization of supply and demand in an exchange's open call method to begin trading in IPOs contributes to a reduction in the ex-post uncertainty as to IPO value. The NASDAQ IPO opening cross increases the centralization of supply and demand and therefore should reduce ex-post uncertainty. It therefore serves as a good test of our hypothesis. If we view the degree of centralization of supply and demand as a continuum then the NASDAQ IPO Open Cross can be viewed as moving NASDAQ closer to the level of centralization at the NYSE and AMEX. Thus we expect that following the implementation of the opening cross that our proxy for ex-post uncertainty would be smaller than in our earlier sample and that the amount of under pricing would be smaller on NASDAQ as well.

To test our hypothesis of less ex-post uncertainty on NASDAQ following the start of open cross, we extract from SDC all IPOS after May 30, 2006. To avoid contagion from the financial crisis in the last half of 2008, we end our sample on May 30, 2008. Following the criteria established in the data section we end up with 277 IPOs in the opening cross sample. Of those 195 are NASDAQ IPOs and 82 are NYSE, AMEX, or ARCA IPOs. Examining the microstructure of markets in this latter sample, we find some challenges in determining the opening trade as well as order types. Our first challenge was that in the latter period some stocks had a number of trades prior to the first trade on the listing exchange. For example FCSX had 266 trades on ARCA before it began trading on NASDAQ. Therefore, we set the opening of the stock as the first trade on the listing exchange. The opening quote is then set as the BBO quote occurring at or near the opening trade.[12]

Regulation National Market System, enacted in 2005 led to the implementation of new order types which are frequently used in our latter period. For example inter-market sweep and NYSE DIRECT orders each account for about 15% of the trade condition codes over the first two days of trading in IPOs. These trades are included in our sample of trades.[13] To calculate BBNO quotes we include individual exchange quotes market as opening quotes (condition code 10), closing quotes (condition code 3), regular one-sided quotes (condition code 99), as well as regular quotes (condition code 12).

The descriptive statistics for our latter sample are contained in Table 4. Comparing these results with those in Table 1, we find that the IPO offering sizes arev much larger than in the previous period. Overall the average IPO is $178 million in the latter period, but only $58 million in the former. We find that offering prices are higher as well. Average first day share volume is much larger in the latter period (6.7 million versus 1.4 million shares) which probably reflects the

[12] we find that opening quote sometimes predate the opening trade by 2 seconds.

[13] As an aside, we find that trade condition codes M and Q, which are found in the TAQ dataset for our sample, are not defined in the TAQ manual. For these codes we consulted the NASDAQ Trader website and find that they most likely represent the NASDAQ official closing and opening prices respectively. These trades are also included in our dataset.

advent of high frequency trading noted in other studies. Turning to the percentage of shares traded in the first four minutes we find that for NASDAQ firnms, the percenatge traded in the first four minutes in 150% larger than the former sample. This would be consistent with a quicker resolution of ex-post uncertainty resulting from the opening cross.

We also find that the riskiness of NASDAQ firms in our sample, as measure by the standard deviation of daily returns, is fairly close in our latter sample (3.27% versus 3.37%). On average IPOs are being underwritten by firms with higher ranking than in our former sample. Turning to the amount of underpricing (first dayb return), we find that while in the former period NASDAQ IPOs were underpriced by almost double that of NYSE/AMEX stocks; in the instant period NASDAQ and other IPOs are underpriced by virtually the same amount. This is consistent with our hypothesis.

Our hypothesis suggests that this reduction in underpricing is the result of a reduction in ex-post uncertainty. Our proxy for this is the standard deviation of quote midpoints in the first two hours of trading. Comparing these results with those from Table 1, we find that while in the former period, the average NASDAQ IPO exhibits a higher level of ex-post uncertainty than NYSE/AMEX IPOs, the ranking is reversed in the latter period. Again this is consistent with our hypothesis.

In Table 5 we report the results of regressions for the latter period similar to those reported earlier in Table 2. The variable of interest is the parameter estimate for our ex-post uncertainty measure. While our hypothesis makes no predictions as to any changes in this variable, it should still be significant and positive, as it is for both NASDAQ and other IPOs. Of note is the finding that the parameter estimate for NYSE/AMEX/ARCA IPOs is an order of magnitude larger than in the former period (0.258 versus only 0.023). The R^2 for the latter period is also nearly 3 times larger than in the former sample. Over the interval between our sample periods, the percentage of volume traded off-exchange for NYSE stocks increased dramatically from 20% to nearly 80%.

We also find that the amount of underpricing and ex-post uncertainty on NYSE stocks increased. This suggests that the increase in off exchange trading may be related to the observed increase in ex-post uncertainty on NYSE IPOs.

