Trading Mechanism, Ex-post Uncertainty and IPO Underpricing

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Abstract

Recent literature shows that IPO underpricing is affected by ex-post uncertainty (Falconieri et al.) that is by uncertainty surrounding the value of the firm going public that persists in the secondary market. In this paper we investigate both theoretically and empirically the link between ex-post uncertainty and different methods to open trading in the IPO aftermarket. Our results show that ex-post uncertainty indeed 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 a 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 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 use a natural experiment resulting from the introduction of the Nasdaq IPO opening cross in 2006 to test the robustness of our findings. The opening cross effectively moved Nasdaq closer to the level of centralization at NYSE or AMEX and thus allows us to test whether such change has resulted, as our model predicts, in a lower level of ex-post uncertainty and hence underpricing for Nasdaq IPOs. The results of this additional test provide further support to our theory, 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 IPO 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 IPO participants as well as uncertainty about the firm value is not fully resolved in the primary market but persists in the after-market. However, they do not explicitly investigate the link between residual uncertainty and IPO underpricing which is instead empirically explored by Falconieri et. al. (2009). Falconieri et al. label "ex-post uncertainty" this residual uncertainty in the IPO aftermarket and develop proxies for it. Their findings document that higher ex-post uncertainty is reflected in a higher IPO underpricing.

If ex-post uncertainty affects IPO underpricing, then the question raises as what determines ex-post uncertainty. This paper addresses this question by investigating, both theoretically and empirically, whether different mechanisms to open trading in the aftermarket have an impact on the level of ex-post uncertainty and consequently of the 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

1While 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
Our model extends that by Ellul and Pagano (2006) to enable us to compare the two trading platforms. The key feature of the model is the existence of a double adverse selection effect determined by the fact that the value of the firm consists of two signals $s_1$ and $s_2$ which are revealed, to some investors, in the primary and secondary market respectively. Hence, $s_2$ captures the idea of some residual uncertainty in the secondary market. The aim of the model is to show that auction markets are superior in reducing information asymmetry and uncertainty and thus lead to less underpricing than dealership markets. While dealership markets are modeled as in Ellul and Pagano, we characterize auction markets as having a specialist who aggregates all the orders on the market, and, based on these, sets up a bid-ask spread. We then construct a measure of the ex-post uncertainty as defined by the ex-post variance of the signal $s_2$ and show that this is positively related to the IPO underpricing. Next, we conduct simulations to compare the level of ex-post uncertainty on the two trading platforms. The results of the simulations clearly suggest that auction markets are better at resolving the residual uncertainty than 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 on which to test the validity of our theory because based on our hypothesis we would expect less ex-post uncertainty and thus less underpricing on Nasdaq IPO following the introduction of the opening cross. We find that, after 2006, the underpricing of Nasdaq IPOs is 64% smaller than the underpricing of Nasdaq IPO in the previous sample (14.91% vs 23%) and this seems the results of a reduced ex-post uncertainty which, in the second part of the sample, becomes much closer to the level of ex-post uncertainty found for the NYSE/Amex IPOs in the sample 1993-1998. Overall, these findings provide strong support to theory.

The reminder of the paper is organized as follows. Related papers are discussed in the next section. Section 3, sets up and solves the theoretical model. The sample used for our empirical analysis in detailed in Section 4 and the results of the analysis are grouped in Section 5. Section 6 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.

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.
2 Literature Review

In the market microstructure literature several papers have investigated the efficiency of alternative opening procedures. For instance, Madhavan and Panchapagesan (2000) examine the opening procedures on the NYSE. They show empirically that specialists significantly facilitate price discovery because they learn from observing the evolution of the limit order book. In a pure single-price call auction, the opening price would be the one clearing as many shares as possible. However, on the NYSE the specialist sets a price, which may be different than the price that would prevail in a pure auction market with only public orders. This is because of his obligation to provide price continuity. As a consequence, the opening price is set to provide minimum variation from the previous day’s close and is shown to be more efficient than the price resulting from an auction market without specialists. Cao, Ghysels, and Hatheway, (2000) examine instead the pre-opening on NASDAQ for existing stocks and find that market makers seem to use the pre-opening quotes to signal each other as to their supply and demand.

Few papers have also tried to compare IPOs on the Nasdaq and NYSE but without reaching consistent results. Corwin and Harris (2001) examine the initial listing decisions of firms going public. Using a sample of IPOs from 1991 to 1996 that either listed on the NYSE or met the NYSE’s minimum-listing requirements and listed on the NASDAQ National Market, they identify relevant variables in determining which market a newly public firm will choose for its secondary trading. By looking at the results of a Probit model, they conclude that the firm size is the most important determining factor. Smaller and riskier firms list on NASDAQ to avoid the higher listing fees on the NYSE. However, given the higher level of underpricing on NASDAQ, listing on NASDAQ could also be a strategic decision of underwriters to increase their compensation.

Corwin and Harris also identify some of the determinants of underpricing. They conclude that the amount of underpricing is related to the aftermarket standard deviation of return (5 day returns over a 100 day window). However, they do not control for industry effects in their regressions. Therefore, given that NASDAQ stocks are more typically in industries like genetic engineering or technology firms, it is entirely possible that the standard deviation of return used in their regressions may be a proxy for industry membership. In our analysis, we instead control for the industry by matching NYSE IPOs to NASDAQ IPOs based on 4 digit SIC (Standard Industry Classification) code and offering size (in US dollars). We also perform control regressions that include other variables known to related to the level of underpricing.

Affleck-Graves, Hegde, Miller, and Reilly (1993) find, for a sample of IPOs from 1983 to 1987, no statistically significant difference in the amount of underpricing for NYSE v. NASDAQ/NMS issues (4.82% v. 5.56%). This is in contrast with the findings of Corwin and Harris who instead
document marginally significant differences in the underpricing levels on NYSE v. NASDAQ issues. Therefore, there is disagreement in the literature as to whether the amount of underpricing differs across US markets.

Beatty and Ritter (1986) argue that the amount of ex ante uncertainty as to true firm value is the main determinant of the level of underpricing in IPOs. They build on Rock (1986) which interprets underpricing as a premium to uninformed investors for the winner’s curse problem they face vis-à-vis the informed investors, who observe the true firm value. Beatty and Ritter further develop this idea by claiming that more ex ante uncertainty worsens the winner’s curse problem and, consequently, requires larger underpricing. They test their theory by using as a proxy for ex ante uncertainty the inverse of the gross proceeds raised in the offering as well as the number of uses mentioned in the prospectus; Ritter (1984) uses instead the standard deviation of the daily aftermarket return. Although they (and others) find empirical support for their proxy, Jenkinson and Ljungqvist (1996) point out that using standard deviation of return may be an inadequate proxy since it may reflect the relationship between risk and return. In this paper we propose a more direct measure of ex ante uncertainty, which does not suffer from the problems associated with typical risk measures.

Recent papers have investigated the possibility that IPO underpricing be related to the characteristics of the aftermarket trading. Ellul and Pagano (2003) theoretically show that IPO underpricing increases with the bid-ask spread. They interpret the bid-ask spread as a measure for the uncertainty about the level of liquidity in the aftermarket. They test their theory on a sample of IPO on the LSE between 1998 and 2000, examining several measures of aftermarket liquidity uncertainty including the volatility of quoted and effective spread measured over the first four weeks of trading in the aftermarket. Their results provide support to the theory. Our paper differs from Ellul and Pagano (2003) in two respects: firstly, we focus on the resolution of residual uncertainty in the aftermarket and we, thus, construct measures for it that are more precise than the simple bid-ask spread; secondly, while their model only look at dealership markets, we also model an auction market and compare the degree of ex-post uncertainty on both.

