The Efficiency of IPO Stocks

Abstract

I test whether there is a difference in the level of efficiency between IPO stocks and a matched sample of seasoned stocks. My findings show that IPO stocks are less efficient than seasoned stocks during my testing period of 175 trading days. I attribute the lower level of efficiency for my testing period to the higher amount of information asymmetry inherent in IPO stocks. I contend that the presence (or quality) of financial intermediaries is related to the level of information asymmetry for IPO stocks. Consistent with this argument, I find that IPOs with prestigious underwriters, with venture capital backing, or with large managing syndicates have a higher level of efficiency than IPOs with less prestigious underwriters, no venture capital backing, or small managing syndicates. Finally, I show that stocks with higher levels of efficiency have higher long-run performance, consistent with efficient stock prices being an important input for firms to make sound financing and investment decisions.

Keywords: IPOs, Seasoned stocks, Price efficiency, Underwriters, Venture capitalists, Managing syndicates, Long-run performance

JEL classification: G14; G23; G24; G32

Introduction

In this paper, I investigate the efficiency of initial public offering (IPO) stocks by comparing to a matched sample of seasoned stocks. I address three research questions. My first research question is whether IPO stocks are more or less efficient than a matched sample of seasoned stocks during the first week of trading, or if it takes some time for the IPO stock's efficiency to become similar to the level of the matched stock.

My second research question is whether the presence of (or quality of) financial intermediaries is related to the level of efficiency of IPO stocks. This can either be due to financial intermediaries affecting the level of information asymmetries for these IPO firms or through the selection process (i.e., better intermediaries bringing IPO firms to the market that are more likely to have efficient stock prices). For this second research question, I examine how the prestige of the IPO's book underwriter, whether the IPO is venture capital (VC) backed, and the size of the IPO's managing syndicate is related to the efficiency of IPO stocks. I employ a propensity scoring method to circumvent selection bias.

In a well-functioning financial market without market imperfections, similar stocks should have similar levels of efficiency without regard to the length of time the stock has been trading. However, if some IPO stocks have a lower efficiency level, management and investors are faced with a noisy measure of the cost of capital and firm performance. This leads to poorly-informed investment and financing decisions (Harris, 2003) and it makes it more difficult to discipline / monitor management. This leads to my third research question: Do IPO stocks with lower efficiency have lower long-term performance.

My main proxy for the level of efficiency is the standard deviation of pricing error (SDPE) from Hasbrouck (1993), although I also check the robustness of my results using four other measures of efficiency: autocorrelation, variance ratio, short-term return volatility, and price delay. I find that IPO stocks are less efficient (i.e., have a higher SDPE) than seasoned stocks during my testing period (through the 35th week). With respect to my second research question, I find that IPOs with more prestigious book underwriters and more managers have more efficient stock prices in the immediate aftermarket. VC-backed IPOs also have more efficient stock prices than non-VC-backed IPOs, but the evidence is weaker. Finally, answering my third research question, I find that firms with more efficient stock prices outperform firms with less efficient stock prices in the long-term.

1. Literature review and hypothesis development

In the following section, I discuss reasons for why an IPO stock might be less or more efficient than a matched seasoned stock. I start with arguments for why IPO stocks might be less efficient followed by reasons they might be more efficient.

1.1. Why IPO stocks should be less efficient than seasoned stocks

The main reason IPO stocks might have a lower level of efficiency than seasoned stocks is because of a higher level of asymmetric information. This higher level of asymmetric information should cause a divergence of opinions among traders, resulting in a deviation of the stock's price from its fundamental value[1]. However, this divergence of opinion should decrease through time as traders become better informed and information asymmetries are reduced. As traders become informed through the collection of information, the price impact of their trading, as they act on this information, should move prices toward their fundamental values (Harris, 2003).

There are at least four reasons why IPO firms could have a higher level of asymmetric information than seasoned firms. First, there are regulations and restrictions which affect IPO firms. For instance, there is the quiet period, which lasts for 25 calendar days after the IPO offering date. (The quiet period was extended to 40 calendar days after July 2002 as one of the regulatory changes associated with the "Global Settlement" between regulators and ten large securities firms) During this period, insiders and affiliated underwriters are not permitted to make earnings forecasts or buy-sell recommendations. According to Bradley, Jordan, Ritter, and Wolf (2004) "The general premise behind the quiet period is to give investors enough time to do their due diligence and allow market forces to establish a fair value without influence from the firm's management or affiliated analysts who may try to hype the stock." This raises the possibility that some investors are

[1] An efficient price is defined as a price that is close to its fundamental value, which is the "true value" of the instrument (Hasbrouck 1993; Boehmer and Kelley 2009).

better informed through a greater level of due diligence than other investors during this quiet period.

Another restriction imposed on IPO stocks is the lock-up period, a period of time during which insiders are not allowed to sell their shares. If insiders are better informed, then preventing their participation in the market should retard the price discovery process. Consistent with this view, Field and Hanka (2001) argue that information asymmetry increases between traders at the expiration of the lock-up as evidenced by a permanent 40% increase in average trading volume.

Further evidence of inefficiency in IPO stocks can be seen through event studies conducted at the end of the quiet and lock-up periods. Namely, Bradley, Jordan, and Ritter (2003) document positive abnormal returns after the end of the quiet period while Field and Hanka (2001) document negative abnormal returns after the end of the lockup period. Evidence of abnormal returns run counter to the notion of market efficiency since the timing of these periods are known to investors in advance. Thus, market imperfections such as the quiet period and lock-up period provide a plausible reason why IPO stocks may be less efficient than seasoned stocks.

A second reason IPO stocks might have greater information asymmetries, and therefore lower levels of efficiency than season stocks, is price stabilization. Hanley (1993) suggests that price stabilization (i.e., price support) temporarily inflates the price of IPO stocks and allows underwriters to disguise overpriced offerings. In this situation, informed traders know that the stock price for weak issues are heightened during this period, but will drop back to a normal level as price support ebbs away. However, uninformed traders, especially individual investors, might not sense the deviation of price from its fundamental value. Jenkinson and Ljungqvist (2001) argue that price support retards the price discovery process in the aftermarket by obscuring the true demand and supply conditions. Ruud (1993) argues that underwriters stabilize aftermarket trading prices at the offering price, thus minimizing the occurrence of overpricing. This leads to censoring of the initial return distribution and a spurious impression of positive underpricing on average. That is, Ruud (1993) views stabilization by underwriters as a manipulative action that could disrupt natural market forces of demand and supply, which are essential to determining the market price of securities.

The third reason IPO stocks may have higher levels of information asymmetry centers on the role of the IPO's book underwriter. Since the IPO's lead underwriter aggregates information during the book-building process and produces most of the relevant information in the IPO, it can be argued that the book underwriter is the most informed trader during the early period of IPO trading. Ellis, Michaely, and O'Hara (2000) find that the book underwriter becomes the most active market maker, handling the lion's share of trading volume and taking 4% (22%) of the inventory position of the stock offered for hot (cold) IPOs. Several papers (Corwin, Harris, and Lipson, 2004; Li, McInish, and Wongchoti, 2005; Van Bommel, Dahya, and Shi, 2010) show that the bid-ask spread for IPO stocks is low at the start of trading and increases with time until it reaches an equilibrium level. Hegde and Miller (1989) argue that this result obtains because the book underwriter, as the most informed trader in the early aftermarket, is not threatened by presence of other (better) informed investors. This allows the book underwriter to keep a low spread in order to facilitate the development of liquid secondary market and to be compensated by repeat business from new firms. There is, however, a possibility that other investors are better informed about the stock's true value, but the influence of the book underwriter on prices in terms of trading activity and the level of inventory may obscure any impact these better informed investors have on the IPO stock's price during this period of trading shortly after the IPO offer date.

Finally, even if the imperfections described above are not present, it is possible that it might simply take some time for information asymmetries to be reduced for newly issued stock. In other words, the "seasoning" of a firm's stock might be related to information asymmetry and thus its level of efficiency. Taken together, regulations and restrictions, price stabilization, the book underwriter's role as a major market maker in the early IPO aftermarket, and the lack of seasoning of the IPO firm's stock should increase asymmetric information among traders and cause IPO stock prices to be initially less efficient than seasoned stocks.

1.2. Why IPO stocks should be more efficient than seasoned stocks

In contrast to arguments that support the notion that IPO stocks may be less efficient than seasoned stocks, IPO stocks may be more efficient than seasoned stocks because of lower asymmetric information in the early IPO aftermarket. There are at least two reasons why this may be the case. First, going public is probably the most important capital raising event for a firm and it draws a lot of attention from potential investors – both investors who are trying to decide whether to purchase shares in the IPO and those that are considering whether to buy shares in the immediate aftermarket. Thus, IPOs generate high levels of attention by both investors and the media. For example, Demers and Lewellen (2003) find that the marketing effect of the initial return through the media is positively associated with the creation of publicity for the issuers. High levels of trading in the immediate aftermarket for IPOs (as will be shown later in this dissertation) is consistent with this increased attention. It is possible that this high level of attention by investors and the media generates more information about the IPO firm than a comparable seasoned firm, thereby reducing information asymmetry and making the IPO firm more efficient than a comparable seasoned firm. Empirical support for this argument is found by Li, McInish and Wongchoti (2005). They show that the level of asymmetric information is lower for approximately 40 days after the IPO compared to its level after a period of seasoning.

Second, in contrast to my argument above that stabilization (i.e., price support) reduces efficiency, it is possible that stabilization may contribute to a lowering of information asymmetry in the aftermarket and therefore increase efficiency. Stabilization is a commitment offered by an underwriter that it will repurchase shares at the offer price in the event the IPO stock's price falls below the offer price. Chowdhry and Nanda (1996) argue that stabilization by the underwriter is similar to selling put options to investors because stabilization gives the right to investors to sell IPO stocks back to the underwriter at the offer price. Lewellen (2006) argues that stabilization encourages an underwriter to produce more information about the IPO before the offering, and thus resulting in the reduction of adverse selection problems at the offering stage and improvement on liquidity. This extra information production by underwriter, that is unique to IPO stocks, may lead the price of IPOs to be more efficient in the initial aftermarket than homogenously matched seasoned stocks. Similarly, Benveniste, Busaba, and Wilhelm (1996) maintain that price support is the efficient form of compensation in favor of regular investors, thus reducing the underwriter's incentive to exaggerate investor interest. This implies that price support by underwriters motivates informed investors to voluntarily reveal useful information. Consistent with this argument, the implicit agreement by the underwriter to support the IPO's stock price may cause prices to be closer to their fundamental value by enticing informed investors to the market, thus increasing the efficiency of the IPO stocks.

In conclusion, it is possible that IPO stocks are either less efficient or more efficient than matched seasoned stocks. The first set of tests of my dissertation will be to determine which of these two hypotheses are supported by empirical evidence. My argument that IPO stocks are either less efficient or more efficient than matched seasoned stocks leads to my first hypothesis.

Null Hypothesis 1: There is no difference in the efficiency of IPO stocks and matched seasoned stocks in the initial aftermarket.

