Re-visiting Bookbuilding versus Auction IPOs: A Perspective of Informationally Efficient Prices in the Aftermarket

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Abstract

Our study is conducted to compare the degree of price efficiency between auction and bookbuilding IPOs. Although theoretical arguments prevail for bookbuilding IPOs, our empirical results fail to support the conjecture that bookbuilding IPOs are more price efficient than auction IPOs. Instead, our results show weak evidence for the opposite finding. Our study adds to the auction approach in that auction IPOs yield aftermarket price efficiency, as well as fairness and transparency. We also examine whether the underlying forces of price efficiency are the relative presence of informed institutional investors with respect to retail investors, aftermarket price support, and analyst coverage.

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1. Introduction

One of the interesting questions asked in recent initial public offering (IPO) studies is why the bookbuilding method dominates other selling procedure methods, such as the auction method. This is a puzzling and unresolved phenomenon after one observes the abuses associated with bookbuilding IPOs, such as spinning and laddering (Liu and Ritter, 2010; Hao, 2007). Wilhelm (2005, page 55) states: "If bookbuilding is so obviously flawed, anyone who believes in the power of markets to wring out inefficiency must ask why this practice has not only survived for over two centuries, but has in fact gained considerable market share worldwide in recent years." Despite the scandals and abuses related to bookbuilding, the auction method has gained only modest popularity as an alternative choice. In particular, only 22 IPOs in the U.S. were using the auction method as of the end of 2013, all of which belonged to WR Hambrecht + Co. (hereafter, WR Hambrecht).

In this study, we suggest an answer for the scarcity of auction IPOs in the scope of aftermarket price efficiency. Price efficiency occurs when intraday prices of a stock closely trace all fundamental attributes of IPO firms in that they precisely resemble a random walk of prices. Formally, we address the following research question: is there a difference in the level of price efficiency in the immediate aftermarket for bookbuilding versus auction IPOs? We focus on price efficiency because a lower level of price efficiency implies a noisy measure of the cost of capital, therefore leading to poorly informed investment and financing decisions (Harris, 2003). Deviation from the fundamental value distorts a firm's true value; as a result, stakeholders find it difficult to make an informed decision. Subrahmanyam and Titman (2001, page 2389) show a link between informationally efficient prices of equity and firm's cash flows by stating: "Feedback from financial market prices to cash flows arises when a firm's nonfinancial stakeholders, for example, its customers, employees, and suppliers, make decisions that are contingent on the information revealed by the price." Aftermarket price efficiency is especially more critical for initial public offerings (IPOs) because new entrants into the public market presumably have greater asymmetric information than seasoned firms with subsequent stock offerings. More efficient stock prices more accurately reflect a firm's fundamentals during the early stage of the IPO process, which allows external investors, who are exposed to potentially severe information uncertainty in the IPO market, to make an informed investment decision.

Using methodologies from Boehmer and Kelley (2009), we use several price efficiency measures, such as standard deviation of pricing error, intraday autocorrelation, variance ratios, and price delay, for book-built and auctioned IPOs during 1999-2005. Prior studies on bookbuilding versus auction IPOs generally conclude that the bookbuilding process has a more identifiable attribute to promote aftermarket efficiency; therefore, in our hypotheses, we conject that the bookbuilding process promotes more price efficiency in the aftermarket. However, to our surprise, our empirical results fail to support our null hypothesis. The bookbuilding process does not yield aftermarket price efficiency. Instead, we present weak evidence of the opposite finding: auction IPOs tend to have a higher level of price efficiency with some of the measurements mentioned above, while both types of IPOs tend to have statistically insignificant differences with various efficiency measurements. Our findings cast doubts on the bookbuilding approach and support the auction approach as a viable complement in an IPO market.

There are at least three mechanisms that can link IPO selling procedures to different levels of price efficiency. The first is the relative ownership of institutional versus retail investors in the aftermarket during the IPO process. One of the perceived advantages of the auction method over the bookbuilding method is that an auction places shares with those who value them the most and allows for greater participation of retail investors compared to bookbuilding IPOs. WR Hambrecht's website (http://www.wrhambrecht.com/index.html) touts that their "open IPO" auction method treats all investors, including individuals, equally.

Despite the well-known advantages of the auction process, such as a uniform market valuation via a clearing price that meets the supply and demand of market forces, this exact market-driven valuation may not reflect an optimal level of prices. Because of a wide spectrum of investors, including retail investors, a lower quality and sub-optimal number of bidders are vulnerable to inaccurate pricing or overbidding. In her model, Sherman (2005) shows that an auction open to a large number of potential bidders creates a "winner's curse" problem.[1] On the other hand, bookbuilding IPOs are primarily sold to a smaller group of informed institutional investors, who are likely to be insulated from the winner's curse problem.[2] Institutional investors are also important in promoting price efficiency in broad stock markets in general (Chemmanur, Hu, and Huang, 2010; Boehmer and Kelley, 2009). Thus, conditional on institutional investors holding significant private information that is not easily available to small, uninformed investors, bookbuilding IPOs are more likely to promote price efficiency in the IPO aftermarket.[3] The discretionary allocation of bookbuilding IPOs generates another force that promotes overall price efficiency and reduces the indirect costs of IPO firms (Ljungqvist and

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[1] Sherman (2005) shows that a winner's curse is a phenomenon that may occur in common value auctions with incomplete information. She states that winners tend to overpay in such an auction. With a sufficient number and random quality (good or bad) of bidders, the average bid price is likely to be accurate, leading to a smaller valuation gap (the degree of winner's curse) between an average bidder and the highest bidder. However, a smaller number and lower quality of bidders worsen the problem of incomplete information, leading to a higher valuation gap and thus a more serious winner's curse problem.

[2] Aggarwal, Prabhala, and Puri (2002) find using a 617 bookbuilding IPO sample, that a median of approximately three-quarters of shares are allocated to institutional investors.

[3] Chemmanur, Hu, and Huang (2010) study the role of institutional investors in IPOs and find that institutions trade much more actively in IPO stocks than retail investors in the immediate post-IPO period. Because the overwhelming majority of IPOs use the bookbuilding method, this is further evidence that institutions are the major stockholders of these firms.

Wilhelm, 2002). Through discretionary allocation, an underwriter is not obliged to serve a wide array of small bidders and can focus on more valuable information acquisition, thereby reducing either underpricing or aftermarket volatility (Sherman, 2005).

Second, aftermarket services such as price support, analyst coverage, and market-making should be more supported by bookbuilding IPOs than auction IPOs. The success of bookbuilding depends on how closely linked underwriters are to a set of sophisticated and knowledgeable investors, who provide valuation information (through their bids) to help set an accurate offer price and also play an important role in supporting IPOs in the aftermarket. Even for weak offerings that show low demand from market participants, underwriters can maintain their reputation by providing price support and protecting investors from a price drop to a level below the offer price (Aggarwal, 2000). In the premarket, the underwriter can reward these investors with more IPO allocations (Wilhelm, 2005; Chemmanur, Hu, and Huang, 2010). In the aftermarket, the underwriter can maintain good relations with these investors, with the provisions of price support, analyst coverage, and market-making. A good relationship yields more future business from the same investors.

Several studies have shown a significant short-term association between market-making activity and underwriting. For example, Degeorge, Derrien and Womack (2007) find evidence from the French IPO sample that issuers are willing to pay a higher direct and indirect cost of bookbuilding in return for expanded and more supportive research coverage. Lowry, Officer and Schwert (2010) argue that to the extent that bookbuilding underwriters provide additional aftermarket services, some issuers may accept a higher level of underpricing as compensation for these follow-on services. Valuable service is created when market makers stand ready to buy or sell an asset for an investor anxious to sell or buy the asset. Therefore, market-making provides immediacy for impatient investors. This service is likely to be especially important in the early aftermarket for IPOs because of high volatility and abnormally high trading volumes. It is well documented that the lead underwriter, as a major market maker, takes the responsibility for executing orders and, in doing so, maintains substantial inventory positions. Being a major market maker, the lead underwriter, using the bookbuilding method, is likely to utilize its broad network to get a large block order executed in an orderly and timely manner out of a large inventory positon. Ellis, Michaely and O'Hara (2000), among others, examine the relationship between market-making in the IPO aftermarket and the underwriting of IPOs. They find a strong association between the market-making of IPOs using the bookbuilding method and the underwriting activity over the short term.

While the above-mentioned attributes support bookbuilding IPOs, maintaining good relations with the purchasers of auction IPOs, which are mainly occasional retail investors, may not be important for the underwriter. We have not found any papers that document the extent of market-making services provided by the lead underwriter under the auction method. Given the lack of long-term relationships with the purchasers in these auction IPOs, we hypothesize that IPOs using the auction method would experience fewer market-making services from the lead underwriter.

Third, the level of divergence in opinion among investors in the aftermarket may differ due to the different constituents of investors, resulting in different levels of price efficiency between the two IPO methods. There is a growing theoretical and empirical body of literature in finance that examines the effects of heterogeneous investor expectations (Garfinkel and Sokobin, 2006; Houge et al, 2001; Diether, Malloy, and Scherbina, 2002; Doukas, Kim, and Pantzalis, 2006). The literature attempts to understand how heterogeneity in investor opinion affects the aggregate and the cross-sections of asset returns. We investigate whether bookbuilding IPOs have less divergence in investors' opinions than auction IPOs. If the investors participating in a bookbuilding IPO have more consensuses in opinions regarding the price of an IPO stock, they then move the price closer to its fundamental value, leading to higher price efficiency. We hypothesize that a higher proportion of institutional investors, as a group of better informed investors in bookbuilding IPOs, will have more opinions in agreement regarding the fundamentals than the set of mainly retail investors purchasing the IPO stock via the auction method.