Below we replicate Regression 4 for our new sample of data.

$$\begin{aligned} ExPostUncert_i &= \underset{-0.91}{-0.174} + \underset{0.45}{4.118} Volatility + \underset{6.86^{***}}{0.868} Hot + \underset{2.56^{**}}{0.073} Ln(1+age) - \underset{-0.16}{0.008} Tech_i \\ &\quad + \underset{2.17^{**}}{0.036} Rank_i - \underset{-2.30^{**}}{0.072}\, Exch\Pr ed \end{aligned}$$

To control for the self-selection bias discussed earlier, we again perform the two-stage regression described in Equations 2 and 3 for our NASDAQ Opening Cross sample. Recall that the first stage is to perform a logistic regression to determine the probability that a firm will list on the NYSE, AMEX, or ARCA based on its characteristics. In the second stage, we use the predicted value of ExchDum from the first stage in the second stage. As explained earlier, the NASDAQ IPO Opening Cross is supplemental to their traditional process of market maker quotes. Thus, the opening call auction process employed by exchanges should still have a lower level of ex-post uncertainty than NASDAQ'sn Opening Cross.

Therefore, we would expect, ceteris paribus, the parameter estimate for $ExchPred$ will be negative, but smaller than for the earlier sample. Examining the parameter estimate of interest in Equation 5, we find that indeed the parameter estimate for $ExchPred$ is negative and statistically significantly. However, when compared to the model *regressed on pre-Opening Cross data, it is less than one third the size. That is, after controlling for variables thought to be associated with firm specific ex-post uncertainty, Exchanges still exhibit lower ex-post uncertainty - but the differences are much smaller. (isn't it te opposite?the economic effect is stronger)*

6 Conclusion

This paper develops a theoretical model that compares the effect of different trading platforms on IPO underpricing. Specifically, we look at order-driven market (NYSE, Amex) as opposed to dealership markets (Nasdaq). Recent papers (Chen and Wilhelm (2006); Falconieri et al. (2009)) show that the uncertainty surrounding newly listed firms is not completely resolved on the primary market and in fact moves on to the secondary market. Falconieri et al. (2009) label this type of uncertainty, ex-post uncertainty. They construct proxies for it and show that there is a positive relationship between the degree of ex-post uncertainty and the level of IPO underpricing.

Building on their results, in this paper we argue and show, both theoretically and empirically, that the underpricing differentials observed between Nasdaq IPOs and NYSE IPOs might then be the explained by the different degree of ex-post uncertainty on the two trading platforms. Specifically, our model shows that a centralized system like the NYSE is more efficient in reducing ex-post uncertainty as opposed to a more fragmented system like the one used to open trade on the Nasdaq.

The model's prediction are tested on a sample of IPOs between January 1993 and December 1998. The empirical analysis supports the model's prediction and confirms that the degree of ex-post uncertainty and consequently the level of underpricing is lower on exchanges than on Nasdaq.

The introduction of the opening cross on the Nasdaq in 2006 which effectively moved Nasdaq closer to the level of aggregation of demand and supply typical of an exchange represents an excellent natural experiment to check the robustness of our findings. Therefore, we replicate our analysis on a new sample of IPOs between June 1, 2006 and May 30, 2008. As we would expect, we find that after the implementation of the opening cross, Nasdaq IPOs exhibit a much lower underpricing and surprisingly closer to the level of underpricing of NYSE and Amex IPOs.

In term of policy recommendation, our finding suggests that if NASDAQ were to adopt a call auction to begin trading, as some have suggested, the result would be a lower level of underpricing for IPOs traded there.

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7 Appendix 1: The Proofs

Proof of Proposition 1: Let us start by noticing that given

$$P_0^D = V - (1 - 2\pi^D)\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon \tag{22}$$

and since $0 \leq \pi^D \leq 1$, it is easy to check that Eq.(3) holds, so the participation constraint by informed traders is satisfied by the offer price.

Starting from its definition, we can rewrite the probability π^D as follows

$$\begin{aligned} \pi^D &= \Pr(\widetilde{s}_1 = \eta \mid \text{uninformed get shares}) \\ &= \frac{\frac{M}{2(N+M)}}{\frac{M}{2(N+M)} + \frac{1}{2}} = \frac{\frac{M}{(N+M)}}{\frac{M}{(N+M)} + 1} = \frac{\pi}{1+\pi}. \end{aligned}$$

where $\pi = M/(M+N)$ is the (unconditional) probability that uninformed agents receive high quality shares in the offering. Replacing this into Eq.(8) allows to rewrite the offer price as

$$P_0^D = V - (\frac{1-\pi}{1+\pi})\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon. \tag{23}$$

By definition, underpricing is measured by the following difference $E(\widetilde{P}_1^D) - P_0^D$ where $\widetilde{P}_1^D$ is the expected price in the secondary market at $t = 1$ and is equal to

$$E(\widetilde{P}_1^D) = \Pr(\text{buy order})E(P_1^{Da}) + \Pr(\text{sell order})E(P_1^{Db})$$

where $\Pr(\text{buy order}) = (x+q)/(2q+x+z)$ and, similarly, $\Pr(\text{sell order}) = (z+q)/(2q+x+z)$ which finally yields that $E(\widetilde{P}_1^D) = V$. From this, it is then straightforward to derive the level of undepricing in dealership markets.