Finally, in a recent paper Ligon and Liu (2011) explicitly explore the effect of the trading system on IPO underpricing by studying a natural experiment following the change in the order handling rules (OHR) for all Nasdaq IPOs mandated by the SEC in 1997. The new OHR required market makers on the Nasdaq to post all limit orders that are better than a dealer’s quote. Such change has meant an improvement of the aftermarket liquidity on the Nasdaq and as such the authors expect to have impacted on the underpricing of IPOs listed on the Nasdaq after 1997. They indeed document a decrease of the underpricing for cold IPOs after the change of the order
handling rule. They attribute this result to the fact that the increased liquidity reduces the need for underwriter price support in cold IPOs.

3 The Theoretical Model

Our model adapts and extends Ellul and Pagano’s model (2006). We consider an IPO market for new shares over 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 our set up 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.

Similarly to Ellul and Pagano (2006), our model captures the interactions between the primary and the secondary market resulting from a double adverse selection effect due to the existence of information asymmetries on both markets. However, the novelty of our model and what distinguishes us from Ellul and Pagano (2006), is that we explicitly analyze the impact of the market structure on the information linkages between the primary and the secondary market and ultimately on IPO performances.

Consequently, the information technology in our model is as follows: it is commonly known that the shares’ fundamental value is \( \bar{V} = V + \bar{s}_1 + \bar{s}_2 \) where \( V \) is a positive constant representing the non conditional expected value of new shares and \( \bar{s}_1 \) and \( \bar{s}_2 \) 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 are simple binary signals about the quality of the issuer. The variable \( \bar{s}_1 \) is a private signal observed by a number of informed investors during the IPO process. It can take value \( \eta \) or \( -\eta \) with probability 1/2. This signal becomes public before the opening of the trading on the secondary market. Some uncertainty about the shares’ value however remains in the secondary market and is captured by the signal \( \bar{s}_2 \) which can take values \( -\varepsilon \) or \( \varepsilon \) with probability 1/2. Given this information structure, the share value is then equal to \( V + \bar{s}_1 \) at \( t = 1 \) and to \( V + \bar{s}_1 + \bar{s}_2 \) at \( t = 2 \).

In the primary market, there are \( M \) uninformed traders who enter the IPO process using only the available public information and a group of \( N \) informed investors who instead observe the value of \( \bar{s}_1 \). Similarly, at \( t = 1 \), when trade opens in the secondary market, each trader has a probability \( Q \) of becoming informed and learning the signal \( \bar{s}_2 = -\varepsilon \) or \( \bar{s}_2 = \varepsilon \) so with probability \( 1 - Q \) no additional information is learned in which case \( \bar{s}_2 = 0 \).\(^3\) This second signal captures in our

\(^2\)In line with our empirical analysis we have in mind the very first hours after trading opens.

\(^3\)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. In other words, an investor that has learnt \( \bar{s}_1 \) will not necessarily learn \( \bar{s}_2 \) as well.
model the idea that there is some residual uncertainty about the firm’s value that persists in the aftermarket and in Section 4 we will construct an exact measure for what we will call hereafter ex-post uncertainty, following Falconieri et al. (2011).

Adverse selection in the secondary market arises as a consequence of the liquidity needs that agents may face. Since we are concerned with understanding the link between the market structure and the residual uncertainty in the aftermarket we model the liquidity needs in a richer way than in Ellul and Pagano. 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 implies two important differences with respect to Ellul and Pagano (2006): firstly, in their model liquidity sellers can only be those investors who have purchased shares in the primary market. We instead allow those investors to be liquidity buyers as well and this is consistent with empirical evidence (Ellis, 2006) that document that a relevant fraction of the aftermarket trades come from investors who want to build up on the allocations received in the primary market. Secondly, we also allow for the possibility that an investor does not become a liquidity trader in the secondary market but simply sticks to his share allocation till $t = 2$. This way of modelling liquidity needs is more appropriate to capture the idea that there is residual uncertainty that persists in the secondary markets whereas the Ellul and Pagano framework is more restrictive and can only look at liquidity uncertainty because the it is essentially centered on the sell-side of the trades in the aftermarket.

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.

The secondary market

The secondary market begins at $t = 1$. At this stage, all investors learn the signal $\bar{s}_1$. The prices determined on the secondary market will affect the investors’ strategies on the primary markets.
The price determination mechanism in the secondary market depends in turn 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 $P_{Db}^1$ and $P_{Da}^1$ respectively, are given by

\[ P_{Da}^1 = E \left( \tilde{V} \mid \tilde{s}_1, \text{buy} \right) \quad \text{and} \quad P_{Db}^1 = E \left( \tilde{V} \mid \tilde{s}_1, \text{sell} \right) \]

**Order-book market**

Considering an order-book market structure along with the dealership one represents the innovative part of the model. The peculiar feature of auction markets, such as the NYSE, is that all the submitted orders are collected by the specialist who therefore has much more information about the demand than a dealer on a dealership 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 $y_1, y_2, \ldots, y_m$ the price per share is then given by the following

\[ P_{A}^1 = E \left( \tilde{V} \mid y_1, y_2, \ldots, y_m \right) \]

Note that in this market, informed agents will have an incentive to hide their orders behind liquidity orders in order not to reveal their information. Consequently, since we know that uninformed traders will trade at most one unit, informed traders have no incentive to trade more than one unit either. Therefore, informed investors have to decide whether to sell or buy one unit or, alternatively, to maintain their position. As specified above, uninformed agents submit orders for liquidity reasons whereas 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 $E \left( \tilde{V} \mid s_2, P_i^Q \right) - P_i^Q > 0$.

Moving backward to the the IPO stage, an investor will bid for shares on the primary market only if his expected return in the next period given his trading strategy and his information exceed the IPO offer price $P_0^M$ where $M = \{D, O\}$ is the index for dealership and order-book market, respectively. Consequently, taking into account that each potential buyer on the primary market
will subsequently sell the share on the secondary market with probability \( z \), or he will buy a new share with probability \( x \) or, finally, he will keep the same allocation in \( t = 1 \) and liquidate his position in \( t = 2 \) with the remaining probability \( 1 - z - x \), we can write the participation constraint for the primary market of informed and uninformed investors as follows:

\[
\begin{align*}
E(P_{1}^{Mb} | \Phi_{0}^j) + (1 + x - z)E(P_{2} | \Phi_{0}^j) - xE(P_{1}^{Ma} | \Phi_{0}^j) & \geq \underbrace{P_{0}^{M}}_{\text{IPO offer price}}.
\end{align*}
\]

where \( j = \{i, u\} \) is the index for informed and uninformed investors respectively; \( P_{1}^{Mb} \) and \( P_{1}^{Ma} \) denote the bid and ask price respectively in \( t = 1 \); and \( P_{2} \) represents the share price in \( t = 2 \) which does not depend on the market structure because it is equal to the expected liquidation value. We next derive the optimal prices and, hence, the conditions for the IPO underpricing in both market structures. We proceed by backward induction. All the proofs can be found in Appendix 1.