Alternative Hypothesis 1: The efficiency of IPO stocks is different than matched seasoned stocks in the initial aftermarket

1.3. Financial intermediaries and price efficiency

The possibility that IPO stocks are, on average, more or less efficient than matched seasoned stocks in the period following the offer date leads to my second research question: what determines the cross-sectional variation in the efficiency of IPO stocks? My main explanatory variables explore the role of financial intermediaries in the efficiency of IPO stocks – namely, the reputation of the IPO's book underwriter, whether the IPO is VC backed, and the size of the IPO's managing syndicate. Many IPO studies examine the relation between these variables and underpricing. I posit that these variables are also related to the efficiency of IPOs in the aftermarket. Because high levels of information asymmetries can cause the IPO's stock price to drift away from its fundamental value, then if there are entities that can reduce the level of asymmetric information, they should move the IPO stock's price closer to its fundamental value.

Prestigious book underwriters and VC firms play a significant certification role in the premarket (Megginson and Weiss, 1991). Similarly, I hypothesize that these intermediaries also play a role in reducing information asymmetries in the aftermarket and therefore increase the efficiency of IPO stocks. There are five channels through which underwriter's reputation reduces information asymmetry among investors in the premarket. First, IPOs with high reputation book underwriters draw more informed purchasers who are induced to truthfully reveal their private information during the IPO pricing process (Benveniste and Spindt, 1989). As a group, institutional investors are more likely to be informed than individual investors. Field and Lowry (2009) show that institutional ownership is positively associated with underwriter prestige and VC backing, indicating that institutions are drawn to offerings certified by these intermediaries. High institutional ownership should improve efficiency in the aftermarket as these institutional investors trade quickly and aggressively to benefit from any observed mispricing. Boehmer and Kelley (2009) find that it is not only the presence of institutional investors but also active institutional trading that is associated with greater efficient prices. Second, high reputation investment banks are likely to serve as book underwriters on more IPOs than investment banks with lower reputation and therefore gain experience in pricing IPOs. With more knowledgeable purchasers and more accumulated experience, these prestigious underwriters should be better able to assess demand and set a more accurate offer price. Third, underwriters investigate the company and substantiate all claims in the preliminary prospectus through their due diligence. They also promote the IPO by distributing the prospectus and coordinating the road show thorough which company officers make presentations to potential investors. Prestigious underwriters are likely to have an advantage in this process over lower prestige underwriters due to their broad customer network and accumulated expertise. Consistent with this argument, Carter and Manaster (1990) and Carter, Dark and Singh (1998) find that IPOs with prestigious underwriters have less underpricing.[2] In addition, Chan, Cooney, Kim, and Singh (2008) find that IPOs with prestigious underwriters have less underperformance over the three years following the offer. In the similar vein, I argue that prestigious underwriters may also reduce information asymmetry in the aftermarket, resulting in the IPO's stock price being more efficient than comparable seasoned stocks. Prestigious underwriters may be able to reduce information asymmetry by supporting the price more aggressively (Lewellen, 2006), thereby preserving their reputation. As mentioned above, aggressive stabilization means more compensation to regular investors (Benveniste, Busaba, and Wilhelm, 1996), motivating these investors to reveal useful information and thus leading to more efficient stock prices. Fourth, prestigious underwriters may draw a higher level of media attention than low-reputation underwriters and thus generate more information about the IPO firm that they take public, thereby reducing information asymmetry. Finally, high-reputation underwriter's role should continue in the aftermarket via better analyst coverage. High-reputation underwriters should be able to employ more experienced analysts with better financial resources. Thus, these analysts should produce higher-quality analyst reports thereby reducing information asymmetries in the aftermarket. Consistent with this argument, Gleason and Lee (2003) maintain that the price adjustment process is faster and more complete for "all-star" analysts and for firms with greater analyst coverage than for more obscure yet highly accurate analysts (Wall Street Journal Earning-Estimators) and firms with low analyst coverage.[3]

VC-backed IPOs should also have more efficient prices. First, as mentioned above, VC-backed IPOs tend to have more institutional purchasers than non-VC backed IPOs. Field and Lowry (2009) argue that institutional investors invest more in VC-backed IPOs

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[2] Starting in the 1990s, the relation between underwriter prestige and IPO underpricing became positive. Loughran and Ritter (2004) argue that this positive relation holds because the issuing firm's managers became less concerned about underpricing and more concerned about being able to receive shares in underpriced IPOs of other firms (i.e., "spinning") and receiving coverage from highly-ranked analysts.

[3]Chemmanur and Krishnan (2009) make an opposite argument about the role of high reputation underwriters in IPOs' valuations. High reputation underwriters induce a greater number of higher quality market participants such as institutional investors, analysts, and co-managing underwriters to IPOs backed by them, thereby making retail investors more optimistic about the IPO firm's prospects. Such higher optimism of retail investors increases the heterogeneity in investor beliefs and leads the price of IPOs further away from intrinsic value.

rather than non-VC-backed IPOs because they recognize that the former IPOs outperform the latter. Second, as Megginson and Weiss (1991) point out, venture capitalists provide a valuable screening and monitoring role in IPOs that should result in reduced information asymmetry. VCs do this by evaluating the progress of the firm through series of stages (a screening process), so when it meets certain criteria they require, the VC provides further stage financing, but discontinues funding in firms that are not likely to be able to go public. Thus, VCs also play a certification role in judging the health of the firm via good screening and the market incorporates its role in the form of lower underpricing and greater long-run performance. Megginson and Weiss (1991) also maintain that VCs are able to reduce the cost of going public by attracting prestigious underwriters and auditors as well as a larger institutional following. I argue that this lower cost of going public is reflected in higher efficiency of IPO stocks. Brav and Gompers (1997) find that VC-backed IPOs outperform non-VC-backed offerings in the five years following the offer, when returns are calculated on equal weighted basis. Chan, Cooney, Kim and Singh (2008) find that IPOs with prestigious underwriters and VC backing significantly outperform in the long run. Furthermore, Chemmanur, Krishnan and Nandy (2011) argue that firms that receive VC stage financing are more likely to hire quality employees, thus producing a better quality of products to boost their sales. Compared to large public firms, small private firms have reduced free cash flow problems due to the monitoring and screening role of VCs. Consistent with this argument, Chemmanur, Krishnan and Nandy (2011) find that the total factor productivity of VC-backed firms is higher than that of non-VC-backed firms due in large part to operational improvement through the higher quality of its employees. I hypothesize that the VC's role via certification, monitoring and screening should result in a lower amount of information asymmetry and therefore a higher level of efficiency in the aftermarket. Thus, I hypothesize that VC-backed IPO should have more efficient stock prices than non-VC-backed IPOs.

Finally, the size of the IPO's managing syndicate (i.e., the combined number of book managers and co-managers) should also impact the level of information asymmetry for IPO stocks and hence their efficiency. Corwin and Schultz (2005) show that large managing syndicates benefit IPOs in several ways. Specifically, they find that IPOs with a large managing syndicate size experience larger changes from the filing range midpoint to final offer price, consistent with greater information production. They also show that IPOs with large managing syndicates produce more analyst coverage and market-making services in the aftermarket. Information asymmetry should be lower with more information production and better non-price services. Bradley, Jordan, and Ritter (2003) also argue that more managers mean more analysts, again consistent with greater information production in the aftermarket. Based on these arguments, I hypothesize that IPOs with a greater number of managers will yield a higher level of efficiency.

As control variables, I include the number of trades, market capitalization, dummy variables to indicate where the stock is listed, and industry and year dummies. Both greater number of trades and larger market capitalization are likely to produce more information, resulting in enhanced price efficiency. Stocks listed on different exchanges may also exhibit different level of efficiency. Lowry, Officer and Schwert (2010) maintain that underwriters are better able to value firms on the NYSE than those firms on the NASDAQ because more mature firms tend to be listed on the NYSE.

There are four other control variables that I plan to include in future research: institutional ownership, analyst coverage, the extent of short selling, and a measure of liquidity. Boehmer and Kelley (2009) find that stocks with greater institutional ownership and greater analyst coverage have higher price efficiency, indicating that institutions and analysts are well informed (Boehmer, Jones, and Zhang, 2008). As discussed above, IPOs with prestigious book underwriters and VC backing should attract greater institutional ownership and higher quality analysts. Likewise, IPOs with more managers should have more analyst coverage. I plan to control for institutional ownership and analyst coverage to determine if prestigious underwriters, VC backing, and large managing syndicates improve efficiency independently or only through their association with the efficiency mechanism through greater institutional ownership and higher quality / more analysts. Harris (2003) find evidence that short sellers hold superior information compared to other traders and their trades are important contributors to more efficient prices. In a liquid market, trading can be executed cheaply and quickly allowing prices to move closer to their fundamental values. However, liquidity should be distinguished from efficiency because the price can deviate away from its fundamental value even in liquid market. Nonetheless, I expect the liquidity to be positively associated with efficiency of IPO stocks.

The above discussion of the role of financial intermediaries as it relates to price efficiency is based on assumption that financial intermediaries are randomly matched with private firms which they take public through the IPO process. However, it is more likely that financial intermediaries consider a number of attributes of the private firm in deciding whether to bid on the role of book or co-managing underwriter or whether to provide VC financing. One of these attributes might be the expected level of efficiency of this firm's stock after it starts trading (or factors that are correlated with efficiency). Benveniste, Busaba and Wilhelm (1996) argue that choice of underwriter and issuers are mutual based on underwriter ability and issuer quality. Thus, it is important to examine this potential sample selection problem. I address this sample selection issue using the propensity scoring approach.

Apart from the endogeneity issue, my argument that financial intermediaries including prestigious underwriters, VC-backing, and large managing syndicates improve price efficiency leads to my three hypotheses in the second research question.

Null Hypothesis 2: IPOs with prestigious book underwriters do not have higher efficiency in the initial aftermarket than IPOs with low-prestige book underwriters.

Alternative hypothesis 2: IPOs with prestigious book underwriters have higher efficiency in the initial aftermarket than IPOs with low-prestige book underwriters.

Null Hypothesis 3: IPOs with venture capital backing do not have higher efficiency in the initial aftermarket compared to IPOs without venture capital backing.

Alternative hypothesis 3: IPOs with venture capital backing have higher efficiency in the initial aftermarket than IPOs without venture capital backing.

Null Hypothesis 4: IPOs with large managing syndicates do not have higher efficiency in the initial aftermarket compared to IPOs with small managing syndicates.

Alternative hypothesis 4: IPOs with large managing syndicates have higher efficiency in the initial aftermarket than IPOs with small managing syndicates.

1.4. The long-term firm performance and price efficiency

Carter, Dark, and Singh (1998) show that IPO firms brought to the market by high-reputation underwriters outperform IPOs with low-reputation underwriters. Brav and Gompers (1997) find that IPO long-run underperformance is limited to small IPO firms that are not venture-capital backed. As discussed above, there should be a relation between the prestige of the IPO's book underwriter, venture capital backing, and efficiency. Thus, efficiency could be a common factor that ties together the results of these two papers, or is perhaps another factor that explains the long-run performance of IPO firms.