Proof of Proposition 2: Let's start from the participation constraint of uninformed investors which is

$$zE(\widetilde{P}_1^O \mid sell, \Phi_0^u) + (1+x-z)E(\widetilde{P}_2 \mid \Phi_0^u) - xE(P_1^O \mid \text{buy,}\Phi_0^u) \geq P_0^O$$

Uninformed investors are aware that they will receive shares only when informed investors do not bid for them i.e. when they have bad information about the value of the stock.

So, let π^O be the probability that uninformed traders get shares of a high quality firm when they bid P_0^O and $(1-\pi^O)$ be the probability that they get shares of low quality firms. We can then write

$$\begin{aligned} E(\widetilde{P}_1^O \left| sell, \Phi_0^u, P_0^O \right.) &= \pi^O \left(E(\widetilde{P}_1^O \left| sell, \widetilde{s}_1 = \eta \right.)\right) + (1-\pi^O)\left(E(\widetilde{P}_1^O \left| sell, \widetilde{s}_1 = -\eta \right.)\right) \\ &= \pi^O (V + \eta - \varphi_1 \varepsilon) + (1-\pi^O)(V - \eta - \varphi_1 \varepsilon) \\ &= (V - \varphi_1 \varepsilon) - (1 - 2\pi^O)\eta \end{aligned}$$

Similarly

$$\begin{aligned} E(P_2|\Phi_0^u, P_0^D) &= \pi^O (V+\eta) + (1-\pi^O)(V-\eta) \\ &= V - (1-2\pi^O)\eta. \end{aligned}$$

and

$$\begin{aligned} E(\widetilde{P}_1^O \left| buy, \Phi_0^u, P_0^O \right.) &= \pi^O \left(E(\widetilde{P}_1^O \left| buy, \widetilde{s}_1 = \eta \right.) \right) + (1-\pi^O) \left(E(\widetilde{P}_1^O \left| buy, \widetilde{s}_1 = -\eta \right.) \right) \\ &= \pi^O (V+\eta+\varphi_2\varepsilon) + (1-\pi^O)(V-\eta+\varphi_2\varepsilon) \\ &= (V+\varphi_2\varepsilon) - (1-2\pi^O)\eta \end{aligned}$$

Substitution into Eq.(16) gives

$$z\left((V-\varphi_1\varepsilon) - (1-2\pi^O)\eta\right) + (1+x-z)\left(V-(1-2\pi^O)\eta\right) - x\left((V+\varphi_2\varepsilon)-(1-2\pi^O)\eta\right) \geq P_0^O$$

$$V - (1-2\pi^O)\eta - (z\varphi_1 + x\varphi_2)\,\varepsilon \geq P_0^O \tag{24}$$

As in Rock (1986), the company will choose the highest price P_0^D that meets the participation constraint of uninformed investors to ensure that the whole quantity of shares is sold (since $N < S$). So, the price set will make this constraint holds with equality, *i.e.*,

$$P_0^O = V - (1-2\pi^O)\eta - (z\varphi_1 + x\varphi_2)\,\varepsilon \tag{25}$$

Note that since $0 \leq \pi^O \leq 1$, we can easily see that Eq.(15) holds, so that the participation constraint by informed traders is satisfied. For π^O, we have

$$\begin{aligned} \pi^O &= \Pr\left(\widetilde{s}_1 = \eta \mid \text{uninformed get shares}\right) \\ &= \frac{\frac{M}{2(N+M)}}{\frac{M}{2(N+M)} + \frac{1}{2}} = \frac{\frac{M}{(N+M)}}{\frac{M}{(N+M)} + 1} = \frac{\pi}{1+\pi} = \pi^D. \end{aligned}$$

with $\pi = M/(M+N)$ is the probability that uninformed agents receive shares of a high quality firm. Substitution in Eq.(25) gives

$$P_0^O = V - (\frac{1-\pi}{1+\pi})\eta - (z\varphi_1 + x\varphi_2)\,\varepsilon \tag{26}$$