Overall, we hypothesize that bookbuilding IPOs are more price efficient than auction IPOs in the initial aftermarket. To test our hypothesis, we examine the efficiency of stocks in the nine-month period after the IPO date using rigorous methods from prior price efficiency studies. The nine-month testing period corresponds to IPO lock-up expirations when stocks reach the equilibrium stage. Our main proxy for the level of efficiency is the standard deviation of pricing error (SDPE) from Hasbrouck (1993), along with four other efficiency measures (autocorrelation coefficient, variance ratio, short-term volatility, and price delay), which are used to check for robustness.

After the initial testing stage, we next empirically test whether bookbuilding IPOs do indeed have more institutional owners, better post-IPO services, and a lower degree of divergence in investor opinion. Specifically, we examine differences in post-IPO services between auction IPOs and bookbuilding IPOs, including price support, analyst coverage, and the number of market makers. We expect that bookbuilding IPOs provide better non-price related services in the post-IPO market. Following Ruud (1993) and Prabhala and Puri (1999), we measure price support by examining the distribution of the initial return. Specifically, we treat an

IPO as stabilized if the IPO closes on the first trading day at the offer price and as not stabilized if the IPO closes below the offer price.

Our study complements a growing body of literature on the debate regarding different IPO selling mechanisms by examining market-micro aspects of the offering. Earlier papers provide evidence that the bookbuilding method has become a dominant selling method around the world and argue that it has a better pricing and allocation mechanism. However, there is only indirect evidence regarding whether the bookbuilding method leads to more efficient stock prices. We build on these findings by directly investigating the relationship between IPO pricing techniques and the informational efficiency of actual transaction prices.

The remainder of this paper will proceed as follows. Section 2 discusses the previous literature and develops the hypotheses tested. Section 3 describes the data and gives sample descriptive statistics. Section 4 provides empirical results, while section 5 concludes.

2. Literature Review and Hypothesis Development

In this section, we will summarize previous literatures on IPO methods and present three reasons why companies going public via the auction method have a different level of price efficiency in the aftermarket than those going public via the bookbuilding method. We present several hypotheses with respect to these three reasons in more detail below.

2.1. Differences in the types of investors

First, the constitution of investors in IPOs using the auction method, as opposed to the bookbuilding method, leads to a different level of efficiency in IPOs in the aftermarket. One advantage of the auction method is that it ensures that all bidders, whether institutional or retail investors, are on equal footing through a market-driven approach in such a way that the market forces determine the supply and demand of the IPO volume. The WR Hambrecht website touts that the openness and fair treatment of the auction method free the process from underwriters' abuses in allocating IPO shares, while bookbuilding IPOs are often criticized for their opaque, discriminatory process against retail investors because lead underwriters seek for indicative bids mainly from institutional investors. Biais, Bossaerts and Rochet (2002) even suggest collusion between an underwriter and an issuer in the bookbuilding process at the expense of retail investors.

Empirically, DeGeorge, Derrien, and Womack (2010), using the 19 auction IPOs of WR Hambrecht, support auctioned IPOs as an effective alternative to traditional bookbuilding. Using the data from the French stock market, Derrien and Womack (2003) find that the auction method is optimal in that it leads to lower underpricing and lower variability of underpricing. Kandel, Sarig and Wohl (1999) find from the 27 Israeli auction IPOs, that auctions elicit fairly elastic demand, a sign that the auction process ensures accurate investor information and high future liquidity, as reflected in the price. In sum, the auction method seems to be better at drawing the demand of investors than the bookbuilding method because it is open to a broad base of retail investors, as well as to institutional investors.

Despite its immediate advantages, WR Hambrecht has managed only 10 auctioned IPOs in the decade since the famous Google IPO on August 19, 2004. Why? The answer lies in the dominance of "regular" institutional investors in the bookbuilding process.

In her theoretical model, Sherman (2005) shows that the auction method is vulnerable to inaccurate pricing and to variations in the number of noisy bidders, leading to the winner's curse and free rider problems. In other words, an increase in the number of potential noisy bidders in an auction leads to more risk and to potentially lower returns for each bidder, thus discouraging both entry and evaluation. Thus, the Sherman (2005) model runs counter to the general merit of the auction method, which is known for greater participation of investors and not a limited or preferential investor population, as is common in bookbuilding.[4] Similarly, Jagannathan and Sherman (2005) claim "The main problem with uniform-price auctions is their failure to guarantee an adequate reward for those who gather information and carefully evaluate a new equity offering. When allocation priority is given to the highest bids while holding the same price for all bidders, some investors may free-ride on the efforts of others by submitting high bids." Thus, auction may "crowd out" institutional investors because of overbidding by retail investors.

Thus, it is natural to conjecture that there are more uninformed, noisy individual investors in IPOs that use the auction method, while there are more informed institutional investors in IPOs that use the bookbuilding method. Consistent with this view, Sherman (2005) shows the possibility that the auction method may not generate an adequate evaluation of an offering. Further, Google warns, on page 18 of its prospectus: "To the extent our auction process results in a lower level of participation by professional long-term investors and a higher level of participation by retail investors than is normal for initial public offerings, our stock price may decrease from the initial public offering price and be more volatile."

A large branch of literature discusses the role of informed / institutional investors in the premarket of IPOs. Benveniste and Spindt (1989) argue that it is the "regular" (informed) investors that produce valuable information for the underwriters rather than the "occasional" investors. Regarding the existence of market frictions, Benveniste and Spindt (1989) view

[4] Using detailed bidding data from the WR Hambrecht auction IPOs, Degeorge, Derrien, and Womack (2010) find that free-riding by retail investors and low participation by institutional investors do not interrupt the auction IPO mechanism's ability to extract information from investors, despite the evidence of some free-riding by retail investors.

underpricing as a "natural" cost that private firms must bear to sell equity for the first time publicly—the cost to compensate informed investors for truthfully revealing their information to issuers and, therefore, to establish the demand curve of new shares (see also Chemmanur, 1993). Moreover, a bookbuilding IPO can optimally elicit private information from informed investors in the presence of agency conflicts between an underwriter and an issuer (Biais, Bossaerts and Rochet, 2002; Benveniste and Spindt, 1989).

From its advertisements, it is clear that WR Hambrecht's target group is the retail or small investors using auction IPOs that Benveniste and Spindt (1989) calls "occasional" investors. Conversely, Benveniste and Spindt's (1989) "regular" investors are most likely to be institutions that regularly buy bookbuilding IPOs. Field (1995) finds that in the long run, IPOs having larger institutional shareholdings significantly outperform those with smaller institutional shareholdings. Chemmanur, Hu and Huang (2010) investigate the role of institutional investors in IPOs empirically and find that institutions trade more actively in the aftermarket; however, their level of trading conforms to that of seasoned stocks in approximately the seventh quarter post-IPO. Their trading also outperforms a buy-and-hold investment strategy in IPOs, suggesting that institutions continue to possess private information regarding IPO firms even after the IPO offer date. This implies that these informed institutional investors are active owners / traders of the stock after the IPO offer date. In a non-IPO study, Boehmer and Kelley (2009) states "Intraday prices of stocks with greater institutional ownership more closely track fundamental values, in that they more precisely resemble a random walk, than prices of stocks with less institutional ownership."

In sum, this evidence suggests an important distinction between the types of investors that purchase auction versus those that purchase bookbuilding IPOs and who hold onto these stocks after the offering. We hypothesize that a higher proportion of informed institutional investors in bookbuilding IPOs will lead to a lower level of information asymmetry and a higher level of price efficiency.

Hypothesis One: Bookbuilding IPOs will have a higher level of price efficiency in the initial aftermarket than auction IPOs.

Our second hypothesis, although not exclusive to the first hypothesis, argues that the bookbuilding method entices more institutional investors in the premarket because of the nature of its network-base. It seeks the opinion of a relatively narrow, but influential, pool of institutional investors, while IPOs using the auction method (as WR Hambrecht explains on its Open IPO website) are open to all investors, including individual investors. Thus, we hypothesize that the bookbuilding method induces more institutional investors. One of the main criticisms regarding bookbuilding is that it discriminates among initial investors in the premarket. However, the discrimination, representing preferential allocations or preferential prices, seems to crucially matter because those who reveal particularly useful information get compensated in the form of share allocations in underpriced IPOs. Therefore, it is natural to assume that a firm going public via the bookbuilding method will have a higher proportion of institutional investors than a firm using IPOs via auctions. This logic leads to our second hypothesis.

Hypothesis Two: Bookbuilding IPOs should have a higher proportion of institutional owners in the initial aftermarket than auction IPOs.

