The European Journal of Finance

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rejf20

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THE EUROPEAN JOURNAL OF FINANCE
https://doi.org/10.1080/1351847X.2023.2206972

Routledge
Taylor & Francis Group

The cost of fragmentation: lessons from initial public offerings*

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ABSTRACT

This paper investigates both theoretically and empirically the impact of market structure on the price discovery process at the opening of trading of IPOs. Some papers suggest that IPO value uncertainty is not fully resolved at the offering but continues into the aftermarket. Our model predicts that this *ex-post uncertainty,* i.e. the residual uncertainty about the firm value in the aftermarket, is related to the level of fragmentation in the aftermarket. Our model further predicts that consolidated markets are more efficient in resolving ex-post uncertainty than fragmented markets. Using the introduction of the opening IPO Cross on Nasdaq as a natural experiment, our empirical analysis provides compelling evidence that IPOs in fragmented markets exhibit larger levels of ex-post uncertainty and, consequently, larger underpricing than in consolidated markets.

ARTICLE HISTORY
Received 9 May 2022
Accepted 4 April 2023

KEYWORDS
Trading structure; fragmentation; uncertainty; IPOs

1. Introduction

Today's markets are increasingly fragmented. The SEC website lists over 20 national securities exchanges, over 50 dark pools, and over 200 internalizing broker-dealers.[1],[2] Fragmentation in the after-market for IPOs has also dramatically increased. For example, on the day that Lucent Technologies went public (April 4, 1996) by listing on the New York Stock Exchange (NYSE), over 93% of the share volume occurred on the NYSE. Fifteen years later, on the day that LINKEDIN was listed on the NYSE (May 19, 2011), only 23% of the share volume occurred on the NYSE.

Regulators and practitioners have attempted to improve market quality in this fragmented market structure. Nasdaq recently proposed concentrating the trading of low-volume stocks onto a single exchange to improve ongoing liquidity.[3] The current proposal echoes previous comments by Nasdaq chairman Nelson Griggs who in 2017 argued that the current market fragmentation might be responsible for the decline in IPOs, suggesting that issuers should be allowed to concentrate their liquidity on a single exchange.[4] This paper theoretically and empirically examines whether fragmentation of trading in the after market leads to a decline in IPO market quality as measured by the amount of underpricing.

One of the traditional advantages of a consolidated trading structure is an enhanced price discovery process (Madhavan 1992), leading to higher price efficiency. Price discovery is crucial for newly listed stocks that are, by their very nature, characterized by high asymmetric information regarding their intrinsic value. The traditional literature on initial public offerings has mostly focused on the design of the primary market as a way to improve the price discovery process and therefore allow for more accurate pricing that results in a lower cost of going public, as measured by underpricing.[5] However, Chen and Wilhelm (2008) theoretically show that information disclosure is not limited to the primary market but continues in the secondary market. Thus, some uncertainty

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*A previous version of this paper has circulated under the title "Fragmentation, Ex-post uncertainty and IPO Underpricing". We thank the editor and two anonymous referees for their guidance. We are also grateful to Giovanni Cespa, Richard Payne, Federico Maglione as well as seminar participants at ESSEC (France), Paris-I, and Surrey Business School, for insightful comments. All remaining errors are our sole responsibility.

about the firm's market value continues in the aftermarket. Falconieri, Murphy, and Weaver (2009) empirically find that a higher level of value uncertainty in the aftermarket, which they label *ex-post uncertainty*, results in higher IPO underpricing. Then the question arises as to whether the resolution of this ex-post uncertainty and, consequently, underpricing is affected by the trading structure of the listing exchange and, more specifically, its degree of fragmentation in the IPO aftermarket trading.

In a consolidated market structure, all orders (and the information they contain) come together in a single location. In a fragmented structure, orders are instead dispersed. We develop a theoretical model characterized by a double adverse selection problem in the primary and secondary market to study how fragmentation impacts the information discovery process in the aftermarket and, as a result, the resolution of the ex-post uncertainty. We model our fragmented market structure as a single market maker in a multiple market maker exchange (Nasdaq) and compare it with a consolidated structure designed as having a specialist-like agent who aggregates all the orders in the market and then sets the call price (NYSE). In our theoretical framework, ex-post uncertainty is captured by the variance of prices conditional on the trading-based information.

Our theoretical model delivers two key testable implications: (1) underpricing in both trading structures is positively correlated with ex-post uncertainty; (2) increasing the consolidation of trading decreases ex-post uncertainty.

Historically, the main US financial markets exhibit different levels of trading fragmentation. On the NYSE and AMEX, trading starts with a call auction where public orders are consolidated in a single location – the limit order book. In contrast, during our sample period, the opening of IPO trading on the Nasdaq was much more fragmented. In particular, the first trade is preceded by a period (pre-opening) during which multiple liquidity providers (dealers) display the prices at which they are willing to buy and sell. However, these quotes are non-binding and do not necessarily reflect all information from public orders placed with dealers before the opening. These differences in the degree of fragmentation allow us to examine the relationship between fragmentation and ex-post uncertainty.[6]

We test the model's empirical predictions on a sample of U.S. IPOs between January 1, 2002, and May 2008.[7] We choose this period to exploit the introduction on the Nasdaq of the opening IPO Cross on May 30, 2006. Under this new trading system, market makers are able to send investor orders to participate in a call auction. This innovation results in a reduction in the fragmentation of the order flow on the Nasdaq, and therefore represents an ideal natural experiment on which to test our model predictions. [8] Our model suggests that we should expect less ex-post uncertainty and, thus, less underpricing for Nasdaq IPOs as a result of the increased consolidation. We employ a difference-in-difference analysis to test this hypothesis and find that new issues on Nasdaq exhibit a lower level of ex-post uncertainty after the introduction of the opening IPO Cross. Overall, our empirical findings strongly support the predictions of our model that IPOs are characterized by less ex-post uncertainty, and hence lower underpricing, in a more consolidated market structure.

Our paper is one of very few in the IPO literature to explore the links between the aftermarket trading structure and IPO performances. In a related paper, Ellul and Pagano (2006) theoretically show that IPO underpricing is negatively correlated with uncertainty about aftermarket liquidity. They test their theory on a sample of IPOs on the London Stock Exchange between 1998 and 2000 and find support for their model predictions for several alternative measures of aftermarket liquidity uncertainty, including the volatility of quoted and effective spread measured over the first four weeks of trading in the aftermarket. In contrast with Ellul and Pagano (2006), our paper focuses on resolving residual *value* uncertainty in the aftermarket – for which we use a specific measure – rather than on liquidity and, most importantly, on how this is affected by the degree of fragmentation of the trading venue.

Ligon and Liu (2011) also examine the relationship between aftermarket liquidity and IPO underpricing. They study a natural experiment created by the introduction, by the SEC, of the 1997 Order Handling Rules (OHR) for all NASDAQ IPOs. The OHR requires market makers on the NASDAQ to post all customer limit orders that are better than a dealer's quote. Such change leads to an improvement in the aftermarket liquidity for Nasdaq stocks. The authors thus expect this to reduce the underpricing of IPOs listed on the Nasdaq after 1997, which would be consistent with Ellul and Pagano (2006). They indeed document a decrease in underpricing for cold Nasdaq IPOs after implementing the OHR.[9] They attribute this result to the fact that the increased liquidity reduces the need for underwriter price support in cold IPOs.

Busaba and Chang (2010) develop a theoretical model where informed traders can trade strategically in the aftermarket and show that this implies larger underpricing in both bookbuild and fixed-priced IPOs. They further show that, in these circumstances, it might be efficient for the underwriter to limit the participation to bookbuilding to a small set of informed investors. Their paper is similar to ours in that it focuses on the price discovery process in the secondary market rather than liquidity. However, they are interested in understanding how the primary process can be best adjusted when accounting for strategic informed trading in the aftermarket. In contrast, we are interested in what is the most preferable secondary market structure that optimizes the aftermarket price discovery process.

Finally, Bessembinder, Hao, and Zheng (2015) show that competition among liquidity providers in the aftermarket can be inefficient and lead to complete market failure where the IPO does not take place or partial market failure where the IPO price is heavily discounted. The authors show that the problem is exacerbated for firms subject to higher value uncertainty. In their paper, allowing for Designated Market Maker (DMM) contracts enhances liquidity in the secondary market, thereby reducing the likelihood of market failures and thus improving social welfare. In contrast to their paper, we explicitly model the impact of asymmetric information in the aftermarket on the pricing decision in the ex-ante market and investigate the role of market fragmentation on the price discovery process.

Our paper also contributes to the extensive market microstructure literature on the cost and benefits of market fragmentation. The theoretical literature generally supports the view that market fragmentation is harmful (Chen and Duffie 2021) as it hampers the price discovery process. This then leads to an exacerbation in adverse selection and information asymmetries (Chowdry and Nanda 1991), with a detrimental effect also on liquidity (Madhavan 1995). The empirical evidence is, however, mixed. Some papers document that market fragmentation improves market quality by reducing transaction costs and bid-ask spreads as a result of the increased competition among liquidity suppliers (e.g. O'Hara and Ye 2011; Aitken, Haoming, and Foley 2017). Other papers, however, provide evidence of a harmful impact of market fragmentation. For instance, in a recent paper, Baldauf and Mollner (2021) use Australian data to show that fragmentation increases competition, but this benefit is outweighed by the creation of large arbitrage opportunities, which amplifies adverse selection problems. Gentile and Fioravanti (2011) analyze the impact of fragmentation on European exchanges and conclude that while liquidity improves, the price efficiency and the price discovery process deteriorate. Finally, using a sample of 52 Dutch stocks, Degryse, De Jong, and Kernel (2015) document a differential impact of fragmentation on large versus mid-cap stocks and that the latter are generally harmed by more fragmentation.

In this paper, we re-examine the cost of fragmentation from the perspective of newly listed firms which are by their very nature subject to high levels of asymmetric information. Our findings have relevant policy implications in light of the concerns recently raised by the SEC about the potential detrimental impact of excessive trading fragmentation on transparency and price discovery.[10] In line with Degryse, De Jong, and Kernel (2015), our analysis suggests that the benefits of fragmentation might not be the same for all companies and that newly listed stocks, in particular, could be harmed by increased fragmentation.

The remainder of the paper is organized as follows. Section 2 sets up and solves the theoretical model. The sample used for our empirical analysis is detailed in Section 3, and the empirical results are in Section 4. Section 5 concludes.

2. The theoretical model

The basic model consists of three dates (Figure 1). The primary market takes place at $t = 0$. We do not explicitly model the IPO process. We assume that underpricing results from Rock's (1986) winner's curse effect (Ellul and Pagano 2006). At $t = 1$, shares start trading on the secondary market.[11] Finally, at $t = 2$, all shares are liquidated.