There are at least two reasons the efficiency of the IPO firm's stock could affect long-run performance. First, stocks with higher efficiency should provide more accurate and timely information concerning the firm's cost of capital, leading to the optimal allocation of capital (Harris, 2003). Consistent with this view, Wurgler (2000) finds that countries with more developed financial markets have better ability to allocate their capital towards more growing industries and reduce allocation of capital towards decaying industries. Second, efficient prices provide market participants with an accurate measure of firm performance. This allows the IPO firm's stockholders and outsiders to monitor and discipline management for poor performance and reward for good performance. Conversely, less efficient prices imply a noisier measure of the firm's cost of capital and firm performance, leading to errors in resource allocation (e.g., rejecting positive NPV projects / accepting negative NPV projects) and making it more difficult to monitor / disciple or reward management.[4] I use performance delists within five years of the IPO date as a proxy for long-run underperformance. For robustness, I also employ a calendar time portfolio approach and test if the alpha from the three factor and four factor models

[4] Campello and Graham (2012) argue that overvalued stocks may help to improve efficiency during bubble period. They find evidence that high stock prices allow the firms to make good investment decisions due to less financial constraints, thus to improve price efficiency.

are significant. I predict that less efficient stocks are more likely to be delisted and to generate a smaller alpha.

Null Hypothesis 5: A stock's level of efficiency does not impact a firm's long-term performance.

Alternative hypothesis 5: Stocks that are less efficient are more likely to have poorer long-term performance.

2. Sample description and measure of efficiency

My initial sample consists of all IPOs reported by Thomson's SDC new issues database between 1993 and 2005. From this sample, I impose several filters as set out in Table 1. First, I exclude ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, and IPOs with an offer price below $5 per share. Second, I delete IPO stocks that are not found on both the Center for Research in Security Prices (CRSP) and the NYSE Trade and Quote (TAQ) database (TAQ begins in 1993). I also require IPO stocks to contain at least 100 valid trades[5] during the first 175 trading days following the IPO. (The requirement of at least 100 valid trades allows for the calculation of my measures of efficiency.) This process yields a final sample of 3,486 IPOs. I match these 3,486 IPOs with seasoned stocks based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of the IPO stock as measured at the close of the IPO stock's first day of trading. Among matched seasoned stocks, I also impose the same filters as that of IPOs. That is, I require seasoned stocks to be included in

[5] My definition of a valid trade is from Boehmer and Kelley (2009). Specifically, I use trades and quotes only during regular market hours between 9:30 am and 4:00 pm and exclude overnight price changes. For trades, I require that TAQ's CORR field is equal to zero, and the COND field is either blank or equal to *, B, E, J, or K. I delete trades with non-positive prices or sizes. I also exclude a trade if its price differs by more than 30% from the previous trade price. I include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. I exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. I require that the difference between bid and ask be less than 25% of the quote midpoint.

the TAQ database and to have at least 100 valid trades during the first 175 trading days after the IPO offering.[6]

The TAQ database provides intraday quote and trade information for all securities listed on the New York Stock Exchange (NYSE), NASDAQ, and American Stock Exchange (Amex) listed securities as well as regional exchanges such as Boston, Cincinnati, and Pacific etc. I only keep trades and quotes from the NYSE, NASDAQ, and AMEX for the sample of IPO stocks and corresponding matched seasoned stocks (and therefore deletes trades and quotes from the regional exchanges). For each stock, I aggregate all trades that are executed at the same price at the same second and retain only the last quote for every second if multiple quotes are issued (Boehmer and Wu, 2013). Following Lee and Ready (1991), I adjust trade times under the assumption that time stamps on trades are reported five second late from 1993-1998. After that period, I assume no reporting delay and thus make no time adjustment following Bessembinder (2003). Finally, as mentioned above, I eliminate stocks not on TAQ and those with less than 100 valid trades during the first 175 trading days after the IPO to ensure meaningful estimates of the stock's level of efficiency. The number of stocks that are dropped due to these last two criteria is larger for my sample of seasoned stocks than IPOs stocks. Therefore, the final number of matched seasoned stocks (3,292) is less than the final number of IPO stocks (3,486).

My main measure for efficiency in my dissertation is the pricing error that is first termed by Hasbrouck (1993). He uses a vector autoregression model (VAR) to decompose stock price into the efficient price (random-walk component) and pricing error (stationary component), which is the difference between the efficient price and the actual transaction price (refer to Appendix 1 for details). Following Hasbrouck (1993)'s paper, I calculate the standard deviation of the pricing error (SDPE) for the first 175 trading days after the IPO offer day for the sample of IPO stocks and for the sample of matched seasoned stocks using

[6] I match with replacement. Therefore, one seasoned firm can match with more than one IPO firm. According to Roberts and Whited (2012), "Matching with replacement allows for better matches and less bias, but at the expense of precision. We prefer to match with replacement since the primary objective of most empirical corporate finance studies is proper identification. Additionally, many studies have large amounts of data at their disposal, suggesting that statistical power is less of a concern."

the same 175 days. I also calculate the SDPE over the 35 five-trading day periods (35 “weeks”) during these first 175 trading days to show the dynamics of change in price efficiency. These weekly SDPEs are used in Figures 1-4. Higher values of SDPE indicate lower levels of efficiency. Boehmer and Kelley (2009) argue that SDPE is superior measure than other efficiency measure such as autocorrelation and variance ratio in that it can distinguish the transient price change due to inefficient pricing from the transient price due to efficient pricing. In contrast, other measures can only give an indication of whether the price is deviated from a random walk, but cannot indicate whether the deviation stems from efficient or inefficient pricing.

Table 2 presents descriptive statistics of my sample. Descriptive statistics of variables from TAQ are given in panel A. The average SDPE across the 175 trading days for IPO and seasoned stocks are 0.0076 and 0.0062, respectively, indicating that IPO stocks during the 175 trading days since the offer date are, on average, are less efficient than seasoned stocks. The p-value from a t-test of the difference of SDPE between IPO and seasoned stocks shows that the means are significantly different at the 1% level. Using large stocks in NYSE, Hasbrouck (1993) find that SDPE is about 0.243% of stock price and about only 16% of the spread. Roll model assuming that spread were entirely due to liquidity and non-information related transaction cost indicates that pricing error take up about half of the spread. Consistent with this finding, I find that the SDPE of IPOs and SS is about 2.5% (= 0.0076/0.3062) and 2.4% (= 0.0062/0.259) of the spread respectively. I also compute three spread measures: the absolute spread, the relative spread, and the effective spread. Absolute spread is defined as the dollar difference between the ask and bid price. Relative spread is the absolute spread scaled by the average of the bid and ask price. The effective spread is twice the absolute value of the difference between the trade price and the quote midpoint. Regardless of how spread is measured, the means of the spreads for IPOs are larger than the means of the spreads for seasoned stocks. Glosten and Milgrom (1985) argue that the market-maker increases the spread to compensate for the greater risk of dealing with informed traders. Consistent with their argument, larger mean spreads for IPO indicate that there might be more informed traders in IPO stocks.

The next set of variables presented in panel B of Table 2 provides information about the IPO firm and seasoned firm and also information about the offering. Market capitalization for the IPO firm is calculated as the closing price on the first day of trading times the number of shares outstanding. Market capitalization for seasoned stocks is calculated on the same day as the IPO stocks. The mean value of market capitalization for the IPO stocks is slightly smaller than that for seasoned stocks and the difference is not statistically significantly different from zero. This result follows from using market capitalization as one of the matching criteria. To compute the number of trades, I combine all trades occurring at the same second and price. Boehmer, Broussard and Kallunki (2002) argue that these individually reported trades are in fact part of the same order, and should therefore be combined by summing the number of shares. After this process, I count the number of valid trades executed over the 175 trading days. (Valid trades are those that meet the criteria listed in footnote 5 and also in Table 2.) Seasoned stocks exhibit a significantly higher number of trades relative to IPO stocks, but the median is smaller. This indicates that some of seasoned stocks have a very large number of trades. This also can be confirmed by a large standard deviation.

Financial intermediary variables are only applicable for the IPO firms. They include the prestige ranking of the IPO's book underwriter, a venture capital backing dummy, and the number of underwriters included in the IPO's managing syndicate. In the section of empirical results, I test whether these financial intermediaries are related to the efficiency of IPO stocks. The prestige of the IPO's book underwriter is measured with the Carter and Manaster (1990) underwriter reputation rank, as updated by Loughran and Ritter (2004). For IPO stocks that has more than one book underwriter, I keep only the first book underwriter as ordered in SDC database. The average underwriter's reputation rank for the IPO's book underwriter (UW rank) is 7.3 on a 0 to 9 point scale (higher values indicate more prestigious underwriter), indicating that my sample of issuing firms was brought to the market by relatively prestigious underwriters. About 44 % of issuing firms are financed by venture capitalists and the number of lead, co-lead, and co-managers is, on average, 2.9.

It is more common for IPO stocks to be listed on the NASDAQ while seasoned stocks are listed more on the NYSE and AMEX exchange. Specifically, 2,937 (84%) of 3,486 IPO firms are listed on the NASDAQ while 2,160 (66%) of 3,292 seasoned stocks are listed on the NASDAQ. Almost twice as many seasoned stocks are listed on the NYSE exchange. Small, young, high-tech firms tend to list on NASDAQ, suggesting that underwriters may have difficulty in valuing these firms. More mature firms tend to go public on the NYSE, suggesting that underwriters will have the better means for valuing these firms. Following Lowry, Officer, and Schwert (2010), I create a bubble period dummy that equals one for IPO offer dates between September 1998 and August 2000, and zero otherwise. About 21% of my IPO sample is in the bubble period.

In panel A of Table 3, I show the breakdown of IPO stocks by year of the offering. I next sort the sample by Fama-French 49 industry and show the top 10 and bottom 10 in terms of number of IPOs in panel B. Finally, I sort the Fama-French 49 industries and show the top 10 and bottom 10 in terms of SDPE in panel C. Panel A shows the number of IPOs, and mean values for IPO offer price, the rank of the IPO's book underwriter, the proportion of IPOs that are VC-backed, the IPO managing syndicate size, the IPO's SDPE. The number of matching seasoned stocks and mean SDPE of the seasoned stocks follows with the p-value from a t-test of the difference of mean SDPE for IPO stocks and seasoned stocks. The number of firms that went public increases from 1993, peaks during 1999, and drops after the tech bubble burst in 2000. The mean offer price appears to be somewhat higher after 1998 than before. The mean underwriter rank increases from 1993 and peaks in 2000 (the end of bubble period) with an average underwriter's rank of 8.21 for 328 firms. After the bubble period, the average underwriter rank generally decreases. The same pattern also appears in the proportion of VC-backed IPOs. 71% of issuing firms are financed by venture capitalists in 2000, but the proportion of newly issuing firms receiving financing from venture capitalists also drops after the end of the bubble and draws back below the level of 1993 by the end of the sample period. The managing syndicate size is approximately 2.88 over the full sample period and is largest in 2004 (4.383) and smallest in 1994 (1.972). The mean value of SDPEs for IPO stocks is higher than for seasoned stocks in most of years, the exceptions being1998, 2002, and 2005. This pattern is consistent with my finding that IPO stocks are less efficient than seasoned stock on average. Interestingly, IPO stocks are substantially less efficient than seasoned stocks in 1999 and 2000 (two of the three bubble years), as indicated by far higher value of SDPE.

Panel B provides the breakdown of IPO stocks by 49 industry group classification in the order of the number of IPOs. For expositional reasons, I present only the top ten and the bottom ten of industries. The largest number of IPOs in my sample comes from the software industry (FF36). Many firms that went public during the sample period are tech-related industries such as software (FF36), chips (FF37), telecommunication (FF32), and medical equipment (FF12). In contrast, a small number of firms went public during my sample period in traditional bricks and mortar industries including ships (FF25), boxes (FF24), agriculture (FF1), and coal (FF29).