Another advantage of the bookbuilding method comes from the discretionary allocation of shares by underwriters. Despite criticism toward bookbuilding IPOs for possible spinning and laddering, Ljungqvist and Wilhelm (2002) argue that discretionary allocation enhances the price discovery process in the IPO market and reduces indirect issuance cost. Wilhelm (2005) also supports the underwriter's discretionary allocation, citing that it is not easy to incorporate complex "human judgment" into the electronic auction mechanism. Globally, it is the underwriter's flexibility that enables bookbuilding to dominate any other IPO selling mechanism around the world (Ljungqvist, Jenkinson and Wilhelm Jr, 2003). Once popular in Europe and Asia, the auction method almost disappeared on those continents because the pricing and allocation of shares cannot be as well implemented as those in bookbuilding.

Conversely and ironically, one criticism regarding bookbuilding is that *too much* discretion is given to the underwriter. The underwriter, as an agent, may not act in the best interest of the issuer or the principal. Biais and Faugeron-Crouzet (2002) compare various IPO mechanisms from theoretical perspectives and find that bookbuilding and the Mise en Vente auction method, which works similarly to bookbuilding, can lead to optimal information elicitation and price discovery. The finding from Biais and Faugeron-Crouzet (2002) suggests that there might not be significant agency problems with bookbuilding IPOs. However, an underwriter's discretionary allocation may yield negative consequences if underwriters do not act in the best interests of the issuers. Realizing the agency problem and facing the winner's curse problem, retail investors may be discouraged from participating in bookbuilding IPOs.

2.2. Differences in the level of aftermarket services

Next, we present another cause of a different level of price efficiency in the aftermarket between the two selling procedures: different levels of aftermarket services, such as price support, analyst coverage, and market-making services.

Price support is an act of cooperation among IPO syndicates to stabilize the price of the shares in the aftermarket to prevent a decrease below the IPO's offer price. Because sales of shares are determined through an online auction in the auction method and not by a set of regular investors, as in the bookbuilding method, the underwriter may feel a lesser obligation to provide price support for auction IPOs. There are two broad views regarding the impact of price support on the fundamental value. Ruud (1993) views the stabilization by underwriters as a manipulative action that could disrupt the natural market forces of demand and supply, which are essential to determining the market prices of securities. In this sense, more extensive price support would mean less efficient stock prices, at least through the end of the price support period[5]. Conversely, Benveniste, Busaba, and Wilhelm (1996) argue that price stabilization is the efficient form of compensation in favor of informed investors, thus reducing the underwriter's incentive to exaggerate investor interest. Within this perspective, price support increases participation by informed investors and therefore should increase efficiency.

In some cases, issuers may value these non-price-related services more than accurate pricing at the time of an IPO. Price support is a commitment to repurchase shares at the offer price. If this commitment is violated, the underwriter may lose reputation and experience a decrease in future underwriting revenues (Lewellen, 2006). Because the relationship between

[5] Although there are no formal rules regarding the length of the price support period, it is generally assumed to conclude within approximately three weeks. Lowry, Officer, and Schwert (2010) calculate the volatility of initial returns based on the 21^{st} trading day after trading (rather than at the end of the first day of trading) because they believe price stabilization activities have subsided at this point. Hanley et al. (1996) document that closed-end fund IPOs exhibit significant price declines following three weeks after the IPO. They attributes this price decline to the withdrawal of price support.

underwriter and investors under the bookbuilding method is more long-term-based and repetitive than that under the auction method, bookbuilding underwriters are likely to provide more aggressive price support (such as positive coverages) to live up to their reputation (see also the result of Degeorge, Derrien and Womack, 2007). Some studies show significant short-term association between market-making activity and underwriting (Aggarwal and Conroy, 2000; Ellis, Michaely and O'Hara, 2000). Being equipped with a broad network of investors and syndicate members, bookbuilding underwriters may implement orders (in particular, block orders) in a smooth and orderly manner. For example, when an investor wants to place a large block order to buy stock, he/she often calls on a market maker to sell the stock out of its inventory. The lead underwriter, as a major market maker, may play an important role in processing the block order without a large price impact and accumulate most of the order imbalance. In contrast, because the lead underwriter under the auction method has less of an ongoing relationship with the auction bidders than with bookbuilding IPOs, he/she is less likely to be concerned regarding price impact or order imbalance.

Even though it is not legally binding, abundant evidence shows that price support is provided due to the repetitive nature of underwriting activities. Because it is likely that bookbuilding IPOs will have a more regular set of purchasing investors, we expect underwriters to provide more price support in bookbuilding IPOs than in auction IPOs. Chemmanur, Hu, and Huang (2010) find that institutions play an important role in supporting IPOs in the aftermarket and are rewarded by underwriters for playing such a role. Benveniste, Erdal, and Wilhelm Jr (1998) argue that the main beneficiary of price support should be the institutional investors that participate in the bookbuilding process. They find that it is overwhelmingly large institutional traders that execute sell orders in stabilized offerings, rather than small retail traders. This information, along with our expectation that more institutional investors are purchasers and liquidity creators in bookbuilding IPOs, supports our contention that bookbuilding IPOs receive more price support.

The level of analyst coverage is another aspect that may differ between the two IPO selling mechanisms. There is evidence that IPO firms strategically purchase aftermarket research coverage when choosing their underwriters and that underwriters release positively biased research recommendations in the first year after an IPO. Krigman, Shaw and Womack (2001) find that the most important reason that issuers switch underwriters between their IPO and their first follow-on (or seasoned) equity offer (SEO) is to enhance analyst coverage. Degeorge, Derrien and Womack (2007) asks in their study, “Why do we observe the ostensible failure of auctions despite strong financial characteristics in their favor?”; they find empirical evidence that underwriters employing bookbuilding implicitly commit to providing more favorable coverage to the companies they take public in the aftermarket. More specifically, they find that analysts affiliated with the lead underwriter of the offering issue more favorable recommendations for recent bookbuilding IPOs than for auction offerings. Analyst reports contain large amounts of information apart from the specific buy or sell recommendation made by the analyst. This greater quantity of information coming from analysts’ reports may push prices closer to their efficient level despite the biased recommendation. Supporting this argument, Malmendier and Shanthikumar (2014) find that analysts intentionally distort information regarding recommendations in their reports in an attempt to generate more business for their clients, though they are honest in their forecasts.

Lastly, different levels of market-making provided by both selling procedures may lead to different levels of efficiency in the aftermarket. How smoothly market-making goes depends on the ability of a dealer to deal with inventory position and immediacy. For this, dealers should make themselves available so that other traders can trade when they want to trade. In general, the lead underwriter is the IPO stock's major market maker in the early market. In particular, Ellis, Michaely, and O'Hara (2000) find that lead underwriters do most of the trading activity, as dominant market makers, in the first 60 trading days after an IPO and can accumulate a relatively large inventory position in the stock to prepare for price support. The ability of the lead underwriter to smoothly make a market in the IPO stock probably depends on the accumulated experience and network of potential investors who take the other side of the position. Certainly, IPOs brought to the market, via the bookbuilding method, by large and established investment banks, such as Goldman Sachs and Merrill Lynch, have more experience in market making and better networks than WR Hambrecht, who brought to the market the entire auction IPO sample in this study. Because it is difficult to measure the quality of the market making by a particular underwriter, we will proxy based on the number of market makers.

In sum, the plausibility that companies going public via the bookbuilding method should have a higher quality of aftermarket services, such as stronger price support, more analyst coverage, and more stable market-making, leads to our third hypothesis.[6]

Hypothesis Three: IPOs using the bookbuilding method should provide a higher quality of aftermarket services than IPOs using the auction method. Thus, IPOs using the bookbuilding method should have more price support, more analyst coverage, and more market-making services.

[6] However, given the two possible results of price support, whether a greater amount of price support would worsen or enhance price efficiency in the aftermarket is unclear.

2.3. Differences in the divergence of opinion

The third cause of different levels of efficiency in the aftermarket between the two selling procedures is the divergence of opinions among the different types of investors participating in the two IPO selling methods. Investors differ with respect to the ability to process information, which could result in a divergence of investors' opinions regarding the IPO stock's value. Theoretical arguments can be made for the increase in opinion divergence either improving or exacerbating the price efficiency. On the one hand, informed investors, with a better ability to process information than uninformed individual bidders, may have an information advantage when participating in auction IPOs, thereby increasing the divergence of opinion and also improving price efficiency. On the other hand, the free rider problem (Jagannathan and Sherman, 2005), arising in auction IPOs due to the possibility that individual investors have incentive to rely on institutional investors to collect information regarding the IPO stocks, may discourage sophisticated investors from dedicating their time and effort to correctly valuing the shares. Thus, a low participation rate of the better informed institutional investors may lead to high divergence of opinion among individual investors, resulting in lower price efficiency. We test for cross-sectional differences in the association between divergence of investors' opinions and price efficiency based on the auction vs. book-building methods in our empirical analysis below.

Because bookbuilding IPOs are purchased by mostly informed institutional investors, while auction IPOs, by less informed retail investors, investors participating in bookbuilding IPOs should yield more consensuses in opinion than investors in auction IPOs. Because traders (investors) have similar opinions regarding what the actual price of stocks should be, they should move the price closer to its fundamental value, therefore resulting in greater efficiency for bookbuilding IPOs. Based on this argument, we compare the divergence of opinion for bookbuilding IPOs with that of auction IPOs using various measures, such as bid ask spread from the NYSE TAQ intraday price and volume-based measures, including unexplained volume and standardized unexplained volume (Garfinkel, 2009). This leads to our fourth hypothesis.

