Come On In, the Water’s Fine! An Experimental Examination of Hybrid IPO Auctions with a Public Pool

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Abstract. We offer experimental and theoretical evidence that the auction method for initial public offerings (IPOs) may be improved through the use of hybrid auctions with separate retail tranches or ‘public pools’. Such hybrids, which combine a price-setting tranche (an auction or book building) with a separate tranche that allows investors to place orders without specifying a price (the public pool), have been used for IPOs around the world. We develop theory, then run laboratory experiments to examine the effects of a public pool on multi-unit uniform price auction IPOs. Our experimental auction design incorporates key features of the IPO process such as endogenous bidder entry, costly information acquisition, differing capacity constraints and uncertainty with respect to the intrinsic value. Simulations are used to characterize the Symmetric Bayesian Nash Equilibria (SBNE) for both pure and hybrid auctions in a model that is calibrated to key parameters from our experimental data, generating predictions for the remaining variables. As predicted, a public pool tranche improves auction performance by increasing proceeds, lowering price volatility, reducing price error and reducing the incentive for small bidders to free ride by submitting extremely high bids. Underpricing occurs in both treatments but is less severe with the public pool. We also show that in collusive-seeming multi-unit auction equilibria, it may be optimal for informed, rational bidders to place clinching bids strictly above the expected value per unit, leading to very steep demand curves. Overall, our results imply that both IPO auctions and crowdfunding may be improved by restricting retail investors to a separate, non-price-setting tranche.

Keywords: Common value auction, Experimental, Competitive bidding, Initial public offering, Uniform price auction, Hybrid auction, Retail tranche, Public pool, IPO auction, crowdfunding, JOBS Act.

JEL Classification: C92, D02, D44, G02
I. Introduction

The method used for initial public offerings (IPOs) in the United States (US), known as book building, has long been controversial because of the magnitude of average underpricing, the variability of initial returns and the conflicts of interest between issuers and underwriters. Ritter (2011) discusses the CLAS controversies (Commissions for IPOs, Laddering, Analyst conflicts of interest and Spinning) and argues that agency problems between issuers and underwriters are of first-order importance in explaining the magnitude of underpricing, leading to questionable allocation practices that preclude participation by many investors.\(^1\) Many have suggested auctions as an alternative, given the success of auctions in other financial markets such as for issuing government debt securities. After all, the surest way to prevent agency conflicts is to take decisions out of the hands of the agent, which is what a standard sealed bid auction does for IPO pricing – uses pre-established rules to price the shares based on bids, rather than giving discretion to the underwriter. IPO auctions offer transparent allocation and pricing rules, and open access to retail investors.

Surprisingly, however, auctions have not so far been a successful alternative for IPOs, either in the US or elsewhere. Sealed bid auctions have been tried for IPOs in more than two dozen countries, but issuers have consistently abandoned the auction method in favor of other alternatives.\(^2\) The experimentation with new IPO methods such as auctions began with the trend

\(^1\) On the other hand, Sherman (2000) models the effect of the one price rule for US IPOs when there is more than one type of investor. If IPO shares must be underpriced for some investors (for example, to attract attention or induce costly evaluation), then the one price rule means that other investors will get excess returns unless the underwriter can somehow recapture some of that excess. Thus, many of the allocation practices described by Ritter (2011) may occur without affecting the level of underpricing. See also Loughran and Ritter (2004) for discussion of the scandals and overall trends in IPO underpricing, and Ritter and Welch (2002), Ljungqvist (2007), and Wilhelm (2005) for reviews of the academic IPO literature.

\(^2\) Jagannathan, Jirnyi and Sherman (2015) document the disappearance of auction IPOs, and find that it was not driven by regulatory changes that restricted their use (although in some cases, such as France and Japan, the shift was made possible by regulations allowing greater use of other methods).
in the 1980s and 1990s toward privatization of formerly government-owned companies in areas such as telecommunications. Auctions were often initially popular for IPOs, but then issuers returned to their traditional method, the fixed price public offer. Most countries later adopted the book building method that originated in the US. The only country in which IPO auctions are commonly used today is Vietnam, which is still transitioning away from a planned economy through the privatization of state-owned enterprises.

Given the many well-established advantages of auctions and yet their consistent unpopularity for IPOs, one explanation for the discrepancy is that the standard sealed bid auction format is not as well suited to IPOs as to, say, Treasury securities. Price discovery is less of an issue for Treasury securities, which are high quality debt instruments that are already trading in many forms (the when issued market, the off the run issue, etc.), with a stable number of large dealers that bid for them regularly. IPO firms tend to be small, young companies that have not been previously traded, companies likely to grow and change dramatically and unpredictably in the next few years. They come from a variety of industries and may each appeal to a different set of investors. Such different securities may require a different auction format.

Thus it is worth exploring ways to design auctions that are better suited to an IPO environment. Biais and Faugeron-Crouzet (2002) was the first paper to model this, exploring the effects of the frequent IPO auction practice of setting the offer price strictly below the market clearing price (known as a “dirty” auction or as “leaving something on the table”). We focus on

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3 A public offer, also known as an open offer, a universal offer or often simply as “the IPO method,” is one in which the price is set in advance and the issuer/underwriter does not have discretion regarding individual allocations. Typically, the process is open to all retail investors in the country on a more or less equal basis, and balloting (a type of lottery) is used to allocate shares in case of oversubscription. A public offer is strictly an allocation method, as opposed to a price-setting method.

4 The differences are even wider between Treasury securities and equity investments in early stage private companies. Thus this research has implications for the crowdfunding made possible in the US by the JOBS (Jumpstart Our Business Startups) Act. These implications are discussed briefly in the conclusion.
another common feature of IPOs – the use of hybrids, with separate retail tranches or ‘public pools’.\(^5\) Our paper offers experimental and theoretical evidence that the inclusion of a public pool may improve the auction method for IPOs.

We first examine the extent to which free-riding, inaccurate pricing and variability in auction outcomes arise in a uniform price auction with endogenous costly information acquisition. Next, we determine whether the introduction of a public pool tranche can be used to reduce the problems that have been identified. We accomplish this by conducting a laboratory experiment which incorporates key features of an IPO auction environment, including endogenous entry and bidders of different bidding capacities. A major advantage of experimental over ‘real world’ bidding data is that we know the information set and budget constraints of each bidder, and thus do not have to speculate over, for example, whether a bidder is informed. The hypotheses that we test are based on the use of simulations to identify the Symmetric Bayesian Nash Equilibrium (SBNE) for both the pure and the hybrid auctions.\(^6\)

We employ a uniform price auction in order to highlight the implications of free riding for auction performance: under uniform pricing, all shares are sold at the market clearing (stop-out) price, with at least partial allocations received by all bidders with bids at or above this price. Therefore, sufficiently small bids at high prices can be used to lock in allocations with potentially no impact on price. If small bidders expect the market clearing price to be

\(^5\) These public pools originated from the traditional fixed price public offer method, where investors could ask for share allocations but were not involved in setting the offer price. Given the long tradition of allowing all retail investors to order shares in each IPO, most countries that experimented with first the auction and then the book building method continued to allow retail investors to participate – in much the same way as before – through a retail tranche or public pool. Thus, hybrid IPOs with a public pool are common internationally, although usually the book building rather than the auction method is used to set the offer price.

\(^6\) Throughout the paper, we use the term “symmetric” to mean symmetric within each investor group, given that our experiments each have four large and four small bidders, with different capacity constraints. Thus we consider a set of strategies to be symmetric even if large and small bidders follow different strategies, as long as there are no strategy differences within each size group.
appropriately set by informed bidders, a uniform price auction allows them to “free ride” off of the information of others through these high bids.\(^7\)

Our analysis highlights the problem of endogenous entry in multi-unit sealed bid auctions. Sherman (2005) models both uniform price and discriminatory multi-unit auctions in an environment with two key IPO features: endogenous entry and costly information acquisition.\(^8\)

A major problem with auctions that are open to large numbers of potential bidders is that, when there are many potential entrants and each is not compelled to evaluate or participate in any particular offering, bidders face an environment of substantial uncertainty. Bidders in a common value auction need to shave their bids for the winner’s curse, and the degree of that shaving should depend on the number of other bidders. Without coordination however, bidders do not know how much to shave their bids because they do not know the number of other bidders.

Ex post, IPO auction bidders may learn that they have shaved their bids either too little or too much, leading to mispricing: too few entrants may result in excessive underpricing or even

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\(^7\) Sherman (2005) was the first to point out this potential problem for uniform price multi-unit auctions that are open to large numbers of potential bidders. Examples of such excessively high bids are provided by Degeorge, Derrien and Womack (2010) for the US and by Jagannathan, Jinji and Sherman (2015) for several countries.

\(^8\) Both uniform price and discriminatory sealed bid auctions have been used for IPOs in various countries. There has been considerable progress in analyzing these two main types of multi-unit auctions, but the definitive determination of the optimal mechanism is difficult because the strategy space is large and there often exist multiple equilibria. The theory of multi-unit auctions shows that there exist noncooperative equilibria under the uniform price format that support outcomes in which the auction’s stop-out or market clearing price is much lower than the value of the asset offered for sale (See for example Wilson (1979), Back and Zender (1993), Ausubel and Cramton (1996) and Wang and Zender (2002)). Since the discriminatory auction does not allow such equilibria, the question becomes whether the more severe winner’s curse of the discriminatory format is less costly than the “collusive-looking” outcomes that are possible with uniform pricing. Morales-Camargo, Sade, Schnitzlein, and Zender (2013) use experimental methods to compare uniform and discriminatory auctions with both symmetric and asymmetric information and find similar performance with symmetric information, but higher seller revenue with the discriminatory auction under asymmetric information. Recent studies (Kremer and Nyborg (2004a, b), Back and Zender (2001), and Damianov (2005)) have investigated whether collusive-like equilibria still obtain if features of the auction are modified (changing demand functions from continuous to discrete, changing the rationing rule, and introducing endogenous supply). All these studies show that the set of underpricing equilibria can be eliminated or reduced. Sade, Schnitzlein, and Zender (2006a,b) use experimental methods to show that endogenous supply or differing capacity constraints among bidders promote competitive outcomes in uniform price auctions. We show that endogenous entry (and hence endogenous, uncertain demand) serves the same role, and arises naturally for IPOs.
in a failed offering, while too many entrants may lead to overpricing. If bidders shave their bids even more on average because of this risk, then the seller’s expected proceeds are reduced. If an IPO auction could be structured to lower this uncertainty, the auction method might be more popular with issuers.