In panel C, I sort the Fama-French industry classifications by the magnitude of SDPE. Stock prices of IPOs in utility industry (FF31) appear to trade closest to their fundamental value during the first 175 days of trading, as shown in the value of SDPE (0.0031), the smallest mean value for SDPE of all industries. However, IPO stocks from industries related to large-scale or large market capitalization (oil, steel, finance, and insurance) are also ranked as highly efficient. This suggests that information is impounded into stocks with large market capitalization faster and more accurately than small size stocks. I take note of this pattern here and defer further discussions to subsequent sections.

Table 4 presents a correlation matrix among regression variables used in the analysis of IPO and matched seasoned stocks. Several interesting points stand out. As expected, the market capitalization and number of trades are both negatively correlated with SDPE, suggesting that the big and liquid stocks tend to be more efficient than small or illiquid stocks. IPOs with high-reputation book underwriters, VC-backing, and large managing syndicates are more efficient than IPOs with low-reputation underwriters, non-VC backing, and smaller managing syndicate size. IPOs that list on NASDAQ tend to be young, small, and tech firms while those that list on NYSE tend to be more established firms. Thus, underwriters find it more difficult to value IPOs listed on NASDAQ compared to IPOs listed on the NYSE (Lowry, Officer, and Schwert, 2010). Accordingly, IPOs listed on NYSE should be more efficient than IPOs listed on the NASDAQ as evidenced by the negative correlation between SDPE and NYSE, but positive correlation between SDPE and NASDAQ. UW Rank and Syndicate size are also positively correlated with NYSE, indicating again that IPOs with high reputation book underwriters and large syndicate size are more established issuing firms than other IPOs. It is commonly known that VCs primarily invest in small and young private firms with large growth potential (Lowry, Officer, and Schwert, 2010). The positive correlation between VC dummy and NASDAQ confirm this prior.

3. Empirical Results

In this section, I use ordinary least squares (OLS) regressions to test for differences in the level of efficiency between IPO stocks and matched seasoned stocks. Specifically, I create a variable called "IPO dummy" which takes on a value of one for my sample of IPO stocks and zero for my sample of matched seasoned stocks. I test four model specifications concerning the relation between IPO dummy and the standard deviation of pricing error (SDPE). In particular, I test whether IPOs are more or less efficient than seasoned stocks during the first 175 trading days following the IPO offering date. I also test whether this result is robust to year dummies (1994-2005) and industry dummies using the Fama French 49 industry classification. Results are presented in Table 5. Next, I test how the efficiency of IPO and seasoned stocks change over time by estimating 35 weekly regressions—one for each five-trading day period (or "week") following the IPO offer date. I show the result of the first week's regression in Table 5 and the results for all 35 weeks in Figure 1. In the second section, I test the role of financial intermediaries on the efficiency of IPO stocks. I test seven model specifications concerning the relation between financial intermediaries' variables (underwriter reputation dummy, VC dummy, and syndicate size dummy) and SDPE. In particular, I test whether IPOs with prestigious underwriters, VC-backing, and large syndicates are associated with higher levels of efficiency during the 175 day testing period and present the results in columns 1 – 4 of Table 6. I also show the effect of these variables on the efficiency for the first week in columns 5, 6, and 7 of Table 6 and present the results for all 35 weeks in Figures 2-4.

3.1. Regression analysis of IPO vs. Seasoned stocks

In Table 5, I show the results that answers my first research question: Is there difference in the level of efficiency in the early aftermarket following the offer date between IPO stocks and seasoned stocks? To test for differences in efficiency, I estimate OLS regressions using the sample of 3,486 IPO stocks and 3,292 seasoned stocks (i.e., 6,778 total stocks). The dependent variable in the regressions, SDPE, is calculated over the 175 trading days following the offer date in all regressions but column 4. In column 4, I use the SDPE calculated over the first five trading days (i.e., first week) after the IPO offer date. The main variable of interest is IPO dummy, which takes on a value of one for IPO stocks and zero for seasoned stocks. As discussed earlier, a low value of SDPE is consistent with higher levels of efficiency. Thus, a positive (negative) value for IPO dummy indicates that IPO stocks are less (more) efficient than seasoned stocks. I use the variables ln (numtrades), ln (mktcap), and exchange dummies (NYSE, NASDAQ) as control variables that are likely to affect the price efficiency. Ln (numtrades) is the natural log of the total number of valid trades executed during 175 trading period. As long as trades produce information about the security, more trades is expected to move the price toward the equilibrium level. Thus, there should be a negative relation between the number of trades and the level of inefficiency (SDPE). ln (mktcap) is the natural log of the number of outstanding shares times the closing price on the first trading day. To the extent that large stocks have less information asymmetry, then there should be negative relation between the market capitalization and the level of inefficiency (SDPE). Since NYSE stocks are typically more established companies than those listed on the NASDAQ, I predict that the exchange variables, NYSE and NASDAQ, will be negative and positive respectively. I also include industry fixed effects based on 49 Fama-French (1997) industries and year fixed effects in all but the first two regressions. To account for error dependencies across industry and year, the standard errors are adjusted for two-dimensional clustering at the industry and year level.

The equation for my main regression, given in Table 5, column (3), is as follows:

$$\text{SD}PE_i = a_0 + a_1 IPO\ dummy + a_2 \ln(numtrades) + a_3 \ln(mktcap) + a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \qquad (1)$$

where Industry dummy_j is the industry fixed effects for industry j, Year dummy_t is the year fixed effects for year t. T is the number of years in the sample (equal to 13). The excluded year is 1993 and the excluded industry is computers (Fama French industry 35)

In column 1 of table 5, I present the results for a univariate regression with just IPO dummy as an independent variable. IPO dummy is 0.0013 and significant at the 1% level, indicating that IPO firms are less efficient than matched seasoned firms over the first 175 trading days after the IPO offer date. This result is consistent with the findings reported in table 2, where the mean of SDPE for IPO (0.0076) is more than that for seasoned stocks (0.0062). Using similar match criteria (Fama French 49 industry classification, year, the same exchange, has been listed at least three years, and the closest market capitalization in the year pre-IPO), Chemmanur, Hu, and Huang (2010) find evidence that it takes about eight quarters after an IPO offer date for IPO stocks to become similar to seasoned stocks in terms of institutional turnover rate. In column 2, I add the control variables ln(numtrade), ln(mktcap), NYSE, and NASDAQ. IPO dummy remains positive and significant. In column 3, I report the results for my main regression model, equation (1), by adding industry and year fixed effects. IPO dummy is still significantly positive. The estimate of 0.0005 suggests that on average, IPO have a 7.4% (0.0005/0.0068, the mean SDPE for the full sample) higher SDPE than seasoned stocks.

The sign of most of the control variables are consistent with my priors as mentioned earlier. Based on the general view that more trades will produce more information, a greater number of trades push the prices of stocks toward their intrinsic values. Consistent with my prior, market capitalization is positively related to efficiency implying that the prices of large stocks closely track their intrinsic values. Both exchange dummies (NYSE and NASDAQ) are positively associated with the SDPE, indicating that stocks listed on the NYSE and NASDAQ are less efficient than stocks listed on the AMEX, other things equal.

However, untabulated results show that both NYSE and AMEX are significantly negatively associated with SDPE when I take out the variable NASDAQ, but instead include NYSE and AMEX dummies. In general, these untabulated results show that NYSE and AMEX listed stocks have more informative prices than NASDAQ listed stocks. The year dummies show that the market is more efficient in years 1994 to 2005 compared to the excluded year (1993). Untabulated result shows that drugs, medical equipment, financials, and software industries are more efficient compared to other industries.

In column 4, I show the regression results for the first week following the offer date. In line with the results in column 3 which uses the 175 trading day period, IPO stocks are less efficient than matched seasoned stocks for the first five trading days after the offer date. The estimate of 0.0011 suggests that on average, IPO stocks have a 15.1% (0.0011/0.0073, the mean SDPE for the first week of the full sample) greater SDPE than seasoned stocks on the first week of the trading since the IPO date. Figure 1 plots the estimated coefficients of IPO dummy variable and corresponding 95% confidence interval from 35 regressions for each of the 35 weeks in the first 175 trading days. The first entry in the figure is drawn from the results in column 4 of table 5. I compute the 95% confidence interval of lower and upper end points for each of the weekly regressions as the coefficient for IPO dummy + / - 1.96 times the standard error.

Addressing my first research question, IPO stocks are less efficient than matched seasoned stocks during my 175 trading day testing period as evidenced by the fact that all of confidence interval bars lie above zero. As discussed in the previous section, a lower level of efficiency for IPO stocks is consistent with market imperfections inherent in IPOs and the associated higher levels of information asymmetry. Another reason for a lower efficiency level for IPO stocks is that it may simply take time for IPO stocks to become "seasoned."

3.2. Do financial intermediaries enhance the efficiency of IPO stocks?

As discussed in section 1.3, a large body of IPO literature discusses the role of financial intermediaries on premarket and aftermarket. Of them, the most important intermediary is the IPO's book underwriter. Prestigious book underwriters may draw more institutional purchasers (Field and Lowry, 2009) and have more expertise via accumulated experience. They may generate more information by drawing more media and investor's attention (Demers and Lewellen, 2003). Finally, they may have higher quality analysts.

Venture capital firms are also important entities that are deeply involved with the issuing firm. They evaluate the progress of the firm through series of stages (a screening process). VCs also play a certification role in judging the health of the firm via good screening (Megginson and Weiss, 1991) and the market incorporates its role in the form of lower underpricing and greater long-run performance. Furthermore, firms that receive VC stage financing are more likely to hire quality employees, thus producing a better quality of products to boost their sales (Chemmanur, Krishnan, and Nandy, 2011). Compared to large public firms, small and private firms have reduced free cash flow problems due to the monitoring and screening role of VCs. I conjecture that the market participants have a high regard for VC's role via certification, monitoring and screening. These roles should be reflected in the form of a lower amount of information asymmetry and therefore a higher level of efficiency in the aftermarket.

Underwriting syndicates play an important role in selling IPOs, valuing IPOs, and offering aftermarket services (Corwin and Schultz, 2005). IPOs with large managing syndicates tend to revise the price range more than IPOs with small managing syndicates indicating more information production (Corwin and Schultz, 2005). They also produce more analyst coverage and market-making services in the aftermarket. Information asymmetry should be lower with more information production and better non-price services. Thus, IPOs with large syndicate sizes should have more efficient prices.