### 3.1 Market equilibrium in dealership markets

At \( t = 2 \) all information is public and the price \( P_{2} = \tilde{V} \). 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.\(^4\) There is a probability \( Q \) that a trader observes the realization of \( \tilde{s}_{2} \) which can be equal either to \( \varepsilon \) or \( -\varepsilon \) with the same probability, \( 1/2 \). So from dealers’ perspective \( \tilde{s}_{2} = \varepsilon \) 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 \( \tilde{s}_{1} \), which is public, and on receiving a sell order:

\[
P_{1}^{Db} = E(\tilde{V} | \tilde{s}_{1}, \text{sell}) = \frac{q}{q + z} (V + \tilde{s}_{1} - \varepsilon) + \frac{z}{q + z} (V + \tilde{s}_{1}) = V + \tilde{s}_{1} - \frac{q}{q + z} \varepsilon.
\]

Similarly, conditionally upon receiving a buy order, the probability that it comes from an informed trader is \( q/(q + x) \) and the probability that it is instead an uninformed order is \( x/(q + x) \). Hence, the dealer will set the ask price as

\[
P_{1}^{Da} = E(\tilde{V} | \tilde{s}_{1}, \text{buy}) = V + \tilde{s}_{1} + \frac{q}{q + x} \varepsilon.
\]

\(^4\)As explained earlier, 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

\[ S^D = \frac{q}{q+x} \varepsilon + \frac{q}{q+z} \varepsilon = q \varepsilon \left( \frac{1}{q+x} + \frac{1}{q+z} \right) \]

with \( S^{Da} \) denoting the ask-spread and \( S^{Db} \) the bid-spread.

We use the expected bid and ask prices derived above into Eq.(1) that ensure the participation of investors in the IPO process and then derive the optimal IPO price in dealership markets.

As far as informed traders are concerned, at \( t = 0 \) they observe the value of \( s_1 \) and, thus, they will be willing to buy shares in the IPO only if the offering price is lower than their expected revenues in the aftermarket. In other words, given Eq.(1), prices should satisfy the following condition

\[ zE(P_{1b} | s_1 = \eta) + (1 + x - z)E(P_2 | s_1 = \eta) - xE(P_{1a} | s_1 = \eta) \geq P_0^D \geq \]

\[ zE(P_{1a} | s_1 = -\eta) + (1 + x - z)E(P_2 | s_1 = -\eta) - xE(P_{1b} | s_1 = -\eta). \]

which, after replacing into the random variables and \( P_{1b}, P_{1a} \) can be rewritten as

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

This latter equation states that informed agents will bid for shares in the IPO only if they receive good information about the quality of the firm, i.e. if \( s_1 = \eta \). 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

\[ zE(\tilde{P}_{1b} | \Phi_0^u) + (1 + x - z)E(P_2 | \Phi_0^u) - xE(\tilde{P}_{1a} | \Phi_0^u) \geq P_0^D \]

where \( \Phi_0^u \) 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 receive a negative signal about the firm’s value. Thus, let \( \pi_u^D \) be the probability that uninformed traders get high quality shares when they bid \( P_0^D \) and \( 1 - \pi_u^D \) be the probability that they get low quality shares. Then, the expected bid and ask prices from their perspective are as follows

\[ E(\tilde{P}_{1b} | \Phi_0^u, P_0^D) = \pi_u^D \left( V + \eta - \frac{q}{q+z} \varepsilon \right) + (1 - \pi_u^D) \left( V - \eta - \frac{q}{q+z} \varepsilon \right) \]

\[ = V - \frac{q}{q+z} \varepsilon - (1 - 2\pi_u^D) \eta. \]

Similarly

\[ E(\tilde{P}_{1a} | \Phi_0^u, P_0^D) = \pi_u^D \left( V + \eta + \frac{q}{q+x} \varepsilon \right) + (1 - \pi_u^D) \left( V - \eta + \frac{q}{q+x} \varepsilon \right) \]

\[ = V + \frac{q}{q+x} \varepsilon - (1 - 2\pi_u^D) \eta. \]
\[ E(P_2|\Phi^u, P_0^D) = \pi^D_u (V + \eta) + (1 - \pi^D_u) (V - \eta) \]
\[ = V - (1 - 2\pi^D_u) \eta. \tag{6} \]

Substitution into Eq.(4) finally gives the condition that ensure the uninformed investors’ participation on the primary market:

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

As in Rock (1986), the equilibrium price on the primary market is dictated by the above constraint. Because \( N < S \), the company will set the highest price \( P_0^D \) that satisfies the uninformed investors’ participation constraint in the IPO process in order to ensure that all the shares are placed. That is, \( P_0^D \) is chosen so that the above constraint holds as an equality in equilibrium,

\[ P_0^D = V - (1 - 2\pi^D_u) \eta - q \left( \frac{z}{q + z} + \frac{x}{q + x} \right) \varepsilon. \tag{8} \]

In the next Proposition we state the next result about the size of underpricing in dealership markets:

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

\[ E(\bar{P}_1^D) - P_0^D = \left( \frac{1 - \pi}{1 + \pi} \right) \eta + q \varepsilon \left( \frac{z}{q + z} + \frac{x}{q + x} \right) \]

where \( q \varepsilon \left( \frac{z}{q + z} + \frac{x}{q + x} \right) \) measures the ex-post uncertainty on the secondary market.

The above result suggests that IPO underpricing consists of two main components. The first one \( \left( \frac{1 - \pi}{1 + \pi} \right) \eta \) is related to the uncertainty on the primary market consistently with the traditional explanation of underpricing as a risk premium for the ex-ante uncertainty about the firm value (Ritter, 1984; Beatty and Ritter, 1986). The second component \( q \varepsilon \left( \frac{z}{q + z} + \frac{x}{q + x} \right) \) \( \varepsilon \) is the one of interest for us as it captures the *ex-post (value) uncertainty*, that is the residual uncertainty on the secondary market after trading starts. As we will show in the next section, the difference in the size of the underpricing between the markets is only driven by this second component. Also, note that the formula 9 can be rewritten in term of the bid and ask spreads:

\[ E(\bar{P}_1^D) - P_0^D = \left( \frac{1 - \pi}{1 + \pi} \right) \eta + (z S_A^D + x S_B^D) \]

this shows that the underpricing is increasing in the bid and in the ask spread which in a way represent itself a measure of the ex-post uncertainty as it increases with \( \varepsilon \). Notice, also, that contrary to Ellul and Pagano (2006) where the IPO underpricing is solely determined by the sell side of the secondary market trading, in our model IPO underpricing is also affected by the buy side of the secondary market trading. The reason for this lies in the richer trading strategies available.
to investors in our model. Finally, it is important to point out that if the probability of informed trading $q = 0$ the second component of the underpricing goes to zero and underpricing will solely be determined by the uncertainty on the primary market. This is because in the absence of informed trading on the secondary market there is no further information that can be extracted. Conversely, ex-post uncertainty is exacerbated by higher uncertainty on liquidity trading, that is by larger $x$ and $z$. Again, this is intuitive because the higher the probability of noise trading the more difficult to disentangle it from informed trading.