Hypothesis Four: The divergence of opinion for bookbuilding IPOs is smaller than the divergence of opinion for auction IPOs.

3. Data and descriptive statistics

We collect an initial sample of 16 auction IPO firms, managed by WR Hambrecht, that went public in the 1999 to 2005 time period. We end the sample period at 2005 because high frequency trading began to have significant dominance in 2006 (Duhigg, 2009), which we suspect accounts for a great portion of trading volume. As of year 2010 in the U.S. markets, the high frequency trading accounts for about 70 percent of trading volume (Zhang and Powell, 2011). The emergence of high frequency trading has transformed the markets and trading fundamentally (O'Hara, 2015). For example, high frequency traders tend to shorten holding period, rarely carry the position overnight, and employ multiple strategies in less than the blink of an eye speed (less than 300 milliseconds) (Zhang and Powell, 2011). Limiting the time period to 2005 insulates our sample from idiosyncratic price behaviors from high frequency trading.

We dropped Instinet from this set of 16 auction IPOs because it only sold a part of its shares using the auction method. Therefore, our final sample of auction IPOs is 15.[7] Because comparing auction IPOs to the full sample of traditional IPOs can be problematic (Lowry, Officer, and Schwert, 2010; Rosenbaum and Robin, 1983), as there is likely to be selection bias

[7] WR Hambrecht has taken seven more firms public via auction methods since 2005 (i.e., from 2006-2013). The list of all auction IPOs can be seen at http://www.wrhambrecht.com/clients/.

regarding the type of firm undertaking an auction IPO, we create a matched sample of bookbuilding IPOs over the 1999 to 2005 period by using a propensity-scoring method. Following the study by Lowry, Officer, and Schwert (2010), we estimate a probit model to get a predicted value (propensity score) for each auction IPO. The model is specified as follows:

$$Auction = \beta 0 + \beta 1 Log(Shares) + \beta 2 Tech + \beta 3 VC + \beta 4 Log(Firm\ Age + 1) + \beta 5 FF9 + \beta 6 MTH \quad (1)$$

Auction is equal to one if IPO shares are sold via the auction method and zero otherwise. The variable Log(Shares) is the natural logarithm of the number of shares (in millions) offered in the IPO. Tech equals one if the firm is in a high-tech industry and zero otherwise. VC equals one if the firm received financing from venture capitalists prior to the IPO and zero otherwise. Log (firm age +1) is the natural logarithm of the number of years since the firm was founded at the time of the IPO plus one. Jay Ritter's website (http://bear.warrington.ufl.edu/ritter/FoundingDates.htm) provides the founding dates for IPO stocks. The variable FF9 equals one for firms in the wholesale/retail industry (Fama-French industry group 9, SIC codes 5000–5200, 7200–7299, and 7600–7699) and zero otherwise. Auction IPOs might be most successful for well-known firms. The firms in the FF9 industry are retail-oriented ones that are likely to be widely exposed to the general public. Finally, MTH is a time trend variable based on the month of the IPO offer date, varying from one for the first month of our sample (March 1999) to eighty-two for the last month (December 2005). The estimate of this model is shown in Table 1. To create the sample of bookbuilding IPOs for use in the probit regression, we start with all IPOs in Thomson's SDC new issue database, then delete

ADRs, REITs, closed-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ. To calculate our main efficiency measure (SDPE), we also eliminate any IPO firm with less than 100 valid trades during the first 175 trading days after the IPO. Note that all 15 of the auction IPOs meet the above criteria.

Similar to Lowry, Officer, and Schwert (2010), for every firm that chooses the auction IPO method in Table 1, we pick two firms that choose the traditional bookbuilding method that have the closest propensity scores to the propensity scores of the auction IPO firm.[8] Specifically, we sort all IPOs based on the propensity scores and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. By selecting bookbuilding IPOs matched with slightly higher and slightly lower propensity scores, the average propensity score for the matched bookbuilding IPO sample (0.044495) is close to the average propensity score for the auction sample (0.044414).[9]

[Insert Table 1]

The probit regression results in Table 1 show that firms that offer small numbers of shares are more likely to choose the auction method. Older firms are also more likely to use the auction method. Finally, as an alternative IPO selling method, the auction method seems to gain more popularity with time, as evidenced by more deals being completed later in the sample period. This result is consistent with the findings of Lowry, Officer, and Schwert (2010).

[8] Other than IPOs taken public by WR Hambrecht, we have assumed that all other IPOs in my database are bookbuilding IPOs.
[9] We select bookbuilding IPOs without replacement so that the 30 matched bookbuilding IPO firms are distinct.

4. Empirical results

4.1. Empirical results of efficiency measures

Descriptive statistics of the matched sample of 30 bookbuilding IPOs and the 15 auction firms are shown in Table 2 and 3. Table 2 reports firm and IPO characteristics. Not surprisingly, due to the propensity score matching, these comparable firms that choose the bookbuilding method are statistically similar to the firms that choose the auction format for all variables other than gross spread (i.e., the fees charged by the underwriters to take the firm public). Bookbuilding IPOs have an average gross spread of 7.1%. This result is consistent with Chen and Ritter (2000), who find that most IPOs have a gross spread of 7%. Apparently, WR Hambrecht charges a lower fee for their auction IPOs (equal to an average of 5.5%).

[insert Tables 2 and 3]

In Table 3, we compare efficiency, divergence of opinion measures, aftermarket services, and institutional holdings between the two IPO selling methods. We use five measures of price efficiency: autocorrelation coefficient (AR|30|), variance ratio (|1-VR(30,60)|), standard deviation of pricing error (SDPE), short-term volatility (STVOL), and price delay (PD). The first four measures use intraday data from TAQ, while the last measure uses daily return data from CRSP. Trades and quotes used in the calculation of micro-level efficiency measures must meet the criteria used by Boehmer and Kelley (2009).[10] Higher values of all five measures indicate lower levels of efficiency. The details of SDPE are summarized in Appendix 2.

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[10] Specifically, we use trades and quotes only during regular market hours between 9:30 am and 4:00 pm and exclude overnight price changes. For trades, we require that TAQ's CORR field be equal to zero and that the COND field be either blank or equal to *, B, E, J, or K. We delete trades with non-positive prices or sizes. We also exclude a trade if its price differs by more than 30%

We use five proxies for the divergence of investors' opinions. The first three measures are from the NYSE TAQ database (absolute bid ask spread, relative bid ask spread, and effective bid ask spread). The other two are unexplained volume (UV) and standardized unexplained volume (SUV), following Garfinkel (2009). Garfinkel (2009) concludes that unexplained volume is the best proxy for divergence in investors' opinions. We show the details of the five proxies in Appendix 2.

Table 3 shows that IPOs using the auction method show higher efficiency than IPOs using the bookbuilding method according to the four market microstructure-based measures of price efficiency (AR|30|), |1-VR(30,60)|, SDPE, STVOL) and lower efficiency when using the price delay measure (PD). Contrary to our conjecture that bookbuilding IPOs have a higher price efficiency than auction IPOs, the differences for all five measures are statistically insignificant. A possible explanation for the lack of significance is the small sample size. The result implies that auction IPOs are not inferior to bookbuilding IPOs with respect to price efficiency in a univariate setting. We further test for differences in significance in a multivariate setting in the next section.

Two measures of divergence of opinion, i.e., SUV and absolute spread, differ significantly between auction and bookbuilding IPOs. Specifically, auction IPOs have a smaller SUV and absolute spread. This evidence is consistent with argument that investors' opinions are less dispersed in auction IPOs. The result is in contrast to our initial conjecture that an auction IPO shows a higher divergence of opinion due to the high proportion of retail investors.

To examine the differences in post-IPO ownership structures between auction IPOs and bookbuilding IPOs, we collect 13f institutional ownership data from Thomson-Reuter's

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from the previous trade price. We include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. We exclude quotes with non-positive ask or bid prices, or those in which the bid price is higher than the ask price. We require that the difference between bid and ask prices be less than 25% of the quote midpoint.

institutional holdings database, formerly known as CDA/Spectrum 3, 4. This database provides institutional, common stock holdings and transactions reported on form 13f, filed with the U.S. Securities and Exchange Commission (SEC) for institutional managers with $100 million or more in assets under management. Form 13f must be filed within the 45-day period after the end of a calendar quarter. Thus, for each auction and book-building IPO in our sample, we will obtain the level of 13f institutional shareholders and the fraction of the firm they hold at the end of the first three calendar quarters following the IPO. We use three calendar quarters because three quarters of institutional investors' holdings match the period of our calculations for SDPE. We expect book-building IPOs to have a greater portion of institutional ownership.

For analyst coverage, we use the IBES database to count the number of analysts. Lastly, we use the MMCNT variable of the Center for Research in Security Prices (CRSP) database to count the number of registered market makers as a proxy for the service of market-making. We use only NASDAQ stocks for the test of the number of market makers because the MMCNT variable is only presented in CRSP for issues trading on NASDAQ.