Given the important role of financial intermediaries, the purpose of this section is to examine whether these financial intermediaries are associated with higher levels of efficiency in the early aftermarket. I test the role of financial intermediaries by including dummies for each financial intermediary. Specifically, high-rep dummy is equal to one if the book underwriter for the IPO has an underwriter's rank (according to Loughran and Ritter, 2004) of 8 or above on a 0 to 9 scale and zero otherwise. VC-back dummy equals one if the IPO is financed by a venture capital firm and zero otherwise. Large syndicate dummy equals one if the IPO has three or more managers and zero otherwise. The three regression equations (2), (3), and (4) are as follows:

$$\mathrm{SD}PE_i = a_0 + a_1 High\ rep\ dummy + a_2 \ln(numtrades) + a_3 \ln(\mathrm{mktcap}) + a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \quad (2)$$

$$\mathrm{SD}PE_i = a_0 + a_1 VC\ back\ dummy + a_2 \ln(numtrades) + a_3 \ln(\mathrm{mktcap}) + a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \quad (3)$$

$$\mathrm{SD}PE_i = a_0 + a_1 Large\ syndicate\ dummy + a_2 \ln(numtrades) + a_3 \ln(mktcap) + a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \quad (4)$$

$$\mathrm{SD}PE_i = a_0 + a_1 Highrep\ dummy + a_2 VC\ back\ dummy + a_3 Large\ syndicate\ dummy + a_4 \ln(numtrades) + a_5 \ln(mktcap) + a_6 NYSE + a_7 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \quad (5)$$

I hypothesize that IPOs with prestigious underwriters, VC-backing, and large syndicates will be negatively associated with SDPE, and thus, indicate a higher level of efficiency.

In table 6, I initially show the results from regressions covering the entire 175 trading day period (columns 1-4), followed by the results for the first week of trading (columns 5-7). I include the three financial intermediary dummy variables one at a time in columns 1-3, and then all three financial variables are included in the same regression in column 4. The first week regressions in columns 5-7 are similar to the regressions in columns 1-3 (i.e., the financial intermediary variables are included one at a time). Since these three financial intermediary variables only apply to the sample of 3,486 IPO stocks, I exclude the sample of matched seasoned stocks from the analysis. All regressions include the set of control variables.

Columns 1-3 show that all three financial intermediary variables are negatively related to SDPE, and therefore are associated with higher levels of efficiency. Specifically, in column 1, the coefficient of high reputation is -0.0019, significant at the 1% level, suggesting that IPOs with prestigious underwriters are more efficient than IPOs with less prestigious underwriters. The mean value of SDPE for IPO stocks is 0.0076 as shown in table 2. The point estimate of -0.0019 for high reputation dummy is about 25% of the mean value. The effect of prestigious underwriters on efficiency, thus, is not only statistically significant, but economically large as well.

Column 2 shows that the coefficient of VC back dummy is negative, but not significant (the p-value is 0.2267). This suggests that IPO stocks that are financed by VCs do not show greater efficiency in the immediate aftermarket. However, the positive effect of VCs on the efficiency is present when I examine the first week of trading, as shown in column 7. This indicates that VC's role in the price process of IPO stocks may be short-term.

In column 3, I test the effect of syndicate size on the efficiency. I observe a negative coefficient for large syndicate size as predicted, with a point estimate of -0.0034 and significance at the 1% level. When all three financial intermediary variables are included in the same regression (column 4), high-rep dummy and large syndicate dummy continue to have a significant negative relation to SDPE, and VC back dummy remains insignificant. Overall, this result suggests that prestigious underwriters and large managing underwriting syndicates play a role in enhancing the efficiency of IPO stocks.

Figures 2-4 show the 95% confidence intervals for the three financial intermediary dummy variables across each of the 35 weeks following the IPO, with columns 5-7 in table 6 showing the effect of financial intermediaries on the first week following the IPO date. The three figures indicate that IPOs with high-reputation underwriters (Figure 2) and those with large managing syndicates (Figure 4) have higher levels of efficiency throughout most of the first 35 weeks of trading compared to IPOs with low-reputation underwriters and small managing syndicates, respectively. However, IPOs with VC backing have higher levels of efficiency than IPOs without VC backing only for the first week (Figure 3). This evidence suggests that the role of VCs as it relates to efficiency may be limited compared to roles of the book underwriter and the size of the managing syndicates.

Overall, the results for the control variables are similar to those presented in table 5: IPOs with a large number of trades and large market capitalization have greater efficiency and IPOs listed on the NASDAQ have lower efficiency across all seven regression models. The signs and significance levels for the year dummies are consistently negative, indicating that the level of efficiency in IPO stocks is higher than in 1993 (the excluded year).

4. How is efficiency related to long-term performance of IPO firms?

In this section, I link efficiency to long-term performance of IPO stocks. Harris (2003) argues that an inefficient stock price implies a noisy measure of the firm's cost of capital and could lead to bad financing and investment decisions. Inefficient stock prices can also make it difficult to monitor and discipline management. I measure the effects of efficiency on long-run performance by creating a dummy variable (Delist dummy) which equals one if the IPO firm delists due to poor performance within five years of the IPO date. As in the previous sections, I measure efficiency by SDPE. If performance is related to efficiency, then SDPE should be positively related to Delist dummy.

As described in more detail in my discussion of robustness tests in Section 5, I also perform a long-term event study analysis using a calendar time portfolio approach as another way for investigating how the performance of the IPO stocks is related to efficiency. The calendar time portfolio approach has advantages over measuring long-run performance using cumulative abnormal returns (CARs) or buy and hold abnormal returns (BHARs). CARs suffer from not taking the compounding effect on the long term returns into account. BHARs are also vulnerable to biases including new listing bias, a skewness bias, and a rebalancing bias (Barber and Lyon, 1997; Kothari and Warner, 1997). To overcome bias inherent in CAR and BHAR, I calculate calendar time portfolio abnormal returns (both equally and value weighed returns). As pointed out by Mitchell and Stafford (2000), the use of calendar time portfolios controls for cross-sectional dependence among sample firms and is less sensitive to the problem of a poorly specified asset pricing model(Mitchell and Stafford, 2000). (I use the Fama-French (1993) three factor model, and the Carhart (1997) four factor model to construct the benchmark return. I perform sorting procedures, such as single and double sorting (conditioned on financial intermediary variables), to examine how portfolios based on different levels of SDPE are related to long run returns).

4.1 Can the SDPE predict the probability of delisting due to poor performance?

In this section I examine whether the IPO firm or the matched seasoned firm delists from their current exchange due to poor performance during the five years (1,825 calendar days) after the IPO date. CRSP provides a list of reasons why stocks are delisted from exchange. The main delisting events include mergers, issue exchanges, liquidation, and being dropped from the exchange. I define a firm as being delisted due to poor performance if CRSP gives the reason for delisting as "dropped." Specifically, my variable Delist dummy equals one if the stock delist within 1825 calendar days of the IPO date and the CRSP delist code is 500 or between 510 and 591, zero otherwise. (Note, delist codes 501 – 505 indicate being dropped from the current change in order to become listed on the NYSE, AMEX, NASDAQ, NYSE Arca, or Mutual funds, which I deemed to be a positive reason for delisting). With this newly created variable, I investigate how SDPE is related to the probability of a performance delist. I model the dependent variable as a binomial choice variable of either (a) IPO stocks or seasoned stocks being delisted for poor performance within five years (in which case the dependent variable equals one) or (b) IPO stocks or seasoned stocks not delisting within five years due to poor performance (in which case the dependent variable equals zero). As a result of the bivariate nature of the dependent variable, I employ a logistic regression methodology and estimate the following two models:

$$\text{Logit}(p_i) = a_0 + a_1\text{IPO dummy} + a_2\text{SDPE} + a_3 \ln(numtrade) + a_4 \ln(\text{mkt}cap) + a_5 NYSE + a_6 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \quad (6)$$

where Delist dummy is 1 if IPO stock or seasoned stock is delisted within five years due to poor performance, and zero otherwise. The remaining variables have been previously defined. I hypothesize that there is a positive relation between the probability of a performance delist and the level of SDPE.

In the second model, I test how SDPE is related to the probability of a performance delist after controlling for role of financial intermediaries. In this model, I use only IPO firms because the financial intermediary variables are only associated with IPO firms.

$$\text{Logit}(p_i) = a_0 + a_1\text{SD}PE + a_2 financial\ intermediries\ dummy + a_3 \ln(numtrade) + a_4 \ln(mktcap) + a_5 NYSE + a_6 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t \quad (7)$$

where financial intermediaries dummy include whether IPOs are underwritten by prestigious underwriters, whether IPOs are financed by venture capitalists, or whether IPOs have a large syndicate size.

Table 7 shows the result of logistic regression on the probability of delists. The model in column 1 tests the univariate relation between IPO dummy and delisting probability. Consistent with Ritter (1991), IPO stocks underperform seasoned stocks (i.e., IPO stocks are more likely to be delisted within 5 years of offer date for poor performance than seasoned stocks). Column 2 shows the results of a univariate logistic regression of SDPE with Delist dummy as the dependent variable. SDPE is significantly positively associated with the probability of delists, supporting my hypothesis that stocks with lower levels of efficiency (i.e., high values of SDPE) underperform stocks with high levels of efficiency. I include both IPO Dummy and SDPE in column 3. The coefficients on both IPO dummy and SDPE remain positive and significant. When the other control variables are included in column 4, SDPE and IPO dummy remains positive and significant. Thus, efficiency, as measured by SDPE, is negatively related to the future performance of firms.

In columns 5-8, I show how financial intermediaries (i.e., the prestige of the IPO's book underwriter, whether the IPO is VC backed, and the size of the IPO's managing syndicate) affect delisting probability. Since my financial intermediary variables only apply to IPO firms, I remove seasoned stocks in this analysis. The signs of financial intermediary variables are consistent with my prior. More specifically, IPO stocks with prestigious underwriters or large syndicate sizes are significantly negatively related to the probability of delists, suggesting that they are less likely to be delisted in five years for poor performance relative to IPO stocks with low reputation underwriters or small syndicate sizes. Carter, Dark and Singh (1998) document that IPOs brought to the market by prestigious underwriters have better long-run performance and I document in table 6, columns 1 and 4, a positive relation between underwriter prestige and efficiency. The results in column 5 of table 7 shows that both efficiency and underwriter prestige are related to long-run performance for IPO stocks.

Similar to the results in table 6, the effect of VC-backing is not statistically significant, but the negative sign is consistent with my prior. In column 8, I include all three financial intermediary variables. The effect of prestigious underwriters and large syndicates on the probability of delists become somewhat weaker, but remain statistically significant with the expected sign; VC-back dummy is still insignificant. Most importantly, the effects of SDPE on the probability of delist remains positive and statistically significant for the sample of IPO firms with control and financial intermediary variables included (columns 5, 6, 7, and 8). This result indicates that SDPE is a predictor of the firm performance whether they are newly issued firms or seasoned firms.

5. Robustness

My key findings can be summarized as the following:

i) IPO stocks are less efficient than seasoned stocks in the initial aftermarket.

ii) IPOs with prestigious underwriters, VC-backing, and large syndicate size are associated with higher levels of efficiency. However, IPOs with VC-backing is weakly associated with higher level of efficiency as there is only a significant difference in VC-backed versus non-VC-backed IPOs for the first week following the IPO offer date.

iii) Stocks with high levels of efficiency outperform stocks with low levels of efficiency.

In this section, I provide various tests and analyses from four other dimensions of efficiency to show the robustness of my key findings. Next, I implement the propensity scoring method to help control for sample selection bias when examining the relation between financial intermediaries and efficiency. Next, I test whether price support enhances or worsens the price efficiency of IPO stocks. Finally, I implement a calendar time portfolio approach to test the robustness of my long-term performance results.