3.2 Market equilibrium in order-book markets

As for dealership markets, at $t = 2$ all information is public and the price $P_2 = \tilde{V}$. To keep things tractable, we make the simplifying assumption that in $t = 1$, there is at most one informed trader and one liquidity trader who, as before, trades depending on the shock received at $t = 1$. As before, then, uninformed agents trade because of liquidity reasons whereas informed agents trade if their expected profits conditional on their information and the information transmitted by the market price is strictly positive. For the same reasons explained earlier, it is never optimal for the informed trader to trade more than one share.

The specific feature that distinguish an auction market from a dealership market is the existence of a specialist who collects all the order and is thus able to observe the aggregate demand denoted by $A = \{-2; -1; 0; 1; 2\}$. Consequently, the specialist is able to extract more information than a dealer on a dealership market who only knows the order submitted to him, and in some circumstances he can effectively infer all the information available to the informed investor.

The table below describe in details of all the possible vectors of orders depending on the trading strategies of the liquidity and informed traders along with the relative probabilities of each of these vectors. Sell orders have a negative sign and buy orders a positive sign, whereas 0 denotes "no order".

<table>
<thead>
<tr>
<th>Informed order</th>
<th>Liquidity trader</th>
<th>Total demand</th>
<th>Probability</th>
<th>Expected alue</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>-1</td>
<td>-2</td>
<td>$q z$</td>
<td>$V + \tilde{s}_1 - \varepsilon$</td>
</tr>
<tr>
<td>-1</td>
<td>+1</td>
<td>0</td>
<td>$q x$</td>
<td>$V + \tilde{s}_1 - \varepsilon$</td>
</tr>
<tr>
<td>-1</td>
<td>0</td>
<td>-1</td>
<td>$q(1 - x - z)$</td>
<td>$V + \tilde{s}_1 - \varepsilon$</td>
</tr>
<tr>
<td>0</td>
<td>-1</td>
<td>-1</td>
<td>$(1 - 2q) z$</td>
<td>$V + \tilde{s}_1$</td>
</tr>
<tr>
<td>0</td>
<td>+1</td>
<td>+1</td>
<td>$(1 - 2q) x$</td>
<td>$V + \tilde{s}_1$</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>$(1 - 2q)(1 - x - z)$</td>
<td>$-$</td>
</tr>
<tr>
<td>1</td>
<td>-1</td>
<td>0</td>
<td>$q z$</td>
<td>$V + \tilde{s}_1 + \varepsilon$</td>
</tr>
<tr>
<td>1</td>
<td>+1</td>
<td>+2</td>
<td>$q x$</td>
<td>$V + \tilde{s}_1 + \varepsilon$</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>+1</td>
<td>$q(1 - x - z)$</td>
<td>$V + \tilde{s}_1 + \varepsilon$</td>
</tr>
</tbody>
</table>

In this environment, the specialist will set a price $P_1^O(A) = E(\tilde{V} | \tilde{s}_1, A)$ for each possible value of $A$ conditional on the available information as well as the information revealed by the orders.
submitted by the investors. Before that, we introduce the following piece of notation: let $\alpha_A$ be the probability of having an aggregate order equal to $A$, then we have

$$
\alpha_{-2} = \Pr(A = -2) = qz \\
\alpha_{-1} = \Pr(A = -1) = q(1-x-z) + (1-2q)z \\
\alpha_0 = \Pr(A = 0) = q(x+z) + (1-2q)(1-x-z) \\
\alpha_1 = \Pr(A = 1) = q(1-x-z) + (1-2q)x \\
\alpha_2 = \Pr(A = 2) = qx
$$

Given the above probabilities, we can now define the market prices for each possible vector of orders.

When $A = -2$, the specialist can infer the informed investor’s information, specifically that they have received a negative signal. The price will thus reflect such information

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

Symmetrically, when $A = 2$, the specialist infers that the informed investor has received a positive signal, and hence sets the price equal to

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

If instead, the specialist 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, and he will then factor this into his calculation of the price that will be given by

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

And symmetrically, for $A = 1$ we get the following price

$$
P_1^O(1) = E \left( \tilde{V} \mid \tilde{s}_1, 1 \right) \\
= \frac{q(1-x-z)}{\alpha_{-1}} (V + \tilde{s}_1 + \varepsilon) + \frac{(1-2q)x}{\alpha_{-1}} (V + \tilde{s}_1) \\
= V + \tilde{s}_1 + \left( \frac{q(1-x-z)}{\alpha_{1}} \right) \varepsilon
$$
We are now left to calculate the price when the aggregate demand is equal to $A = 0$. This can occur either when the specialist receives two offsetting (one buy and one sell) or when no order is submitted. It follows that the price when $A = 0$ is determined as

$$P_{1O}(0) = E \left( V \mid \tilde{s}_1, 0 \right)$$

$$= \frac{qx}{\alpha_0} (V + \tilde{s}_1 - \varepsilon) + \frac{(1 - 2q)(1 - x - z)}{\alpha_0} (V + \tilde{s}_1) + \frac{qz}{\alpha_0} (V + \tilde{s}_1 + \varepsilon)$$

$$= V + \tilde{s}_1 + \frac{q(z - x)}{\alpha_0} \varepsilon$$

It is important to notice that in an auction market there is some information transmission even when the aggregate demand is zero and in fact, the price in this case is different from $V + \tilde{s}_1$ which would be the price based on all the publicly available information. More interestingly, the information transmitted depends on the relative values of $z$ and $x$, measuring the liquidity sell and buy pressures, respectively. Specifically, if liquidity traders are more likely to be sellers, i.e., $z > x$, observing $A = 0$ implies that there is a higher probability of an informed investor with a good signal who is willing to buy the shares, hence the price goes up. Conversely, if liquidity traders are more likely to be buyers, the specialist will infer that there is a higher likelihood of having a negative signal, hence the price will go down compared to $V + \tilde{s}_1$.

At this point, we need to check that given the prices calculated above, informed agents will behave consistently with the information they receive. In other words, an informed investor with a bad signal will submit a sell order if his conditional expected profit is positive and vice versa an informed investor with a negative signal will submit a buy order if his conditional expected profit is negative.

In $t = 1$ informed investors’ expected price conditionally on receiving a negative signal is given by

$$E(P_{1O}^O \mid \tilde{s}_1, u_i = -\varepsilon) = zP_{1O}^O(-2) + (1 - x - z) P_{1O}^O(-1) + xP_{1O}^O(0)$$

$$= V + \tilde{s}_1 - \left( z + \frac{q(1 - x - z)^2}{q(1 - x - z) + (1 - 2q)z} - \frac{qz(z - x)}{q(x + z) + (1 - 2q)(1 - x - z)} \right) \varepsilon$$

which can be shown to be larger than $V + \tilde{s}_1 - \varepsilon$, that is his payoff if he liquiditates his shares in $t = 2$.