Adding a public pool tranche has potentially important implications for the performance of the auction. It allows less sophisticated retail investors to participate without directly affecting the market clearing price, which may in turn encourage the participation of retail investors and “democratize” access to equity offerings. Institutional investors may also be more willing to participate and acquire information if there is less risk of mispricing, and issuers may prefer a more stable process.

Recent empirical evidence calls into question the ability of retail investors to accurately price IPO shares. For example, in a study of IPO discriminatory auctions in Taiwan, Chiang, Qian, and Sherman (2010) show that individual retail investors as a group exhibit return-chasing behavior, are uninformed, and systematically overbid. Chiang, Hirshleifer, Qian and Sherman (2011) further show that the individual retail bidders in Taiwan suffer from naïve reinforcement learning – those that get a high return in their first auction are more likely to bid again, but they bid more aggressively and their returns get significantly lower until they finally give up. Institutional bidders, on the other hand, are informed and do not suffer from these problems. Neupane and Poshakwale (2012) study IPOs in India and find evidence that, due to aggressive bidding by overconfident investors, retail investors are on average unlikely to make positive returns even in a setting where they do not have to compete with institutional investors.

Although a public pool tranche has not yet been employed for IPO auctions in the United States, a seemingly similar approach – noncompetitive bids – are a standard feature of U.S.
Treasury auctions. According to the Joint Report on the Government Securities Market (1992), the Treasury permits noncompetitive bidding in order to make it easier for smaller, less sophisticated bidders to participate. However, noncompetitive bids as used in Treasury auctions do not have the same advantages as a separate retail or public pool tranche, because the number of noncompetitive bids is not limited (although the size of each bid is). Instead, the total quantity of noncompetitive bids is simply subtracted from the number of shares to be auctioned, and thus noncompetitive bids function similarly to high free-riding bids, rather than reducing uncertainty in the way that a public pool might.

In this paper, we first use simulations to find the SBNE. With no uncertainty over the number of bidders and with rational bidders following symmetric strategies, we find that it is optimal for even informed investors to appear to ‘free ride’ by placing some high clinching bids, strictly above the expected value based on the informed investor’s signal. The collusive-seeming equilibria involve both bidding strictly below the expected value for some units, so that the market-clearing bid prices the shares at a discount, and bidding strictly above the expected value for others, in order to lock in or clinch a certain number of shares. The key is that the high bids are for carefully-limited quantities, to avoid the risk that they will set the clearing price.

When we add uncertainty over the number of bidders, we find that the optimal number of high bids is reduced. This result is consistent with theoretical work such as Back and Zender (2001), Damianov (2005) and McAdams (2007), as well as experimental work in Sade, Schnitzlein and Zender (2006a), that collusive-seeming equilibria can be reduced by creating uncertainty or variation regarding the supply of shares. In an IPO setting, substantial uncertainty over the number of bidders occurs naturally, generally offsetting the need to introduce artificial uncertainty to discourage collusive-seeming equilibria. Instead, reducing risk may offer greater
benefits for both issuers and investors, as we show.

Next we calibrate our model to the observed entry and information-purchase probabilities of our experimental results, and analyze the resulting SBNE for both the pure and hybrid auctions. This generates predictions regarding the effects of adding a public pool, which we compare to the results of our experiments. We expect hybrids to have less underpricing, less apparent free riding by both small and large investors, less risk of a failed auction (from too few bids), less price uncertainty and lower pricing error.

Our main experimental results are as follows. We find that incorporating a public pool tranche improves performance, resulting in significantly higher seller’s proceeds, lower price error and lower price volatility. Consistent with the predictions from our simulations, significant underpricing occurs in both treatments but is less severe for the hybrid auction. The public pool option significantly increases the small investor participation rate and reduces small bidder free riding. These benefits occur even though the pool is optional, with small, uninformed investors freely allowed to participate in the price-setting or auction tranche.

The plan of the paper is as follows. In section 2 we discuss the relevant literature, while in section 3 we explain the experimental design. In section 4, we theoretically analyze the environment that is used in our experiments, using simulations to find the optimal symmetric strategies for each of the two bidder types, and characterize the SBNE given the observed entry and information purchase probabilities. This gives us predictions regarding the effects of adding a public pool. In section 5, we present our results and compare them to the predictions from section 4. In section 6 we discuss our results and conclude.

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9 In addition to information and opportunity costs, the decisions to enter an auction and to purchase information may depend on risk preferences and expectations, neither of which are modeled.
2. Relevant Literature

This paper contributes to both the finance literature on IPOs and the economics literature on auctions. We will first discuss empirical work on IPO auctions. Although more than two dozen countries have used the sealed bid auctions for IPOs, the auction method often died out too soon to produce a large sample. Nevertheless, much work has been done with the relatively limited amount of data available.

The most successful IPO auctions were in France, where auctions were used for many years alongside the fixed price public offer method and even survived the first few years after a restricted form of book building was introduced. Initially, the hybrid book building method in France was sequential rather than simultaneous, meaning that the book-build was done first, followed by a minimum delay of 5 days for the public pool to be conducted. As the modeling in Chowdhry and Sherman (1996) demonstrates, requiring the price to be set far in advance adds risk, leading to higher levels of underpricing. Derrien and Womack (2003) found that the delay put book building at a significant disadvantage in France. Once the more common simultaneous hybrid book building method was allowed in France in 1999, auctions quickly vanished from the regulated exchanges.

In terms of numbers, the largest sample of IPO auctions is from Japan, which required all issuers to use sequential hybrid discriminatory auctions from 1989 to 1997. Once book building was allowed in 1997, auctions quickly vanished. Kutsuna and Smith (2004) found a small but statistically significant increase in initial returns under book building, relative to the earlier

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10 They found that the differences in underpricing between auctions and book building were “small and statistically insignificant when examined unconditionally” (page 47), but auctions were better than the sequential hybrid book-builds in their “ability to incorporate more information from recent market conditions into the IPO price” (abstract).

11 With the exception of two IPO auctions in 2005, Cafom and MG International, which were arguably an echo of the Google IPO auction in 2004. Simultaneous hybrids are also described as “open pricing”.
auctions (after adjusting for market conditions), and also found that a wider range of companies, including younger start-ups, were able to go public under book building.

Taiwan used both auctions and fixed price public offers from 1995 to 2003, completing more than 90 auctions. Taiwan’s discriminatory hybrid auctions were very similar to Japan’s original design (which Japan later changed due to problems with overpricing). Taiwan’s data has been analyzed by Liu, Wei and Liaw (2001), Hsu and Chiu (2004), Chiang, Qian and Sherman (2010) and Chiang, Hirshleifer, Qian and Sherman (2011), among others.

Other papers have examined smaller samples. The US has completed a total of 23 IPO auctions between 1999 and 2014, the most recent of which was Truett-Hurst Winery in June of 2013. DeGeorge, Derrien and Womack (2010) examined detailed data on 19 of these (with flipping data on 11 of the 19), while Lowry, Officer and Schwert (2010) studied the first 16 US IPO auctions, through the end of 2005, and Pukthuanthong Varaiya, and Walker (2006) examined the first 11 IPO auctions, through the end of 2004.12 Kandel, Sarig and Wohl (1999) explored 28 IPO auctions in Israel, and Jagannathan, Jirnyi and Sherman (2015) examined the full sample of 20 IPO auctions done in Singapore.

In summary, empirical research on IPO auctions has examined many different types of auctions: uniform price or discriminatory, simultaneous or sequential hybrids, some with special features such as in France or the US. The results have varied, and often the available sample was too small to draw more than tentative conclusions. Hence there is a role for experimental

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12 US IPO auctions also have some unusual features, the most striking of which is the fact that, for most or all of the later WR Hambrecht OpenIPOs, the underwriter reserved the right to communicate “general auction trends” to institutional, but usually not retail, bidders. This practice brings the auctions closer to the book building method but makes it difficult to interpret the findings in DeGeorge, Derrien and Womack (2010) that the final bids of institutional investors were more clustered around the offer price, relative to the final bids of retail investors. The two-way flow of information between WR Hambrecht and institutional bidders makes these ‘elasticities’ difficult to interpret. Rather than using elasticities/bid clusters, Chiang, Qian and Sherman (2010) use the auction theory in Sherman (2005) to develop tests of whether specific groups of auction bidders are informed.
research on how to improve the auction method within the IPO setting. Bonini and Voloshyna (2013) took this approach, using experiments to compare standard uniform price auctions and book building to competitive IPOs and Ausubel auctions. In our paper, we focus on a relatively straight-forward change to standard auctions, to improve their performance by simply adding a public pool such as those frequently added to book building outside the US.

In terms of theory, the first paper to explore ways that standard auctions could be adjusted to suit IPO characteristics was Biais and Faugeron-Crouzet (2002), which showed that although the optimal mechanism resembles book building in their environment, a modified auction can come close to the same outcome. Spatt and Srivastava (1991) took a mechanism-design approach, finding that the optimal auction in their environment incorporates both pre-play communication and participation restrictions.