Our model captures the interaction between the primary and secondary markets resulting from a double adverse selection problem due to the existence of information asymmetries in both markets. Thus, the linkage between the two markets derives from the impact of secondary market prices on the primary market price. Specifically, the information technology in our model is as follows: it is commonly known that a share's fundamental value is $\tilde{V} = V + \tilde{s}_1 + \tilde{s}_2$ where V is a positive constant representing the unconditional expected value of new shares and $\tilde{s}_1$ and $\tilde{s}_2$ are independently distributed random signals that will be observed by a fraction of

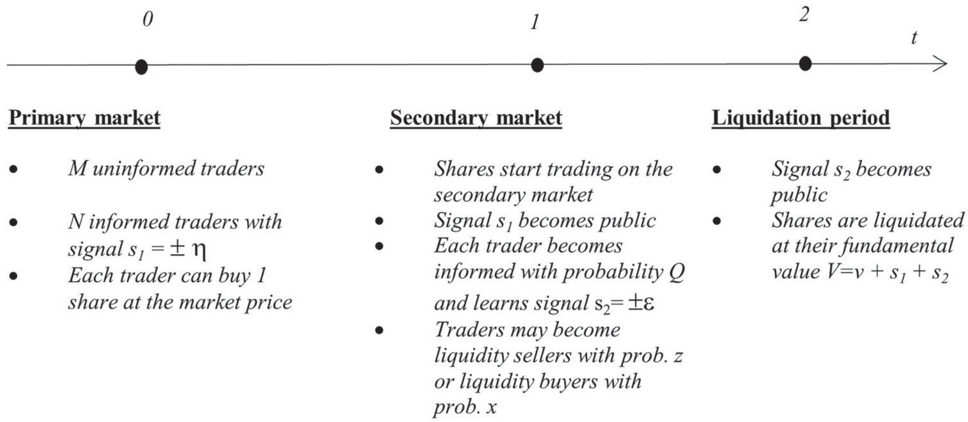

Figure 1. Timeline of the model.

the market participants at $t = 0$ and $t = 1$, respectively. Both signals are binary and provide information about the quality of the issuer. The variable $\tilde{s}_1$ is a private signal observed by a number of informed investors during the IPO process. It can take value η or $-\eta$ with probability 1/2. This signal becomes public before the opening of trading on the secondary market. Some residual uncertainty about the shares' value, however, remains in the secondary market and is captured by a second signal, $\tilde{s}_2$, which can take values ε or $-\varepsilon$ with probability 1/2. It should be noted that in our model, we abstract from modeling the information the firm chooses to reveal to the market prior to going public, for instance, through the prospectus and/or the subsequent marketing effort.[12] The reason for this is twofold: firstly, we implicitly assume that the information the firms reveal would be public by the beginning of the primary market. Secondly, and more importantly, as it will become clearer later on, in the context of our model, the firm would have an incentive to reveal as much information as possible because this reduces the volatility of the signal, $\tilde{s}_1$, which in turn reduces the level of underpricing irrespective of the market structure.

2.1. Timing of the market

2.1.1. Primary market

We assume that the company sells an exogenous number, S, of shares in the IPO. The objective of the issuer and the underwriter is to maximize the IPO proceeds given by $S \times P_0$ by choosing the highest offer price P_0 that guarantees to place all the shares on sale.

In line with Rock's (1986) model, we assume that participants in the primary market are either informed or uninformed. Specifically, 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 $\tilde{s}_1$. Each trader can buy at most one share. Finally, to allow for the winner's curse effect, we assume that uninformed traders are able to buy the entire issue, i.e. we assume that $M \geq S$ while informed investors cannot do so, i.e. $N < S$. Hence, the issuer needs to attract bids from uninformed traders in order to place all the shares. Finally, we denote by π the proportion of uninformed investors in the primary market, i.e. $\pi = \frac{M}{M+N}$.

2.1.2. Secondary market

The secondary market begins at $t = 1$. At this stage, the signal $\tilde{s}_1$ becomes public, and new traders come to the market. Each trader has a probability Q of learning the signal $\tilde{s}_2 = \{-\varepsilon; \varepsilon\}$. With probability $(1 - Q)$ no additional information is learned, in which case $\tilde{s}_2 = 0$.[13] Hence there is a positive probability that no additional information is learned in the secondary market.

Without loss of generality, we assume that the probability of being informed in either period is independent of the other period.[14] In addition, there are no restrictions on short selling since investors with unfavorable information in the secondary market may submit a sell order without being buyers in the primary market. It is worth clarifying that the secondary market we describe refers to the very beginning of the trading.

Adverse selection in the secondary market arises because of the liquidity needs agents may face. Specifically, we assume that each liquidity trader in the secondary market may be a *liquidity seller* with probability z and a *liquidity buyer* with probability x. We allow investors who bought shares in the IPO stage to be liquidity sellers or buyers. For them, liquidity selling might be related to flipping activities (Aggarwal 2003), while liquidity buying is related to a desire to increase the allocation received in the primary market (Ellis 2006). As a result, the probability that they do neither, i.e. they hold on to the shares bought in the primary market until $t = 2$, is equal to $1 - x - z$. Liquidity trading in the secondary market may also be related to liquidity shocks from investors who did not receive shares at the IPO stage.

The expected price on the secondary market affects investors' strategies in 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 fragmented or a consolidated market. Below we detail the differences between the two market structures and how these are reflected in the aftermarket prices.

2.2. The market structure

2.2.1. Fragmented markets

Our definition of a fragmented market is similar to Ellul and Pagano (2006), and it is typified by the pre-Order Handling Rules Nasdaq structure. That is, market makers only see the public orders they receive – not all the public orders entered. Further, public customers must submit their orders to market makers. Hence, with no loss of generality, we assume that each liquidity trader is matched with one market maker and can place an order for at most one share.[15] Orders are anonymous, and the market is assumed to be perfectly competitive. Therefore, the price is equal to the security's expected value conditional on available information, i.e. the publicly known value of s_1 and the type of order received (buy or sell). For a buy order, the market maker will propose a selling price (ask), whereas for a sell order, the market maker will propose a buy price (bid). In other words, the bid and ask prices, denoted by P_1^{Fb} and P_1^{Fa} respectively, are given by

$$P_1^{Fa} = E(\tilde{V}|\tilde{s}_1,\ \text{buy}) \text{ and } P_1^{Fb} = E(\tilde{V}|\tilde{s}_1, \text{sell}).$$

2.2.2. Consolidated markets

In a consolidated market, orders come together in a single location – either physical or in cyberspace. In contrast to a fragmented market, the specificity of a consolidated market is that the market maker observes all submitted public orders, which are then entered into the order book.[16] Hence, we assume that the market maker has more complete information about supply and demand than a market maker in a fragmented market. This implies that given the set of orders $y_1, y_2, \ldots, y_m$, the price per share is then given by the following[17]

$$P_1^C = E(\tilde{V}|\tilde{s}_1, y_1, y_2, \ldots, y_m).$$

This price might be a bid or an ask price depending on the total net demand on the market (the sum of the orders y_1 to y_m). In such a market, informed agents have the incentive to hide their orders behind liquidity orders so that their information is not revealed. Consequently, since we know that uninformed traders will trade at most one unit, informed traders have no incentive to trade more than one unit. Therefore, informed traders must decide whether to sell or buy one unit or stay out of the market. As specified above, uninformed traders submit orders for liquidity reasons, whereas informed traders trade on the new information signal, s_2. Hence, an informed trader i will sell if and only if her expected profit from trading is positive, i.e. if and only if $(E(\tilde{V}|s_2, P_1^C) - P_1^C) > 0$.

Moving backwards to the IPO stage, an uninformed trader would bid for shares on the primary market only if her expected profit is non-negative. Let $K = \{F, C\}$ the index for fragmented and consolidated markets, respectively. Let $j = \{i, u\}$ denoting the index for informed and uninformed traders, respectively. At $t = 0$, trader j, with the information set Φ_0^j, will buy the share only if:

$$\underbrace{zE(P_1^{Kb}|\Phi_0^j) + (1+x-z)E(P_2|\Phi_0^j)}_{\text{investors' expected payoff on the secondary market}} \geq \underbrace{P_0^K}_{\text{IPO offer price}} \tag{1}$$

where P_1^{Kb} and P_1^{Ka} denote the bid and ask prices respectively at $t = 1$ for $K = \{F, C\}$, z is the probability that j is a seller, and x is the probability that j is a buyer. P_2 represents the share price at $t = 2$, which does not depend on the market structure because it is equal to the expected liquidation value. We next derive equilibrium prices and, hence, the conditions for IPO underpricing in each market. We proceed by backward induction. All proofs are in Appendix 1.

2.3. Market equilibrium

2.3.1. Fragmented markets

At $t = 2$ all information is public, and the price $P_2 = \tilde{V}$. At $t = 1$, market makers set their bid and ask prices conditional on the information inferred from the order received from a trader. With probability Q the informed trader observes the realization of $\tilde{s}_2$ which is either ε or $-\varepsilon$ with equal probability, $\frac{1}{2}$. From the market makers' perspective, $\tilde{s}_2 = \varepsilon$ with probability $\frac{Q}{2} = q$. Because of the existence of liquidity traders, the conditional probability that a sell order is informed is $\frac{q}{q+z}$, and the probability that it is uninformed is $\frac{z}{q+z}$. Therefore, at $t = 1$, the bid price set by the competitive market makers is the share's expected value conditional on the value of $\tilde{s}_1$, which is public, and on receiving a sell order:

$$\begin{aligned} P_1^{Fb} = E(\tilde{V}|\tilde{s}_1, \text{sell}) &= \frac{q}{q+z}(V + \tilde{s}_1 - \varepsilon) + \frac{z}{q+z}(V + \tilde{s}_1) \\ &= V + \tilde{s}_1 - \frac{q}{q+z}\varepsilon \end{aligned} \tag{2}$$

Similarly, conditional on receiving a buy order, the probability that it is submitted by an informed trader is $\frac{q}{q+x}$ and the probability that it is instead an uninformed order is $\frac{x}{q+x}$. Hence, the ask price is

$$P_1^{Fa} = E(\tilde{V}|\tilde{s}_1, \text{buy}) = V + \tilde{s}_1 + \frac{q}{q+x}\varepsilon. \tag{3}$$

Conditional on $\tilde{s}_1 = \eta$, the probability that uninformed traders receive shares in the primary market is equal to $\pi = \frac{M}{M+N}$.The level of underpricing in IPOs in a fragmented market is then stated in Proposition 1.

Proposition 2.1: *In fragmented markets, the level of underpricing is given by*

$$UP^F = E(\tilde{P}_1^F) - P_0^F = \left(\frac{1-\pi}{1+\pi}\right)\eta + q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon \tag{4}$$

Examining Equation (4) *reveals that underpricing consists of two main components. First,* $\left(\frac{1-\pi}{1+\pi}\right)\eta$ *is related to the uncertainty on the primary market in line with the traditional explanation of underpricing as a risk premium for the ex-ante uncertainty about firm value* (Ritter 1984; Beatty and Ritter 1986). *More interestingly, our model clearly shows that underpricing also depends on a second component* $q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon$, which *is associated with the residual uncertainty in the IPO aftermarket. The residual uncertainty is measured by* ε *as well as the degree of asymmetric information captured by the probability*q*. Specifically, the residual uncertainty is an increasing function of the probability of informed trading and is equal to zero if there is no informed trading (i.e. if* $q = 0$*). In this case, underpricing will be determined solely by the uncertainty on the primary market because, in the absence of informed trading on the secondary market, no further information can be extracted, even though some uncertainty persists in the aftermarket. Conversely, underpricing is exacerbated by more active liquidity trading in the secondary market, i.e. by larger values of* x *and* z*.*

Table 1. Order book in the consolidated market.