The auction method is not inferior to bookbuilding with respect to the aftermarket services. There is no statistical difference between these two methods with respect to the provision of price support, number of market makers or analyst coverage. Price support is a dummy variable that is equal to one if the IPO closes on the first trading day at the offer price (stabilized) and is equal to zero if it closes below the offer price (not stabilized). One noteworthy detail is the institutional holdings. To measure institutional holdings, we take the average of three quarters of institutional holdings following the month of the IPO date. Surprisingly, a higher proportion of institutional investors appears to be drawn to the auction IPO, despite statistical indifference between the two IPO selling groups (the p-value is 0.15). This may indicate that informed investors use their informational advantage in auction IPOs, perhaps resulting in higher price efficiency. Along with the efficiency measures, the next section will explore aftermarket services and the divergence of opinions in a multivariate setting.

In sum, descriptive statistics provide little support for the notion that a bookbuilding IPO is superior to an auction IPO. With the caveat that the sample size is small, it appears that the measures of efficiency and aftermarket services are similar for the two methods.

Table 4 shows cross-sectional regression results comparing the efficiency of IPOs using the auction method with that using the bookbuilding method. Each panel tests whether IPOs that use the auction method are more or less efficient than those that use the bookbuilding method by using the five different efficiency measures. We use a dummied auction IPO, which is equal to one if an IPO is auctioned and zero otherwise. The results look similar across all measures. In general, there is no significant difference in the levels of price efficiency between auction and bookbuilding methods, either in a univariate regression or with the inclusion of various control variables. The exception is in panel A and panel B. In panel A, which uses the variance ratio as the efficiency measure, the auction dummy is insignificant in model specifications (1), (2), and (3); however, when the model includes all of the control variables in the model specification (4), including industry dummies, the auction dummy becomes significant, with a negative sign at the 10% level. In other words, IPOs with the auction method appear to show higher efficiency than IPOs with the bookbuilding method in model specification (4). Similarly, IPOs sold via the auction method show higher efficiency than IPOs sold via the bookbuilding method at a 10% level in panel B, regression (4), where panel B uses the autocorrelation coefficient as the measure of efficiency. This result is contrary to our prior expectation that IPOs using the book-building method would have higher levels of efficiency than IPOs using the auction method.

While our finding is preliminary due to the small sample of auction IPOs, the auction method does not seem inferior to the bookbuilding method with respect to price efficiency.

In sum, except in the two regression models discussed above, we find no differences between the efficiency of IPO stocks using these two methods, indicating that the selling method is not an important factor in determining the efficiency of IPO stocks with the set of IPOs used in our study.

[Insert Table 4]

4.2. Empirical results of aftermarket services, including price support, analyst coverage, and number of market makers

For the multivariate tests for aftermarket services using either the auction method or the bookbuilding method, we proceed with only analyst coverage, measured as the number of analysts for the three quarters following the IPO date.[11] Table 5 shows the cross-sectional regression of the number of analysts of the selling method and control variables. Consistent with the univariate analysis in Table 3, there is no significant difference in the number of analysts between the two methods, with the inclusion of various control variables. This result is inconsistent with our prior expectation that the book-building IPO method would provide a better quality of aftermarket service. Rather, the auction method does not seem inferior to the bookbuilding method in terms of aftermarket services. As before, it is noted that given the small

[11] There are only 15 observations for the measure of price support and 19 observations for the measure of number of market makers. Thus, it would not be meaningful to perform multivariate tests with such a small number of observations.

sample of auctions, our evidence does not conclude that the auction method is more beneficial than the bookbuilding method but rather only suggests that this may be the case.

[Insert Table 5]

4.3. Empirical results of divergence of opinions

Table 6 shows cross-sectional regressions of divergence of opinion using the five measures on selling methods and controls. Each panel tests whether IPOs using the auction method have a higher or lower divergence of opinion than those using the bookbuilding method by using the different divergences of opinion measures. The results look similar across all five measures. In general, there is no significant difference in the levels of divergence of opinion between the auction and bookbuilding methods, either in a univariate regression or with the inclusion of various control variables. The exception arises in panel A and panel B. In panel A, which uses the unexplained volume (UV) as the measure of divergence of opinion, the auction dummy is insignificant in model specifications (1), (2), and (3); however, when the regression analysis includes all of the control variables, including industry dummies (model 4), the auction dummy becomes significantly negative at the 10% level. In other words, in this model, IPOs using the auction method show lower divergence of opinion than IPOs using the bookbuilding method when divergence of opinion is measured based on unexplained volume. Similarly, IPOs sold via the auction method show lower divergence of opinion than IPOs sold via the bookbuilding method at a 10% level in panel B, model (1), i.e., the univariate regression. Panel B uses the standardized unexplained volume (SUV) as the measure of divergence of opinion. Again, this result is consistent with the idea that an auction IPO yields a higher level of consensus of opinion among investors compared to bookbuilding. This lower level of divergence of opinion can contribute to enhancing price efficiency. Once again, while our results are subject to the small sample bias, the alternative price mechanism, i.e., the auction method, may yield more agreed valuation of the price and thus higher price efficiency.

[Insert Table 6]

In summary, our results provide little support for the idea that firms receive better aftermarket services when they choose the bookbuilding method of underwriting. Moreover, we do not find that bookbuilding IPOs have lower divergence of opinion than auction IPOs. This, coupled with our results that show that bookbuilding IPOs do not have a higher level of price efficiency than auction IPOs, adds support to the argument made by Lowry, Officer, Schwert (2010) that IPO firms may not need to continue using the traditional bookbuilding method because it does not give much advantage in various dimensions over the auction method.

5. Conclusion

Regulators, the popular press, and many academic researchers have noted the abuses of bookbuilding IPOs in the process of pricing and allocating shares. The class-action lawsuit against Facebook, as a recent example, alleged that the firm and the lead underwriters (Morgan Stanley and Goldman Sachs) withheld material information from retail investors while sharing that information with large institutional clients. Despite these unjust practices inherent in the bookbuilding method, bookbuilding has become the predominant IPO selling mechanism in most countries. In this study, we explore the different levels of price efficiency in IPO stocks using the bookbuilding method and the auction method. We conjecture that higher levels of efficiency of the bookbuilding method may be another explanation for why the bookbuilding method dominates the auction method in spite of well-known drawbacks. However, our empirical results fail to support this conjecture. Using a sample of IPO stocks between 1993 and 2005, we find that bookbuilding IPO stocks are not more efficient than auction IPO stocks in the initial aftermarket. Rather, our result shows that auction IPOs may be more efficient than bookbuilding IPOs, although the evidence is weak. Auction IPOs are also not inferior to bookbuilding IPOs with respect to many dimensions, such as aftermarket services, institutional holdings, and the degree of divergence of opinion among investors. The purpose of this paper is to fill the knowledge gap of why the bookbuilding method dominates the auction method in spite of its well-known abuses. Contrary to prediction, this study indicates many positive aspects of the auction method that may help complement the negative aspects of bookbuilding abuses.

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Appendix 1. Variable definitions.

Variable	Definitions
Auction	Auction equals one if the IPO shares are sold by auction and zero otherwise.
SDPE	The standard deviation of pricing error, termed by Hasbrouck (1993). It measures the magnitude of deviations from the efficient price. Refer to detailed description of how to estimate the SDPE in the appendix of Boehmer and Wu (2013).
|AR(30)|	The absolute value of the thirty-minute quote midpoint return autocorrelation.
|1-VR(30,60)|	The absolute value of one minus the ratio of the sixty-minute quote midpoint return variance divided by twice the variance of the thirty-minute quote midpoint return.
STVOL	Short-term volatility (O'Hara and Ye, 2011) is the quote midpoint return volatility over the thirty-minute interval.
PD	Price delay, from Hou and Moskowitz (2005), which is calculated as the average delay with which information is impounded into stock prices by first regressing stock returns for each firm based on the contemporaneous (restricted model) and four lagged weekly market returns (unrestricted model), as follows: 1-(R2restricted / R2unrestricted).
Initial return (%)	The percent difference between the closing price on the first trading day and the offer price.
Log (firm age + 1)	The logarithm of the number of years since the firm was founded at the time of an IPO plus one. The data for founding dates are obtained from Jay Ritter's website (http://bear.warrington.ufl.edu/ritter/FoundingDates.htm).
Price update	The percentage difference between the midpoint of the preliminary price range and the final offer price.
Absolute spread	The dollar difference between ask and bid from the NYSE TAQ data.
Relative spread	Absolute spread scaled by price (absolute spread/trading price) from the NYSE TAQ data.
Effective spread	Twice the absolute value of the difference between trade price and midpoint from the NYSE TAQ data.
Offer price	The offer price for the IPO.
Tech	Tech equals one if the firm is in a high-tech industry (biotech, computer equipment, electronics, communications, and general technology (as defined by SDC)) and zero otherwise. This definition of Tech is from Lowry, Officer, and Schwert (2010).
Market capitalization ($ million)	The closing price on the first day of trading times the number of outstanding shares.
VC	VC equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC) and zero otherwise.
Rank	Rank of the book underwriter. The rank is from Loughran and Ritter (2004), using a method similar to that of Carter and Manaster (1990). [http://bear.warrington.ufl.edu/ritter/rank.htm]
Gross spread (%)	The percentage of the proceeds paid as fees to the underwriters.
Log (Shares)	The logarithm of the number of shares (in millions) offered in the IPO.
MTH	MTH is a time trend variable, varying from 1 for March 1999 to 82 for December 2005.
NASDAQ	NASDAQ equals one if the IPO is listed on NASDAQ and zero otherwise.