French and McCormick (1984) were the first to model endogenous entry in single-unit auctions, showing that auction bidders may recover their fixed evaluation costs (in other words, that there will be underpricing). However, they assume that entry is coordinated so that the ex post number of entrants is always optimal and known in advance by each bidder, thus greatly reducing the risk each bidder faces. Levin and Smith (1994) and Bajari and Hortacsu (2003) also model endogenous entry in a single-unit, endowed information setting. Hausch and Li (1993) and Harstad (1990) model both endogenous entry and costly information production in a single-unit, common value setting. Matthews (1987) considers information production in single-unit auctions with risk-averse buyers. Sherman (2005) comes closest to the environment in our experiments, modeling the two standard types of multi-unit sealed bid auctions (discriminatory and uniform-price) with endogenous entry and costly information acquisition, but in a setting in which each bidder is identical (ex ante) and can bid for only one unit.
In their divisible (i.e., multi-unit) common value auction models, Back and Zender (1993) and Wang and Zender (2002) consider the role of noncompetitive bidding, finding that the equilibrium stop-out price increases monotonically with random noncompetitive demand. Noncompetitive demand creates uncertainty regarding the competitive supply, leading to a higher expected stop-out price than in a fixed supply setting. Thus, they show that noncompetitive bids can increase uncertainty in a setting (such as Treasury auctions) in which greater uncertainty may be needed to prevent collusive-seeming equilibria. However, most IPO auctions face a different problem – excess uncertainty because of the very large numbers, in the millions, of both shares and potential bidders, which makes it hard for bidders to place their bids.

In this paper, we show that hybrid auctions with public pools play the opposite role from the noncompetitive bids in the Back and Zender (1993) and Wang and Zender (2002) models, by helping to decrease uncertainty for bidders. Our experimental design deviates from the model of Wang and Zender in a number of important ways. First, there is an information acquisition cost as well as an opportunity cost to participating in the auction. This requires bidders to decide on entry, make an information acquisition decision and choose a bidding strategy after making a conjecture as to the actions of other potential bidders. Second, we incorporate both small and large bidders. Since the information cost is fixed, informed large bidders hold an advantage in recovering the cost of evaluation, relative to informed small bidders.

3. Experiment Design and Procedure

We will describe our experimental design in this section, and then discuss the theoretical predictions in the next section. The design is discussed first because we use it to parameterize our simulations in the next section.
3.1. Experimental Design Overview

Each experiment session consists of 18 periods, in each of which 30 shares of stock are sold to 8 bidders, 4 of them large and 4 small. Subjects are randomly assigned to being large or small in each period, but will be assigned each role 9 times by the end of the session. A large bidder can order up to 15 shares while a small bidder can order no more than 3 shares. Imposing differential bidding capacity is motivated by the observation that in the equity IPO market there are typically two groups of investors, institutional and retail, with different budget constraints and hence different bidding capacities.

Before an auction begins, subjects each learn their bidder type (large or small), and then face an entry decision. Those who decide not to participate receive a \( L\$1 \) nonparticipation payment, which represents the risk-free return to an alternate activity. Those who participate in the bidding have an option to purchase private information about the intrinsic value. We include this feature in the experiment because gathering costly information about the fundamental value of the firm is a key characteristic of the equity IPO market. A bidder who purchases information receives a private signal that narrows down the intrinsic value to within a range of \( L\$3 \) above or below the true value \( V \), distributed uniformly across the integer values so that each of the seven values from \( V+3 \) to \( V-3 \) is equally likely. The information cost is \( L\$3 \).

We design two treatments: the Pure Auction treatment, which is a standard uniform price auction for all 30 shares; and the Hybrid treatment, where 20 shares are auctioned while the other 10 shares are allocated to the public pool. In the Hybrid treatment, both large and small bidders may order up to 3 shares in the public pool. Auction orders specify both price and quantity, while public pool orders specify only quantity. All shares, including those in the public pool, are

\[ \text{All payments are in lab dollars (L$), where the exchange rate from lab dollars to US dollars is 0.04.} \]
sold at the clearing price from the auction.

In both treatments, the competitive bidding is conducted in a common value auction where the intrinsic value is randomly selected from the integer interval of \([L\$12, L\$28]\), with \(L\$1\) as the price grid. The uniform distribution of the true value is known to all participants from the start, while the true value is unknown until the auction has been completed. If demand in an auction is so low that a stop-out or market clearing price does not exist, then the auction fails and no shares are distributed. Appendix A gives the sequence of events for the Hybrid treatment, while Appendix B gives the sequence of events for the Pure Auction treatment.

We employ a “pro rata” (or proportional) rationing rule. According to this rationing rule, all orders either at or above the stop-out price are rationed proportionally. This rule differs from the conventional “pro rata on the margin” rule, in which demand above the stop-out price is fully served and only bids at the stop-out price are rationed. Kremer and Nyborg (2004a) and Damianov (2005) show that a proportional rationing rule can reduce underpricing in a uniform-price auction. The first three IPO auctions in the US (Ravenswood, Salon.com and Andover.net, all in 1999) used pro rata on the margin, but the twenty since then have all used pro rata. Pro rata has also been the standard rationing rule for IPO auctions in most other countries that have used uniform price auctions. This rationing method offers extra benefits for auctions that may be “dirty” or priced strictly below the stop-out or market clearing price, a practice that is common for IPO auctions but virtually unheard of for other types of auctions.\(^\text{14}\)

Each bidder starts the session with an initial cash balance of L$500. Before the first auction, subjects are told that they will each receive an additional random payment ranging from US$1 to US$5, with the exact number disclosed only at the end of the session. The random

\(^{14}\) See Jagannathan, Jin, and Sherman (2015) regarding the use of dirty auctions for IPOs.
additional payment is designed to enhance experimental control when bidders have low balances.

3.2. Subjects and Procedures

We conducted a total of 16 sessions, with 8 sessions for each treatment. Each session consisted of 18 auctions with a cohort of 8 subjects. The experiment was programmed and conducted with z-Tree software (Fischbacher 2007). In May, June, and October of 2009, and June of 2010, we recruited graduate and undergraduate students at the University of Central Florida. The majority of the subjects were undergraduates of the College of Business Administration. Subjects’ level of experience includes inexperienced, experienced, and twice-experienced. In the “inexperienced” session, the subjects were those who have no experience in this type of experiment before. In the “experienced” session, the subjects participated in the experiment for the second time. In the “twice-experienced” session, the subjects participated in the experiment for the third time.

At the beginning of each session, subjects were given written instructions. The instructions explained the auction rules and the basis on which cash payments would be made, and included the bidding interface that introduced subjects to the software used to conduct the experiment. The experimenter read the instructions to the subjects, and subjects were then given the opportunity to ask questions. Next each subject was assigned to a computer terminal. At the end of each auction, subjects learned the market clearing price, the true value, and their own allocations, profits and cash balances. Each auction was independent, with the exception of the cash balances which carried over from period to period.¹⁵ Subjects were not allowed to communicate with each other.

¹⁵ Although cash balances carried forward, a bidder’s cash balance did not affect bidding capacity because, if necessary, an interest free loan was automatically extended. Cash balances never constrained bidding capacities.
4. Theoretical Analysis and Hypotheses

As discussed in Section 2, numerous papers model various aspects of auction design relevant to equity IPOs, although the complexities of the setting have required modeling tradeoffs for tractability. The setting implied by our experimental design – endogenous entry and costly information acquisition with the strategic complexity implied by multi-unit offerings – is relatively simple compared with institutional arrangements in practice, and yet it includes a combination of features that, to our knowledge, have not yet been included in a tractable model.

We thus turn to simulations to determine the symmetric Bayesian Nash Equilibrium (SBNE) strategies, in order to use these strategies to develop the hypotheses that guide our data analysis. We use simulations in three ways: 1) to show that, with no uncertainty or noise over participation levels, the SBNE is collusive-seeming, with steep individual demand curves for informed bidders that include some shares bid strictly above and some strictly below the expected value; 2) to demonstrate the crucial effect of uncertainty regarding the number of bidders; and 3) to generate predictions for our experimental setting by parameterizing two key variables (entry and information purchase) and then comparing the resulting SBNEs for the pure and hybrid auctions, given our calibration.

Our simulations take advantage of the fact that the environment in our experiments is relatively simple: there are a discrete number of possible true values, with known probabilities for each possible value. When a bidder purchases a signal, S, that bidder knows with probability one that the value of the underlying shares is between S+3 and S-3, with each of the 7 discrete values in that range being equally likely.

Thus for each auction, we generate a true value and related signals for each informed bidder, consistent with the underlying probability distributions, and then determine the results of
that auction given the strategies and signals of the bidders. Next, we examine the expected return to a bidder that deviates in a specific way from the potential equilibrium strategy, relative to the expected return to not deviating. If it is profitable for a bidder to deviate, then that particular strategy is not a Nash equilibrium. A strategy is a SBNE only if there is no incentive to deviate, i.e. if it is optimal for each bidder to follow the particular strategy, given that all other bidders (of the same type) follow the same strategy.

Simulations are, of course, most effective at ruling out possible equilibria, because only one counterexample (in which it is profitable to deviate) is enough to show that the strategy is dominated and hence not part of a Nash equilibrium. It is more difficult to show that a particular strategy is a Nash equilibrium by showing that there is no incentive to deviate, because all reasonable alternatives must be explored. Our focus on symmetric equilibria cuts down on the potential alternatives. It should however be noted that, even when we find an equilibrium, it is not necessarily unique – there may be other, possibly non-symmetric, equilibria as well.