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

This table presents the different trading strategies of traders in a consolidated market, the probability of occurrence of each trading combination and the expected value of the new share given each combination of orders.

2.3.2. Consolidated markets

As in fragmented markets, all information at $t = 2$ is public and the price $P_2 = \tilde{V}$. For tractability, we make the simplifying assumption that at time $t = 1$, there is at most one (potentially) informed trader and one (uninformed) liquidity trader. The assumption, however, works against our result as it minimizes the benefits in terms of information transmission of a consolidated market.

Uninformed traders trade for liquidity reasons, whereas informed traders trade if their expected profits, conditional on their information, are strictly positive. It is never optimal for the informed trader to trade more than one share because otherwise, it would reveal his information.[18]

In contrast to fragmented markets, there is a monopolistic market maker in consolidated markets. Similar to the NYSE specialist, the (designated) market maker competes with traders submitting limit orders who are also liquidity providers. The market maker collects orders and is able to observe the aggregate demand denoted by A with $A = \{-2; -1; 0; 1; 2\}$. Consequently, the market maker can infer more information from orders than market makers in fragmented markets.

Table 1 describes all of the possible combinations of orders depending on the trading strategies of liquidity and informed traders along with the probabilities of each of these combinations. Sell orders have a negative sign, and buy orders have a positive sign, while 0 denotes ‘no order’.

In this environment, the market maker will set a price $P_1^C(A) = E(\tilde{V}|\tilde{s}_1, A)$ for each possible value of $A = \{-2; -1; 0; 1; 2\}$ conditional on the available information as well as the information inferred from the submitted orders. Before deriving these prices, we introduce the following piece of notation.

Definition 1: Let α_A be the probability of having an aggregate order equal to $A = \{-2; -1; 0; 1; 2\}$, then

$$\begin{aligned} \alpha_{-2} &= Pr(A = -2) = qz \\ \alpha_{-1} &= Pr(A = -1) = q(1 - x - z) + (1 - 2q)z \\ \alpha_0 &= Pr(A = 0) = q(x + z) + (1 - 2q)(1 - x - z) \\ \alpha_1 &= Pr(A = 1) = q(1 - x - z) + (1 - 2q)x \\ \alpha_2 &= Pr(A = 2) = qx. \end{aligned} \tag{5}$$

Given the above probabilities, we can now define market prices for each possible combination of orders. When $A = -2$, the market maker can infer the informed trader’s information, specifically that he has received a negative signal. The price will thus reflect such information;

$$P_1^C(-2) = E(\tilde{V}|\tilde{s}_1, -2) = V + \tilde{s}_1 - \varepsilon. \tag{6}$$

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

$$P_1^C(2) = E(\tilde{V}|\tilde{s}_1, 2) = V + \tilde{s}_1 + \varepsilon. \tag{7}$$

Table 2. Descriptive Statistics – Nasdaq Voluntary IPO Opening Cross, 2002–2008.

Variable	Overall	NYSE/AMEX/ARCA	Nasdaq
Panel A. 2002–2006 Pre-IPO Order Book			
N. Observations	380	115	265
O_Size (in millions)	\$177.92	\$312.63	\$119.46***
Offering Price	\$13.94	\$15.54	\$13.24***
UP	11.26%	12.56%	10.70%
Vol	2.77%	2.60%	2.85%
Age of Firm (Years)	23.17	30.43	20.03***
Revision	0.0104	−00.022	0.024
Top-tier	0.715	0.861	0.091***
VC	0.450	0.165	0.573***
All-Star	0.147	0.278	0.091***
N_Pre_IPOs	22.308	24.26	21.46
Overhang	0.913	0.617	1.040
Ind_Q	2.500	2.207	2.627***
Uncert_2H	0.2809	0.285	0.279
Uncert_R	0.1674	0.199	0.153**
Uncert_D2_2H	0.0673	0.084	0.059**
Panel B. 2006–2008 – Post IPO Order Book			
N. Observations	197	49	148
O_Size (in millions)	\$263.04	\$745.68	\$103.25*
Offering Price	\$14.67	\$18.87	\$13.27***
UP	15.12%	14.73%	15.26%
Vol	3.12%	2.67%	3.36%***
Age of Firm (Years)	20.10	34.10	15.47***
Price Revision	−0.03	0.028	−0.055**
Top-tier (dummy)	0.817	0.939	0.777***
VC	0.512	0.082	0.655***
All-Star	0.122	0.163	0.108
N_Pre_IPOs	29.74	33.29	28.56
Overhang	1.433	1.155	1.524
Ind_Q	2.306	2.069	2.385***
Uncert_2H	0.364	0.407	0.351
Uncert_R	0.205	0.247	0.191
Uncert_D2_2H	0.085	0.175	0.055***

This table provides descriptive statistics for a sample of 577 initial public offerings (IPO) of common stock that opened from January 1, 2002, through May 30, 2008, and have complete data for each IPO. This encompasses the beginning of the Nasdaq IPO Opening Cross on June 1, 2006. Our sample includes IPOs that list on the AMEX, ARCA, Nasdaq, or NYSE during the sample period and have no missing observations for any of the listed variables. Listed are the mean for each variable partitioned by exchange type for each variable. All Nasdaq firms are eligible to list on at least one of the NYSE segments, so no further partitioning is necessary. *PostUncert* is proxied by the standard deviation of spread midpoints for the first 2 h of trading, the rest of the first trading day, and the first two hours of the second trading day. Panel A (B) lists the pre (post) IPO Opening Cross period statistics. ***, **, * next to a mean indicates that the difference between that mean, and the NYSE/AMEX mean is significant at the 0.01, 0.05, and 0.10 levels, respectively.

If, instead, the market maker observes $A = -1$, the information is not fully revealed. Such demand may be the result of different combinations of orders, and this will be reflected in the price as follows:

$$\begin{aligned} P_1^C(-1) &= E(\tilde{V}|\tilde{s}_1, -1) = \frac{q(1-x-z)}{\alpha_{-1}}(V + \tilde{s}_1 - \varepsilon) + \frac{(1-2q)z}{\alpha_{-1}}(V + \tilde{s}_1) \\ &= V + \tilde{s}_1 - \left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon. \end{aligned} \tag{8}$$

Symmetrically, for $A = +1$ we get the following price:

$$\begin{aligned} P_1^C(1) &= E(\tilde{V}|\tilde{s}_1, 1) = \frac{q(1-x-z)}{\alpha_{-1}}(V + \tilde{s}_1 + \varepsilon) + \frac{(1-2q)x}{\alpha_{-1}}(V + \tilde{s}_1) \\ &= V + \tilde{s}_1 + \left(\frac{q(1-x-z)}{\alpha_1}\right)\varepsilon \end{aligned} \tag{9}$$

Table 3. Multivariate analysis of the determinants of underpricing in the period 2002–2008.

	Model						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.036	0.045	−0.034	−0.041	−0.067	−0.077	−0.071
	0.70	*1.07*	*−0.73*	*−0.95*	*−1.56*	*1.85∗*	*−1.74∗*
O_Size	0.009	0.123	0.017	0.006	0.009	0.008	0.007
	1.28	*1.83∗*	*2.51∗∗*	*1.09*	*1.57*	*1.47*	*1.28*
Vol	1.204	1.017	1.561	0.159	0.129	0.004	−0.046
	2.65∗∗∗	*2.50∗∗*	*2.87∗∗∗*	*20.46*	*0.38*	*0.01*	*−0.14*
Revision	0.073	0.067	0.063	0.026	0.022	0.005	0.0001
	4.76∗∗∗	*4.72∗∗∗*	*4.85∗∗∗*	*2.87∗∗∗*	*2.34∗∗*	*0.43*	*0.01*
Ln(1 + age)	−0.001	−0.009	−0.012	−0.004	−0.002	−0.003	−0.003
	−0.12	*−1.73∗*	*−2.12∗∗*	*−0.88*	*−0.40*	*−0.68*	*−0.66*
Tech	0.0001	−0.015	−0.0166	−0.017	−0.022	−0.019	0.021
	0.01	*−1.68*	*−0.81*	*−0.91*	*1.17*	*−1.01*	*1.17*
Internet	0.006	0.007	0.006	0.009	−0.013	−0.026	−0.026
	0.27	*0.29*	*0.28*	*0.45*	*−0.61*	*−1.21*	*−1.19*
Top-tier	0.004	0.005	−0.001	−0.002	0.002	0.001	0.001
	0.30	0.40	*−0.10*	*−0.17*	*0.16*	*0.08*	*0.12*
VC	0.012	0.001	0.019	0.011	0.009	0.002	0.004
	0.80	*0.91*	*1.53*	*0.99*	*0.87*	0.18	*0.31*
All-Star	−0.002	−0.016	−0.003	−0.002	−0.002	0.005	0.004
	−0.93	*−1.03*	*−0.22*	*−0.17*	*−0.19*	*0.33*	*0.28*
VCx All-Star	0.022	0.038	0.006	0.004	0.011	0.002	0.003
	0.62	*1.30*	*0.21*	*0.19*	*0.41*	*0.09*	*0.11*
N_Pre_IPOs	−0.00002	−0.0002	−0.0003	−0.0001	−0.0001	−0.0002	−0.0002
	−0.07	*−1.14*	*−1.59*	*−0.92*	*−0.52*	*−1.30*	*−1.15*
Overhang	0.002	0.001	0.001	0.00005	0.001	0.001	0.009
	0.56	*0.60*	*0.83*	*0.56*	*0.73*	*1.033*	*1.05*
Ind_Q	−0.002	0.015	−0.021	−0.011	−0.009	−0.007	−0.007
	−1.60	*−2.13∗∗*	*−3.30∗∗∗*	*−1.85∗∗*	*−1.67∗*	*−1.22*	*−1.29*
*Uncert*_2H				0.269	0.298	0.241	0.234
				12.43∗∗	*8.24∗∗∗*	*6.77∗∗∗*	*6.37∗∗∗*
Uncert_R						0.218	0.214
						5.42∗∗∗	*5.24∗∗∗*
Uncert_D2_2H$_i$							0.058
							1.06
Interact					−0.057	−0.151	−0.148
					−1.30	*−4.01∗∗∗*	*3.90∗∗∗*
Exchange					0.009	0.027	0.023
					0.68	*2.19∗∗*	*1.95∗*
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes
N	515	525	516	519	516	514	515
Adj. R^2	0.085	0.188	0.215	0.478	0.483	0.535	0.534

Our sample includes 577 initial public offerings (IPOs) of common stock listed on the AMEX, Nasdaq, or NYSE between e table reports the results of the several different specifications of the OLS regression for underpricing as per Equation (18). The variable of interest is *PostUncert_2H*, defined as the standard deviation of spread midpoints for the first two hours of trading. The other control variables are defined in Appendix 2. Year fixed effects based on the IPO year and industry fixed effects based on the 49 Fama-French industries are included. We exclude outliers with a DFFITS statistic $>$ than $2 * \sqrt{(P/N)}$, where *P* is the number of parameters in the model and *N* is 577. White consistent t statistics are in italics below each parameter estimate. ***,**,* Denote significant at the 0.01, 0.05, and 0.10 levels, respectively.