Turnover	Turnover is calculated as the CRSP-reported first day volume divided by the number of shares issued. NASDAQ volume numbers are divided by 2 for 1983-January 2001, by 1.8 for the rest of 2001, and by 1.6 for 2002-2003 to make them comparable to the Amex and NYSE volume. The data and definition of Turnover are from http://bear.warrington.ufl.edu/ritter/ipodata.htm.
Bubble	Bubble equals one for IPO offer dates between September 1998 and August 2000 and zero otherwise, similar to the bubble period definition of Lowry, Officer, and Schwert (2010).
FF9	FF9 equals one for firms in the wholesale/retail industry (Fama-French industry group 9, SIC codes 5000–5200, 7200–7299, and 7600–7699) and zero otherwise.
Price support	Price support is a dummy variable that is equal to one if the IPO closes below the offer price on the first trading day, otherwise zero.
# Market makers	The number of market makers for issues traded on NASDAQ on the 21st trading day after the IPO.
The number of analysts	The mean number of unique financial analysts that post forecasts for a firm at the end of each fiscal quarter over the 9 months following the offer date.
Institutional holding	The mean of the percentage of shares held by institutional investors (institutional investment managers with assets greater than $100 million) out of the total outstanding shares at the end of each fiscal quarter over the 9 months following the offer date.
Unexplained volume (UV)	Unexplained volume (UV) is computed as follows. First, firm-specific turnover is computed by dividing the firm's daily volume on a given day by its outstanding shares. Second, market-adjusted turnover is calculated by subtracting market-wide turnover from firm-specific turnover. Third, market-adjusted turnover is de-trended by subtracting the moving 180-day median market-adjusted turnover. To address the issue of double-counting of volume for NASDAQ securities, we use the findings reported by Anderson and Dyl (2005). They proposed a rough rule of thumb to scale down the volume of NASDAQ securities by 38% after 1997 and by 50% before that to make it roughly comparable with the volume of NYSE. This definition of unexplained volume is from Garfinkel (2009).
Standardized unexplained volume (SUV)	Standardized unexplained volume (SUV) is calculated as a standardized prediction error from a regression of trading volume of the absolute value of returns for time t and firm i. This definition of standardized unexplained volume is from Garfinkel (2009).
Valid trades when using TAQ efficiency measures	Following Boehmer and Kelley (2009), we use trades and quotes only during regular market hours between 9:30 am and 4:00 pm and exclude overnight price changes. For trades, we require that TAQ's CORR field be equal to zero and that the COND field be either blank or equal to *, B, E, J, or K. We delete trades with non-positive prices or sizes. We also exclude a trade if its price differs by more than 30% from the previous trade price. We include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. We exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. We require that the difference between bid and ask be less than 25% of the quote midpoint.

Appendix 2. The detailed explanation regarding the measures of price efficiency

We follow the approach of Boehmer and Wu (2013) to calculate SDPE. Boehmer and Kelly (2009) scaled SDPE based on the standard deviation of prices to make comparisons across stocks meaningful. However, in our study, using the unscaled Hasbrouck (1993)'s standard deviation of pricing error (SDPE) is more appropriate due to the fact that IPO stock prices typically have a very high standard deviation of prices in the early aftermarket when compared to seasoned stocks. Because SDPE is inversely related to price efficiency, the smaller this value is, the more efficient the stock price is.

Our first alternative measure of price efficiency is $|AR_{30}|$, which is the absolute value of the thirty-minute quote midpoint return autocorrelation. If prices follow a random walk, the autocorrelation coefficient should be zero. Because both negative and positive autocorrelation coefficients indicate deviations from a random walk, we use the absolute value of the autocorrelation coefficient as the measure of efficiency. Following Boehmer and Kelley (2009), we compute returns from quote midpoints (rather than from transaction prices) to eliminate bid-ask bounce and compute thirty-minute autocorrelations for both IPOs and seasoned stocks[12]. To circumvent the problem of sparse quotes, we only use consecutive 30-minute returns.[13] We also require at least 100 30-minute returns during the 175-trading-day period following the IPO's offer date.

If stock prices follow a random walk, then the variance of random walk increments must be a linear function of the time interval. In other words, the ratio of the variance of two-period,

[12] We also compute fifteen-minute autocorrelations for both IPOs and seasoned stock. We find no qualitative differences in results between the two different time horizons.

[13] To compute the midpoint return at t+1, the midpoint return should exist at t and t+1: Return(t+1) = ln(midpoint(t+1)/midpoint(t))

continuously compounded returns should be twice the variance of a one-period return. Because we are interested in the deviation of the transaction price from the efficient price in either direction, we compute as our next measure of efficiency $|1 - VR_{(30,60)}|$, where $VR_{(30,60)}$ is the ratio of the quote midpoint return variance calculated over *60* minutes to two times the return variance calculated over *30* minutes. The sample of returns used to calculate $|1 - VR_{(30,60)}|$ is the same as that used to calculate $|AR_{30}|$.

The last metric of measuring efficiency using intra-day return is short-term volatility. Stock market volatility has drawn attention from regulators and has been used by academics to test market efficiency (Shiller, 1981). Barclay and Warner (1993) argue that private information rather than public information causes market volatility. O'Hara and Ye (2011) contend that the SEC views excessive short-term volatility as a negative metric of market quality, in that some groups of traders could be disadvantaged by short-term price movements unrelated to long-term fundamentals. They cite the SEC concept release No. 34-61358, which states: "Short term price volatility may harm individual investors if they are persistently unable to react to changing prices as fast as high frequency traders. As the Commission previously has noted, long-term investors may not be in a position to access and take advantage of short-term price movements. Excessive short-term volatility may indicate that long-term investors, even when they initially pay a narrow spread, are being harmed by short-term price movements that could be many times the amount of the spread."

Using returns from quote midpoints, we compute return volatility over 30-minute intervals and denote this as $STVOL_{30}$.[14]

[14] We divide the trading day into 13 30-minute intervals, starting at 9:30 am. We use the same returns as for autocorrelations and the variance ratio to calculate short-term volatility.

Our final measure of efficiency is the price delay, termed by Hou and Moskowitz (2005). Price delay measures the average delay with which share price responds to market-wide information. According to Hou and Moskowitz (2005), slow response to market frictions, such as poor accounting quality, retards the speed of this reassessment process and therefore delays the incorporation of market-wide news into firm-specific stock prices. We calculate price delay by first estimating two regression models. In the first ("unrestricted regression"), we regress the weekly stock return of an individual firm based on contemporaneous and four lagged weekly market returns. In "restricted regression," we regress the weekly stock return for an individual firm against just the contemporaneous market return.

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \Sigma_{n=1\ to\ 4}\, \delta_{i,n} R_{m,t-n} + \varepsilon_{i,t} \quad \text{(Unrestricted regression)} \qquad (8)$$

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \quad \text{(Restricted regression)} \qquad (9)$$

We then calculate R^2 from each regression, with price delay (*PD*) calculated as: *PD* = 1 – (R^2restricted / R^2unrestricted). *PD* is larger when the proportion of the return variation explained by the lagged market return is higher. Thus, higher values of *PD* imply lower levels of efficiency.

Table 1. Probit model for predicting the use of the auction method to sell shares in an initial public offering.

This table shows maximum likelihood estimates of a probit model to explain the choice to use the auction method to sell shares in the IPO. The sample consists of IPOs between March 1999 and December 2005. Auction equals one if the IPOs are sold by auction and zero otherwise. See Appendix 1 for other variable definitions. The large sample standard errors are used to calculate the *t*-statistics in parentheses under the coefficient estimates. The Likelihood Ratio Statistic measures the joint significance of the model with the *p*-value in parentheses. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) from March 1999 through December 2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of bookbuilding IPOs is from Thomson's SDC new issue database from 1999 to 2005 and excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO. All auction IPOs meet the criteria used to select the sample of bookbuilding IPOs.

$$Auction_i = \beta_0 + \beta_1 Log(Shares_i) + \beta_2 Tech_i + \beta_3 VC_i + \beta_4 Log(Firm\ Age_i + 1) + \beta_5 FF9_i + \beta_6 MTH_i$$

Intercept	18.213
	(3.03)
Log (Shares)	-1.6702
	(3.92)
Tech	0.543
	(0.82)
VC	0.706
	(1.139)
Log (Firm Age + 1)	0.557
	(1.93)
FF9	1.3772
	(0.91)
MTH	0.026
	(2.98)
Likelihood ratio statistic	22.008
(p-value)	(0.0012)
Sample size	1254

Table 2. Descriptive statistics of IPO characteristic variables between auction IPOs and matched bookbuilding IPOs from 1999 to 2005.

This table shows descriptive statistics for the IPO characteristic variables for our sample of 15 auction IPOs and 30 propensity score matched bookbuilding IPOs. The propensity score matched sample of bookbuilding IPOs is generated using the probit, model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The definition of variables is in Appendix 1. The last column provides the p-value from a t-test of difference of means for auction IPOs and bookbuilding IPOs, assuming either equal or unequal variances based on an equality of variance test. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) from March 1999 through December 2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of bookbuilding IPOs is from Thomson's SDC new issue database from 1999 to 2005 and excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO. All auction IPOs meet the criteria used to select the sample of bookbuilding IPOs.