4.1. Free riding bids in a rational equilibrium

With the ability to place multiple bids, the optimal strategy generally involves downward sloping “demand curves”, i.e. bid schedules, rather than all bids being placed at only one price. With a sufficiently small, stable number of bidders, the demand curves may be very steep, allowing collusive-seeming equilibria with substantial underpricing. Such is the case in our setting: the marginal, potentially market-clearing bids by each bidder are well below the

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16 For example, Wang and Zender (2002) derive equilibrium bidding strategies in multi-unit common value auctions under the assumptions of asymmetric information and random noncompetitive demand. They show that an important consequence of the assumption of multiple identical units with a limited number of bidders is the presence of multiple equilibria, with a continuum of Nash equilibria differentiated by the extent to which bidders employ their strategic advantage or “market power”. Market power arises because the steep demand curves submitted by bidders make the marginal cost higher than the price for additional units, thus inhibiting price competition among the bidders in equilibrium. The high infra-marginal bids that support the equilibrium are costless to the bidders, since winning bidders pay only the lower stop-out or clearing price. A crucial assumption is that the number of bidders is low enough for the bidders to retain market power.
expected value of the shares, and yet the highest bids are strictly above the expected value. We describe these high bids as “clinching” bids. Clinching bids are, to an outside observer, difficult to distinguish from “free riding” bids – high bids placed by uninformed investors on the assumption that the auction price will be appropriately set by other bidders, allowing the uninformed to do well in the auction without producing costly information. The number of both clinching and free riding bids should be low enough that they do not set the clearing price.

To understand why bids strictly above the expected value may be optimal, consider a simplified case with only 4 large potential bidders for 29 shares (we focus on 29 rather than 30 shares so that there will be a pure strategy Nash equilibrium for this example). Later we will add in the small bidders, but for now, imagine that only the four large bidders are allowed to participate in the pure auction. One might guess that the equilibrium strategy would be to bid 7 shares at the signal S (i.e. at the expected value), followed by the remaining shares bid strictly below S. If the four bidders each bid for 7 shares at their respective signals, they could each get shares without overwhelming the auction (because the clinching bids would add up to only 28 of the 29 shares), and the price would be set by a shaved bid rather than a bid at a bidder’s signal. However, our simulations show that this at-the-signal strategy is dominated by one of placing the clinching bids strictly above the signal.

A pure strategy SBNE (symmetric Bayesian Nash equilibrium) is for all four large bidders to: a) purchase a signal; b) bid 7 units at anywhere from S+1 to S+3 (i.e., between one and three lab dollars per share above the expected value given S); and c) shave substantially by bidding S-5 (L$2 per share below the lowest possible true value, S-3, given the signal) on their 8th and subsequent shares. Each bidder clinches shares in every auction, while the substantial shaving on the potentially-marginal bids means that the price is always below the true value,
resulting in positive returns on every auction. Our simulations show that if a bidder deviates by bidding the first 7 shares at $S$ rather than $S+1$ or above, that bidder’s expected return is lower (while if others are bidding 7 shares each at $S$, the expected return is higher for a bidder that deviates by bidding above $S$). Thus, the symmetric equilibrium is one where bidders bid strictly above the expected value per share, for a carefully limited number of shares.

This is a collusive-seeming equilibrium, where all four bidders essentially split the profits on each and every auction. There is no incentive to deviate because trying to clinch fewer than 7 units means giving up returns, while trying to clinch 8 or more means that the price is set by the clinching bids rather than the highest shaved bid. Moreover, trying to free ride by not acquiring a signal and bidding 7 units very high lowers the bidder’s total expected returns because the expected allocation of shares falls from 7.25 to 5.36 shares, and the lost profits due to this lower allocation more than offset the saving of L$3 in information costs. We confirm through our simulations that deviating leads to a lower expected return for the deviating bidder, and thus the equilibrium strategy obtains.

Therefore, bidding 7 shares strictly above the expected value is optimal in this case, while bidding 8 or more shares at that same price is suboptimal, at least in terms of a symmetric equilibrium. The key to these clinching bids is to carefully limit the number, so that the clearing

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17 The reason bids above $S$ dominate is that, in our setting, the highest and lowest signals may be up to six units apart, ranging from $V+3$ to $V-3$. If two of the four bidders got the highest possible signal ($S=V+3$), and if another bidder got the lowest possible signal ($S=V-3$) and placed her highest bid only at $S$, then the bidder with the low signal would not get any shares (because the $S-5$ bids of those with the highest signals would be above her signal) and thus would miss out on an offering that was priced at $V-2$.

18 This is due to pro rata allocation. In equilibrium, if a bidder gets the highest signal and thus places the highest shaved bid (which happens one-fourth of the time, ignoring ties), there are a total of 36 orders for 29 shares, so that the bidder with the highest signal gets 12.08 shares and each of the other three bidders gets 5.64 shares. A deviating free rider never gets more than 5.64 shares.

19 In terms of the amount of shaving of the bid for the 8th and subsequent shares, there are incentives to deviate if other bidders are bidding $S-6$, $S-4$, $S-3$, etc. rather than $S-5$, so those alternatives are not equilibria. The dominance of $S-5$ is presumably related to the fact that the lowest possible true value, given a signal of $S$, is $S-3$, and the lowest possible signal that might go to another investor, given a true value of $V=S-3$, would be $S-6$, i.e. one below the ‘shaved’ bid of $S-5$. 

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or stop-out price is never, or at least rarely, set by them. This approach works best in a predictable environment: a clinching bid that is safe and highly profitable with precisely four bidders who all follow the optimal strategy could instead lead to losses if a fifth large bidder were to emerge and follow the same strategy.

When we add in the small bidders, the solution is largely the same except that each small bidder is able to free ride for three of the shares that would otherwise have been clinched by the large bidders. Because the small bidders can only order 3 rather than 15 shares, it is not profitable in our environment for them to purchase information. Thus they are free riders – relying on the information collection of others without doing any of their own. The optimal strategy for the four small bidders in the SBNE is for each to free ride for 3 shares. This lowers the clinching capacity of the four large bidders from 7 to 4 shares, giving a total number of high bids of 16 (from large bidders) + 12 (from small bidders) = 28. The large bidders again shave their bids below their signal (to S-5) for the remaining bids, so that the clearing or stop-out price is always below the true value.

Thus in this SBNE, everyone wins shares in every auction and gets a positive return 100% of the time. The free riding of the small bidders reduces the total expected return of the large bidders, but they do not add risk as long as they are anticipated. With no uncertainty about the number or size of small free riding bidders, the strategies of large sophisticated bidders are adjusted, essentially turning an X unit auction into an X – K unit auction, where K is the free riding demand of the small uninformed bidders.

4.2. The effects of uncertainty on the optimality of free riding/clinching

Next we consider the effect of uncertainty over the number of bidders, which will open the way to a potential benefit from having a public pool tranche. Although such uncertainty
should not occur in the equilibrium of our simple example, it is frequently observed in practice. Variations in the number of bidders may be due to bidders facing constraints that prevent them from learning of or participating in every auction; or to out-of-equilibrium behavior; or to there simply being too many potential bidders in practice for it to be optimal for all of them to enter every auction. When there is noise, for example due to uncertainty over the number of bidders, then a separate tranche may be a way to pre-commit not to add noise to the price-setting process.

We compare two cases, both with the same expected number of bidders for 30 shares: the certainty case, where it is known that there will be 2 large and 3 small bidders; and the uncertain case, with 4 potential large bidders each with a 50% probability of participation and 4 potential small bidders, each with a 75% chance of entry. In both cases, it is not optimal for small bidders to gather information, so they each free ride (i.e. bid high) for all 3 of their shares. It is optimal in both cases for large bidders to purchase information and make their bids dependent on their signals. Table 1, Column A shows the returns to large and small bidders if, in the certainty case, large bidders place clinching bids for 10 shares by bidding at S+2, and bid the remaining shares at S-6, giving them an expected rate of return of 26.4% with no chance of losing money. The expected dollar return is $55.6 for large and $12.9 for small investors, with a standard deviation of dollar returns of $20.7 for large investors and $3.0 for small investors. Although there is uncertainty regarding the return, it is only over the level of profits rather than the risk of loss. The shares are never overpriced ex post, due to the marginal bid being at S-6.

However, the same strategy that leads to large, riskless positive returns in the certainty case leads to substantially lower, risky returns for the same expected number of bidders when

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20 We are examining a case in which the number of bidders is low enough that they can make excess expected profits, particularly with no uncertainty. However, if the number of potential bidders is large and entry is endogenous, then the underpricing of the shares will be driven down to the level that just compensates bidders for their information costs, as modeled in Sherman (2005).
there is uncertainty. Table 1, Columns B and C show the returns if the expected number of both large and small bidders is held constant but there are 4 potential bidders of each type. We see in column B that, if each entering bidder follows the strategy that worked so well in the certainty case, the expected rate of return in the auction falls to 4.9% with a 15.8% standard deviation and with positive returns to only 36.1% of all bidders (versus an average rate of return of 26.4% with 100% of the returns positive in the certainty case).

The optimal response to uncertainty is to lower the degree of free riding/clinching, in this case for each large investor to go from bidding 10 shares to bidding only 5 shares at S+2. As column C of Table 1 shows, this brings the expected return to 19.9%. Although this new expected return of 19.9% may not seem substantially lower than the 26.4% auction return in the certainty case, the lower return comes with a much higher level of risk – only 67.7% of returns are positive in the uncertain case, relative to 100% in the certainty case. With lower average returns and higher risk, both large and small bidders are clearly worse off. The lower returns to bidders do not mean higher expected seller’s revenue, however: the average clearing price falls from $15.00 to $10.01 (for shares with an average true value of $20.00). With uncertainty, about 31% of all auctions fail (receive too few bids to sell all shares) while price error and price volatility increase, leading to higher risk and lower returns for both bidders and sellers. These results confirm the theoretical predictions of Sherman (2005) that uncertainty over the number of bidders leads to problems even when all bidders are bidding optimally.

4.3. Predictions regarding our experimental data, via calibration

Having established the importance of incorporating uncertainty, we next turn to predictions regarding our experimental results. The outcomes of the experiments are not as simple and clear as the pure strategy SBNEs we’ve explored, and it is important to note that most
collusive-seeming strategies are only optimal if everyone follows them. Bidders might expect more randomness from their fellow bidders, which in turn affects their own optimal strategies. Thus we turn to calibration to match some of the parameters of our data – specifically, entry and information purchase – and then formulate optimal mixed strategy equilibria that we will use to generate predictions regarding the key remaining variables. Then, in the next section, we will test these predictions. We will continue to focus on symmetric equilibria.\textsuperscript{21}

More specifically, we now focus on SBNE strategies under the assumption that the entry and information production probabilities for large and small bidders match those observed in our sample. We identify the optimal strategies for both a pure and a hybrid auction, given the observed probabilities of entry and information production. For the hybrid auction with a public pool, we identify the optimal number of bids to put into the pool versus the auction, for both large and small investors. Because they are following mixed strategies, putting part of the free riding bids in the pool reduces the risk that randomness in bids affects the auction price.