Given this price, the average underpricing is equal to $E(\widetilde{P}_1^O) - P_0^O$ where $\widetilde{P}_1^O$ is the average price in the secondary market. So,

$$\begin{aligned} E(\widetilde{P}_1^O) &= \sum_A \Pr(Order = A) P_1^O(A) \\ &= V \end{aligned}$$

$$
\begin{aligned}
E(\widetilde{P}_1^O) &= \sum_A \Pr(Order = A) P_1^O(A) \\
&= qz\left(V + \widetilde{s}_1 - \varepsilon\right) + \alpha_{-1}\left(V + \widetilde{s}_1 - \left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon\right) + \alpha_0\left(V + \widetilde{s}_1 + \frac{q\,(z-x)}{\alpha_0}\varepsilon\right) \\
&\quad +\alpha_1\left(V + \widetilde{s}_1 + \left(\frac{q(1-x-z)}{\alpha_1}\right)\varepsilon\right) + qx\left(V + \widetilde{s}_1 + \varepsilon\right) \\
&= V^{14}
\end{aligned}
$$

From here the result on the size of the underpricing is straighforward.

8 Appendix 2: SIMULATIONS RESULTS

We define the following functions:

$$
\begin{aligned}
f(q,z,x) &= \frac{z}{q+z} + \frac{x}{q+x} \\
g(q,z,x) &= z\left(1 - \frac{q\,(z-x)}{q\,(x+z) + (1-2q)(1-x-z)} + \frac{(1-2q)(1-x-z)}{q(1-x-z) + (1-2q)z}\right) + \\
&\quad x\left(1 + \frac{(1-2q)(1-x-z)}{q(1-x-z) + (1-2q)x} + \frac{q\,(z-x)}{q\,(x+z) + (1-2q)(1-x-z)}\right)
\end{aligned}
$$

representing the values of underpricing in dealership and in auction markets, respectively. Because of the complex structure of underpricing in auction markets, we are notre able to compare analytically. We run simulations in order to make these comparison.

We begin by the case where liquidity buying pressure and selling pressure are the same in the market, i.e., $x = z$. Figure 1 depicts underpricing in both markets in that case. Clearly, we have that underpricing is positive for all values of q and z belonging to $(0, 0.5)$ and that underpricing in dealership markets is larger almost everywhere.

We simulate underpring in both markets by fixing each time the variable affecting it in both markets. By fixing q, Figure 2, Figure 3 and Figure 4 depict the way fixing q affects underpricing in both markets for $q = 0.5$, a low value of q (0.01) and a large value of q (0.99), respectively.

Note that for q very small, i.e., when information asymmetry is not important in the market, underpricing in both markets are very close since our model captures only the asymmetric information effect. However, as adverse selection problems increase, undepricing in dealership markets increases more that in auction markets leading to a higher difference. When q is very close to 1, the difference shrinks again since informed traders are more likely and the occurence of liquidity trading does not create enough noise in both markets. Note however that when q is very close

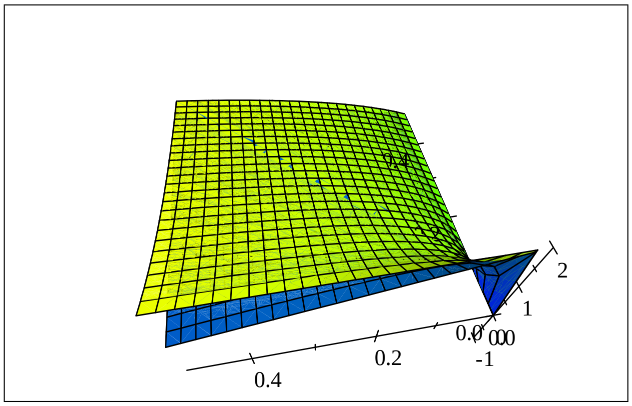

Figure 1: Underpricing in auction and dealership markets when $x = z$ as a function z and q : Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity trading pressure (z) and of information asymmetry (q) where both q and z are between 0 and 0.5.

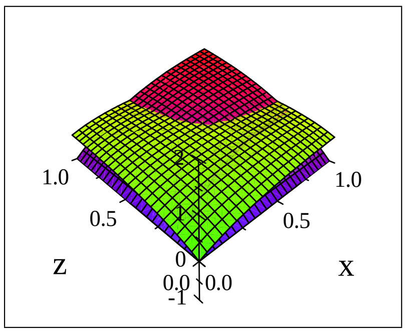

Figure 2: Underpricing in auction and dealership markets as a function of x and z for a fixed q $(q = 0.5)$: Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity selling pressure (z) and liquidity buying pressure (x) both lying between 0 and 1 and with the constraint that $x + z \leq 1$ and with a fixed $q = 0.5$