We are now left to calculate the price when the aggregate demand is equal to $A = 0$. This can occur either when the market maker receives two orders that offset each other (one buy and one sell) or when no order is submitted.[19] It follows then that the price when $A = 0$ is given by,

$$\begin{aligned} P_1^C(0) &= E(\tilde{V}|\tilde{s}_1, 0) = \frac{qx}{\alpha_0}(V + \tilde{s}_1 - \varepsilon) + \frac{(1-2q)(1-x-z)}{\alpha_0}(V + \tilde{s}_1) + \frac{qz}{\alpha_0}(V + \tilde{s}_1 + \varepsilon) \\ &= V + \tilde{s}_1 + \frac{q(z-x)}{\alpha_0}\varepsilon. \end{aligned} \tag{10}$$

Table 4. Diff-in-Diff analysis- Nasdaq IPO opening cross.

	Model (1)	Model (2)
Intercept	0.087	−0.008
	1.05	*−0.13*
O_Size	0.021	0.027
	1.59	*2.87* ***
Vol	2.711	2.818
	3.96 ***	*4.74* ***
Revision	0.151	0.110
	6.41 ***	*9.69* ***
Ln(1 + age)	−0.004	−0.005
	−0.48	*−0.77*
Tech	−0.018	−0.013
	−0.76	*−0.55*
Internet	−0.015	−0.002
	−0.60	*−0.08*
Top-tier	−0.008	−0.011
	−0.50	*−0.69*
VC	0.023	0.017
	1.18	*1.11*
All-Star	−0.016	−0.009
	−0.72	*−0.46*
VC x All-Star	0.033	0.043
	0.74	*1.19*
N_Pre_IPOs	−0.0002	−0.0003
	−0.58	*−0.96*
Overhang	−0.001	−0.002
	−1.33	*−1.54*
Ind_Qs	−0.002	−0.011
	−0.24	*−1.17*
Nasdaq		0.072
		*4.09****
Post	0.016	0.089
	0.44	*2.72****
*Post*Nasdaq*		−0.059
		*−2.09***
Adj. R^2	0.194	0.267

This table provides the results of a diff-in-diff analysis of the determinants of ex-post uncertainty for a sample of 577 initial public offerings (IPO) of common stock that opened from January 1, 2002, through May 30, 2008. on the AMEX, ARCA, Nasdaq, or NYSE during the sample period and have no missing observations for any of the listed variables. For this sample, all Nasdaq firms are eligible to list on at least one of the NYSE segments; the dependent variable is *PostUncert_2H*defined as the standard deviation of quote midpoints for the first two hours of trading on the first day of trading. All control variables are defined in Appendix 2. Year fixed effects based on the IPO year and industry fixed effects based on the 49 Fama-French industries are included but omitted for brevity. Outliers with a DFFITS statistic $>$ than $2 * \sqrt{(P/N)}$ where P is the number of parameters in the model and N is 577. White consistent t statistics are in italics below each parameter estimate. ***, **, * Denote significant at the 0.01, 0.05, and 0.10 levels, respectively.

Equation (10) shows that some information can be inferred even when the aggregate demand is zero in a consolidated market. Indeed, the price set in this case is different from $V + \tilde{s}_1$ which would be the price based on all the publicly available information. Interestingly, the information transmitted depends on the relative values of z and x, measuring the liquidity sell and buy pressure, respectively. Indeed, if liquidity traders are more likely to be sellers, *i.e.* $z > x$, observing $A = 0$ implies that there is a higher probability that an informed investor has a good signal and hence is willing to buy shares. As a result, the price is higher than $V + \tilde{s}_1$. The opposite occurs when $z < x$, that is when liquidity traders are more likely to be buyers.

We formalize the result for the underpricing in consolidated markets in the next proposition:

Proposition 2.2: *In consolidated markets, the level of underpricing is given by*:

$$UP^C = E(\tilde{P}_1^C) - P_0^C = \left(\frac{1-\pi}{1+\pi}\right)\eta + (z\varphi_b + x\varphi_a)\varepsilon \tag{11}$$

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

From Proposition 2.2, we infer that underpricing in consolidated markets has the same structure as in fragmented markets. Therefore, we can identify and distinguish the amount of underpricing due to uncertainty in the primary market, $\left(\frac{1-\pi}{1+\pi}\right)\eta$, *which (as expected) is identical in the two markets, and the amount of underpricing due to the uncertainty in the secondary market, captured by the second term* $(z\varphi_b + x\varphi_a)\varepsilon$. *Hence, propositions 2.1 and 2.2, taken together, clearly demonstrate that ceteris paribus, the difference in underpricing is driven by the secondary market trading structure and their ability to reduce the aftermarket uncertainty. In other words, by comparing Equations* (4) *and* (11), *it can be seen that the difference in underpricing between the two markets is solely driven by the difference between the terms* $(z\varphi_b + x\varphi_a)$ *and* $q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)$.

In the next section, we compare the two terms and also show that these measures are closely related to the level of uncertainty in the secondary market, i.e. the signal $\tilde{s}_2$.

2.4. Underpricing and ex-post uncertainty

In our model, uncertainty in the secondary market arises because of the arrival of a second signal $\tilde{s}_2$. We have shown that the way this uncertainty is processed by each trading structure is conditional on the order flow and the information that can be inferred from it. In this section, we formalize a measure of the uncertainty conditional on the order flow of each trading structure, which we name *ex-post uncertainty*. The results of this section lay the theoretical foundation for the proxy we will later employ in our empirical analysis.

2.4.1. Fragmented markets

From a dealer's perspective, the distribution of $\tilde{s}_2$, when orders start arriving, is given by $\tilde{s}_2^p = \varepsilon, 0, -\varepsilon$ with probability q, $(1-2q)$, q, respectively. The uncertainty before trading starts is equal to the unconditional variance of $\tilde{s}_2$, $2q\varepsilon^2$. Once trading in the secondary market starts, a market maker can update her prior distribution of $\tilde{s}_2$ conditionally on the orders received. Following a buy order, the conditional distribution of $\tilde{s}_2^p$ is ε or 0 with probability $q/q+x$ and $x/q+x$, respectively. Consequently, the conditional variance is equal to $qx\varepsilon^2/(q+x)^2$. Symmetrically, the conditional variance following a sell order is $qz\varepsilon^2/(q+z)^2$. Finally, the probability of receiving a buy order (sell order) by the dealer is equal to $(q+x)$ $((q+z))$. We can define the ex-post uncertainty in fragmented markets as

$$\begin{aligned} PostVar^F &= \Pr(\text{buy})var(\tilde{s}_2|\text{buy}) + \Pr(\text{sell})var(\tilde{s}_2|\text{sell}) \\ &= (q+x)\frac{qx}{(q+x)^2}\varepsilon^2 + (q+z)\frac{qz}{(q+z)^2}\varepsilon^2 \\ &= q\left(\frac{x}{(q+x)} + \frac{z}{(q+z)}\right)\varepsilon^2 \end{aligned} \tag{12}$$

This variance measures the residual uncertainty in the aftermarket given the distribution of orders and their information content and is intuitively lower than the ex-ante variance $(2q\varepsilon^2)$. It is easy to see that the ex -post uncertainty in Equation (12) is closely related to the aftermarket-specific component of the underpricing in Equation (4). Hence, we can rewrite the underpricing in fragmented markets, as defined in Equation (4), as a function of the ex-post uncertainty measure as follows:

$$UP^F = \left(\frac{1-\pi}{1+\pi}\right)\eta + \frac{1}{\varepsilon}PostVar^F. \tag{13}$$

2.4.2. Consolidated markets

In the case of consolidated markets, the market maker updates the distribution of the residual uncertainty $\tilde{s}_2$ after observing the aggregate demand $A = \{-2; -1; 0; 1; 2\}$. Conditional on A, the share price will be $P_1^C(A)$ with probability β_A for $A = \{-2, -1, 0, 1, 2\}$ with,

$$\beta_A = \frac{\alpha_A}{1 - (1-2q)(1-x-z)}. \tag{14}$$

The ex-post uncertainty, measured by the ex-post variance of $\tilde{s}_2^p$, is then defined as

$$PostVar^C = \sum_A \beta_A var(\tilde{s}_2^p | A). \tag{15}$$

If $A = 2$ or $A = -2$, then the dedicated market maker 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 $(1-2q)x/\alpha_1$ and $q(1-x-z)/\alpha_1$, respectively. The variance of $\tilde{s}_2^p$ conditional on $A = 1$ is then equal to $(q(1-x-z)(1-2q)x)\varepsilon^2/\alpha_1^2$. Symmetrically, for $A = -1$, the possible values of $\tilde{s}_2^p$ are 0 and $-\varepsilon$ with probabilities $(1-2q)z/\alpha_{-1}$ and $q(1-x-z)/\alpha_{-1}$, respectively. Then, the variance of $\tilde{s}_2$ conditional on $A = -1$ is then equal to $(q(1-x-z)(1-2q)z)\varepsilon^2/\alpha_{-1}^2$. Finally, for $A = 0$, the possible values of $\tilde{s}_2^p$ are $-\varepsilon$ and ε with probabilities $qx/\alpha_0$and qz/α_0, respectively. The variance of $\tilde{s}_2^p$ conditional on $A = 0$ is equal to $(4q^2xz)\varepsilon^2/\alpha_0^2$. Substitution of these values in Equation (15) yields the following expression for the ex-post uncertainty in consolidated markets:

$$\begin{aligned} PostVar^C &= \sum_A \beta_A var(\tilde{s}_2|A) \\ &= \left(\alpha_1\left(\frac{q(1-x-z)(1-2q)x}{\alpha_1^2}\right) + \alpha_{-1}\left(\frac{q(1-x-z)(1-2q)z}{\alpha_{-1}^2}\right) + \alpha_0\left(\frac{4q^2xz}{\alpha_0^2}\right)\right)_1 \varepsilon^2 \\ &= \varepsilon^2(x\varphi_a + z\varphi_b). \end{aligned} \tag{16}$$

which we can replace in Equation (12) to rewrite the underpricing as

$$UP^C = \left(\frac{1-\pi}{1+\pi}\right)\eta + \frac{1}{\varepsilon}PostVar^C. \tag{17}$$

Given Equations (13) and (17), we can conclude that: 1. higher ex-post uncertainty always leads to more underpricing irrespective of the secondary market structure; 2. comparing the levels of underpricing on the two trading structures is equivalent to comparing the levels of ex-post uncertainty i.e. $PostVar^C$ with $PostVar^F$. The market that, ceteris paribus, can resolve the ex-post uncertainty more effectively will exhibit less underpricing. We address this question in the next section.