\footnote{To keep calculations simple, we include in the calculation of the price the case where no order is submitted. However, our results remain qualitatively unchanged even if we condition the calculation on the specialist receiving at least one order.}

\footnote{We just need to show that

$$z + \frac{q(1 - x - z)^2}{q(1 - x - z) + (1 - 2q)z} - \frac{qz(z - x)}{q(x + z) + (1 - 2q)(1 - x - z)} \leq 1$$}
Simmetrically, for an informed agent with a good signal, in \( t = 1 \) the expected price to pay for a buy order is

\[
E(P_{t+1}^O \mid \tilde{s}_1, u_t = \varepsilon) = xP_{t+1}^O(2) + (1 - x - z) P_{t+1}^O(1) + zP_{t+1}^O(0)
\]

\[
= V + \tilde{s}_1 + \left( x + \frac{q(1 - x - z)^2}{q(1 - x - z) + (1 - 2q)x} + \frac{qz(1 - x - z)}{q(1 - x - z) + (1 - 2q)(1 - x - z)} \right) \varepsilon
\]

which again can be shown to be smaller than the payoff he will receive if he liquidates his shares in \( t = 2 \), \( V + \tilde{s}_1 + \varepsilon \).

We now turn to deriving the share price in the primary market. Both types of agents will use Eq.\((1)\) in order to choose their strategies. Remember that, at \( t = 0 \) informed agents observe the value of \( \tilde{s}_1 \), hence they will bid for shares in the IPO only if the offer price is lower than their expected profit from trading in the secondary market given their private signal. In other words, their participation constraint requires that the following condition is met:

\[
zE(\tilde{P}_{t+1}^O \mid \text{sell}, \tilde{s}_1 = \eta) + (1 + x - z)E(\tilde{P}_t^O \mid \tilde{s}_1 = \eta) - xE(P_t^O \mid \text{buy}, \tilde{s}_1 = \eta) \geq P_0^O \quad (15)
\]

Note that the expected value of \( \tilde{P}_t^O \) conditional on the value of \( \tilde{s}_1 \) is equal to \( V + \eta \) \( V - \eta \) when the signal is good (bad). On the contrary, \( E(P_t^O \mid \text{buy}, \tilde{s}_1 = \eta) \) depends on the aggregated demand in the secondary market, and, conditionally on the informed investor submitting a sell order at \( t = 1 \), can be either \( P_{t+1}^O(2), P_{t+1}^O(-1) \), or \( P_{t+1}^O(0) \). Hence,

\[
E(\tilde{P}_{t+1}^O \mid \text{sell}, \tilde{s}_1 = \eta) = qE(\tilde{P}_{t+1}^O(2) \mid \tilde{s}_1 = \eta) + (1 - 2q)E(\tilde{P}_{t+1}^O(-1) \mid \tilde{s}_1 = \eta) \]

\[
+ qE(\tilde{P}_{t+1}^O(0) \mid \tilde{s}_1 = \eta)
\]

which, by substitution into the expected prices at \( t = 1 \), can be re-written as follows

\[
E(\tilde{P}_{t+1}^O \mid \text{sell}, \tilde{s}_1 = \eta) = q(V + \eta - \varepsilon) + q \left( V + \eta + \frac{q(z - x)}{\alpha_0} \varepsilon \right) + (1 - 2q) \left( V + \eta - \left( \frac{q(1 - x - z)}{\alpha_{-1}} \right) \varepsilon \right)
\]

\[
= V + \eta + q \left( 1 - \frac{q(z - x)}{\alpha_0} - \frac{(1 - 2q)(1 - x - z)}{\alpha_{-1}} \right) \varepsilon
\]

\[
= V + \eta - \varphi_b \varepsilon
\]

where

\[
\varphi_b = q \left( \frac{1 - q(z - x)}{\alpha_0} + \frac{(1 - 2q)(1 - x - z)}{\alpha_{-1}} \right)
\]

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

\[
\frac{q(1 - x - z)^2}{q(1 - x - z) + (1 - 2q)x} - \frac{qz(x - x)}{q(x + z) + (1 - 2q)(1 - x - z)} = 1 - \frac{(1 - 2q)(1 - x - z)}{q(1 - x - z) + (1 - 2q)(1 - x - z)}
\]

\[
= 1 - \frac{2qzx + x(1 - 2q)(1 - x - z)}{q(x + z) + (1 - 2q)(1 - x - z)}
\]

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).
Similarly, the expected price conditional on a buy order is given by

\[ E(\bar{P}_1^O \mid \text{buy}, \bar{s}_1 = \eta) = qE(\bar{P}_1^O(2) \mid \bar{s}_1 = \eta) + (1 - 2q)E(\bar{P}_1^O(1) \mid \bar{s}_1 = \eta) \]

\[ + qE(\bar{P}_1^O(0) \mid \bar{s}_1 = \eta) \]

\[ = q(V + \eta + \varepsilon) + (1 - 2q) \left( V + \eta + \left( \frac{q(1 - x - z)}{\alpha_1} \varepsilon \right) \right) + q \left( V + \eta + \frac{q(z - x)}{\alpha_0} \varepsilon \right) \]

\[ = V + \eta + \varphi_a \varepsilon \]

where

\[ \varphi_a = q \left( \frac{1}{2} (1 - 2q)(1 - x - z) + \frac{q(z - x)}{\alpha_0} \right) \]

By replacing into 15 it is easy to check that the informed agents’ participation constraint is satisfied.

As in the case of dealership market, we also have to ensure that at \( t = 0 \) the uninformed investors’ participation constraint is satisfied. That is,

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

where \( \Phi_0^u \) contains all public information available at \( t = 0 \), which includes the distributions of all random variables as well as the information inferred from the offer price \( P_0^O \). Also, uninformed investors anticipate that they will be allocated all the shares when informed investors do not bid for them because they have received a negative signal and they will take this into account when deciding to participate to the IPO or not. So, let \( \pi_u^O \) be the probability that, at the offer price \( P_0^O \), uninformed traders get shares of a high quality firm (\( \bar{s}_1 = \eta \)) and \( (1 - \pi_u^O) \) be the probability that they get shares of a low quality firm (\( \bar{s}_1 = -\eta \)). Consequently, at \( t = 1 \) the expected prices from the perspective of uninformed investors are defined as follows

\[ E(\bar{P}_1^O \mid \text{sell}, \Phi_0^u, P_0^O) = \pi_u^O \left( E(\bar{P}_1^O \mid \text{sell}, \bar{s}_1 = \eta) \right) + (1 - \pi_u^O) \left( E(\bar{P}_1^O \mid \text{sell}, \bar{s}_1 = -\eta) \right) \]

\[ = \pi_u^O (V + \eta - \varphi_b \varepsilon) + (1 - \pi_u^O) (V - \eta - \varphi_b \varepsilon) \]

\[ = (V - \varphi_b \varepsilon) - (1 - 2\pi_u^O)\eta \]

and

\[ E(\bar{P}_1^O \mid \text{buy}, \Phi_0^u, P_0^O) = \pi_u^O \left( E(\bar{P}_1^O \mid \text{buy}, \bar{s}_1 = \eta) \right) + (1 - \pi_u^O) \left( E(\bar{P}_1^O \mid \text{buy}, \bar{s}_1 = -\eta) \right) \]

\[ = \pi_u^O (V + \eta + \varphi_a \varepsilon) + (1 - \pi_u^O) (V - \eta + \varphi_a \varepsilon) \]

\[ = (V + \varphi_a \varepsilon) - (1 - 2\pi_u^O)\eta \]

\[ \text{The index used stand for bid and ask respectively.} \]
Similarly, the expected price in $t = 2$ is
\[
E(P_2|\Phi^u_0, P^O_0) = \pi^O_u (V + \eta) + (1 - \pi^O_u) (V - \eta)
\]
\[
= V - (1 - 2\pi^O_u) \eta.
\]
Substitution into Eq.(16) finally gives
\[
z ((V - \varphi_b \varepsilon) - (1 - 2\pi^O_u) \eta) + (1 + x - z) (V - (1 - 2\pi^O_u) \eta) - x ((V + \varphi_a \varepsilon) - (1 - 2\pi^O_u) \eta) \geq P^O_0
\]
\[
V - (1 - 2\pi^O_u) \eta - (z\varphi_b + x\varphi_a) \varepsilon \geq P^O_0
\]
(17)