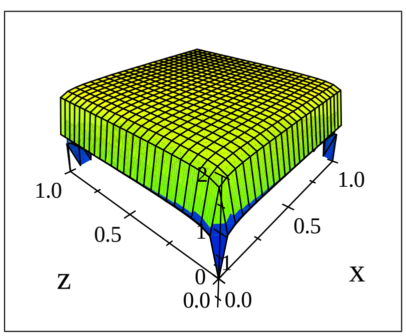

Figure 3: Underpricing in auction and dealership markets as a function of x and z for a fixed q $(q = 0.01)$: Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity selling pressure (z) and liquidity buying pressure (x) both lying between 0 and 1 and with the constraint that $x + z \leq 1$ and with a fixed $q = 0.01$

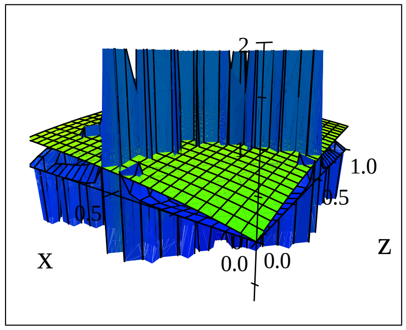

Figure 4: Underpricing in auction and dealership markets as a function of x and z for a fixed q ($q = 0.99$) : Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity selling pressure (z) and liquidity buying pressure (x) both lying between 0 and 1 and with the constraint that $x + z \leq 1$ and with a fixed $q = 0.99$

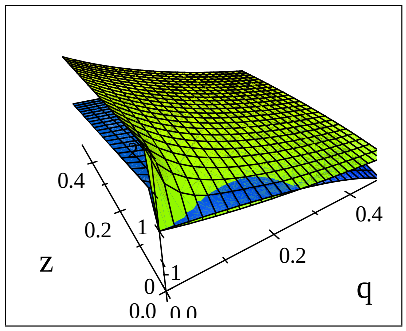

Figure 5: Underpricing in auction and dealership markets as a function of q and z for a fixed x ($x = 0.5$) : Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity selling pressure (z) is between 0 and $1 - x$ and information asymmetry (q) lies between 0 and 0.5 and with a fixed $x = 0.5$

to 1, underpricing in auction markets presents several undefined values because numerators can sometimes be very close to 0.

Figures 5, 6 and 7 depict underpricing as functions of z and q for $x = 0.5$, 0.01 and 0.99, respectively. Like in the other cases, underpricing in dealership markets is almost higher almost everywhere.

Note that the last case should be the most representative of hot IPOs since in that case investors will be incited to buy new shares in the secondary market increasing buying pressure with respect to selling pressure. In this case the underpricing is larger in dealership markets for all values of q and z.

Finally, we fix z and simulate underpricing as function of q and x. Results are the same as for x and are not presented here but are available upon request.

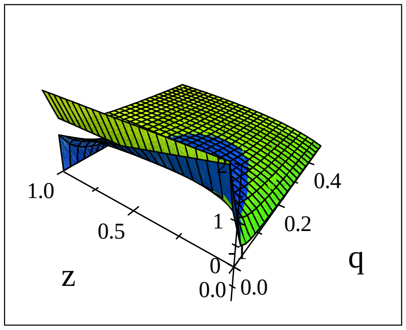

Figure 6: Underpricing in auction and dealership markets as a function of q and z for a fixed x $(x = 0.01)$: Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity selling pressure (z) is between 0 and $1 - x$ and information asymmetry (q) lies between 0 and 0.5 and with a fixed $x = 0.01$

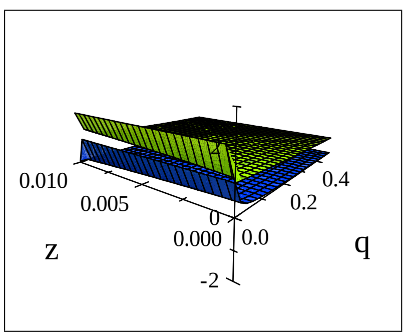

Figure 7: Underpricing in auction and dealership markets as a function of q and z for a fixed x $(x = 0.99)$: Underpricing in auction markets (blue curve) and in dealership markets (green curve) as a function of the liquidity selling pressure (z) is between 0 and $1 - x$ and information asymmetry (q) lies between 0 and 0.5 and with a fixed $x = 0.99$

9 Appendix 3: EMPIRICAL RESULTS

Table I. Descriptive Statistics

This table provides descriptive statistics for a sample of 2,029 initial public offerings (IPO) of common stock that opened from January 1993-December 1998. Our sample includes IPOs that list on the AMEX, NASDAQ, or NYSE during the sample period and have no missing observations for any of the listed variables. Listed are the mean for each variable partitioned by exchange type for each variable. NYSE eligible NASDAQ firms are those whose offering size in excess of $40 million and are thus able to choose to list on the NYSE.