5.1 Other efficiency measures

In the previous analysis, the standard deviation of pricing error (SDPE) is used as a measure of a stock's level of efficiency. Using this measure, I find that IPO stocks are less efficient than seasoned stocks, financial intermediaries help to keep prices in line with their intrinsic value, and stocks with high efficiency outperform stocks with low efficiency. In this section, I test the robustness of my results using four other measures of efficiency: autocorrelation coefficient, variance ratio, short-term volatility, and price delay. The first three measures use intraday data from TAQ and the last measure uses daily return data from CRSP. I use the same screens as used in the calculation of SDPE to calculate the intraday data measures. (The screens are listed in footnote 5.)

My first alternative measure of 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, I use the absolute value of the autocorrelation coefficient as the measure of efficiency. Following Boehmer and Kelley (2009), I compute returns from quote midpoints (rather than from transaction prices) to eliminate bid-ask bounce, and I compute thirty-minute autocorrelations for both

IPOs and seasoned stocks[7]. To circumvent the problem of sparse quotes, I only use consecutive 30-minute returns.[8] I also require at least 100 30-minute returns during 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, continuously compounded returns should be twice the variance of a one-period return. Because I am interested in the deviation of the transaction price from the efficient price in either direction, I compute as my 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 of the return variance calculated over *30* minutes. The sample of returns used to calculate $|1 - VR_{(30,60)}|$ is the same as those 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 the regulators and has been used by the academics to test market efficiency (Shiller, 1981). Barclay and Warner (1993) argue that private information causes market volatility rather than public information. 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."

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

[8] 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))

Using returns from quote midpoints, I compute return volatility over 30-minutes intervals and denote this $STVOL_{30}$.[9]

My 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, retard the speed of this reassessment process and therefore delays the incorporation of market-wide news into firm-specific stock prices. I calculate price delay by first estimating two regression models. In the first (the "unrestricted regression"), I regress the weekly stock return of an individual firm on contemporaneous and four lagged weekly market returns. In the "restricted regression," I regress the weekly stock return for the individual firm against just the contemporaneous market return.

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

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

I then calculate the 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.

In the next section, I present the results of testing my three hypotheses using these four additional efficiency measures.

5.2 The results using alternative efficiency measures

As a review, the following are my three research questions:

- Is the efficiency of IPO stocks different than matched seasoned stocks in the initial aftermarket?

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

- Do IPO stocks with prestigious underwriters, VC-backing, and large syndicate sizes have higher levels of efficiency?

- Do stocks with high levels of efficiency outperform stocks with low levels of efficiency in the long-run?

The panels in table 8 (A, B, and C) answer these questions in order using the results of the different efficiency proxies. The signs of my four additional efficiency measures are interpreted in the same manner as standard deviation of pricing error, SDPE, my main efficiency proxy. Specifically, higher values for $|AR_{30}|$, $|1 - VR_{(30,60)}|$, $STVOL_{30}$, and PD, all imply lower levels of efficiency.

Table 8, panel A addresses the first research question: Is the efficiency of IPO stocks different than matched seasoned stocks in the initial aftermarket? The first column in table 8, panel A repeats the results from the regression in table 5, column 3 where SDPE is the dependent variable and the independent variables include IPO dummy, ln (numtrade), ln (mktcap), NYSE dummy, NASDAQ dummy, and year and industry dummies. Proceeding to columns two to five, the only difference is reflected by changing my efficiency measure from SDPE to the other four proxies: $|AR_{30}|$, $|1 - VR_{(30,60)}|$, $STVOL_{30}$, and PD. The results for three of the four new measures of efficiency are similar to my main measure SDPE. More specifically, $|1 - VR_{(30,60)}|$ is greater for IPOs than for seasoned stocks, suggesting that IPO prices show more deviation from a random walk in comparison to seasoned stocks. IPOs also significantly augment price delays, indicating that newly issued stocks incorporate public information significantly slower into prices than seasoned stocks. Greater short term volatility in IPO stocks suggests that there is more trading friction due to higher information asymmetry or less information availability inherent in IPO stocks. Examining the results where efficiency is measured with autocorrelation, however, reveals insignificant results. I attribute this insignificant result to the different dimensions that autocorrelation may measure. Boehmer and Kelley (2009) argue that a simple autocorrelation cannot distinguish price changes due to trade reversal from price changes due to new information. Just like my efficiency measures are not interpreted in the same manner, they may contain multiple dimensions of how information is incorporated into the prices.

Taken together, these results indicate that seasoned stocks dominate IPO stocks in terms of efficiency as shown in four of the five proxies of efficiency. This suggests that the inferior efficiency present in IPO stocks manifests itself both in intraday transactions prices and in daily returns using the price delay measure.

Panel B in table 8 addresses my second research question using the alternative efficiency measures. Similar to the results with my main measure of efficiency (SDPE), I find that IPOs with prestigious book underwriters and large managing syndicates are associated with higher levels of efficiency, but evidence of an association of VC backing and efficiency is weak. First, prestigious underwriters are associated with higher levels of efficiency as evidenced by negative and statistically significant coefficient for High-rep dummy for three of the five efficiency proxies (SDPE, PD, and stvol).[10] Second, the effect of VCs on price efficiency is statistically significant in only one of the five regressions (when efficiency is proxied by autocorrelation). Finally, the size of the syndicate has the most pronounced impact on the price efficiency, with a significant negative coefficient with all five efficiency proxies. This result strengthens my argument that financial intermediaries (especially prestigious underwriters and large underwriting syndicates) enhance the price efficiency of IPO stocks.

Panel C of table 8 addresses my third research question about whether stocks with lower levels of efficiency tend to underperform when compared to stocks with higher levels of efficiency. All five proxies for efficiency support my third hypothesis – namely that firms with less efficient stock prices are more likely to be delisted due to poor performance within five years. This suggests that IPO stocks that fail to impound information in timely manner and fail to monitor mangers well are more likely to have inferior performance. One interesting observation from this panel is that IPO stocks are more likely to be delisted

[10] Untabulated results show that prestigious underwriters are associated with higher levels of efficiency when I use daily returns from CRSP (rather than intraday data from TAQ) for the two measures that show insignificant results in Table 8, Panel B: autocorrelation and variance ratio.

within five years than seasoned stocks after controlling for all five of my efficiency proxies. This result corroborates Ritter's (1991) finding that IPO stocks underperform seasoned stocks on average in the long-term.

In panel D, I test the delisting probability with only IPO stock and include the financial intermediary variables. Three proxies support my hypothesis that efficiency is related to performance. Standard deviation of pricing error (SDPE), variance ratio ($|1 - VR_{(30,60)}|$), and price delay (PD) are positively associated with the probability of being delisted within five years, but autocorrelation, and short-term volatility are not statistically significant. These variables are positively associated with the probability of delisting in the univariate setting (untabulated); however, their significance disappears when I include other financial intermediary variables. As to the financial intermediary variables, IPOs with high reputation underwriters and large syndicate sizes are less likely to delist for poor performance within five years. Market capitalization also shows consistent significance across all efficiency proxies (i.e., large firms are more likely to survive). In sum, the tests shown in table 8 provide confirmation of the earlier analysis and support my three hypotheses across other efficiency proxies.

6. Are better intermediaries bringing IPO firms to the market more likely to have efficient stock prices?

The finding that financial intermediaries are related to the level of efficiency of IPO firms that they take public raises a question about the selection process. An ideal setting for an empirical analysis of the role of financial intermediaries is if financial intermediaries are randomly matched with IPO firms.[11] If so, we can observe the marginal contribution to efficiency coming from these intermediaries. However, it might be the case that IPO firms brought to the market by better intermediaries (high-reputation underwriters and large syndicate sizes) may have firm characteristics that lead to higher efficiency.[12] Then, my

[11] One of the key assumptions needed for OLS to produce consistent estimates of the parameters is a random sample of observation on dependent variable and independent variables.
[12] Since the effect of VC-backing on the efficiency is generally not significant, my tests for selection bias are limited to underwriter reputation and syndicate size.

empirical results that IPO firms underwritten by reputable underwriters or IPO firms with large syndicates are more efficient may be spurious.[13] Fernando, Gatchev, and Spindt (2005) present a theoretical model (and provide empirical support for this model) which asserts that firms and underwriters choose each other mutually. Similarly, Sorensen (2007) finds that firms brought to the market by more experienced VCs are more likely to go public not only because more experienced VCs add more value ("influence" in his terminology) but also because more experienced VCs choose and invest in better companies. The findings of these studies suggest that my results that the presence of financial intermediaries are associated with higher levels of efficiency could be because these intermediaries select issuing firms based on their anticipated level of efficiency in the aftermarket (or other factors that are related to this efficiency level).

To circumvent the selection bias in the type of IPO firms brought to the market by prestigious underwriters, I create a matched sample of firms taken public by low reputation underwriters by using the propensity-scoring method[14] (This is similar to the method used by Lowry, Officer, and Schwert (2010) to match IPOs using the auction selling method to IPOs using the book-building method.) Specifically, I first estimate a logit model to predict which type of the firm chooses prestigious underwriters,

$$Highrep\ dummy_i = a_0 + a_1 initial\ return + a_2 prcupdate + a_3\, ln(numtrades) + a_4\, ln(mktcap) + a_5 age + a_6 VC - back\ dummy + a_7 large\ syndicate\ dummy$$

As defined before, High-rep dummy equals one if IPO stock have underwriter's rank 8 or above and zero if IPO stocks have underwriter's rank below 8. The initial return is the percentage difference between the closing price on the first trading day and the IPO offer price, divided by the offer price. The prcupdate (the price update) is percentage

[13] Selection bias causes some of sample to be excluded, resulting in a biased sample. Non-random sample of a population in turn leads to biased coefficient estimate.

[14] There are some of issues to be considered in the propensity-scoring method. For example, should one match with replacement or without? Which covariates should one use to match? Despite these issues, Roberts and Whited (2012) contend that the propensity-scoring method can offer a nice robustness test, although matching will not solve a fundamental endogeneity problem.

difference between the midpoint of the preliminary price range and the final offer price. Age is defined as the year of the IPO minus the year of founding, and all other variables are as defined previously. The results (presented in table 9, panel A) are not unpredictable. For example, IPO firms brought to the market by prestigious underwriters are less likely to be underpriced and are likely to have a small number of trades during the first 175 trading days. However, prestigious underwriters are more likely to change the price between the period of the initial price range and final offer price and are more likely to bring larger and older firms public Also, IPO firms backed by VCs and consisting of large number of syndicates are more likely to have prestigious underwriters, which is consistent with the positive relation between my three financial intermediary variables. In this analysis, I also tried other specifications that include industry dummy variables and year dummies, for example, but they do not improve the fit of the model dramatically.

Next, I select the two IPO firms that choose a non-prestigious underwriter (i.e., rank less than 8) that have the closest-propensity scores (predictions from the logit model) to the propensity score of the IPO firm that chooses a prestigious underwriter (rank of 8 or greater). Specifically, I sort all IPOs by the propensity score and match each IPO with a high reputation underwriter to two IPOs with low reputation underwriters with propensity scores just above and just below the propensity score of the IPO. By selecting low reputation IPOs with a bit higher and a bit lower propensity scores, the average propensity score for the matched low reputation IPO sample (0.1957) is very close to the average propensity score in the high reputation IPO sample (0.1955). These scores are not presented in a separate table. As a result, I have a matched sample of 4,464 IPOs with low reputation underwriters to compare with the 2,232 IPOs with high reputation underwriters. These samples are used in the analysis in table 10. Due to the propensity score matching, these two samples are very similar.