By calibrating our model on eight parameters from our experimental results (entry and information purchase probabilities for large and for small investors, for Pure and for Hybrid auctions), we can compare the resulting SBNEs to derive predictions for auctions with versus without a public pool. Below is a summary of the theoretical predictions for our data:

\textit{Hypothesis 1: Underpricing (i.e. positive returns on average)}

(1) exists in both Hybrid and Pure Auction treatments;
(2) will be lower in the Hybrid than in the Pure Auction treatment.

\textit{Hypothesis 2: Under the Hybrid treatment}

(1) the clearing price will be higher;

\textsuperscript{21} The optimal strategies depend on each bidder’s expectations of the strategies of all other bidders, so there are a near-infinite number of possible equilibria for even our simple case with only 8 bidders. However, given that the bidders are ex ante identical in budget, information, etc., except that they are assigned as either large or small for a specific auction, symmetric strategies are somewhat intuitive and offer a relatively non-arbitrary way for us to focus on a subset of possible equilibria.
Hypothesis 3: In terms of only auction returns, both large and small bidders will have lower expected payoffs under the Hybrid treatment. In terms of total expected payoff (including information costs and public pool shares), large bidders will be worse off in the Hybrid than in the Pure treatment, while small bidders will be slightly better off under the Hybrid treatment.

Hypothesis 4: In terms of risk, large bidders will be better off in the Hybrid than in the Pure Auction treatment, while small bidders will be unaffected.

Hypothesis 5: Both large and small investors will place orders in the public pool tranche; however, small investors will place larger public pool orders on average.

Hypothesis 6: Free-riding/clinching will occur for both large and small bidders in both treatments, but the quantity of such bids will be lower for both types in the Hybrid treatment.

5. Experimental Results

We will now compare our experimental outcomes to the results predicted by theory. First, however, we examine the parameters used to calibrate the model.

5.1. Participation and information purchase rates

One potential benefit of adding a public pool mechanism is to attract retail investors to participate. Figure 1 depicts the bidder participation rate for each bidder type in both treatments. The Hybrid treatment has participation rates of 97% for large and 82% for small bidders, while the Pure Auction treatment has rates of 96% for large and only 72% for small bidders. The large bidder participation rate is significantly higher in both treatments ($p < 0.01$). Across treatments, the small bidder participation rate in the Hybrid treatment is about 10% higher than in the Pure Auction treatment, which is statistically significant ($p = 0.04$). There is little difference in the

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22 We test hypotheses by treating the average from each session as a single observation. In Table 6 we report results using auction-level data that controls for the random draws, experience within a session, and experience in previous sessions.
large bidder participation rates across treatments. Thus, our results indicate that incorporation of a public pool option significantly increases small bidders’ incentives to participate.

Figure 2 graphs the information purchase rate by bidder type in each treatment. For Hybrids, the information purchase rate is 80% for large bidders, but only 6% for small bidders. In the Pure Auction treatment, the rate is 76% for large bidders and 13% for small bidders. Information acquisition increases large bidders’ profits but reduces small bidders’ profits. Pricing accuracy is increasing in the rate of information acquisition.

The difference between large and small bidders in their probability of becoming informed is statistically significant ($p < 0.01$) in each treatment, consistent with the “real world” empirical results in Chiang, Qian and Sherman (2010) and DeGeorge, Derrien and Womack (2010) that institutional investors in auctioned IPOs are better informed. Across treatments, large bidders are more willing to purchase information in the Hybrid than in the Pure Auction while small bidders are less willing to purchase information in the Hybrid than in the Pure Auction. However, the difference across treatments is statistically insignificant for each type of bidder. The information purchase rates in Figure 2, in addition to the participation rates in Figure 1, are used to parameterize our simulations.

5.2. Auction performance from the issuer’s standpoint

Table 2 summarizes the theoretical predictions of Hypotheses 1 and 2, and compares them to our experimental data. Consistent with Hypothesis 1, underpricing is pervasive, with less than 20% of auctions leading to overpricing under either treatment. The average initial return for Hybrids, 3.14%, is lower than that for Pure auctions, 5.01%, with the difference being significant ($p = 0.08$). Moreover, the total IPO proceeds (number of shares sold times the market clearing price) are higher in the Hybrid treatment, L$564.38, compared to the Pure Auction
treatment, L$549.23. The clearing price in the Hybrid treatment is also higher than in the Pure Auction treatment, but the clearing prices in both treatments are significantly below the true value ($p < 0.01$), another indicator of significant underpricing.

Thus, issuers have reason to prefer the Hybrid auction format, since a lower initial return, a higher clearing price and higher proceeds are all ways of measuring a higher average return to the seller. The issuer might, however, also care about the accuracy and risk of the process, so we next look at measures of volatility in the pricing process. We use the standard deviation of the difference between the market clearing price and the true value to measure price volatility and find that the price volatility in the Hybrid (1.81) is smaller than in the Pure Auction (2.12). The pricing error, measured by the absolute value of the difference between the market clearing price and the true value, is significantly lower in the Hybrid treatment (1.58) than in the Pure Auction treatment (1.92) ($p = 0.049$), again implying more accurate pricing in the Hybrid treatment.

Last, our theoretical analysis predicts only a small probability of auction failure – where the number of units ordered is strictly below the number offered – but also predicts that failure is less likely for a Hybrid auction (0.51% probability) than for a Pure auction (1.42% probability). In our experiments, none of the 144 Hybrid auctions failed while one of the 144 Pure auctions failed, a result that is consistent with the theoretical predictions, although we would need a much larger sample to reliably estimate such a low probability event.

All of these results are consistent with the predictions from our theoretical analysis. We conclude that the hybrid auction with a public pool mechanism provides better performance with significantly higher proceeds, less price volatility, and smaller pricing error. From the issuer’s standpoint, a public pool has significant advantages.
5.3. Investor profit and risk by investor size and auction type

Table 3 summarizes the theoretical predictions in Hypotheses 3 and 4, and reports the experimental results related to each prediction. The significant average underpricing in both treatments implies significant profits for both large and small bidders under either type of auction. Nevertheless, both large and small investors have significantly lower auction returns in the Hybrid treatment \((p < 0.01)\), consistent with Hypothesis 3.

In both treatments, large bidders earn higher profits and receive significantly more shares than small bidders. After adjusting for information acquisition costs, nonparticipation payments (i.e., opportunity costs) and public pool returns, both the mean and the standard deviation of total payoffs are significantly lower for large investors in the Hybrid treatment \((p < 0.01\) for the difference of the means, \(p = 0.02\) for the difference of the standard deviations), as predicted in Hypotheses 3 and 4 and shown in Table 3. The prediction for small investors is for a slightly higher average payoff with no change in the risk (i.e., the standard deviation). In our experimental data, as seen in Table 3, the payoff for small investors is slightly higher on average, by 5 lab cents (from L$1.07 to L$1.12), and the standard deviation is slightly lower, by 23 lab cents (from L$3.84 to L$3.61). These results are not statistically significant.

Thus, large investors have a lower but still positive payoff and less risk under the Hybrid treatment, while small investors face no more than slight changes in both expected return and risk while still receiving positive expected payoffs after adjusting for all costs. Therefore, if issuers choose the Hybrid method due to benefits such as higher proceeds, less pricing error and less risk of a failed offering, there is no reason for either large or small investors to refuse to participate in future Hybrid auctions.
5.4. Bid aggressiveness and the public pool

Figure 3 displays the average total demand submitted by each type of bidder in the Hybrid and Pure Auction treatments. The average number of shares ordered is close to the maximum for both types in both treatments, with no significant difference in total demand for either type of bidder. In the Hybrid treatment, small bidders submit more public pool orders than large bidders: Public pool demand is 1.77 shares for small bidders and 1.28 for large bidders, with the difference statistically significant ($p = 0.02$). For small bidders, the size of public pool demand (1.77) is significantly higher than their competitive demand (1.21) ($p < 0.01$).

Figure 4 shows that small bidders are more likely than large bidders to use the public pool. In the Hybrid treatment, 71% of small bidders place orders in the public pool, of which 47% order three units, their full capacity. In contrast, 43% of large bidders do not order any units in the public pool. This is consistent with Hypothesis 5 on public pool orders.

In both settings, price discovery only occurs in the auction tranche. We further examine bidders’ competitive bidding behaviors by looking at the aggressiveness of the bids in Table 4 Panel A. Table 4 Panel B provides a comparison of competitive bidding behavior by bidder type. Panel C examines the treatment effect on competitive bidding behavior. Panel D examines the behavioral difference between information and non-information buyers.

First we examine bidding aggressiveness. As shown in Table 4, Panel A, the average

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23 We report WBP-V, the difference of the quantity-weighted bid price and true value; WBP-Signal, the difference of the quantity-weighted bid price and private signal; HBP-V, the difference of the highest bid price and true value; HBP-Signal, the difference of the highest bid price and private signal; $Q$ at HBP, the quantity demanded at the highest bid price; and Std, the standard deviation of the bidder’s bids, which is calculated by

\[ \sigma_y = \sqrt{\sum_{k=1}^m W_{q_k}^2 (p_{q_k} - p_y)^2}, \]

where $p_y$ is WBP, the quantity-weighted bid price for bidder $i$ in auction $j$, which is calculated by

\[ p_{ij} = \sum_{k=1}^m W_{q_k} p_{q_k}, \]

where $W_{q_k}$ is the demand schedule submitted by bidder $i$ in auction $j$, and $m$ is the number of bids bidder $i$ submitted.
quantity-weighted bid price for large bidders in both treatments is significantly lower than true value (-L$1.71 in the Hybrid and -L$1.24 in the Pure Auction, $p < 0.01$). For large bidders who purchase information, the quantity-weighted bid price is significantly below their private signals (-L$1.75 in the Hybrid and -L$1.22 in the Pure Auction, $p < 0.01$). For the uninformed, the quantity-weighted bid price is also below the true value (-L$0.77 in the Hybrid and -L$0.79 in the Pure Auction), but the difference is not significant.