Variable	Overall	NYSE/AMEX	All NASDAQ	NYSE eligible NASDAQ
Number of Observations	2,029	361	1,668	444
Offering Size	$58,395,135	$170,768,337	$34,074,556	$70,464,907
Offering Price	$11.98	$16.16	$11.08	$15.34
First Day Return	16.3%	9.87%	17.65%	23.00%
First Day Volume	1,366,201	1,458,836	1,402,809	1,507,823
20 Day Standard Deviation of Return	3.84%	2.69%	4.08%	4.09%
Age of Firm	12.78 Years	21.06 Years	10.99 Years	13.92 Years
Hot	-0.4%	-0.7%	-0.3%	8.83%
Underwriter Rank	6.6	6.4	6.6	6.5
Opening Spread	$0.48	$0.21	$0.54	$0.45
Closing Spread	$0.28	$0.16	$0.31	$0.29
Percentage of Shares Traded in 1st Four Minutes	18.9%	38.5%	14.67%	13.62%
σ Quote Midpoints Day 1 – 1st 2 hours	27.63%	21.08%	29.137%	40.19%
σ Quote Midpoints Day 1 – Rest of day	13.77%	13.58%	13.81%	22.82%
σ Quote Midpoints Day 2 – 1st 2 hours	16.73%	14.13%	17.28%	26.52%
σ Quote Midpoints/Offering Price Day 1 – 1st 2 hours	2.42%	1.27%	2.67%	2.57%

Table 2
Regression Results

This table examines the relationship between the first day return (offer to close) and our ex-post uncertainty measure for a sample of 2,029 initial public offerings (IPO) of common stock that opened from January 1993-December 1998. Our sample includes IPOs that list on the AMEX, NASDAQ, or NYSE during the sample period and have no missing observations for any of the listed variables. We report the results of the following regression

$$\%Under_i = \alpha + \beta_1 ExPostUncert_i + \beta_2 Offering_i + \beta_3 Volatility + \beta_4 Hot_i + \beta_5 Ln(1+age) + \beta_6 Internet_i + \beta_7 Tech_i + \beta_8 Rank_i$$

where *%Under$_i$* is defined as (Closing Trade Price – Offering Price) / Closing Trade Price, *ExPostUncert* is the standard deviation of spread midpoints for the first 2 hours of trading, *Offering$_i$* is the log of the dollar size of firm *i*'s offering (in millions), and *Volatility$_i$* is the standard deviation of daily returns over the 20 days following the IPO. *Hot* is defined as (*Offering Price – Mid Range)/Mid Range*; where *Mid Range* is the midpoint of the original filed price range. *Ln(1+age)* is the log of 1 plus the age of the firm. *Internet* and *Tech* are dummy variables assigned the value of 1 if the IPO is an internet or technology IPO, respectively. *Rank* is the rank of the lead underwriter based on Loughran and Ritter (2004) and varies from 1 to 9. The results are given for the overall sample and partitions nased on exchange type. We report the adjusted R^2 and the number of observations for each regression in the last two rows. t statistics are in italics.

(table on following page)

Table 2
Regression Results
(continued)

Variable	Overall	NYSE/AMEX	NASDAQ
Intercept	0.29 *3.48****	-0.057 *-0.54*	0.494 *4.88****
Offering	-0.016 *-3.45****	0.006 *1.03*	-0.029 *-4.91****
Volatility	1.476 *6.47****	2.273 *4.70****	0.549 *2.42***
Hot	0.344 *12.80****	0.378 *8.83***	0.277 *10.25****
Ln(1+age)	-0.003 *-0.78*	-0.003 *-0.64*	-0.002 *-0.33*
Tech Dummy	0.017 *0.55*	0.028 *1.39*	0.036 *0.69*
Internet Dummy	0.078 *3.00****	-0.183 *-2.38***	0.016 *0.65*
RANK	0.001 *0.30*	-0.001 *-0.54*	-0.0001 *-0.0487*
ExPostUncert	0.346 *31.75****	0.023 *2.31***	0.513 *40.77****
Adjusted R^2	0.52	0.24	0.64
N	2029	361	1,668

*** Denotes significant at the 0.01 level

** Denotes significant at the 0.05 level

* Denotes significant at the 0.10evel

Table 3
Matched Sample Results

This table examines the initial day return (offering price to closing price) for a matched sample of 128 initial public offerings (IPO) The sample consists of all NYSE and AMEX IPOs between January 1993 and December 1998 for which at least one NASDAQ IPO exists that has the same Fama-French industry code and which occurred within 12 months of the NYSE/AMEX IPO. In the case of multiple NASDAQ IPOs, only the closest in value to the NYSE/AMEX IPO is included. For each group, the average percentage amount that an issue was under-priced is given. A difference of means is reported and a paired t statistic is reported.