The previous results provide a theoretical foundation for our proxy of ex-post uncertainty developed in the empirical analysis.

2.5. Implications of the model

We are now able to draw some general conclusions about the comparison of the underpricing on the two trading structures as a function of the key parameters of our model.

Proposition 2.3: *Consider a firm selling S new shares and characterized by the vector of parameters* $(\eta, \varepsilon, \pi, q, x, z)$. *Then the firm's underpricing* UP^K *in a consolidated and fragmented market is characterized as follows:*

(i) UP^K *is decreasing with the proportion of uninformed trading in the primary market* π *for* $K = \{C, F\}$;

(ii) *UP^F is increasing with the probability of informed trading on the secondary market q, while UP^C is increasing with the probability of informed trading in the secondary market q for q sufficiently small and is decreasing with q for q sufficiently large.*

(iii) (iii) *ceteris paribus, $UP^F > UP^C$ when q is sufficiently small or sufficiently large.*

The results of Propositions 1–3 enable us to derive several interesting predictions. In terms of the relationship between underpricing and ex-post uncertainty, propositions 1 and 2 imply that:

1. *Underpricing in both markets depends positively on the level of ex-post uncertainty in the secondary market, that is the expectation of higher ex-post uncertainty in the aftermarket leads to a larger underpricing resulting from the primary market pricing process.*
2. *Differences in the level of underpricing between the two markets are only driven by the specific characteristics of the two trading platforms, ceteris paribus.*
3. *Underpricing will be lower on the market structure, which more effectively reduces ex-post uncertainty.*

As far as the comparison between the two trading structures is concerned, Proposition 3 delivers the following implications:

4. *For comparable levels of informed trading, ex-post uncertainty and underpricing are lower on consolidated markets than fragmented ones.*

This last point is linked to points (ii) and (iii) in Proposition 3, which discuss the relationship between ex-post uncertainty and the probability of informed trading in the secondary market. While this relationship is monotonic (increasing) in fragmented markets, for consolidated markets, ex-post uncertainty initially increases for a small level of informed trading but then starts decreasing for large values of informed trading. This stems from the information transmission that takes place in consolidated markets, whose benefit is greater, the larger the probability of informed trading. It is reasonable to expect that newly listed firms are characterized by a relatively large probability of informed trading in the aftermarket as a result of the high level of value uncertainty. In Point (iii) in Proposition 3, we show that ex-post uncertainty and underpricing are smaller in the concentrated market for small and large values of q, which defines the probability of informed trading in the secondary market.[20] *This, in turn, delivers the main prediction stated in point 4 above.*

3. Data

To test the predictions of our model, we use US IPO data between January 1, 2002, and May 30, 2008. This sample period includes a natural experiment triggered by the implementation of the opening IPO Cross on May 30, 2006, 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. The IPO Cross applies to all new issues and sets the official opening price. Its purpose *is 'to maximize transparency at the opening of secondary trading of an initial public offering (IPO) and provide fair executions at a single price that maximizes volume and is reflective of supply and demand in the market'* (Nasdaq 2006).[21] The Nasdaq IPO Cross therefore encourages by design the consolidation of supply and demand. Our hypothesis is that the consolidation of supply and demand contributes to a reduction of the ex-post uncertainty about the IPO value.

It should be noted that all markets were becoming increasingly fragmented post 2006 following the introduction of Regulation NMS towards the end of 2005 which encouraged the emerging of new trading venues that began to compete effectively with existing exchanges.[22]Therefore, we expect both samples to exhibit increased ex-post uncertainty due to increased fragmentation. In fact, the NYSE's market share in its listings declined from 79% in 2005 to 25% in 2009, while Nasdaq's combined market share in its listings declined from 52% in 2005 to 33% in 2009 following the introduction of Regulation NMS in 2005 (SEC 2013).[23] This motivates our choice of the sample period. Given the underlying trend towards an increased fragmentation, we would nonetheless expect that this is alleviated on Nasdaq by the introduction of the IPO Cross which is expected to increase consolidation, and in turn reduce ex-post uncertainty, relative to Nasdaq IPOs pre-Open IPO Cross and also to NYSE IPOs, post-IPO Cross.

Our final sample consists of 577 US-incorporated firms that went public on the NYSE, AMEX, ARCA, and Nasdaq between January 2002 and May 2008, extracted from the Securities Data Corporation (SDC) New Issues Database. We begin our sample on January 1, 2002 – after the tech bubble burst. To avoid contagion from the financial crisis in the last half of 2008 and to minimize the impact of the increasing fragmentation on both exchanges, as previously discussed, we end our sample on May 30, 2008.

The SDC offering date and market are cross-checked on the TAQ and CRSP databases. CRSP standard industry classifications (SIC) are used 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 database. Since our hypothesis is that the higher degree of consolidation in the IPO aftermarket on the NYSE and AMEX 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 164 exchange-listed stocks and 413 Nasdaq stocks. Data on the firm's age, underwriter's rank, all-star analysts ranking, as well as internet and tech IPOs are gathered from Jay Ritter's website.

Consistent with the IPO literature, our sample excludes investment funds (including mortgage securities), REITs, and real estate firms. Panels A and B of Table 2 contain a breakdown of the number of IPOs on exchanges versus Nasdaq for each sub-period. Examining the microstructure of markets in this latter sample, we find some challenges in determining the opening trade as well as order types. This is due to the increasing fragmentation of all markets during this latter period. Our first challenge is that in the period surrounding the introduction of the opening IPO Cross, some stocks have 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 stock opening 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.[24]

Regulation National Market System (Reg NMS), enacted in 2005, led to the implementation of new order types that 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 trading days in IPOs. These trades are included in our sample of trades.[25] To calculate BBO quotes, we include individual exchange quotes marked 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). Crossed and locked quotes are excluded, as well as any quote wider than $1.

4. Empirical results

The descriptive statistics for our sample are contained in Table 2. The IPO offering sizes become much larger over time. Overall, the average IPO is $178 million for 2002–2006 and $263 for 2006–2008. We find that average offering prices and first-day share volume follow a similar pattern.

The descriptive statistics reported in Table 2 indicates that the average IPO underpricing is comparable between Nasdaq and NYSE/AMEX IPOs in both sample periods.. Consistent with previous studies, we define the amount of underpricing as the offering price to closing price return on the first day of trading. We find that the NYSE/AMEX/ARCA offerings are around four times as large as the typical Nasdaq offering. In addition, the average exchange-listed IPO offering price is about 25% larger than the average Nasdaq IPO. Consistent with prior studies, we find that Nasdaq firms are younger and have higher daily volatility than exchange-listed firms.

4.1. Ex-post value uncertainty

Our model delivers two main predictions. First, it shows that residual uncertainty about firm value in the aftermarket positively affects the level of underpricing. Secondly, consolidated markets like the NYSE and Amex have lower ex-post uncertainty and underpricing than fragmented markets like Nasdaq. Our theoretical framework provides a clear suggestion as to the appropriate proxy to use to measure ex-post uncertainty. The framework suggests using the ex-post variance of the information revealed in the secondary market. Consistent with our model and Falconieri, Murphy, and Weaver (2009), we employ the standard deviation of quote midpoints over the first two hours of trading as an empirical proxy for ex-post value uncertainty. We focus on the first two hours of trading because, as discussed in our theoretical analysis, we are interested in investigating how different levels of fragmentation at the *opening* of trading of new stocks contribute to resolving any residual uncertainty, which in turn contributes to the level of underpricing.

From Table 2, we find that by the two subperiods of our sample, ex-post uncertainty is higher in exchanges compared to Nasdaq. The difference in means is not, however, statistically significant. Interestingly, the underpricing and ex-post uncertainty increased in both markets over the two subperiods 2002–2006 and 2006–2008. Comparing Panel A and Panel B in Table 2, the overall underpricing increased from an average of 11.26% in the subperiod 2002–2006 to an average of 15.12% in the subperiod 2006–2008. We observe the same trend for ex-post uncertainty (*PostUncer_2H*), which increased from 0.28 to 0.36. We observe the same trend for NYSE/AMEX (column 3) and Nasdaq IPOs (column 4). This suggests that our empirical analysis should disentangle the general trend of increased fragmentation in financial markets between 2002 and 2008 and the impact of the Nasdaq IPO Cross.

4.2. Ex-post value uncertainty, underpricing and market fragmentation

In this section, we test the first of our model's empirical predictions which suggests that underpricing is positively associated with the level of ex-post value uncertainty in the secondary market (as measured by the ex-post uncertainty proxy previously defined).

We do so by regressing the amount of underpricing on our ex-post uncertainty proxy while controlling for other variables known to be associated with underpricing. Hence, we perform the following regression of IPO underpricing

$$\begin{aligned} UP_i = \alpha &+ \beta_1 O\_Size_i + \beta_2 Vol_i + \beta_3 Revision_i + \beta_4 Ln(1+age)_i + \beta_5 Tech_i + \beta_6 Internet_i \\ &+ \beta_7 Top\_Tier_i + \beta_8 VC_i + \beta_9 All\_Star_i + \beta_{10} VC \times All\_Star_i + \beta_{11} N\_Pre\_IPOs_i \\ &+ \beta_{12} Overhang_i + \beta_{13} Ind\_Q_i + \beta_{14} Uncert\_2H_i + \beta_{15} Exchange_i + \beta_{16} Interact_i \\ &+ Year\ FE + Industry\ FE + \varepsilon_i \end{aligned} \tag{18}$$

where *UP* is defined as *(First-Day Closing Price – Offering Price)/Offering Price*. Our variable of interest, *PostUncer_2H*, is defined as the standard deviation of spread midpoints for the first two hours. It is possible that value uncertainty is not fully resolved in the first two hours of trading. To control for this, we also use a measure of the ex-post uncertainty for the remainder of day one (*Uncert_R*) as well as during the first two hours of day two (*Uncert_D*2_2).

We include a number of standard controls such as *O_Size* defined as the log of the IPO firm offering size (in millions of dollars). The offering size is a standard proxy for ex-ante uncertainty about the firm's value (Jenkinson and Ljungqvist 2001). *Vol* is the standard deviation of daily returns which control for market conditions; *Revision* is defined as *(Offering Price – Mid Range)/Mid Range*, where *Mid Range* is the midpoint of the originally filed price range which, according to the partial adjustment hypothesis (Hanley 1993) is expected to be positively related to the level of underpricing.[26] $Ln(1 + age)$ is the measure used in Loughran and Ritter (2004) where age is the number of years since the company was founded. *Internet*and *Tech* are dummy variables assigned the value of 1 if the IPO is an internet or technology IPO, respectively;*Top_Tier* is a dummy variable which takes the value one if the lead underwriter has an updated rank of 8 or higher and 0 otherwise (Carter and Manaster 1990). *VC* is also a dummy variable which is assigned the value one if the IPO is backed by a venture capitalist, and 0 otherwise; *All_Star* is also a dummy variable with the value one if the IPO was covered by an analyst featured by Institutional Investor as one of the top 3 all-star analysts within one year of the IPO and 0 otherwise. We also add the interaction term $VC \times AllStar$ as some papers suggest that the effect of VC backing is due to those IPOs being covered by all-star analysts (Liu and Ritter 2011; Bradley, Incheol, and Krigman 2015). *N_pre_IPO* is the number of IPOs in the same Fama and French 49 industry as the IPO for the previous five years (Liu and Ritter 2011). Aggarwal, Krigman, and Womack (2002) suggest that managers strategically underprice IPOs to create momentum that increases the firm's value so that they are then able to sell their stock at a higher price when the lock-up period expires. To account for this possible explanation of IPO underpricing, we include additional control variables, *Overhang* which is the ratio of retained shares to the percentage of total shares offered; and *Ind_Q* is the median firm Tobin's Q ratio for the year of the IPO for firms in the same Fama French industry.