	Auction	Bookbuilding	Difference in Means (p-value)
Initial return (%)	18.00	27.87	9.871 (0.661)
Log (firm age + 1)	2.494	2.311	-0.183 (0.4679)
Gross spread (%)	5.487	7.143	1.656 (0.0003)
Price update	0.194	0.159	-0.0292 (0.5823)
Market capitalization ($ million)	435.408	376.118	-59.290 (0.7263)
Offer price	16.233	11.388	-4.8460 (0.1652)
VC	0.600	0.5667	-0.033 (0.6866)
Rank	7.133	6.433	-0.7188 (0.2433)
NASDAQ	1.000	0.867	-0.133 (0.1457)
Turnover	0.516	0.573	0.056 (0.7140)
Bubble	0.267	0.433	0.167 (0.2960)
N	15	30	

Table 3. Descriptive statistics of non-IPO characteristic variables (efficiency, divergence of opinion, aftermarket services, and institutional ownership) between auction IPOs and matched bookbuilding IPOs in the period of 1999-2005.

This table shows descriptive statistics for the non-IPO characteristic variables for our sample of 15 auction IPOs and 30 propensity score matched bookbuilding IPOs. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The definition of variables is in Appendix 1. The last column provides the p-value from a t-test of difference of means for auction IPOs and bookbuilding IPOs, assuming either equal or unequal variances based on an equality of variance test. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) from March 1999 through December 2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of bookbuilding IPOs is from Thomson's SDC new issue database from 1999 to 2005 and excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO. All auction IPOs meet the criteria used to select the sample of bookbuilding IPOs.

	Auction	Bookbuilding	Difference in Means (p-value)
Measures of Price Efficiency			
AR|30|	0.0695	0.0842	0.0148 (0.5249)
|1-VR(30,60)|	0.1068	0.1268	0.0200 (0.6099)
SDPE	0.0033	0.0045	0.0012 (0.337)
STVOL	0.0127	0.0166	0.0039 (0.2229)
PD	0.5828	0.5372	-0.0456 (0.6005)
Measures of Divergence of Opinion			
Unexplained volume (UV)	-0.0003	0.0002	0.0005 (0.1690)
SUV	0.0179	0.1440	**0.1260 (0.0906)**
Absolute spread	0.1454	0.1966	**0.0512 (0.0640)**
Relative spread	0.0142	0.0183	0.0041 (0.3500)
Effective spread	0.1203	0.1625	0.0422 (0.1145)
Measures of Aftermarket Services and Ownership Structures			
Price support	0.167	0.364	0.1970 (0.4263)
# Market maker	19.170	16.000	-2.7783 (0.1883)
Number of analysts	3.31	2.70	-0.6100 (0.6449)
Institutional holding	0.254	0.181	-0.0730 (0.1457)
N	15	30	

Table 4. Panel A. Cross-sectional regression of autocorrelation of the auction versus bookbuilding methods.

The dependent variable is autocorrelation, calculated as the absolute value of the thirty-minute quote midpoint returns and denoted as |AR(30)|.The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) from March 1999 through December 2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of bookbuilding IPOs is from Thomson's SDC new issue database from 1999 to 2005 and excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO. All auction IPOs meet the criteria used to select the sample of bookbuilding IPOs.

	(1)	(2)	(3)	(4)
Intercept	0.0842	0.3206	0.3867	0.4596
	(<.0001)	(0.0015)	(0.0005)	(0.0020)
auction dummy	-0.0148	-0.0232	-0.0121	-0.0509
	(0.5249)	(0.3092)	(0.6288)	**(0.0696)**
ln(numtrades)		0.0034	0.0077	0.0342
		(0.7468)	(0.5381)	(0.1597)
ln (mktcap)		-0.0275	-0.0351	-0.0652
		(0.0429)	(0.0231)	(0.0127)
NASDAQ		0.0702	0.0840	0.2265
		(0.0948)	(0.0520)	(0.0443)
Year dummies				
2000			-0.0391	0.0596
			(0.2448)	(0.2098)
2001			-0.1310	-0.2158
			(0.0300)	(0.1445)
2002			-0.0739	-0.0038
			(0.1765)	(0.9519)
2003			-0.0463	0.0344
			(0.3918)	(0.6075)
2004			-0.0242	0.0281
			(0.4811)	(0.5177)
2005			-0.0301	0.0422
			(0.3386)	(0.3643)
Industry dummies	No	No	No	Yes
Adj. R2	0.0095	0.1060	0.1172	0.3655
No. of Obs.	45	45	45	45

Table 4. Panel B. Cross-sectional regression of variance ratios of the auction versus bookbuilding methods.

The dependent variable is the variance ratio, calculated as the absolute value of one minus the ratio of the sixty-minute quote midpoint return variance divided by twice the variance of the thirty-minute quote midpoint return and denoted as |1-VR(30,60)|. The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	0.1268	0.4854	0.5680	0.9203
	(<.0001)	(0.0027)	(0.0017)	(<0.0001)
auction dummy	-0.0200	0.0051	0.0161	-0.0501
	(0.6099)	(0.8887)	(0.7007)	**(0.0755)**
ln(numtrades)		-0.0202	-0.0159	0.0225
		(0.2349)	(0.4449)	(0.3496)
ln (mktcap)		-0.0059	-0.0141	-0.0538
		(0.7830)	(0.5710)	(0.0359)
NASDAQ		-0.1140	-0.0987	0.1228
		(0.0929)	(0.1653)	(0.2588)
Year dummies				
2000			-0.0530	0.0895
			(0.3431)	(0.0678)
2001			-0.1396	-0.5619
			(0.1571)	(0.0009)
2002			-0.1335	-0.0435
			(0.1442)	(0.4958)
2003			-0.0155	0.0748
			(0.8624)	(0.2731)
2004			-0.0337	0.0460
			(0.5562)	(0.2977)
2005			-0.0463	0.0590
			(0.3775)	(0.2119)
Industry dummies	No	No	No	Yes
Adj. R2	0.0061	0.1842	0.3359	0.7754
No. of Obs.	45	45	45	45

Table 4 Panel C. Cross-sectional regression of standard deviation of pricing error (SDPE) of the auction versus bookbuilding methods.

The dependent variable is the standard deviation of pricing error (SDPE). SDPE is the standard deviation of pricing error based on Hasbrouck (1993). The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	0.0046	0.0148	0.0063	0.0164
	(<.0001)	(0.0025)	(0.0218)	(0.0025)
auction dummy	-0.0012	-0.0004	-0.0001	-0.0009
	(0.3366)	(0.7008)	(0.9120)	(0.3543)
ln(numtrades)		-0.0012	-0.0007	-0.0019
		(0.0216)	(0.1334)	(0.0140)
ln (mktcap)		0.0002	0.0003	0.0010
		(0.7517)	(0.5566)	(0.1824)
NASDAQ		-0.0015	-0.0017	-0.0006
		(0.4475)	(0.4241)	(0.8348)
Year dummies				
2000			0.0012	-0.0001
			(0.2182)	(0.9689)
2001			0.0058	-0.0062
			(0.0557)	(0.1827)
2002			-0.0030	-0.0059
			(0.0248)	(0.0275)
2003			-0.0044	-0.0075
			(0.0033)	(0.0120)
2004			-0.0026	-0.0061
			(0.0073)	(0.0019)
2005			-0.0027	-0.0066
			(0.0068)	(0.0054)
Industry dummies	No	No	Yes	Yes
Adj. R2	0.0210	0.2967	0.9078	0.5972
No. of Obs.	45	45	45	45

Table 4. Panel D. Cross-sectional regression of the short-term volatility (STVOL) of the auction versus book-building methods.

The dependent variable is short-term volatility (STVOL), which is the quote midpoint return volatility over the thirty-minute interval. The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	0.0166	0.0271	0.0359	0.0293
	(<.0001)	(0.0571)	(0.0066)	(0.1218)
auction dummy	-0.0039	-0.0049	-0.0021	-0.0009
	(0.2229)	(0.1498)	(0.4953)	(0.8173)
ln(numtrades)		0.0010	0.0010	-0.0019
		(0.5315)	(0.5273)	(0.5741)
ln (mktcap)		-0.0020	-0.0024	0.0008
		(0.2989)	(0.2006)	(0.8162)
NASDAQ		0.0055	0.0016	-0.0153
		(0.3656)	(0.7610)	(0.3154)
Year dummies				
2000			0.0092	0.0075
			(0.0321)	(0.2631)
2001			-0.0006	0.0199
			(0.9343)	(0.3346)
2002			-0.0042	-0.0132
			(0.5343)	(0.1517)
2003			-0.0057	-0.0145
			(0.3950)	(0.1359)
2004			-0.0074	-0.0125
			(0.0888)	(0.0527)
2005			-0.0068	-0.0124
			(0.0866)	(0.0682)
Industry dummies	No	No	No	Yes
Adj. R2	0.0343	0.0705	0.2773	0.3266
No. of Obs.	45	45	45	45

Table 4. Panel E. Cross-sectional regression of price delay (PD) of the auction versus book-building methods.