I repeat the same propensity score method for syndicate size (large vs. small) as below.

$$\text{Large syndicate dummy} = a_0 + a_1 initial\ return + a_2 \text{prcupdate} + a_3 \ln(numtrades) + a_4 \ln(mktcap) + a_5 \text{age} + a_6 VCbackdummy + a_7 High\ reputation\ dummy$$

Table 9, panel B presents the results. IPOs with large syndicate sizes are less underpriced. However, large syndicates are more likely to change the price between the period of the initial price range and final offer price and are more likely to bring larger and older firms public. Also, firms backed by VCs and underwritten by prestigious underwriters are more likely to choose large syndicate size.

Table 10 presents the regression results from the analysis of the propensity score matched samples. As shown in the table, the effect of prestigious underwriters and large syndicates on the level of efficiency is not affected by selection bias. Noting that coefficients on high-rep dummy and large syndicate dummy are negative and statistically significant across all four model specifications, other firm characteristics that may affect the choice of underwriter and syndicate size do not appear to drive the level of efficiency. These results indicate that positive aspects of financial intermediaries (prestigious underwriter and large syndicate size), indeed, help to improve the price efficiency of IPO firms.

7. How does price support by the underwriter affect the price efficiency?

The issue of price support has been documented in a variety of studies. Ruud (1993) examines the distribution of initial returns, producing early evidence that a substantial part of underpricing is explained by the market practice of an underwriter's price support. Hanley (1993) also finds that price support tends to temporarily boost the price of IPO stocks. Jenkinson and Ljungqvist (2001) argue that price support retards the price discovery process in the aftermarket by obscuring the true demand and supply conditions. Thus, these three papers view price support as a manipulative action against the nature of market forces. In contrast, some papers argue that price support indeed helps the price of newly issued stocks to stabilize and be more aligned with their fundamentals. Benveniste, Busaba, and

Wilhelm (1996) maintain that price support is the most efficient form of compensation in favor of regular investors, thus reducing an underwriter's incentive to exaggerate investor interest. This finding implies that price support by underwriters motivates informed investors to voluntarily reveal useful information. Consistent with this argument, price support may cause prices to be closer to their fundamental values by enticing informed investors to the market, thus increasing the efficiency of the IPO stocks.

Motivated by arguments mentioned above, I investigate the connection between price support and the price efficiency of IPO stocks. Specifically, I estimate the extent of price support utilized in Lewellen (2006). Specifically, the dummy variable Price support equals 1 if the IPO closes the first trading day at the offer price (stabilized) and equals 0 if it closes below the offer (not stabilized). All other IPOs (i.e., those with closing prices on the first day of trading above the offer price) are excluded from the analysis. If the price support is truly a manipulative action that causes IPO stocks' price to be away from its fundamentals, I expect the dummy variable Price support to be positively associated with my efficiency proxies (which take higher values for stocks with lower levels of efficiency). By contrast, if price support moves the price closer to its intrinsic value (for instance if it is used as a mechanism to draw more informed investors to the initial market) then these offerings should have more efficient prices and therefore a negative relation should be found between Price support and my efficiency measures.

Table 11 displays the cross-sectional regression of price support on my main proxy for price efficiency, SDPE. The evidence is consistent with price support being a disruptive function to market forces in model (1), (2), and (3). IPO stocks with price support push the price away from its equilibrium price as Price support is positively associated with SDPE. In summary, these results argue in favor of the view that price support appears to be largely responsible for keeping stock prices away from their fundamental values (a price manipulation story). However, models (1), (2), and (3) have no controls for the number of trades. Once I control for this variable, the effect of price support on efficiency completely disappears, as shown in in model (4). Including year and industry dummies do not change the insignificant result of Price support on the efficiency. This result does not support the price manipulation story or efficiency-enhancing story of price support on the fundamental value of IPO stocks. I posit that even though there is abundant evidence that underwriters are engaged in the practice of price support during certain periods of time in the initial aftermarket, the practice does not seem to have a large impact on the fundamentals of IPO stocks. Thus, I reject the argument that the underwriters have incentive to generate more information due to their responsibility to stabilize the prices.

8. Calendar time event study approach using one-way and two-way classifications

In the section 4, I showed that stocks with low efficiency underperform stocks with high efficiency. While I use the full range of different efficiency measures to demonstrate robustness in section 5, my dependent variable (delist dummy) might not be an accurate measure of the long-term performance. To circumvent this problem and corroborate the relationship between efficiency and long-run performance, I employ the calendar time portfolio approach, as I describe in this section.

8.1. How to estimate long-term abnormal returns

For each calendar month, I obtain the return for each sample firm that has its IPO within a certain time period, and then I calculate the average return from that portfolio of firms in that month. I reform the portfolio every month. As a result, I develop a time series of portfolio returns which I can use to run the three-factor model (Fama and French, 1993) or four-factor model (Carhart, 1997) regressions as follows:

$$r_{p,t} - r_{f,t} = \alpha + \beta\left(r_{m,t} - r_{f,t}\right) + sSMB_t + hHML_t + e_t \text{--------------------(9)}$$

$$r_{p,t} - r_{f,t} = \alpha + \beta\left(r_{m,t} - r_{f,t}\right) + sSMB_t + hHML_t + uUMD_{t+}e_t \text{--------(10)}$$

where $r_{p,t}$ is calendar-time portfolio return from IPO samples at month *t*, r_f is the risk-free rate, r_m is the market portfolio return, *SMB* is the small-firm portfolio return minus the big-firm portfolio return, *HML* is the high book-to-market portfolio return minus the low book-to-market portfolio return, and *UMD* is the winner portfolio return minus the loser portfolio return based on the past 12-month return. I obtain these benchmark factors from Ken French's website: (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

The analysis is performed for each month over the period of 1993-2005. I form the calendar-time portfolios by including IPOs starting from the first calendar month after the month of the IPO's first trading date, up until the 9th calendar month (approximately 175 trading days), which correspond to my testing periods in months. To increase the power of the test, if for any month the number of IPOs is less than 3, I drop that month. My results are robust to a different minimum number of IPOs (i.e., a minimum of ten IPOs for each month) that I require in a calendar-time portfolio. I examine the abnormal returns of portfolios sorted in two ways: 1) by SDPE for one-way classification and 2) by SPDE and financial intermediary variables for two-way classifications.

For testing the differences in performance between two extreme portfolios, I use the return difference between two extreme portfolios as the dependent variable in Equation (9) and (10). Moreover, Mitchell and Stafford (2000) and Brav, Geczy, and Gompers (2000) argue that the IPOs underperform seasoned stocks only when portfolio returns are equal-weighted. Therefore, I show both equal- and value-weighted results for robustness.

8.2. Empirical results

In this section, I report one-way classification results, followed by two-way classifications and out-of-the sample post-issue performance results.

A. One-way classification

Table 12 reports my one-way classification results for each quartile and difference in two extreme portfolios. In panel A, I sort IPO firms by year of the offering then sort each year's IPO firms into quartiles based on their calculated SDPE. This SDPE portfolio classification makes the distribution among the four SDPE quartiles roughly even, although the high SDPE quartile has fewer observations compared with others. By construction, the high SDPE quartile (Q4) has IPO firms with a high level of SDPE, and the low SDPE quartile (Q1) has IPO firms with a low level of SDPE.

Consistent with my prior findings in logistic regression examining the probability of a performance delist within five years of the IPO date (table 7), effects of efficiency on the long-run performance using the calendar time portfolio approach are also very strong. I find that for an equal-weighted three factor model, IPO stocks with high SDPE (Q4) have significantly negative long-run abnormal returns (-2.91%), and IPO stocks with the low SDPE (Q1) have significant positive long-run abnormal returns (1.56%). I observe similar results whether I use equal or value-weighted returns or use the three factor or four factor models. More importantly, the efficiency effect is monotonic across quartiles; long-run abnormal returns (the alpha) decrease monotonically from 1.56% with highly efficient IPO stocks (Q1), to -2.91% with highly inefficient IPO stocks (Q4). The difference in the two extreme SDPE quartiles is significantly positive regardless of different model specifications. Specifically, the difference of 4.54% by equally weighted index (4.12% in valued-weighted market index) suggests that the efficient group of IPO firms leads to a 4.54% higher return than for non-efficient group of IPO firms. With a mean market value of about 473 million for my IPO sample firms, this translates into an average value added of almost 21 million for efficient IPO firms. This result indicates that IPO stocks whose transaction prices closely follow fundamentals outperform IPO stocks whose prices are not in line with its fundamentals.

In panel B, I examine whether the efficiency effect lasts beyond my testing period (9 months). For brevity, I report only the equal-weighted four factor model results, but the results therein are qualitatively identical with other model specifications. Although the efficiency effect becomes somewhat weaker, the effect lasts to year 4 following the IPO month. Up to year 2, a monotonic decrease in abnormal returns appears with an increase in SDPE. The monotonic relation weakened in years 3 and 4; however, the highly efficient IPOs still produce significantly positive returns, and the highly inefficient IPO stocks still yield negative returns (although insignificant). The abnormal returns (alphas) from various factor models for the long-short SDPE portfolios are significant in all years. In years 2, 3, and 4, I find that the alpha is 2.02%, 0.89%, and 0.86% respectively. Thus, I confirm that the relationship between the efficiency of IPO stocks and the long-term abnormal return is strong for an extended period of time. I will present a formal, out-of-the-sample test related to this finding in the next section.

Taken together, this long-term portfolio event study approach provides additional support for the hypothesis that a stock's level of efficiency has impacts on a firm's long-term performance.

B. Two-way classification

Although I find a significantly negative relationship between SDPE and long-term abnormal performance, one might ask whether the financial intermediary variables also drive long-term outperformance. As discussed earlier, IPOs with a prestigious book underwriter, VC-backing, and large syndicate size influence the long-term performance of IPOs. Thus, I check to ensure that abnormal performance by low SDPE IPO stocks is not driven by the positive aspects of financial intermediary variables. Therefore, the main purpose of conducting two-way classification of post-issue performance is to test the relation between SDPE and long-term performance, holding the effect of financial intermediary variables constant.

The main results of two-way classifications are presented in table 13, where I examine the effect of efficiency and each financial intermediary variable simultaneously during the nine months following the month of the IPO offer date. For brevity, I use the equal-weighted four-factor model results. My result is qualitatively identical with the other benchmark models employed in table 12.

In table 13, panel A, I examine the effect of efficiency while holding underwriter reputation as a constant, and then the effect of efficiency while holding the VC-backing and syndicate size as a constant in panels B and C. To maintain a reasonable number of IPOs in each cell, I divide the sample into two subsamples (rather that into quartiles) by the SDPE variable. Specifically, I combine the top two (bottom two) SDPE quartiles from table 12 as the high (low) SDPE IPO firms; the three financial intermediary variables are already separated by two groups as defined previously. Each panel presents benchmark-adjusted returns and associated *t*-statistics. The first two rows and two columns of each section within each panel report results from the two-way sort on efficiency and financial intermediary variables. The third row and the third column report results concerning the difference between the extreme portfolios based on both efficiency and financial intermediary variables. The number in the third row, third column (i.e., bottom right-hand corner of the panel) is the difference in abnormal returns between "winners" and "losers." For instance, in panel A, the winner portfolio is the IPO portfolio with low SDPE and a high reputation book underwriter, while the loser portfolio is the IPO portfolio with high SDPE and a low reputation book underwriter.