Our second variable of interest is the interaction term *Interact*, defined as *Uncert_2H* times *Exchange,* where *Exchange* is a dummy variable assigned the value one if the IPO occurred on the NYSE/AMEX and 0 otherwise. Based on the predictions of our model, we expect the parameter estimate for this interaction variable to be negative and statistically significant. Lastly, we include industry (Fama and French 49 industries) and year fixed effects. The definitions of all the variables employed in our analysis are reported in Appendix 2.

The parameter estimates for our multivariate analysis are given in Table 3.[27] Column 1 in Table 3 reports the estimates of the regression model without an ex-post uncertainty measure. We find that the estimates for *Vol* and *Revision* are of the same sign as previous studies and statistically significant. In models (2) and (3), we add year and industry fixed effects, and results remain broadly unchanged compared to model (1) though some new additional variables turn significant with the expected sign. Model (4) includes our variable of interest, the standard deviation of spread midpoints for the first two hours. We find that the parameter estimate for the ex-post uncertainty measure is of the expected sign and statistically significant at the 5% level. We observe that the model R^2 increases from 0.22 to 0.48. This confirms that residual uncertainty is priced and is an important explanatory factor in IPO underpricing. Turning to our interaction variable (Model 5), we find that its parameter estimate is negative but statistically not significant. Ex-post uncertainty also becomes statistically significant at a 1 per cent level.

The interaction term becomes however negative and statistically significant when we also control for the standard deviation of spread midpoints for the remainder of the trading day, *Uncert_R*, (Model 6), and the beginning of the second trading day, *Uncert_D2_2H*, (Model 7). Overall, these results provide support to our model's predictions.[28]

4.3. Ex-post uncertainty and the Nasdaq opening IPO Cross

In this section we investigate the impact of the introduction of the Nasdaq opening IPO Cross. In order to minimize the potentially confounding effect of the underlying increase of fragmentation on both trading venues we estimate two different models.

The first model is the following OLS regression on the sample of Nasdaq IPOs only during our sample period:

$$\begin{aligned} PostUncert_i = \alpha &+ \beta_1 O_{Size\,i} + \beta_2 Vol_i + \beta_3 Revision_i + \beta_4 Ln(1+age)_i \\ &+ \beta_5 Internet_i + \beta_6 Tech_i + \beta_7 Top_{Tier\,i} + \beta_8 VC_i + \beta_9 All_{Star\,i} + \beta_{10} VC \\ &\times All_{Star\,i} + \beta_{11} N_{Pre_{IPOs}\,i} + \beta_{12} Overhang_i + \beta_{13} Ind_{Q_i} + \beta_{14} Post + FE + \theta_i \end{aligned} \quad (19)$$

where we are interested in the difference estimator of the treatment dummy *Post* which takes value 1 if the Nasdaq IPO occurs after the introduction of the IPO Cross and 0 otherwise.

We then also estimate a difference-in-differences regression model where Nasdaq IPOs (treated group) are compared to NYSE IPOS (control group) after the introduction of the IPO Cross (*treatment*) when controlling for variables associated with ex-post uncertainty:

$$\begin{aligned} Uncert_i = \alpha &+ \beta_1 O\_Size_i + \beta_2 Vol_i + \beta_3 Revision_i + \beta_4 Ln(1+age)_i + \beta_5 Internet_i \\ &+ \beta_6 Tech_i + \beta_7 Top\_Tier_i + \beta_8 VC_i + \beta_9 All\_Star_i + \beta_{10} VC \times All\_Star_i \\ &+ \beta_{11} N\_Pre\_IPOs_i + \beta_{12} Overhang_i + \beta_{13} Ind_{Q_i} + \beta_{14} NASDAQ_i + \beta_{15} Post_i \\ &+ \beta_{16} Nasdaq \times Post_i + FE + \theta_i \end{aligned} \quad (20)$$

All but three of the variables are as previously defined. We add *Nasdaq* defined as a dummy variable assigned the value of 1 if the IPO occurred on Nasdaq; *Post* is assigned the value one if the IPO occurs after the adoption of the Nasdaq IPO Cross, and, finally, the interaction term *Nasdaq* × *Post* whose coefficient estimate captures the *treatment effect*, i.e. differential impact of the trading innovation on the level of ex-post uncertainty of Nasdaq IPOs (*treated group*) relative to that of NYSE IPOs (*control group*), which according to our model riable should be negative and significant.

The results of the two estimations are reported in Table 4. Model (1) reports the difference estimator in equation (19). The coefficient of the variable *Post* is positive and not significant which indicates that the implementation of the IPO Cross on the Nasdaq counteracts the underlying trend to more fragmentation that characterizes the last part of our sample period. Model (2) reports instead the results of the Diff-in-Diff model in equation (20). In line with our model expectations, we note that the dummy Nasdaq is positive and statistically significant at 1% level, i.e. IPOs on the Nasdaq exhibit a larger ex-post uncertainty than IPOs on the NYSE over our sample period. Also, it is interesting to observe that the variable *Post* is positive and statistically significant, suggesting that overall IPOs after 2006 do exhibit a higher level of ex-post uncertainty which, as discussed above, might be explained by the increase in the level of fragmentation on all trading venues. Finally, the parameter for our variable of interest, Nasdaq × *Post*, is indeed negative as expected and statistically significant at 5 per cent level in line with our prediction, that following the innovation of the IPO Cross, new issues on Nasdaq tend to exhibit a reduction of the level of ex-post uncertainty relative to NYSE IPOs during the same period. Overall, our findings strongly suggest that a. the increasing fragmentation that characterizes the second part of our sample period did lead to higher ex-post uncertainty; and b. that this effect is mitigated for Nasdaq IPOs by the implementation of the opening IPO Cross.

Taken together, the results of Table 4 provide further support to the prediction of our theoretical model that consolidated trading structures are more effective at reducing ex-post uncertainty than fragmented markets as a result of price discovery being more efficient in consolidated market structures (Chen and Duffie 2021).

4.4. Controlling for price stabilization

One possible concern with the results of our analysis is that they might be biased by price stabilization efforts by the underwriters, which are particularly concentrated at the very beginning of the trading. To the extent that those IPOs that are not underpriced are subject to price stabilization, the proxy of ex-post uncertainty used in this paper will be understated and hence lead to spurious relationships. In our sample, nineteen per cent of our IPOs probably experience some price support since they are equal-priced or over-priced. However, the share of price-stabilized IPOs in consolidated markets is far larger than in fragmented markets (27% vs 17%).

We control for the possible existence of price support by rerunning all our regressions on a subsample of firms that only includes underpriced IPOs, and results remain qualitatively similar.

5. Conclusion

This paper develops and tests a theoretical model that compares the effect of different trading platforms on ex-post uncertainty, i.e. uncertainty about the firm's value in the aftermarket and, through this, on IPO underpricing. For the purpose of our analysis, the key dimension along which the trading structures are differentiated is the degree of fragmentation of the order flow, which is crucial for the resolution of the ex-post uncertainty.

Our model shows that underpricing increases in the ex-post uncertainty, and, more importantly, that a consolidated trading structure is more efficient in reducing ex-post uncertainty than a fragmented one. Our empirical analysis provides support to our model's predictions as it shows that after the introduction of the opening IPO Cross on Nasdaq in 2006, which amounts to an increase of consolidation for newly listed companies, the level of ex-post uncertainty of Nasdaq IPOs declined.

Our paper advances our understanding of the cost of fragmentation for newly listed firms which the existing literature has generally overlooked. In so doing, we contribute to the recent regulatory debate around whether newly listed firms should concentrate their trading on a single venue (Griggs 2017, WSJ). Our findings provide support for this view.

In our analysis, we use the market structure as our fragmentation measure. However, fragmentation might be affected by IPO-specific characteristics, depending on the attractiveness of the new shares. Stock-based measures of fragmentation only became available in 2012 following the introduction of the Market Information Data Analytics System (MIDAS) database. Using such data could allow to address other issues related to the trading strategies of institutional traders, underwriters, and block traders. This represents a promising avenue for future research.

Notes

1. National Securities Exchanges, www.sec.gov/fast-answers/divisionsmarketregmrexchangesshtml.html. Accessed February 12, 2021.
2. Alternative Trading Systems with Form ATS on File with the SEC as of December 31, 2020, accessed Februray 12, 2021.
3. 'Nasdaq Files to Terminate Unlisted Trading Privileges.' Traders Magazine Online, Posted February 6, 2020.
4. Nelson Griggs, 2017, A More Concentrated Market Would Help IPOs – WSJ.
5. See Ljungkvist (2007) for a review.
6. O'Hara and Ye (2011) point out that prior to the 2007 SEC mandate for exchanges to create and employ trade reporting facilities, the only suitable proxy for fragmentation was using design differences in venues such as the NYSE and Nasdaq. Accordingly, we follow the Securities and Exchange Commission (2001), and Bennett and Wei (2006) and use venue (NYSE v Nasdaq) as our proxy for fragmentation.
7. We stop our sample in 2008 to avoid the effect of the financial crisis but also the impact of the dramatic increase of fragmentation on the NYSE. Indeed the market share of the NYSE dropped from 80% in 2004 to 26% in 2009 (Angel et al. 2015).
8. http://www.nasdaqtrader.com/content/ProductsServices/Trading/IPOHalt/ipo_faq.pdf.
9. Cold IPOs are defined as those issued during periods of much lower IPO issuance, and fewer instances of oversubscription.
10. Commissioner Aguilar, L.A., 2015, 'Looking Back at The SEC's Transformation (and a few other things)', https://www.sec.gov/news/statement/commissioner-aguilar-looking-back-at-sec-transformation.html.
11. In line with our empirical analysis, we have in mind the very first hours after trading opens.
12. There are several papers (Hanley and Hoberg 2010; Loughran and McDonald 2011 and 2013; Falconieri and Tastan 2018) that do explicitly investigate whether the content (and tone) of the prospectus does help explain IPO pricing. They generally find that more and/or better information reduces IPO underpricing.
13. We assume that becoming informed in the secondary market is independent from having purchased shares in the primary market (Ellul and Pagano 2006)
14. In fact, assuming that the event 'no new information in the secondary market' occurs with a positive probability is equivalent to assuming that the signals in the two periods are correlated. To see how this is the case, consider the following alternative modeling choice which explicitly allows for a correlation between $\tilde{s}_1$ and $\tilde{s}_2$. In the secondary market investors learn a signal $\tilde{s}_2$ which can take three values 0, ϵ and $-\epsilon$ which are related to the realization of $\tilde{s}_1$ as follows

$$\Pr(\tilde{s}_2 = \varepsilon | \tilde{s}_1 = \eta) = \Pr(\tilde{s}_2 = -\varepsilon | \tilde{s}_1 = -\eta) = \mathrm{Q},$$
$$\Pr(\tilde{s}_2 = -\varepsilon | \tilde{s}_1 = \eta) = \Pr(\tilde{s}_2 = \varepsilon | \tilde{s}_1 = -\eta) = 0$$

and

$$\Pr(\tilde{s}_2 = 0 | \tilde{s}_1 = \eta) = \Pr(\tilde{s}_2 = 0 | \tilde{s}_1 = -\eta) = 1 - \mathrm{Q}.$$