For small bidders, the pattern is different. The quantity-weighted bid price for an average small bidder is above the true value (L$0.65 in the Hybrid and L$3.71 in the Pure Auction). For those who purchase information, the bid prices are significantly below the signals (-L$1.24 in the Hybrid and - L$1.07 in the Pure Auction). However, we have already seen that the majority of small participants do not purchase information. Uninformed small bidders’ average quantity-weighted bid price lies above the true value (L$0.92 in the Hybrid and L$4.55 in the Pure Auction). On average, informed small bidders bid more conservatively than uninformed small bidders (Panel D). Across bidder type, we find that the quantity-weighted bid price submitted by large bidders is significantly lower than that submitted by small bidders in both treatments (Panel B). Comparing the treatments, it appears that bidding is relatively more aggressive in the Pure than in the Hybrid Auction in the sense that the quantity-weighted bid price is higher, relative to the true value, for both large and small bidders (Panel C).

5.5. Free riding/clinching

Now we further examine the competitive bidding behavior by looking at the highest bid price and the quantity demanded at the highest bid price. Bidders are aggressive in submitting their highest bids which are, on average, above the true values by L$1.02 for large bidders/L$1.41 for small in the Hybrid, and L$2.90 for large bidders/L$5.74 for small in the Pure
Auction. For the uninformed in both treatments, the highest bid price is above the true value on average. In the Pure Auction treatment, uninformed small bidder’s highest bid price is L$6.75 above the true value.

Thus we see evidence suggesting free riding/clinching, as predicted in our theoretical analysis. If we were examining data from actual IPO auctions, this would be the best that we could do in terms of judging whether bidders were free riding. However, because this is experimental data, we know exactly what each bidder knew when placing each bid and thus can measure genuine free riding/clinching (bidding above one’s own expectation of the value of the shares). For an investor who has purchased a signal, we define a clinching bid as one strictly above that signal. For uninformed investors, we define a free riding bid as one above L$20, the unconditional expected value.

As seen in Table 5, free riding/clinching bids are placed by both large and small bidders in both types of auctions, but the quantity of these bids is lower for the Hybrid treatment, as predicted in Hypothesis 6 (with the difference significant at the 1% level for small bidders). For both large and small investors, not only is the quantity of high bids lower, but the proportion of bidders who place high bids is lower in the Hybrid auction. Overall, more than half of all bidders free ride or clinch in the Pure auctions (57% of large and 63% of small), while less than half of all bidders do so in the Hybrid auctions (48% of large and 24% of small).

For those who purchased information, we find an interesting phenomenon – that large informed bidders still clinch, but small informed bidders for the most part do not. The highest bid submitted by the average large informed bidder is significantly above the signal (L$0.53 in the Hybrid and L$1.11 in the Pure Auction), but the highest bid submitted by the average small informed bidder falls below the private signal (-L$0.62 in the Hybrid and -L$0.06 in the Pure
Auction). Table 5 shows that the average quantity of clinching shares bid by small informed bidders is less than one-tenth of one share under either treatment.

The lack of clinching on the part of small informed bidders is reasonable, given their choice to pay the cost of information. Small investors may only bid for up to three units but must pay as much for a signal as a large investor who may bid for 15 units. If a small investor expects large investors to purchase information and bid in such a way that the auction is not overpriced in general, despite free riding by small investors, then it is optimal for the small investors to free ride. Presumably, then, a small investor who purchases information does not trust the large investors to become informed and bid reasonably. It makes sense, under those circumstances, for the bidders to avoid the risk of free riding/clinching.

Across treatments, Hybrid bidders are more conservative, with highest bid prices that are much lower than those in the Pure Auction (Table 4, Panel C). The highest bid price submitted by informed bidders is lower than by uninformed bidders (Panel D). Large bidders submit more bids at the highest bid price than small bidders (Panel B). Bidders in the Hybrid treatment submit less demand at the highest bid price than in the Pure Auction treatment, except for uninformed large bidders (Panel C). Both large and small informed bidders submit more demand at the highest bid price than uninformed, in both treatments.

5.6. Regression results

In this section, we study how the treatment, information structure, and bidding experience affect the auction performance, with results shown in Table 6. The regression model is

\[
LHS = \alpha + \beta_1 \text{Hybrid} + \beta_2 (\text{AVE SIG} - V) + \beta_3 \text{SIG ACCURACY} + \beta_4 \#\text{SIGNALS} + \beta_5 E9 + \beta_6 \text{EXP1} \\
+ \beta_7 \text{EXP2} + \text{error}
\]

The first left hand side (LHS) or dependent variable is MCP-V, the difference of the
market clearing price and the true value (a measure of underpricing). The second dependent variable is pricing error, which is measured by \(|\text{MCP-V}|\), the absolute value of the difference of the market clearing price and true value. Hybrid is a treatment indicator with 1 for Hybrid and 0 for Pure Auction. AVE SIG–V is the difference of the mean of signals purchased by all the bidders in an auction and true value. SIG ACCURACY is measured by either \(|\text{AVE SIG–V}|\), the absolute value of the difference of the mean of signals purchased by all bidders and the true value, or STD SIGNAL, the standard deviation of all the signals purchased by all bidders. #SIGNALS is the total number of signals purchased in an auction. E9 is a dummy variable for experienced auctions within a session, with 1 for auctions 10 to 18 and 0 for auctions 1 to 9. EXP1 is 1 for sessions with experienced bidders and 0 for sessions with inexperienced or twice-experienced bidders. EXP2 is a dummy variable with 1 for sessions with twice-experienced bidders and 0 with inexperienced or once-experienced bidders. We report cluster robust t-statistics that account for the serial dependence within each session that may result from the same group of subjects interacting together over 18 auctions.

The regression results show that the coefficients for the treatment indicator Hybrid are statistically significant in all models, indicating that the market clearing price in the Hybrid treatment is significantly higher than in the Pure Auction treatment, while the pricing error is significantly lower in the Hybrid treatment. The significance of the coefficient of AVE SIG–V implies that the market clearing price is significantly positively related to the average signal in an auction. The within-session experience dummy variable E9 is positive but insignificant.
Interestingly, the level of the market clearing price relative to the true value is significantly higher in the experienced sessions but not in the twice-experienced sessions.

For the regression for pricing error, besides the Hybrid dummy variable, the number of signals purchased by bidders is significantly inversely related to the pricing error, which indicates that when more investors are informed, pricing is more accurate and the pricing error is smaller. The within-session-experience dummy variable E9 and across-session-experience dummy variables EXP1 and EXP2 are not significant.

6. Conclusion

This study uses theory and laboratory experiments to evaluate design features of multi-unit uniform price auctions in a setting relevant for the issuance of new equity securities. The experimental design features include: different bidding capacities, endogenous entry, costly information acquisition, and uncertainty in the intrinsic value. Our goal is to determine whether the performance of a standard sealed bid uniform price auction for IPO shares is improved by including a public pool. Research on how to improve standard auctions for the IPO setting began with Biais and Faugeron-Crouzet (2002) and includes Ausubel (2002). The feature that we analyze – a hybrid with a public pool – is commonly used for book building IPOs around the world, and has been used for auction IPOs in a few countries.

We find that including a public pool option increases the market clearing price and total proceeds, lowers price volatility and pricing error, and makes failure of the auction (due to insufficient bids) less likely. These are all changes that issuers are likely to favor. Jagannathan, Jirnyi and Sherman (2015) document that the eventual lack of popularity of the auction method
for IPOs in most countries was due to the fact that issuers, after being initially enthusiastic, were less willing to choose the auction method once they had gained experience with it. A hybrid, by bringing the seller both higher expected proceeds and less risk, might make issuers more willing to use the auction method. Moreover, gains for issuers do not necessarily come at the expense of investors, since both buyers and sellers benefit from a less risky process.

We begin by using simulations to determine the optimal strategies for bidders in our environment, finding that with a low, certain number of bidders, there is room for collusive-seeming Nash equilibria where bidders get high returns. The Symmetric Bayesian Nash Equilibrium (SBNE) involves clinching – the placement of bids strictly above the expected value of the shares – for a certain number of shares, while subsequent bids that are likely to determine the clearing price are set at a substantial discount.

However, collusive-seeming equilibria are unlikely for IPO auctions in practice, because uncertainty over the number of bidders makes clinching more risky. We show that, holding the expected number of bidders constant, the same strategy that leads to high, riskless returns when there is certainty over bidder entry leads to much lower expected returns, with much higher risk, when there is uncertainty regarding the number of bidders. Both bidders and sellers/issuers are worse off when there is uncertainty over the number of bidders, consistent with the theoretical auction predictions of Sherman (2005).

A hybrid with a public pool helps to lower the risk that bidder fluctuations will cause mispricing. Although there is no advantage to a public pool in a noiseless, perfectly coordinated equilibrium where all bidders know the numbers and types of other bidders, there may be substantial advantages to a hybrid format when there is uncertainty over the number of bidders, particularly when, as in most IPO auctions, there are literally millions of potential bidders.
To predict and then test the advantages of a public pool, we use the entry and information production probabilities from our experimental data to calibrate our model, developing theoretical predictions via simulations which are then compared to our experimental data to determine whether the outcomes are consistent with the predictions. We find significant underpricing in both treatments, but with less underpricing in the Hybrid treatment. As predicted, the addition of a public pool leads to higher expected proceeds, less risk of auction failure, and more accurate pricing. The Hybrid Auction also leads to less free riding/clinching: both large and small bidders are less likely to place bids strictly above the expected value per share, and those that still place such bids do so for a lower quantity of shares with the public pool option.