As in dealership markets, by Rock (1986), the company will set the highest price $P^D_0$ that allows the participation of uninformed investors in the market in order to ensure that all the shares are sold (since $N < S$). Therefore, the equilibrium offer price will be such that the above constraint holds with equality, i.e.,
\[
P^O_0 = V - (1 - 2\pi^O_u) \eta - (z\varphi_b + x\varphi_a) \varepsilon
\]
(18)

Note that since $0 \leq \pi^O_u \leq 1$, it is easy to check that Eq.(15) holds, that is the informed investors' participation constraint is also satisfied. The probability $\pi^O_u$ has exactly the same interpretation as in dealership markets, thus it is $\pi^O_u = \pi^D_u = \frac{\pi}{1+\pi}$. 9 Substitution in Eq.(18) finally gives
\[
P^O_0 = V - \left(\frac{1-\pi}{1+\pi}\right) \eta - (z\varphi_b + x\varphi_a) \varepsilon
\]
(19)

It is now possible to calculate the (average) underpricing on order-driven market which is equal to $E(\tilde{P}^O_1) - P^O_0$ where $E(\tilde{P}^O_1)$ is the expected price in the secondary market, in other words
\[
E(\tilde{P}^O_1) = \sum_A \Pr(Order = A) P^O_1(A)
\]
\[
= V^{10}
\]

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
\[
E(\tilde{P}^O_1) - P^O_0 = \left(\frac{1-\pi}{1+\pi}\right) \eta + (z\varphi_b + x\varphi_a) \varepsilon.
\]
(20)

where \( \varphi_b = q \left(1 - \frac{q(z-x)}{\alpha_0} + \frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right) \) and \( \varphi_a = q \left(1 + \frac{(1-2q)(1-x-z)}{\alpha_1} + \frac{q(z-x)}{\alpha_0}\right) \) and where \((z\varphi_b + x\varphi_a) \varepsilon\) measures the ex-post uncertainty.

9Check the proof of Proposition 1 in the Appendix for the derivation of $\pi^D_u$. 

17
Interestingly, the previous result shows that underpricing on auction markets has the same structure as in the dealership market, as such we can identify and distinguish the effect on underpricing due to the uncertainty on the primary market \((\frac{1-x}{1+y})\eta\) which is identical in the two markets; and the effect on underpricing due to the ex-post uncertainty on the secondary market, captured by the second term \((z\varphi_b + x\varphi_a)\varepsilon\). We are then able to establish a very important result: firstly, if the primary mechanism is the same, differences in the level of underpricing between the two markets are exclusively driven by the specific characteristics of the two trading platforms; secondly, these specific characteristics result in a different level of ex-post uncertainty on the secondary market. Ultimately, underpricing will be lower on those markets where the trading structure is more effective at reducing the ex-post uncertainty. We formalize the previous discussion in the next result.

**Proposition 3** The underpricing in order-driven markets is lower than the underpricing in dealership markets if and only if the the ex-post uncertainty on order-driven markets is smaller than that on dealership markets. That is, if and only if the following condition holds:

\[
z\varphi_b + x\varphi_a \leq q \left( \frac{z}{q+z} + \frac{x}{q+x} \right)
\]

The comparison between the level of ex-post uncertainty cannot be done analytically, therefore we need to use simulations to check whether the inequality below holds and under which conditions. We summarize the results of the simulations in Section 5 whereas in the next section we provide an alternative way of measuring the ex-post uncertainty which is more in line with the empirical proxy used in our empirical analysis, that is the standard deviation of the quote mid-points.

4 Ex post uncertainty

In our model, the residual uncertainty on the secondary market is linked to the signal \(\tilde{s}_2\) essentially. Consequently, an intuitive measure of the ex-post uncertainty that captures the risk embedded in the fact that there is more and new information about the firm value that is processed by the secondary market is the ex-post variance of the signal \(\tilde{s}_2\). This is because once the orders are received, the market makers on both markets can update their information about the share value and hence about \(\tilde{s}_2\).

4.1 Ex post variance in dealership markets

From a dealers’s perspective, the posterior distribution of \(\tilde{s}_2\), when order start arriving is given by \(\tilde{s}_2^0 = \varepsilon, 0, -\varepsilon\) with probability \(q, (1-2q), q\), respectively. The ex-post uncertainty prior to the opening of the aftermarket trading is then equal to the unconditional variance of \(\tilde{s}_2\), \(2q\varepsilon^2\). Once
shares start trading in the secondary market, a dealer is able to update her prior probabilities about \( \tilde{s}_2 \) conditionally on the orders received. Hence, following a buy order, the conditional distribution of \( \tilde{s}_2^B \) is \( (\tilde{s}_2^B \mid \text{buy}) = \varepsilon \) or 0 with probability \( q/(q + x) \) and \( x/(q + x) \), respectively. Consequently, the conditional variance is equal to \( \frac{qz}{(q+z)^2} \varepsilon^2 \). Symmetrically, the conditional variance following a sell order is \( \frac{qz}{(q+z)^2} \varepsilon^2 \). Finally, the probability of receiving a buy order (sell order) by the dealer is equal to \( (q + x) \) \((q + z)\). Therefore we can define the ex-post variance in dealership markets as

\[
PostVar_D = \Pr(\text{buy order}) \text{var}(\tilde{s}_2 \mid \text{buy}) + \Pr(\text{sell order}) \text{var}(\tilde{s}_2 \mid \text{sell}) \\
= (q + x) \frac{qx}{(q + x)^2} \varepsilon^2 + (q + z) \frac{qz}{(q + z)^2} \varepsilon^2 \\
= q \left( \frac{x}{(q + x)} + \frac{z}{(q + z)} \right) \varepsilon^2
\]

This variance measures the residual uncertainty in the aftermarket given the distribution of orders and their informational content and it is intuitively lower than the ex ante variance \((2q \varepsilon^2)\). It is easy to see that the ex-post variance is directly linked to our definition of ex-post uncertainty. By the definition of IPO underpricing in dealership markets it is

\[
\text{underpricing}_D = \left(1 - \frac{\pi}{1 + \pi}\right) \eta + \frac{1}{\varepsilon} \text{PostVar}_D
\]

### 4.2 Ex post variance in Exchanges

In the case of order-driven markets, the specialist is able to update the distribution of the residual uncertainty \( \tilde{s}_2 \), by observing the aggregate demand \( A = \{-2; -1; 0; 1; 2\} \). Hence, conditional on the order vector \( A \), the share price will be \( P_1^O(A) \) with probability \( \beta_A \) for \( A = \{-2, -1, 0, 1, 2\} \) where

\[
\beta_A = \frac{\alpha_A}{1 - (1 - 2q)(1 - x - z)}.
\]