This distribution is equivalent to the posterior distribution of $\tilde{s}_2$ in our current setting. The results would remain qualitatively the same although the computations would be more complicated.
15. We do not model the liquidity traders' arrival process. However, the simplifying assumption that a dealer can only handle one order at the time, not only spares us tedious computations that would not however change the quality of our results, but more importantly allows us to better isolate the impact of market fragmentation (Madhavan 1995).
16. We focus on the level of fragmentation as the distinguishing feature of alternative trading structure. In reality, trading platforms differ along other dimensions such as the price setting procedure for instance (Madhavan 1992)
17. This zero expected profits condition in a consolidated market, similar to the one imposed on fragmented markets, is justified because we think of the market maker competing with other liquidity providers. Imposing this condition allows us to focus only of the difference in the price discovery process between the two markets.
18. Although with more than one informed traders there would be more sophisticated stragegies that could emerge.
19. To keep calculations simple, we include in the price calculation the case where no order is submitted. However, our results remain qualitatively unchanged if we exclude this case.
20. While we cannot derive closed form solutions for intermediate levels of the probability of informed trading q, simulation analysis suggests the result also holds for large sets of the other model parameters values. Importantly, it is reasonable to expect a high level of informed trading for IPO firms for which there is a high degree of uncertainty. We omit the simulations for the sake of brevity but they are available from the authors upon request.
21. ipo_faq.pdf (nasdaqtrader.com)
22. The implementation of Regulation NMS was completed in 2007.
23. https://www.sec.gov/marketstructure/research/fragmentation-lit-review-100713.pdf
24. We find that the opening quote sometimes predates the opening trade by 2 s.
25. 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.

26. Hanley (1993) suggests using the price revision as a proxy for the information produced during the book building and shows that it is strongly positively correlated with the first day return. Cornelli and Goldreich (2002) find similar evidence.
27. As recommended by Belsley, Kuh, and Welsch (1980), in order to deal with possible outliers, we adjust for sample size (in this regression as well as all others employed) by excluding any observation that has a DFFITS statistic greater than $2 * \sqrt{(P/N)}$ where P is the number of parameters in the model and N is the number of observations. White consistent t statistics are in italics below each parameter estimate.
28. Jones, Kaul, and Lipson (1994) as well as Barinov (2014) suggest that share turnover is also a good proxy for uncertainty. Our results remain qualitatively similar if we use the percentage of offered shares turned over in the first two hours of trading in an IPO as our proxy for uncertainty. For the sake of brevity, the results are not included here, but are available from the authors upon request.
29. We only need to show that $z + \frac{q(1-x-z)^2}{q(1-x-z)+(1-2q)z} - \frac{qx(z-x)}{q(x+z)+(1-2q)(1-x-z)} \leq 1$. After some manipulations, we can show that the left hand side of Equation(A11) is equal to

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

which is lower than 1.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix 1: The Proofs

Proof of Proposition 1: We use the expected bid and ask prices that ensure the participation of investors in the IPO process (Equation (1)) and then derive the optimal IPO price in fragmented markets.

At $t = 0$, informed traders observe the value of $\tilde{s}_1$. They buy shares in the primary market only if the offering price is lower than their expected profits. From Equation (1), prices should then satisfy the following condition:

$$\begin{aligned} zE(P_1^{Fb}|\tilde{s}_1 = \eta) + (1 + x - z)E(\tilde{P}_2|\tilde{s}_1 = \eta) - xE(P_1^{Fa}|\tilde{s}_1 = \eta) \geq P_0^F \geq \\ zE(P_1^{Fb}|\tilde{s}_1 = -\eta) + (1 + x - z)E(\tilde{P}_2|\tilde{s}_1 = -\eta) - xE(P_1^{Fa}|\tilde{s}_1 = -\eta) \end{aligned} \quad (A1)$$

which, after using Equations (2) and (3), defining P_1^{Fb} and P_1^{Fa}, respectively, can be rewritten as

$$V + \eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon \geq P_0^F \geq V - \eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon. \tag{A2}$$

Equation (A2) states that informed agents will bid for shares in the primary market only if they receive a positive signal about the quality of the firm, i.e. if $\tilde{s}_1 = \eta$. We will check ex-post that the equilibrium offer price will indeed satisfy this condition.

For uninformed traders, Equation (1) can be written as:

$$zE(\tilde{P}_1^{Fb}|\Phi_0^u) + (1 + x - z)E(\tilde{P}_2|\Phi_0^u) - xE(P_1^{Fa}|\Phi_0^u) \geq P_0^F \tag{A3}$$

where Φ_0^u denotes their information set at $t = 0$. This includes only publicly available information at $t = 0$, i.e. the distributions of random variables and the information inferred from the offer price P_0^F. Additionally, uninformed traders anticipate that if they are allocated more shares in the IPO, then informed investors do not want to buy them, i.e. it is more likely that the signal about the firm's value is negative. Let π_u^F be the probability that uninformed traders receive shares when signals are of high quality and they bid P_0^F; and $(1 - \pi_u^F)$ be the probability that they receive shares when the signal is low quality. Then, the expected bid and ask prices from their perspective at t = *1* are

$$\begin{aligned} E(\tilde{P}_1^{Fb}|\Phi_0^u, P_0^F) &= \pi_u^F\left(V + \eta - \frac{q}{q+z}\varepsilon\right) + (1 - \pi_u^F)\left(V - \eta - \frac{q}{q+z}\varepsilon\right) \\ &= V - \frac{q}{q+z}\varepsilon - (1 - 2\pi_u^F)\eta \end{aligned} \tag{A4}$$

and

$$\begin{aligned} E(\tilde{P}_1^{Fa}|\Phi_0^u, P_0^F) &= \pi_u^F\left(V + \eta + \frac{q}{q+x}\varepsilon\right) + (1 - \pi_u^F)\left(V - \eta + \frac{q}{q+x}\varepsilon\right) \\ &= V + \frac{q}{q+x}\varepsilon - (1 - 2\pi_u^F)\eta. \end{aligned} \tag{A5}$$

And at $t = 2$

$$\begin{aligned} E(P_2|\Phi_0^u, P_0^F) &= \pi_u^F(V + \eta) + (1 - \pi_u^F)(V - \eta) \\ &= V - (1 - 2\pi_u^F)\eta. \end{aligned} \tag{A6}$$

Substituting into Equation (A3) gives the condition that ensures the uninformed investors' participation in the primary market:

$$V - (1 - 2\pi_u^F)\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon \geq P_0^F. \tag{A7}$$

As in Rock (1986), the equilibrium price in the primary market is dictated by the above constraint. Because $N < S$, the company will set the highest price P_0^F that satisfies the uninformed investors' participation constraint in the primary market in order to ensure that all the shares are sold. That is, the equilibrium price P_0^F is chosen, so that Equation (A7) holds an equality

$$P_0^F = V - (1 - 2\pi_u^F)\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon. \tag{A8}$$

Together with the feasibility constraint, $0 \leq \pi_u^F \leq 1$, Equation (A8) ensures informed traders' participation constraint holds. By its definition, we can rewrite the probability π_u^F as follows

$$\pi_u^F = \Pr(\tilde{s}_1 = \eta|\text{uninformed get shares}).$$

Uninformed investors get shares with probability one when the signal is bad, which occurs with probability $\frac{1}{2}$, and with probability $\pi = \frac{M}{(N+M)}$ when the signal is good, which again occurs with probability $\frac{1}{2}$. We can then write

$$\pi_u^F = \frac{\frac{M}{2(N+M)}}{\frac{M}{2(N+M)} + \frac{1}{2}} = \frac{\frac{M}{(N+M)}}{\frac{M}{(N+M)} + 1} = \frac{\pi}{1+\pi}. \tag{A9}$$

Replacing this into Equation (A8) allows us to rewrite the offer price as

$$P_0^F = V - \left(\frac{1-\pi}{1+\pi}\right)\eta - q\left(\frac{z}{q+z} + \frac{x}{q+x}\right)\varepsilon. \tag{A10}$$

By definition, underpricing is measured as the difference between the expected price at $t = 1$ and the primary market price, i.e. $E(\tilde{P}_1^F) - P_0^F$ with

$$E(\tilde{P}_1^F) = \Pr(\text{buy})E(P_1^{Fa}) + \Pr(\text{sell})E(P_1^{Fb})$$

where $\Pr(\text{buy}) = \frac{x+q}{2q+x+z}$ and $\Pr(\text{sell}) = \frac{z+q}{2q+x+z}$. Simple computations yield $E(\tilde{P}_1^F) = V$. From this, it is straightforward to derive the level of underpricing in fragmented markets as stated in Equation (4) in Proposition 1. ■

Proof of Proposition 2: Using the prices $P_A{}^C(A)$ with A = −2,−1,0,1,2 derived in Equation (6) to Equation (10), we first need to check that informed traders will behave consistently with the information received. In other words, an informed trader with a negative [positive] signal will submit a sell [buy] order. At $t = 1$ an informed trader's expected price conditional on receiving a negative signal is given by

$$\begin{aligned} E(P_1^C|\tilde{s}_1, u_i = -\varepsilon) &= zP_1^C(-2) + (1-x-z)P_1^C(-1) + xP_1^C(0) \\ &= V + \tilde{s}_1 - \left(z + \frac{q(1-x-z)^2}{q(1-x-z)+(1-2q)z} - \frac{qx(z-x)}{q(x+z)+(1-2q)(1-x-z)}\right)\varepsilon \end{aligned} \tag{A11}$$

which can be shown to be larger than $V + \tilde{s}_1 - \varepsilon$, i.e. his payoff if he liquidates his shares at $t = 2$.[29] Symmetrically, at $t = 1$, the expected price of a buy order for an informed trader with a positive signal is

$$\begin{aligned} E(P_1^C|\tilde{s}_1, u_i = \varepsilon) &= xP_1^C(2) + (1-x-z)P_1^C(1) + zP_1^C(0) \\ &= V + \tilde{s}_1 + \left(x + \frac{q(1-x-z)^2}{q(1-x-z)+(1-2q)x} + \frac{qz(z-x)}{q(x+z)+(1-2q)(1-x-z)}\right)\varepsilon \end{aligned} \tag{A12}$$

which again can be shown to be smaller than the payoff he will receive if he liquidates his shares at $t = 2$. We can now derive the share price in the primary market. Both types of traders will use Equation (1) in order to choose their strategies. At $t = 0$, informed traders observe the value of $\tilde{s}_1$, hence they will bid for shares 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 is

$$\begin{aligned} &zE(\tilde{P}_1^C|sell, \tilde{s}_1 = \eta) + (1+x-z)E(\tilde{P}_2|\tilde{s}_1 = \eta) - xE(P_1^C|buy, \tilde{s}_1 = \eta) \geq P_0^C \geq \\ &zE(\tilde{P}_1^C|sell, \tilde{s}_1 = -\eta) + (1+x-z)E(\tilde{P}_2|\tilde{s}_1 = -\eta) - xE(P_1^C|buy, \tilde{s}_1 = -\eta). \end{aligned} \tag{A13}$$