It is especially striking that we find benefits to a hybrid format in a setting in which participation in the public pool is voluntary for all bidders. Retail investors, as a group, have been shown to be less well informed and less skilled at implementing optimal bidding strategies in auction IPOs. Thus, our results support the recommendations of Jagannathan and Sherman (2005) and Jagannathan, Jirnyi and Sherman (2015) that retail investors in IPO auctions should be restricted to participating only through a retail tranche or public pool.

The difficulties that retail investors face when evaluating a company at the IPO stage are even greater when evaluating an earlier-stage investment in a private startup. The Jumpstart Our Business Start-ups (JOBS) Act was passed in the US in 2012 to make such investments easier for non-accredited investors, but the details of crowdfunding are still being worked out. Our results indicate that crowdfunding of early stage start-ups should be structured in a way that allows retail investors to participate without allowing them to disrupt the price-setting process.

24 See, for example, the Expert Witness testimonies of Dr. Ann Sherman and Ms. Lise Buyer to the U.S. Senate Banking Committee, Subcommittee on Securities, Insurance and Investment, in the Hearing titled “Examining the IPO Process: Is It Working for Ordinary Investors?”, June 20, 2012.
Reference


Table 1. Simulated auction returns with and without uncertainty over the number of bidders – The case with 5 expected bidders

This table reports simulated auction results in three cases: A. with no uncertainty over the number of bidders; B. with uncertainty, but the bidders follow the same strategies as in the certain case; and C. with uncertainty, where the bidders use optimal symmetric strategies given that uncertainty. In all cases, the small bidders bid all 3 of their shares at a very high price ($34, where the highest possible value is $28). In columns A and B, large bidders free ride for 10 shares at S+2 and bid their other 5 shares at S-6. In column C, large bidders free ride for 5 shares at S+2 and bid their other 10 shares at S-6. In column A, there are always 2 large and 3 small bidders. In columns B and C, each of the 4 large potential bidders has a 50% chance of bidding while each of the 4 small potential bidders has a 75% chance of bidding, yielding an expected 2 large and 3 small bidders. The average true value per share is $20.

<table>
<thead>
<tr>
<th></th>
<th>A. No bidder uncertainty</th>
<th>B. Uncertain, but follow certain strategy</th>
<th>C. Uncertain, follow best strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clearing price:</td>
<td>15.00</td>
<td>12.81</td>
<td>10.01</td>
</tr>
<tr>
<td>Rate of return on winning:</td>
<td>26.4%</td>
<td>4.9%</td>
<td>19.9%</td>
</tr>
<tr>
<td>Standard deviation of return to winning:</td>
<td>10.9%</td>
<td>15.8%</td>
<td>17.7%</td>
</tr>
<tr>
<td>% positive returns to winning bidders:</td>
<td>100.0%</td>
<td>36.1%</td>
<td>67.7%</td>
</tr>
<tr>
<td>Average auction $ return, large bidders:</td>
<td>$ 55.57</td>
<td>$ 5.82</td>
<td>$ 21.44</td>
</tr>
<tr>
<td>Average auction $ return, small bidders:</td>
<td>$ 12.89</td>
<td>$ 1.18</td>
<td>$ 6.62</td>
</tr>
<tr>
<td>Std. dev. of auction $ return, large bidders:</td>
<td>$ 20.74</td>
<td>$ 24.11</td>
<td>$ 32.69</td>
</tr>
<tr>
<td>Std. dev. of auction $ return, small bidders:</td>
<td>$ 3.97</td>
<td>$ 6.33</td>
<td>$ 7.42</td>
</tr>
<tr>
<td>Percent of failed auctions (too few bids):</td>
<td>0.0%</td>
<td>31.3%</td>
<td>31.2%</td>
</tr>
<tr>
<td>Auction rationing rate:</td>
<td>86.4%</td>
<td>59.6%</td>
<td>56.7%</td>
</tr>
<tr>
<td># winning bidders w/ strictly positive return:</td>
<td>5.0</td>
<td>1.8</td>
<td>3.7</td>
</tr>
<tr>
<td>Price volatility:</td>
<td>1.6</td>
<td>9.5</td>
<td>7.5</td>
</tr>
<tr>
<td>Price error:</td>
<td>5.00</td>
<td>7.69</td>
<td>10.00</td>
</tr>
<tr>
<td>Elasticity at true value:</td>
<td>3.9</td>
<td>4.4</td>
<td>2.6</td>
</tr>
<tr>
<td>Number of simulations:</td>
<td>100,000</td>
<td>100,000</td>
<td>200,000</td>
</tr>
<tr>
<td>Number of bidders:</td>
<td>5</td>
<td>5.0</td>
<td>5.0</td>
</tr>
</tbody>
</table>
### Table 2. Experimental summary of auction performance by treatment

This table lists the theoretical predictions in Hypotheses 1 and 2 and compares them to the experimental auction results for the Hybrid and Pure Auction treatments. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Theoretical prediction for Hybrid</th>
<th>Pure Auction</th>
<th>Hybrid with Public Pool</th>
<th>Difference (Hybrid - Pure)</th>
<th>T-stat for difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial return</td>
<td>Lower</td>
<td>5.01%</td>
<td>3.14%</td>
<td>-1.87%</td>
<td>-1.49</td>
</tr>
<tr>
<td>Total proceeds</td>
<td>Higher</td>
<td>549.23</td>
<td>564.38</td>
<td>15.14</td>
<td>1.19</td>
</tr>
<tr>
<td>Clearing price</td>
<td>Higher</td>
<td>18.31</td>
<td>18.81</td>
<td>0.50</td>
<td>1.19</td>
</tr>
<tr>
<td>Clearing price - Value</td>
<td>Higher</td>
<td>-1.22</td>
<td>-0.79</td>
<td>0.43</td>
<td>1.78*</td>
</tr>
<tr>
<td>Price volatility</td>
<td>Lower</td>
<td>2.12</td>
<td>1.81</td>
<td>-0.31</td>
<td>-1.46</td>
</tr>
<tr>
<td>Price error</td>
<td>Lower</td>
<td>1.92</td>
<td>1.58</td>
<td>-0.33</td>
<td>-1.97**</td>
</tr>
<tr>
<td>Number of failed auctions</td>
<td>Lower</td>
<td>1 of 144</td>
<td>0 of 144</td>
<td>-1</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3. Experimental payoffs to large and small bidders by treatment

This table lists the theoretical predictions in Hypotheses 3 and 4 and compares them to the experimental auction results for the Hybrid and Pure Auction treatments. Total payoffs include information costs, non-participation payments and returns to public pool shares as well as auction bids. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Theoretical prediction for Hybrid</th>
<th>Pure Auction</th>
<th>Hybrid with Public Pool</th>
<th>Difference (Hybrid - Pure)</th>
<th>T-stat for difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auction payoff, large investor</td>
<td>Lower</td>
<td>$8.37</td>
<td>$4.14</td>
<td>-4.23</td>
<td>-4.42***</td>
</tr>
<tr>
<td>Auction payoff, small investor</td>
<td>Lower</td>
<td>$1.51</td>
<td>$0.33</td>
<td>-1.18</td>
<td>-4.82***</td>
</tr>
<tr>
<td>Total payoff, large investor</td>
<td>Lower</td>
<td>$5.88</td>
<td>$2.51</td>
<td>-3.37</td>
<td>-3.56***</td>
</tr>
<tr>
<td>Total payoff, small investor</td>
<td>Slightly Higher</td>
<td>$1.07</td>
<td>$1.12</td>
<td>0.05</td>
<td>0.22</td>
</tr>
<tr>
<td>Standard deviation of total payoff, large</td>
<td>Lower</td>
<td>$17.43</td>
<td>$13.67</td>
<td>-3.76</td>
<td>-2.69**</td>
</tr>
<tr>
<td>Standard deviation of total payoff, small</td>
<td>Unaffected</td>
<td>$3.84</td>
<td>$3.61</td>
<td>-0.23</td>
<td>-0.47</td>
</tr>
</tbody>
</table>
Table 4. Competitive bidding
This table reports competitive bidding behavior data, excluding one failed auction (Pure Auction treatment Session 2 Auction 3). We remove observations in which investors do not submit any competitive (auction) bids, removing 3 (Large in Pure), 1 (Small in Pure), 6 (Large in Hybrid), and 224 (Small in Hybrid). The total number of observations analyzed are 546 (Large in Pure: 414 informed/132 uninformed), 414 (Small in Pure: 58 informed/356 uninformed), 552 (Large in Hybrid: 450 informed/102 uninformed), and 250 (Small in Hybrid: 25 informed/225 uninformed). # of prices is the number of different prices at which an average bidder places bids. Std is the standard deviation of the bidder’s bids – see Section 5.4 for a definition of how this is calculated. WBP-V is the difference of the quantity-weighted bid price and the true value. WBP-Signal is the difference of the quantity-weighted bid price and the private signal. HBP-V is the difference of the highest bid price and the true value. HBP-Signal is the difference of the highest bid price and the private signal. Q at HBP is the quantity demanded at the highest bid price. *, **, *** indicate significance of the t-statistics at the 10%, 5%, and 1% levels, respectively.