Variable	NYSE/AMEX	NASDAQ	Difference	*t statistic*
Offering Size	$145,675,570	$42,673,721	($103,001,849)	*-4.23******
Amount of Under-Pricing	11.41%	15.30%	3.89%	*1.81**
Volatility	2.72%	3.93%	1.2%	*6.04****
Opening Dollar Spread	$0.22	$0.51	$0.28	*8.80****
Closing Dollar Spread	$0.16	$0.31	$0.15	*8.12***
σ Quote Midpoints	21.4%	27.4%	6.00%	*1.80**

*** Denotes significant at the 0.01 level

** Denotes significant at the 0.05 level

* Denotes significant at the 0.10evel

Table 4. Descriptive Statistics

This table provides descriptive statistics for a sample of 277 initial public offerings (IPO) of common stock that opened from June 1, 2007 - May 30, 2008. Our sample includes IPOs that list on the AMEX, ARCA, NASDAQ, or NYSE during the sample period and have no missing observations for any of the listed variables. Listed are the mean for each variable partitioned by exchange type for each variable. For this sample, all NASDAQ firms are eligible to list on at least one of the NYSE segments, so no further partitioning is necessary.

Variable	Overall	NYSE/AMEX/ARCA	NASDAQ
Number of Observations	277	82	195
Offering Size	$178,188,087	$356,480,488	$103,213,846
Offering Price	$14.33	$17.06	$13.19
First Day Return	13.02%	13.08%	12.99%
First Day Volume	6,726,061	11,149,849	4,865,801
20 Day Standard Deviation of Return	3.29%	3.37%	3.27%
Age of Firm	19.48 Years	30.09 Years	15.02 Years
Hot	-0.4%	-0.2%	-0.5%
Underwriter Rank	8.14	8.26	8.09
Opening Spread	$0.39	$0.66	$0.29
Closing Spread	$0.09	$0.07	$0.10
Percentage of Shares Traded in 1st Four Minutes	31.7%	24.62%	34.69%
σ Quote Midpoints Day 1 – 1st 2 hours	34.96%	37.02%	34.087%
σ Quote Midpoints Day 1 – Rest of day	20.68%	23.39%	19.55%
σ Quote Midpoints Day 2 – 1st 2 hours	8.14%	13.09%	6.06%
σ Quote Midpoints/Offering Price Day 1 – 1st 2 hours	16.74%	19.62%	15.52%

Table 5
Regression Results

This table examines the relationship between the first day return (offer to close) and our ex-post uncertainty measure for a sample of 277 initial public offerings (IPO) of common stock that opened from June 1, 2007 - May 30, 2008. Our sample includes IPOs that list on the AMEX, ARCA, NASDAQ, or NYSE during the sample period and have no missing observations for any of the listed variables. We report the results of the following regression

$$\%Under_i = \alpha + \beta_1 ExPostUncert_i + \beta_2 Offering_i + \beta_3 Volatility + \beta_4 Hot_i + \beta_5 Ln(1+age) + \beta_6 Internet_i + \beta_7 Tech_i + \beta_8 Rank_i$$

where $\%Under_i$ is defined as (Closing Trade Price – Offering Price) / Closing Trade Price, *ExPostUncert* is the standard deviation of spread midpoints for the first 2 hours of trading, $Offering_i$ is the log of the dollar size of firm *i*'s offering (in millions), and $Volatility_i$ is the standard deviation of daily returns over the 20 days following the IPO. *Hot* is defined as (*Offering Price – Mid Range)/Mid Range*; where *Mid Range* is the midpoint of the original filed price range. *Ln(1+age)* is the log of 1 plus the age of the firm. *Internet* and *Tech* are dummy variables assigned the value of 1 if the IPO is an internet or technology IPO, respectively. *Rank* is the rank of the lead underwriter based on Loughran and Ritter (2004) and varies from 1 to 9. The results are given for the overall sample and partitions nased on exchange type. We report the adjusted R^2 and the number of observations for each regression in the last two rows. t statistics are in italics.