The dependent variable is price delay (PD). PD (Hou and Moskowitz, 2005) calculates the average delay with which information is impounded into stock prices by first regressing stock returns for each firm based on the contemporaneous (restricted model) and four lagged weekly market returns (unrestricted model), as follows: 1- (R2restricted / R2unrestricted). The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	0.5372	1.2540	1.0565	1.0512
	(<.0001)	(0.0009)	(0.0067)	(0.0567)
auction dummy	0.0456	0.0821	0.0612	-0.1110
	(0.6005)	(0.3305)	(0.5066)	(0.3134)
ln(numtrades)		-0.0656	-0.0536	0.1298
		(0.0945)	(0.2446)	(0.1867)
ln (mktcap)		-0.0055	-0.0097	-0.1450
		(0.9108)	(0.8595)	(0.1468)
NASDAQ		-0.0403	-0.0188	0.4979
		(0.7919)	(0.9029)	(0.2564)
Year dummies				
2000			0.1050	0.2632
			(0.3922)	(0.1736)
2001			0.1495	-0.0297
			(0.4861)	(0.9593)
2002			0.2306	0.0646
			(0.2486)	(0.8008)
2003			-0.1462	-0.2519
			(0.4601)	(0.3577)
2004			0.1265	0.0426
			(0.3180)	(0.8084)
2005			0.2372	0.2588
			(0.0447)	(0.1758)
Industry dummies	No	No	No	Yes
Adj. R2	0.0064	0.1305	0.1560	0.2585
No. of Obs.	45	45	45	45

Table 5. Cross-sectional regression of number of analysts following an IPO firm of the auction versus bookbuilding methods.

The dependent variable is the number of analysts. The number of analysts is the mean number of unique financial analysts that post forecasts for a firm at the end of each fiscal quarter over the 9 months following the offer date. The number of observations is reduced due to the missing data with respect to the number of analysts. The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	2.6746	-13.63	-11.48	-16.29
	(0.0042)	(0.0412)	(0.1425)	(0.1924)
auction dummy	0.6661	1.4772	1.6957	1.1789
	(0.6385)	(0.1901)	(0.1506)	(0.5049)
ln(numtrades)		2.6472	2.8250	3.2155
		(0.0011)	(0.0045)	(0.0462)
ln (mktcap)		-0.3908	-0.7583	-0.9991
		(0.6676)	(0.5081)	(0.6009)
NASDAQ		-5.502	-5.032	-5.799
		(0.0871)	(0.1110)	(0.2535)
Year dummies				
2000			-0.7858	1.8648
			(0.6461)	(0.5537)
2001			-3.252	4.1677
			(0.2457)	(0.4831)
2002			-1.632	1.6936
			(0.4841)	(0.6609)
2003			-0.3743	3.3896
			(0.8683)	(0.3936)
2004			2.0660	4.3287
			(0.2156)	(0.1280)
2005			0.4186	5.0176
			(0.7880)	(0.1221)
Industry dummies	No	No	No	Yes
Adj. R2	0.0070	0.5670	0.6819	0.8045
No. of Obs.	34	34	34	34

Table 6. Panel A. Cross-sectional regression of unexplained volume of the auction versus bookbuilding methods.

The dependent variable is unexplained volume (Garfinkel, 2009). Unexplained volume (UV) is computed as follows. First, firm-specific turnover is computed by dividing the firm's daily volume on a given day by its outstanding shares. Second, market-adjusted turnover is calculated by subtracting market-wide turnover from firm-specific turnover. Third, market-adjusted turnover is de-trended by subtracting the moving 180-day median market-adjusted turnover. The number of observations is reduced due to the missing data with respect to unexplained volume. The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	0.0002	0.0048	0.0054	0.0069
	(0.3168)	(0.0036)	(0.0089)	(0.0073)
auction dummy	-0.0005	-0.0005	-0.0005	-0.0009
	(0.1690)	(0.1466)	(0.2292)	(0.0692)
ln(numtrades)		0.0002	0.0002	0.0004
		(0.1549)	(0.2793)	(0.1930)
ln (mktcap)		-0.0005	-0.0005	-0.0008
		(0.0282)	(0.0641)	(0.0152)
NASDAQ		-0.0011	-0.0011	-0.0016
		(0.1285)	(0.1524)	(0.1155)
Year dummies				
2000			-0.0001	-0.0002
			(0.8475)	(0.8377)
2001			-0.0004	0.0013
			(0.7066)	(0.3840)
2002			0.0002	0.0000
			(0.8020)	(0.9733)
2003			0.0000	-0.0001
			(0.9837)	(0.9332)
2004			-0.0003	-0.0010
			(0.5748)	(0.2369)
2005			-0.0003	-0.0003
			(0.6350)	(0.7528)
Industry dummies	No	No	No	Yes
Adj. R2	0.0456	0.2980	0.3158	0.5510
No. of Obs.	43	43	43	43

Table 6. Panel B. Cross-sectional regression of standardized unexplained volume of the auction versus bookbuilding methods.

The dependent variable is standardized unexplained volume (Garfinkel, 2009). The standardized unexplained volume (SUV) is calculated as a standardized prediction error from a regression of trading volume on the absolute value of returns with daily frequency for each firm. The number of observations is reduced due to the missing data in the standardized unexplained volume. The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

	(1)	(2)	(3)	(4)
Intercept	0.1440	-0.2053	-0.3056	-0.2291
	(0.0017)	(0.5768)	(0.4860)	(0.7045)
auction dummy	-0.1261	-0.1210	-0.0923	-0.0990
	(0.0906)	(0.1316)	(0.3129)	(0.4103)
ln(numtrades)		0.0019	-0.0511	-0.0448
		(0.9609)	(0.3142)	(0.5204)
ln (mktcap)		0.0287	0.0816	0.0579
		(0.5717)	(0.1906)	(0.4675)
NASDAQ		-0.0199	-0.0807	-0.0093
		(0.9016)	(0.6458)	(0.9712)
Year dummies				
2000			-0.0100	0.1248
			(0.9365)	(0.5385)
2001			0.0894	0.2149
			(0.6777)	(0.5634)
2002			0.1467	0.2991
			(0.4578)	(0.3265)
2003			0.0435	0.2018
			(0.8240)	(0.5320)
2004			0.1502	0.1826
			(0.2524)	(0.3815)
2005			-0.0818	0.0134
			(0.5280)	(0.9512)
Industry dummies	No	No	No	Yes
Adj. R2	0.0683	0.0924	0.1907	0.3063
No. of Obs.	43	43	43	43

Table 6. Panel C. Cross-sectional regression of absolute, relative, and effective spread of the auction versus bookbuilding methods.

The dependent variables are three spread measures. The absolute spread (model 1) is the dollar difference between ask and bid from NYSE TAQ data. The relative spread (model 2) is the absolute spread scaled by the trade price. The effective spread (model 3) is twice the absolute value of the difference between trade price and the midpoint. The variable auction dummy equals one for auction IPO stocks and zero for bookbuilding IPO stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. Ln (mktcap) is the natural log of outstanding shares times the closing price on the first trading day of the IPO. NASDAQ equals one if the stock is listed on NASDAQ and zero otherwise. Year dummy corresponds to the year of the IPO offer date. Industry dummy is the dummy variable for each of the 49 Fama-French industries. P-values are reported in parentheses. The propensity score matched sample of bookbuilding IPOs is generated from the probit model, following Lowry, Officer, and Schwert (2010), and reported in Table 2. Specifically, we sort all IPOs based on the propensity score and match each auction IPO to the closest bookbuilding IPO with a propensity score higher than the auction IPO and to the closest bookbuilding IPO with a propensity score lower than the auction IPO. This produces two matched bookbuilding IPOs for each auction IPO. The sample of auction IPOs is from W.R. Hambrecht's open IPO process (http://www.wrhambrecht.com/ind/auctions/completed.html) through 12/31/2005, excluding Instinet (which sold only part of its shares in an auction format). The sample of auction and bookbuilding IPOs excludes ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, IPOs with an offer price below $5 per share, IPO firms not on CRSP and TAQ, and IPO firms with less than 100 valid trades (as defined in Appendix 1) during the first 175 trading days after the IPO.

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	(1)	(2)	(3)
Intercept	-0.0283	0.0720	-0.1249
	(0.8220)	(0.0004)	(0.2590)
auction dummy	-0.0393	-0.0012	-0.0350
	(0.2319)	(0.7833)	(0.2207)
ln(numtrades)	-0.0275	-0.0026	-0.0154
	(0.1292)	(0.2923)	(0.3182)
ln (mktcap)	0.0428	-0.0026	0.0398
	(0.0287)	(0.3255)	(0.0198)
NASDAQ	-0.0842	0.0004	-0.0713
	(0.1797)	(0.9612)	(0.1902)
Year dummies			
2000	0.0468	0.0170	0.0312
	(0.3754)	(0.0275)	(0.4946)
2001	0.0070	0.0079	0.0090
	(0.9439)	(0.5712)	(0.9168)
2002	-0.0912	-0.0106	-0.1108
	(0.2725)	(0.3600)	(0.1291)
2003	-0.0972	-0.0103	-0.1266
	(0.2676)	(0.3985)	(0.1019)
2004	-0.0164	-0.0034	-0.0724
	(0.7684)	(0.6583)	(0.1429)
2005	-0.0263	-0.0017	-0.0632
	(0.6105)	(0.8088)	(0.1670)
Industry dummies	Yes	Yes	Yes
Adj. R2	0.6004	0.6890	0.6749
No. of Obs.	45	45	45