Note that the expected value of $\tilde{P}_2$ conditional on the value of $\tilde{s}_1$ is equal to $V + \eta$ $(orV - \eta)$ when the signal is positive (negative). However, $E(P_1^C|buy,\tilde{s}_1 = \eta)$ depends on the aggregate demand in the secondary market and, conditional on the informed trader submitting a sell order at $t = 1$, can be either $P_1^C(-2)$, $P_1^C(-1)$, or $P_1^C(0)$. This implies that

$$E(\tilde{P}_1^C|sell, \tilde{s}_1 = \eta) = qE(\tilde{P}_1^C(-2)|\tilde{s}_1 = \eta) + (1-2q)E(\tilde{P}_1^C(-1)|\tilde{s}_1 = \eta) + qE(\tilde{P}_1^C(0)|\tilde{s}_1 = \eta) \tag{A14}$$

which, after substituting Equations (7), (9) and (11), can be rewritten as

$$\begin{aligned} E(\tilde{P}_1^C|sell, \tilde{s}_1 = \eta) &= q(V+\eta-\varepsilon) + q\left(V+\eta+\frac{q(z-x)}{\alpha_0}\varepsilon\right) + (1-2q)\left(V+\eta-\left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon\right) \\ &= V+\eta+q\left(-1+\frac{q(z-x)}{\alpha_0}-\frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right)\varepsilon = V+\eta-\varphi_b\varepsilon \end{aligned} \tag{A15}$$

with

$$\varphi_b = q\left(1 - \frac{q(z-x)}{\alpha_0} + \frac{(1-2q)(1-x-z)}{\alpha_{-1}}\right). \tag{A16}$$

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

$$\begin{aligned} E(\tilde{P}_1^C|buy, \tilde{s}_1 = \eta) &= qE(\tilde{P}_1^C(2)|\tilde{s}_1 = \eta) + (1-2q)E(\tilde{P}_1^C(1)|\tilde{s}_1 = \eta) + qE(\tilde{P}_1^C(0)|\tilde{s}_1 = \eta) \\ &= q(V+\eta+\varepsilon) + (1-2q)\left(V+\eta+\left(\frac{q(1-x-z)}{\alpha_1}\right)\varepsilon\right) + q\left(V+\eta+\frac{q(z-x)}{\alpha_0}\varepsilon\right) \\ &= V+\eta+\varphi_a\varepsilon \end{aligned} \tag{A17}$$

With

$$\varphi_a = q\left(1 + \frac{q(z-x)}{\alpha_0} + \frac{(1-2q)(1-x-z)}{\alpha_1}\right). \tag{A18}$$

By substituting into Equation (A13), we can check that the informed agents' participation constraint is satisfied. As in the case of fragmented markets, we also have to ensure that at $t = 0$ the uninformed investors' participation constraint is satisfied. That is,

$$zE(\tilde{P}_1^C|sell, \Phi_0^u) + (1+x-z)E(\tilde{P}_2|\Phi_0^u) - xE(P_1^C|buy, \Phi_0^u) \geq P_0^C \tag{A19}$$

where Φ_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^C. Uninformed traders anticipate they will receive all the shares when informed investors do not bid because they observed a negative signal. Let π_u^C the probability that, at the offer price P_0^C, uninformed traders get shares when the signal is positive ($\tilde{s}_1 = \eta$) and $(1 - \pi_u^C)$ the probability that they get shares when the signal is negative ($\tilde{s}_1 = -\eta$).

Consequently, at $t = 1$ the expected prices from the perspective of uninformed traders are defined as follows

$$\begin{aligned} E(\tilde{P}_1^C|sell, \Phi_0^u, P_0^C) &= \pi_u^C(E(\tilde{P}_1^C|sell, \tilde{s}_1 = \eta)) + (1-\pi_u^C)(E(\tilde{P}_1^C|sell, \tilde{s}_1 = -\eta)) \\ &= \pi_u^C(V + \eta - \varphi_b\varepsilon) + (1-\pi_u^C)(V - \eta - \varphi_b\varepsilon) \\ &= (V - \varphi_b\varepsilon) - (1 - 2\pi_u^C)\eta \end{aligned} \tag{A20}$$

and

$$\begin{aligned} E(\tilde{P}_1^C|buy, \Phi_0^u, P_0^C) &= \pi_u^C(E(\tilde{P}_1^C|buy, \tilde{s}_1 = \eta)) + (1-\pi_u^C)(E(\tilde{P}_1^C|buy, \tilde{s}_1 = -\eta)) \\ &= \pi_u^C(V + \eta + \varphi_a\varepsilon) + (1-\pi_u^C)(V - \eta + \varphi_a\varepsilon) \\ &= (V + \varphi_a\varepsilon) - (1 - 2\pi_u^C)\eta. \end{aligned} \tag{A21}$$

Similarly, the expected price at $t = 2$ is

$$E(P_2|\Phi_0^u, P_0^C) = \pi_u^C(V + \eta) + (1-\pi_u^C)(V - \eta) = V - (1 - 2\pi_u^C)\eta. \tag{A22}$$

Substituting into Equation (A19) yields

$$V - (1 - 2\pi_u^C)\eta - (z\varphi_b + x\varphi_a)\varepsilon \geq P_0^C. \tag{A23}$$

As in fragmented markets, the issuer will set the highest price P_0^C that allows uninformed investors to participate in the market in order to ensure that all the shares are sold. Therefore, the equilibrium offer price is

$$P_0^C = V - (1 - 2\pi_u^C)\eta - (z\varphi_b + x\varphi_a)\varepsilon. \tag{A24}$$

Since $0 \leq \pi_u^C \leq 1$, we can verify if Equation (A13) holds. We begin by observing that probability π_u^C has exactly the same interpretation in consolidated markets as in fragmented markets and $\pi_u^C = \pi_u^F = \frac{\pi}{1+\pi}$. Substituting these values into Equation (A24) gives

$$P_0^C = V - \left(\frac{1-\pi}{1+\pi}\right)\eta - (z\varphi_b + x\varphi_a)\varepsilon. \tag{A25}$$

Finally, we need only to show that $E(\tilde{P}_1^C) = \text{V}$. We can see that

$$\begin{aligned} E(\tilde{P}_1^C) &= \sum_A \Pr(Order = A)P_1^C(A) \\ &= qz(V + \tilde{s}_1 - \varepsilon) + \alpha_{-1}\left(V + \tilde{s}_1 - \left(\frac{q(1-x-z)}{\alpha_{-1}}\right)\varepsilon\right) + \alpha_0\left(V + \tilde{s}_1 + \frac{q(z-x)}{\alpha_0}\varepsilon\right) \\ &+\alpha_1\left(V + \tilde{s}_1 + \left(\frac{q(1-x-z)}{\alpha_1}\right)\varepsilon\right) + qx(V + \tilde{s}_1 + \varepsilon) = V. \end{aligned} \tag{A26}$$

Using this in the definition of underpricing completes the proof. ■

Proof of Proposition 3: (i) We can easily see that underpricing in both structures is a decreasing function of π.
(ii) The first derivative of UP^Fconcerning q is equal to

$$\frac{z^2}{(\text{q}+z)^2} + \frac{x^2}{(\text{q}+x)^2}$$

Which is always positive. ■

For UP^C, we need the computation of the derivative of $(\text{q}(x\varphi_a + z\varphi_b)\varepsilon)$ with respect to q. After some manipulations, we can write this derivative as follows:

$$\begin{aligned} &(x+z)(1-x-z)\frac{[-2(x+z)(\text{q})^2 + (1-x-z)(1-2\text{q})^2]}{(q(x+z) + (1-2\text{q})(1-x-z))^2} + z(1-x-z)\left[\frac{-2(1-x-z)(\text{q})^2 + z(1-2\text{q})^2}{(\text{q}(1-x-z) + (1-2\text{q})z)^2}\right] \\ &+x(1-x-z)\left[\frac{-2(1-x-z)(\text{q})^2 + x(1-2\text{q})^2}{(\text{q}(1-x-z) + (1-2\text{q})x)^2}\right] + 4xz\text{q}\left[\frac{(\text{q}(x+z) + 2(1-\text{q})(1-x-z))}{(\text{q}(x+z) + (1-2\text{q})(1-x-z))^2}\right] \end{aligned} \tag{A28}$$

When q is small, i.e. when it converges to zero, the first derivative converges to $(2 - x - z)$, which is positive. For large values of q, i.e. when it converges to $1/2$, the first derivative converges to $[[-2(x-z)^2 - 4xz(x+z)]/(x+z)^2]$, which is negative.

iii. We focus on comparing the ex-post variances because the components of the underpricing coming from the primary market are the same for the two structures. Note that for $K = \{C, F\}$, $PostVar^K$ converges to zero when q is close to zero. In addition, From Equation (A27), the first derivative of $PostVar^K$ with respect to q is positive but converges to 2 as q converges. For consolidated markets, as q converges to zero, by Equation (A28), the first derivative of $PostVar^C$ converges to $(2 - x - z)$. Therefore, in both cases, the ex-post variance would originate from zero and increase, but in fragmented markets, it would increase more quickly as the first derivative is larger than in consolidated markets. This implies that $PostVar^F$ is larger than $PostVar^C$ for small values of q.

When q is sufficiently large, i.e. converges to 1/2, then UP^F and UP^C converge to $\left(\frac{1-\pi}{1+\pi}\right)\eta + \frac{1}{2}\left(\frac{x}{\left(\frac{1}{2}+x\right)} + \frac{z}{\left(\frac{1}{2}+z\right)}\right)\varepsilon$ and $\left(\frac{1-\pi}{1+\pi}\right)\eta + \left(\frac{2xz}{x+z}\right)\varepsilon$, respectively. We can show that for all (x, z) such $x + z \leq 1$, the degree of underpricing is lower in consolidated markets at the limit. This should be the case for values sufficiently close to the highest value by continuity.