The posterior variance of \( \tilde{s}_2^P \) is then constructed as follows

\[
PostVar_O = \sum_A \beta_A \text{var}(\tilde{s}_2^P \mid A).
\]

If \( A = 2 \) or \( A = -2 \), the specialist will know the exact value of \( \tilde{s}_2^P \). For \( A = 1 \), the possible values of \( \tilde{s}_2^P \) are 0 and \( +\varepsilon \) with probabilities \( \frac{(1-2q)x}{\alpha_1} \) and \( \frac{q(1-x-z)}{\alpha_1} \) respectively. The variance of \( \tilde{s}_2^P \) conditional on \( A = 1 \) is then equal to \( \left( \frac{q(1-x-z)(1-2q)x}{\alpha_1} \right) \varepsilon^2 \). Symmetrically, for \( A = -1 \), the possible values of \( \tilde{s}_2^P \) are 0 and \(-\varepsilon \) with probabilities \( \frac{(1-2q)x}{\alpha_{-1}} \) and \( \frac{q(1-x-z)}{\alpha_{-1}} \) respectively and the variance of \( \tilde{s}_2 \) conditional on \( A = -1 \) is then equal to \( \left( \frac{q(1-x-z)(1-2q)x}{\alpha_{-1}} \right) \varepsilon^2 \). Finally, for \( A = 0 \), the possible values of \( \tilde{s}_2^P \) are \(-\varepsilon \) and \( \varepsilon \) with probabilities \( \frac{qz}{\alpha_0} \) and \( \frac{qz}{\alpha_0} \) respectively. The variance of \( \tilde{s}_2^P \) conditional on \( A = 0 \) is equal to \( \left( \frac{4q^2xz}{\alpha_0} \right) \varepsilon^2 \). Using these values in the formula above yields the following expression for the
ex post variance in exchanges:

\[
PostVar_O = \sum_A \beta_A \text{var}(\bar{s}_2|A)
\]

\[
= \alpha_1 \left( \frac{q(1-x-z)(1-2q)x}{\alpha_x^2} \right) \varepsilon^2 + \alpha_{-1} \left( \frac{q(1-x-z)(1-2q)z}{\alpha_z^2} \right) \varepsilon^2
\]

\[
+ \alpha_0 \left( \frac{4q^2xz}{\alpha_0^2} \right) \varepsilon^2
\]

\[
= \varepsilon^2(x\varphi_a + z\varphi_b)
\]

and as for the dealership market it is easy to see that the ex post variance enters directly our definition of underpricing as follows:

\[
\text{underpricing}_O = \left( \frac{1-\pi}{1+\pi} \right) \eta + \frac{1}{\varepsilon} PostVar_O
\]

In the next section we discuss the results of the simulations which compare the level of underpricing on the two trading structures by directly comparing the component due to the ex post uncertainty, that is the ex post variance.

5 Simulation results

The two functions of interests for our simulations are the following

\[
f(q, z, x) = \frac{z}{q+z} + \frac{x}{q+x}
\]

\[
g(q, z, x) = z \left( 1 - \frac{q(z-x)}{q(x+z) + (1-2q)(1-x-z)} \right) +
\]

\[
x \left( 1 + \frac{(1-2q)(1-x-z)}{q(1-x-z) + (1-2q)x} + \frac{q(z-x)}{q(x+z) + (1-2q)(1-x-z)} \right)
\]

They represent the level of the ex-post uncertainty in dealership and auction markets, respectively. Recall that by Proposition 2, comparing ex-post uncertainty is equivalent to comparing underpricing between the two markets.

The result of the comparison turns around the value of three key parameters \( x, z, \) and \( q \) so we make three sets of simulations.

In the first set, we take \( x = z \leq 0.5 \) and we fix the value of \( q \). We then simulate the level of underpricing on both markets for three difference values of \( q \), that is \( q = 0.5, q = 0.01 \) and \( q = 0.99 \) respectively. Remember that \( q \) captures the level of asymmetric information in the market. The results of the simulations are illustrated by Figure ??? in Appendix 2. They clearly show that for \( q \)
very small, i.e., when information asymmetry is not important in the market, underpricing in both
markets is very close because the comparative advantage of an auction market is its effectiveness
in reducing the effect of asymmetric information, it asymmetric information is quite small then
such advantage is not relevant. However, as adverse selection problems increase, underpricing in
dealership markets increases more than in auction markets leading to a large difference. Finally,
when \( q \) gets very close to 1, the difference shrinks again because the occurrence of informed trading
is nearly certain whilst the occurrence of liquidity trading does not create enough noise in the
markets. Note however that when \( q \) is very close to 1, underpricing in auction markets presents
several undefined values because numerators tend to 0.

In the second set of simulations we fix the value of \( x \) and draw the underpricing as functions of \( z \) and \( q \) for \( x = 0.5, 0.01 \) and 0.99, respectively. We find that underpricing in dealership markets
is higher than underpricing on auction markets almost everywhere with this difference becoming
very large as \( x \) increases and tends to 1, which can be interpreted as the case of a Hot IPOs where
there would be a strong buying pressure just after the sale.

The last of simulations fixes the value of \( z \) and draw the underpricing as a function of \( x \) and
\( q \) for \( z = 0.5, 0.01 \) and 0.99. This set of simulations perfectly replicates the results of the previous
one.

We see thus that for sufficiently high level of adverse selection, which we think it is the most
appropriate situation to describe the beginning of trading after an IPO, auction markets clearly
dominate dealership markets.

6 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.

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 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.

7 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 than exchange listed firms. We next compare spread patterns for our samples.
7.1 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.

7.2 Ex-post Value Uncertainty

Our model shows that some uncertainty about the firm value persists in the aftermarket and positively affect the level of underpricing. In order to test this relationship we follow Falconieri, Murphy, and Weaver (2009) who 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. Note that this empirical proxy is consistent with our theoretical measure of ex-post uncertainty, the ex post variance of the residual uncertainty. Indeed, an increase of the ex-post variance would increase the variations of prices and thus it would be reflected by a higher standard deviation of the quote mid-point. Furthermore, the standard deviation of the quote mid-point is also able to capture the effect of an increased trading intensity would also result in a higher standard deviation of the quote mid-points.

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.

### 7.3 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

\[
\%\text{Under}_i = \alpha + \beta_1 \text{ExPostUncert}_i + \beta_2 \text{Offering}_i + \beta_3 \text{Volatility}_i + \beta_4 \text{Hot}_i + \beta_5 \ln(1 + \text{age}) + \beta_6 \text{Internet} + \beta_7 \text{Tech}_i + \beta_8 \text{Rank}_i
\]

where \(\%\text{Under}_i\) is defined as \((\text{First Day Closing Price} - \text{Offering Price}) / \text{First Day Closing Price}\); \(\text{ExPostUncert}_i\) is the standard deviation of spread midpoints for the first 2 hours as constructed by Falconieri et al. (2009); \(\text{Offering}_i\) 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; \(\text{Volatility}_i\) is the standard deviation of daily returns. \(\text{Hot}_i\) is defined as \((\text{Offering Price} - \text{Mid Range}) / \text{Mid Range}\); where \(\text{Mid Range}\) is the midpoint of the originally filed price range\(^{11}\). \(\ln(1 + \text{age})\) is the measure used in Loughran and Ritter (2004) where age is the number of years since the company was founded.\(^{12}\) \(\text{Internet}\) and \(\text{Tech}\) are dummy variables assigned the value of 1 if the IPO is an internet or technology IPO, respectively.\(^{13}\) \(\text{Rank}_i\) 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

\(^{11}\)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.