(table on following page)

Table 5
Regression Results
(continued)

Variable	Overall	NYSE/AMEX/ARCA	NASDAQ
Intercept	0.06 *1.26*	0.154 *2.05****	-0.029 *-0.42*
Offering	-0.028 *-2.41****	-0.033 *-1.74**	-0.016 *-0.86*
Volatility	0.066 0.18	0.134 *0.22*	-0.017 *-0.04*
Hot	0.415 *8.16****	0.623 *4.72****	0.326 *5.70****
Ln(1+age)	-0.008 *-0.82*	0.005 *0.31*	-0.007 *-0.52*
Tech Dummy	-0.008 *-0.44*	0.103 *1.58*	-0.019 *2.22***
Internet Dummy			
RANK	0.015 *2.49***	0.006 *1.58*	0.016 *2.22***
ExPostUncert	0.324 *14.43****	0.254 *8.54****	0.409 *11.62****
Adjusted R^2	0.61	0.66	0.61
N	274	82	192

*** Denotes significant at the 0.01 level

** Denotes significant at the 0.05 level

* Denotes significant at the 0.10evel

Figure 1

Spread Patterns

This figure depicts the pattern of spreads during the first 10 minutes of trading for a sample of initial public offerings (IPOs) on the AMEX/NYSE or NASDAQ. Spread is defined as the ask minus the bid. The sample consists of all IPOs between January 1993 and December 1998. Given is the overall spread width as well as spreads partitioned by market type (NYSE/AMEX and NASDAQ).

(Figure next page)

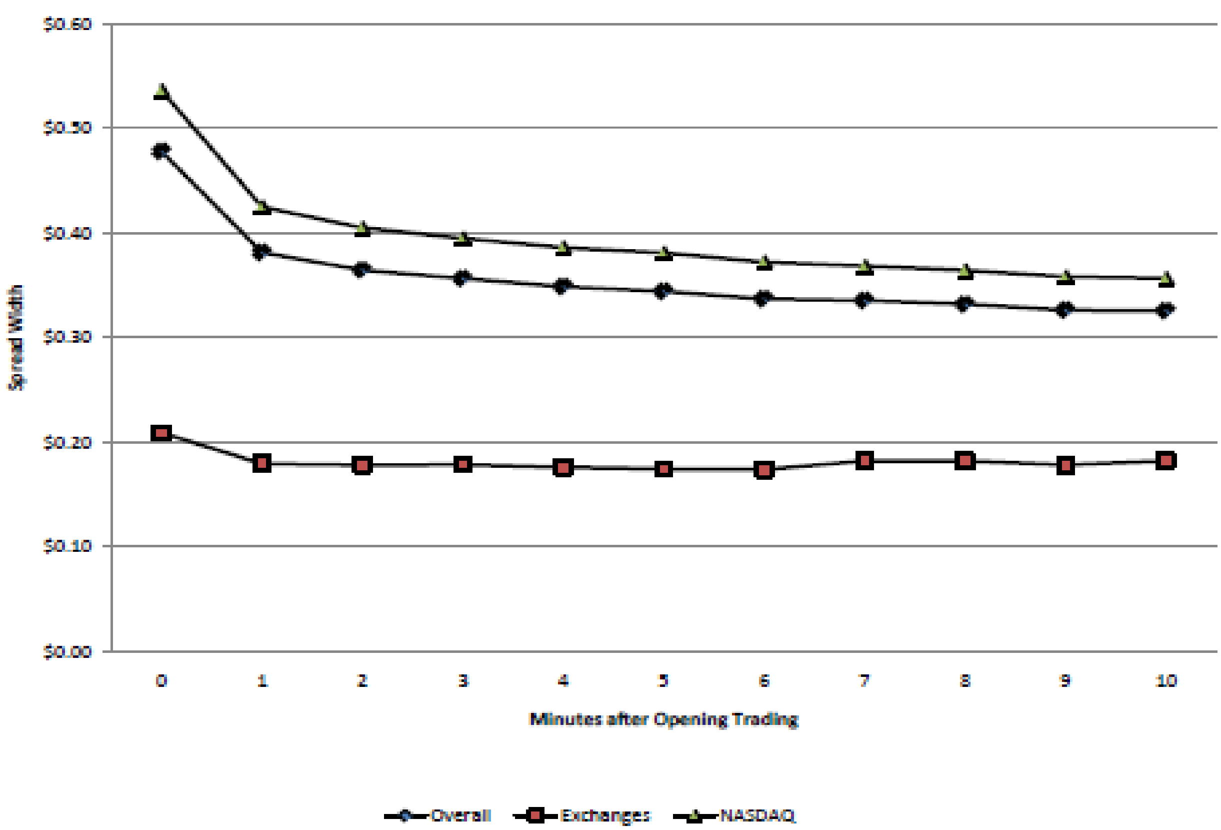

Figure 2

Distribution of NASDAQ Ex-Post Uncertainty Measures By Offering Size Group

This figure compares the distribution of volatility ratios for NASDAQ firms that are large enough to list on the NYSE and those not large enough. After portioning our sample of NASDAQ offerings by ability to list on the NYSE, we round the standard deviation of quote midpoints by 1 and then examine the percentage frequency at each rounded level.

(Figure next page)