### Panel A: Competitive bidding

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Bidder Type</th>
<th>Info Purchase?</th>
<th># of prices</th>
<th>Std</th>
<th>WBP-V</th>
<th>WBP-Signal</th>
<th>HBP-V</th>
<th>HBP-Signal</th>
<th>Q at HBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid</td>
<td>Large</td>
<td>Yes</td>
<td>3.97***</td>
<td>1.41***</td>
<td>-1.98***</td>
<td>-1.75***</td>
<td>0.30</td>
<td>0.53**</td>
<td>4.58***</td>
</tr>
<tr>
<td>Hybrid</td>
<td>Large</td>
<td>No</td>
<td>4.64***</td>
<td>3.05***</td>
<td>-0.77</td>
<td>4.07**</td>
<td>3.00***</td>
<td>4.28***</td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>Large</td>
<td>Yes + No</td>
<td>4.14***</td>
<td>1.69***</td>
<td>-1.71***</td>
<td>1.02**</td>
<td>4.28***</td>
<td>1.89***</td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>Small</td>
<td>Yes</td>
<td>1.58***</td>
<td>0.58</td>
<td>-1.63***</td>
<td>-1.24**</td>
<td>-1.01*</td>
<td>-0.62</td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>Small</td>
<td>No</td>
<td>1.79***</td>
<td>0.65**</td>
<td>0.92</td>
<td>1.70</td>
<td>1.54***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>Small</td>
<td>Yes + No</td>
<td>1.76***</td>
<td>0.64**</td>
<td>0.65</td>
<td>1.41</td>
<td>1.58***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Large</td>
<td>Yes</td>
<td>3.35***</td>
<td>1.44**</td>
<td>-1.44***</td>
<td>-1.22***</td>
<td>0.89*</td>
<td>1.11**</td>
<td>5.35***</td>
</tr>
<tr>
<td>Pure</td>
<td>Large</td>
<td>No</td>
<td>5.34***</td>
<td>4.69**</td>
<td>-0.79</td>
<td>8.64***</td>
<td>2.69***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Large</td>
<td>Yes + No</td>
<td>3.68***</td>
<td>2.27**</td>
<td>-1.24***</td>
<td>2.90**</td>
<td>4.78***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Small</td>
<td>Yes</td>
<td>1.66***</td>
<td>0.82**</td>
<td>-0.77</td>
<td>-1.07*</td>
<td>0.24</td>
<td>-0.06</td>
<td>1.95***</td>
</tr>
<tr>
<td>Pure</td>
<td>Small</td>
<td>No</td>
<td>1.71***</td>
<td>1.75***</td>
<td>4.55***</td>
<td>6.75***</td>
<td>2.18***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Small</td>
<td>Yes + No</td>
<td>1.72***</td>
<td>1.61**</td>
<td>3.71**</td>
<td>5.74***</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Panel B. Comparison: Large − Small

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Info Purchase?</th>
<th># of prices</th>
<th>Std</th>
<th>WBP-V</th>
<th>WBP-Signal</th>
<th>HBP-V</th>
<th>HBP-Signal</th>
<th>Q at HBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid</td>
<td>Yes</td>
<td>2.39***</td>
<td>0.83*</td>
<td>-0.34</td>
<td>-0.51</td>
<td>1.31**</td>
<td>1.14**</td>
<td>2.69***</td>
</tr>
<tr>
<td>Hybrid</td>
<td>No</td>
<td>2.85***</td>
<td>2.39**</td>
<td>-1.68</td>
<td>2.37</td>
<td>1.46**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>Yes + No</td>
<td>2.38***</td>
<td>1.05***</td>
<td>-2.36*</td>
<td>-0.39</td>
<td>2.70***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Yes</td>
<td>1.69***</td>
<td>0.61</td>
<td>-0.66</td>
<td>-0.15</td>
<td>0.65</td>
<td>1.16</td>
<td>3.40***</td>
</tr>
<tr>
<td>Pure</td>
<td>No</td>
<td>3.63***</td>
<td>2.94**</td>
<td>-5.34***</td>
<td>1.89</td>
<td>0.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Yes + No</td>
<td>1.96***</td>
<td>0.66</td>
<td>-4.96***</td>
<td>-2.84*</td>
<td></td>
<td>2.63***</td>
<td></td>
</tr>
</tbody>
</table>
### Table 4- Continued

#### Panel C. Comparison: Hybrid – Pure

<table>
<thead>
<tr>
<th>Bidder Type</th>
<th>Info Purchase?</th>
<th># of prices</th>
<th>Std</th>
<th>WBP-V</th>
<th>WBP- signal</th>
<th>HBP-V</th>
<th>HBP- Signal</th>
<th>Q at HBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large</td>
<td>Yes</td>
<td>0.62*</td>
<td>-0.03</td>
<td>-0.54</td>
<td>-0.53</td>
<td>-0.59</td>
<td>-0.58</td>
<td>-0.77</td>
</tr>
<tr>
<td>Large</td>
<td>No</td>
<td>-0.70</td>
<td>-1.64</td>
<td>0.03</td>
<td>-4.57*</td>
<td>0.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>Yes + No</td>
<td>0.46</td>
<td>-0.58</td>
<td>-0.46</td>
<td>-1.88**</td>
<td>-0.49</td>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>Yes</td>
<td>-0.08</td>
<td>-0.24</td>
<td>-0.86</td>
<td>-1.25</td>
<td>-0.56</td>
<td>-0.64</td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>No</td>
<td>0.08</td>
<td>-1.10***</td>
<td>-3.63**</td>
<td>-5.06***</td>
<td>-0.56**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small</td>
<td>Yes + No</td>
<td>0.04</td>
<td>-0.97***</td>
<td>-3.07*</td>
<td>-4.33**</td>
<td>-0.56**</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Panel D. Comparison: Informed – Uninformed

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Info Purchase?</th>
<th># of prices</th>
<th>Std</th>
<th>WBP-V</th>
<th>WBP- signal</th>
<th>HBP-V</th>
<th>HBP- Signal</th>
<th>Q at HBP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid</td>
<td>Large</td>
<td>-0.67</td>
<td>-1.64*</td>
<td>-1.21</td>
<td>-3.76**</td>
<td>1.58**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hybrid</td>
<td>Small</td>
<td>-0.21</td>
<td>-0.07</td>
<td>-2.55*</td>
<td>-2.71*</td>
<td>0.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Large</td>
<td>-1.99*</td>
<td>-3.25***</td>
<td>-0.65</td>
<td>-7.75***</td>
<td>2.66***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure</td>
<td>Small</td>
<td>-0.05</td>
<td>-0.93**</td>
<td>-5.32***</td>
<td>-6.51***</td>
<td>-0.22</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 5. Quantities of free riding/clinching bids

This table lists the theoretical predictions in Hypothesis 6 and compares them to the average experimental auction bid quantities for the Hybrid and Pure Auction treatments. Clinching bids are defined as informed investor bids above that investor’s signal, while free riding bids are defined as uninformed investor bids above L$20. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Theoretical prediction for Hybrid</th>
<th>Pure Auction</th>
<th>Hybrid with Public Pool</th>
<th>Difference (Hybrid - Pure)</th>
<th>T-stat for difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Large informed (&gt; S)</td>
<td>Lower</td>
<td>2.43</td>
<td>2.06</td>
<td>-0.37</td>
</tr>
<tr>
<td>Small informed (&gt; S)</td>
<td>Lower</td>
<td>0.08</td>
<td>0.02</td>
<td>-0.06</td>
</tr>
<tr>
<td>Large uninformed (&gt; L$20)</td>
<td>Lower</td>
<td>3.48</td>
<td>3.16</td>
<td>-0.32</td>
</tr>
<tr>
<td>Small uninformed (&gt; L$20)</td>
<td>Lower</td>
<td>1.67</td>
<td>0.49</td>
<td>-1.18</td>
</tr>
</tbody>
</table>

41
Table 6. Regression results
The dependent variables are MCP-V (marginal clearing price minus value), a measure of underpricing, and |MCP-V|, the pricing error. Hybrid is a dummy variable with 1 for Hybrid treatment and 0 for Pure Auction treatment. AVE SIG−V is the difference of the mean of signals purchased by all the bidders in an auction and true value. SIG ACCURACY1 is measured by STD SIGNAL, the standard deviation of all the signals purchased by both types of bidders. SIG ACCURACY2 is measured by |AVE SIG−V|, the absolute value of the difference of the mean of signals purchased by all bidders and the true value. #SIGNALS is the total number of signals purchased in an auction. E9 takes on the value of 1 for auctions 10 to 18 and 0 for auctions 1 to 9. EXP1 takes 1 for experienced sessions and 0 for inexperienced and twice-experienced sessions. EXP2 is a dummy variable with 1 for twice-experienced sessions and 0 for either inexperienced or experienced sessions. We report cluster robust t-statistics that account for the serial dependence within each session that may result from the same group of subjects interacting together over 18 auctions. The numbers in italics are t-statistics. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>MCP−V</th>
<th>Pricing Error</th>
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<tr>
<td>Intercept</td>
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<td>3.48***</td>
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<tr>
<td>Hybrid</td>
<td>0.43*</td>
<td>-0.32**</td>
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<tr>
<td></td>
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<td>-2.25</td>
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<tr>
<td>AVE SIG−V</td>
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<tr>
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<td>-0.39***</td>
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<td>N</td>
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</table>
**Figure 1. Participation rate.** The bidder participation rate in each treatment is significantly higher for large than for small bidders ($p < 0.01$). Across treatments, there is no significant difference in large bidder participation, but small bidder participation is significantly higher for the Hybrid than for the Pure treatment ($p = 0.04$).

**Figure 2. Information purchase rate.** In each treatment, the information acquisition rate is significantly higher for large than for small bidders ($p < 0.01$). There is no significant difference across treatments in the rate of information purchase for either type of bidder.

**Figure 3. Total demand.** The graph shows the average bidder’s total demand in various subgroups. For the Hybrid treatment, both public pool demand and auction demand are shown.

**Figure 4. Public pool demand.** This graph displays the percentages of bidders (by type) in the Hybrid treatment whose public pool demand is 3, 2, 1, and 0 shares, respectively. The plurality of small bidders (47%) submit three units for public pool demand, but the plurality of large bidders (43%) submit zero units for public pool demand.
Appendix A: Hybrid treatment - Sequence of events for each auction period

Appendix B: Pure Auction treatment - Sequence of events for each auction period