\(^{13}\)Both are obtained from Jay Ritter’s website and constitute Appendix C and D of Loughran and Ritter (2004).
relative measure are qualitatively similar and hence not reported here.

7.4 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 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:
\[ \text{ExPostUncert}_i = \alpha + \beta_1 \text{Volatility}_i + \beta_2 \text{Hot}_i + \beta_3 \ln(1 + \text{age}) + \beta_4 \text{Internet}_i + \beta_5 \text{Tech}_i \]
\[ + \beta_6 \text{Rank}_i + \beta_7 \text{ExchDum} \] (22)

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 \text{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.

\[ \text{ExchDum}_i = \alpha + \beta_1 \text{ExPostUncert}_i + \beta_2 \text{Offering}_i + \beta_3 \text{Volatility}_i + \beta_5 \ln(1 + \text{age}) + \beta_6 \text{Internet}_i + \beta_7 \text{Tech}_i \] (23)

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, \text{Offering}, as proxy for total firm value at the time of the IPO. We predict a direct relationship. \text{Volatility}, \ln(1 + \text{age}), \text{Internet}, and \text{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 \text{ExchDum}, denoted \text{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):

\[ \text{ExPostUncert}_i = 0.093 + 4.135 \text{Volatility}_i + 0.722 \text{Hot}_i + 0.004 \ln(1 + \text{age}) - 0.025 \text{Internet}_i + 0.407 \text{Tech}_i \]
\[ + 0.004 \text{Rank}_i - 0.012 \text{ExchPred} \]
\[ \text{t statistics: } 2.61^{***} 7.65^{***} 13.88^{***} 0.5 -0.41 7.80^{***} -1.03 -2.34^{**} \] (24)

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 \text{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.

8 Robustness Tests

8.1 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.

8.2 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.\textsuperscript{14}

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.\textsuperscript{15} 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 are 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 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 firms, the percentage traded in the first four minutes is 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 day 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.\textsuperscript{16}

\textsuperscript{14}We find that opening quote sometimes predate the opening trade by 2 seconds.

\textsuperscript{15}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.
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.

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’s 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)

9 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 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.

References

References


10 Appendix 1: The Proofs

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

\[
P^D_0 = V - (1 - 2\pi^D_u)\eta - q \left( \frac{z}{q + z} + \frac{x}{q + x} \right) \epsilon
\]

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.

By its definition, we can rewrite the probability \(\pi^D_u\) as follows

\[
\pi^D_u = \Pr(\tilde{s}_1 = \eta \mid \text{uninformed get shares})
\]

taking into account that uninformed investors get shares with probability 1 when the signal is bad which occurs with probability 1/2 and get shares with probability \(\pi = M/(M + N)\) when the signal is good which again occurs with probability 1/2, we can then write

\[
\pi^D_u = \frac{M}{2(M + N)} + \frac{1}{2} = \frac{M}{M + 1} = \frac{\pi}{1 + \pi}.
\]

Replacing this into Eq. (8) allows to rewrite the offer price as

\[
P^D_0 = V - \left( \frac{1 - \pi}{1 + \pi} \right)\eta - q \left( \frac{z}{q + z} + \frac{x}{q + x} \right) \epsilon
\]

(26)

By definition, underpricing is measured by the following difference \(E(\tilde{P}^D_1) - P^D_0\) where \(\tilde{P}^D_1\) is the expected price in the secondary market at \(t = 1\) and is equal to

\[
E(\tilde{P}^D_1) = \Pr(\text{buy order})E(P^D_{1a}) + \Pr(\text{sell order})E(P^D_{1b})
\]

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 \(E(\tilde{P}^D_1) = V\). From this, it is then straightforward to derive the level of underpricing in dealership markets.

11 Appendix 2: SIMULATIONS RESULTS

We define the following functions:

\[
f(q, z, x) = \frac{z}{q + z} + \frac{x}{q + x}
\]

\[
g(q, z, x) = \frac{q (z - x)}{q (x + z) + (1 - 2q) (1 - x - z)} + \frac{(1 - 2q) (1 - x - z)}{q (1 - x - z) + (1 - 2q) z}
\]

\[
\times \left( 1 + \frac{(1 - 2q) (1 - x - z)}{q (1 - x - z) + (1 - 2q) x} + \frac{q (z - x)}{q (x + z) + (1 - 2q) (1 - x - z)} \right)
\]
representing the values of the ex-post uncertainty in dealership and in auction markets, respectively. Because of the complex structure of underpricing in auction markets, we are not able to compare these two terms analytically. Consequently, we run simulations in order to make these comparison. Remember that by Proposition 2, comparing ex-post uncertainty is equivalent to comparing underpricing between the two markets.

We begin by the case where liquidity buying pressure and selling pressure are the same in the market, i.e., \( x = z \). Figure 11 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.

![Figure 11: Underpricing in auction and dealership markets when \( x = z \) as a function \( z \) and \( q \).](image)

Note for Figure 11: 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.

We simulate underpricing in both markets by fixing each time the variable affecting it in both markets. By fixing \( q \), Figure , Figure and Figure... 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.
Underpricing in auction and dealership markets as a function of $x$ and $z$ for a fixed $q$ ($q = 0.5$)

Note for Figure 11: 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 $q = 0.5$
Underpricing in auction and dealership markets as a function of $x$ and $z$ for a fixed $q$ ($q = 0.01$)

Note for Figure ??: 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 $q = 0.01$.
Underpricing in auction and dealership markets as a function of $x$ and $z$ for a fixed $q$ ($q = 0.99$)

Note for Figure 11: 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 $q = 0.99$

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, underpricing 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 occurrence of liquidity trading does not create enough noise in both markets. Note however that when $q$ is very close to 1, underpricing in auction markets presents several undefined values because numerators can sometimes be very close to 0.

Figures 11, 11 and 11 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.
Underpricing in auction and dealership markets as a function of $q$ and $z$ for a fixed $x \ (x = 0.5)$

Note for Figure 11: 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 $x = 0.5$
Underpricing in auction and dealership markets as a function of $q$ and $z$ for a fixed $x$ ($x = 0.01$)

Note for Figure 11: 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 $x = 0.01$
Underpricing in auction and dealership markets as a function of $q$ and $z$ for a fixed $x$ ($x = 0.99$)

Note for Figure 11: 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 $x = 0.99$

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.

$z = 0.5$
\[ g(q, 0.99, x) = 0.99 \frac{q}{q(x+0.99)+(2q-1)(x-0.01)} (x - 0.99) - x \left( \frac{q}{q(x+0.99)+(2q-1)(x-0.01)} (x - 0.99) + (2q - 1) \frac{x-0.01}{q(x-0.01)+x(2q-1)} \right) + 0.99 \]

\[ 0.99 (2q - 1) \left( \frac{x-0.01}{1.98q+q(x-0.01)-0.99} \right) + 0.99 \]
\[ f(q, 0.99, x) = \frac{0.99}{q+0.99} + \frac{x}{q+x} \]