Consider the first upper left-hand corner of panel A where we find low SDPE/high reputation book underwriter (i.e. highly efficient, more prestigious IPO stocks): the portfolio that should have the highest abnormal return. Consistent with my prior, the group of IPOs with a low SDPE and high reputation book underwriter shows a statistically significant 1.12% benchmark-adjusted monthly return for the nine months following the portfolio formation month. This is compared to a -1.80% return for the group of IPOs with high SDPE and/high reputation book underwriters. The difference between these two groups produces a significant 2.94% abnormal return. This result suggests that the efficiency effects exist even after holding the effect of underwriter reputation (high CMR) constant. The evidence that efficiency plays an important role in determining the abnormal return is weaker in the next row. Specifically, the difference in abnormal return between two extreme portfolios, holding the underwriter reputation (low CMR) constant, is 1.91%, although statistically insignificant (*t*-value is 1.51). When portfolio groups are conditioned on efficiency (both low and high), the statistically insignificant differences between high and low reputation underwriter groups are 1.29% and 0.29%. These differences indicate that the efficiency effect may overwhelm the effect of underwriter reputation.

Lastly, the most powerful test of whether efficiency and underwriter reputation matter is achieved by comparing the best and worst groups: 1) The low SDPE/high reputation winner, in which the prices of IPOs follow the fundamentals closely, and IPOs are brought to the market by more prestigious underwriters and 2) The high SDPE/low reputation loser, in which the prices of IPOs are farthest from their fundamentals, and IPOs are brought to the market by less prestigious underwriters. Since a low SDPE/high reputation outperforms a high SDPE/low reputation by a statistically significant 3.47% in nine-months following the portfolio formation month, I observe strong support for the hypothesis that the combination of efficiency and underwriter reputation matters.

Panels B and C tell the same qualitative story after controlling for VC-backing and syndicate size, respectively. I organize results for these two portfolios by SDPE and VC-backing, then SDPE and syndicate size in the same way as for the previous portfolio sorted by SDPE and underwriter reputation. In that upper left-hand corner of panel B, I show low SDPE/VC-back (i.e. IPO stocks with high efficiency and VC-backing), the portfolio that should produce greater returns among the four groups because of my preliminary evidence of highly efficient stocks outperforming low efficiency stocks and Brav and Gompers (1997)'s evidence of VC-backed IPOs outperforming non-VC-backed offerings in the five years following the offer. This is what I observe, as low SDPE/VC-back has a significant benchmark-adjusted return of 1.4%. In contrast, my high SDPE/Non-VC backing portfolio shows a significant negative return of -1.28%. More importantly, the difference between the two extreme portfolios conditioned on VC-backing and non-VC backing produce significant abnormal returns of 3.26% and 2.68% respectively. However, the difference between the two extreme portfolios conditioned on low SDPE and high SDPE does not produce significant abnormal returns. This result again confirms my argument that efficiency has a more important impact on the long-term performance than backing by VC. Lastly, the test of the abnormal return difference between winner and loser IPO portfolios shows the abnormal return of 2.81% after adjusted for the Carhart (1997) four-factor model.

Panel C shows the abnormal return of portfolio groups sorted by SDPE and syndicate size. A large syndicate size should produce more information in the initial aftermarket because it has a greater number of analysts in general. Consistent with my prior, the portfolio that has low SDPE and large syndicate size produces the largest abnormal return of 1.38% among four portfolios. On the other hand, statistically, the loser portfolio that has high SDPE and small syndicate size experiences the significantly lowest abnormal return of -2.94%. Similar to the previous tests of SDPE and underwriter reputation, my interest lies in whether the better performance of low SDPE portfolios is driven by the size of syndicate. My third column confirms that it is not driven by syndicate size. After controlling the large and small syndicate sizes, the differences between low SDPE and high SDPE portfolios are statistically significant abnormal returns of 3.35% and 2.82%. On the other hand, the difference in abnormal returns in large and small syndicate portfolios conditioned on SDPE does not produce statistically significant abnormal returns at 0.26% and 0.94%. The test of winner (low SDPE/large syndicate size) minus loser (high SDPE/small syndicate size) portfolios yields an abnormal return of 4.49% consistent with my prior.

In summary, my key variable, efficiency measure (SDPE), matters in determining the long-term performance of IPO stocks beyond the effect that the financial intermediaries - the reputation of the underwriter, VC-backing, and the size of syndicate size - have on the long-term performance.

8.3. Does price efficiency of IPO stocks forecast long-term abnormal returns?

In the previous section, the period for calculating my efficiency measure (SDPE) was the same as my long-run return testing period (i.e., the first nine months after the IPO offer date). In this section, I test whether efficiency calculated over the first nine months from the IPO can predict long-run returns after the ninth month. So, in this section, I repeat the same tests as in tables 12 and 13, except I use a different time horizon to examine whether price efficiency of IPO stocks forecasts long-term abnormal returns. The analysis in this section proceeds in two steps. First, I sort IPO stocks into quartiles based on SDPE (one-way classification) and examine whether IPO stocks with high efficiency (low efficiency) produce high (low) abnormal returns. I form an IPO calendar-time portfolio by including IPOs starting from the 10^{th} month after the IPO offer month to the next 19^{th} month. Therefore, the testing period for long-run abnormal returns ($10\text{-}19^{th}$ months after the month of the IPO offer date) is after the period for calculating my efficiency measure (up to the 9^{th} month after the IPO offer date). Second, I implement two-way classifications, sorted based on the SDPE and financial intermediary variables to examine the same out-of-the-sample test period.

Even though post-issue performance in the out-of-the-sample tests draws weaker results compared to the in-sample tests previously shown in tables 12 and 13, it shows consistent patterns that I find in one-way and two-way classifications overall. Panel A presents one-way classification sorted into quartiles based on SDPE. In both the value-weighted three-factor model and four-factor model, the future abnormal returns decrease monotonically as I move from the most efficient IPO stocks to the least efficient IPO stocks. However, using an equal-weighted Fama French three-factor model and a Carhart four factor model, the future abnormal return of the portfolio is not monotonically decreasing with an increase in inefficiency of IPO stocks. It is unclear why the monotonic pattern changes with the use of equal-weighted benchmarks. The bottom row shows the alpha from the high efficiency (Q1) minus low efficiency (Q4) difference portfolio. The difference portfolio is only significant using the value-weighted three-factor model.

Panels B, C, and D examine whether the predictability of the efficiency in IPO stocks still holds conditioned on financial intermediary variables in the same manner as in table 13. One interesting finding emerges in each panel. The effect of efficiency as conditioned on financial intermediary variables is present only when it is conditioned on the positive aspects of the three variables. More specifically, the difference in future abnormal returns between extreme portfolios is statistically significant: 1.22%, 2.33%, and 1.47% after controlling for more prestigious underwriters, VC-backing, and large syndicate size. However, this difference in future abnormal return does not exist when the portfolios are controlled with less prestigious underwriters, Non-VC-backing, and small syndicate size. Lastly, the future abnormal returns between winner (low SDPE/positive financial intermediary) and loser (high SDPE/negative financial intermediary) portfolios are strong across all panels. Winner outperforms losers by a statistically significant 2.06%, 2.26%, and 1.79% in all two-way classification portfolios.

Overall, table 12 shows that efficiency has some return predictability, although the results are weak. This result suggests that past efficiency levels of IPO stocks may play an important role in forecasting future price changes of IPO stocks.

9. Conclusions

My dissertation investigates the efficiency of IPO stocks. In a well-functioning financial market without market imperfections, IPO stocks should be just as efficient as a sample of matched seasoned stocks, without regard to the length of time the stock has been trading. However, there are several distinct environments that could lead to higher information asymmetries for IPO stocks, and therefore deteriorate levels of efficiency. The characteristics of these distinct environments include: regulation and restrictions, such as quiet period and lock-up period in newly issued stocks; price support as a manipulative action that widens the information gap between informed and uninformed investors; and the amount of time it will take for the market to assimilate new information about the newly listed IPO stocks.

My results show that IPO stocks do indeed have a lower level of efficiency than seasoned stocks in the initial aftermarket, and their lower levels of efficiency persist during my 175 trading day testing period following the IPO offering date. Furthermore, I show that intermediaries play an important role in improving an IPO stock's efficiency. Namely, prestigious book underwriters, VC-backing, and large managing syndicates enhance efficiency of IPO stocks. More importantly, I find that the level of stock efficiency is linked to long-term performance. Stocks with low efficiency tend to underperform stocks with high efficiency. These three results are robust to different efficiency measures and model specifications.

My dissertation complements the broad literature that tests the efficiency of stocks. To the best of my knowledge, my dissertation is the first to use the Hasbrouck (1993) measure to show that IPO stocks are significantly less efficient than matched seasoned stocks in the early aftermarket, that it takes a substantial period of time to converge to the efficiency level of seasoned stocks, and that financial intermediaries have a significant effect on IPO stock efficiency. Harris (2003) maintains that more efficient prices facilitate better-informed financing decisions, and consequently, lead to better investment decisions for firms and a well-functioning financial market. Wurgler (2000) provides supportive empirical evidence of this conjecture that countries with more developed financial markets have better ability to allocate their capital towards more growing industries and reduce allocation of capital towards decaying industries. Consistent with this argument, I find that firms with more efficient stock prices have better long-run performance. My finding of intermediaries' efficiency-enhancing role in the aftermarket also adds to the growing literature on the intermediaries' role in the aftermarket. Numerous papers emphasize the role of intermediaries in the IPO primary market (e.g., Lowry and Schwert, 2004), although evidence is mounting that the underwriters' role continues in the secondary market for activities such as market-making and price support. My dissertation adds to this literature by showing the important role of intermediaries in the price discovery process.

Appendix 1. The estimation of standard deviation of pricing error (SDPE)

The description in this appendix of the estimation of Hasbrouck's (1993) standard deviation of pricing error (SDPE), including the notation, description of variables, and description of the estimation process, is from Boehmer and Kelley (2009) and Boehmer and Wu (2013).

Hasbrouck assumes that the observed (log) transaction price at time t, p_t, can be decomposed into an efficient price, m_t, and the pricing error, s_t:

$$p_t = m_t + s_t, \tag{A.1}$$

where m_t is defined as the security's expected value, conditional on all available information at transaction time t. By definition, m_t only moves in response to new information and is assumed to follow a random walk. The pricing error s_t measures the deviation relative to the efficient price. It captures non-information related market frictions, such as price discreteness and inventory control effects, etc. s_t is assumed to be a zero-mean covariance-stationary process, and it can be serially correlated or correlated with the innovation from the random walk of efficient prices. Because the expected value of the deviations is zero, the standard deviation of the pricing error, $\sigma(s)$, measures the magnitude of deviations from the efficient price and can be interpreted as a measure of price efficiency for the purpose of assessing market quality.

In the empirical implementation, Hasbrouck (1993) estimates the following vector AutoRegression (VAR) system with five lags:

$$r_t = a_1 r_{t-1} + a_2 r_{t-2} + \cdots . + b_1 x_{t-1} + b_2 x_{t-2} + \cdots . v_{1,t}$$

$$x_t = c_1 r_{t-1} + c_2 r_{t-2} + \cdots . + d_1 x_{t-1} + d_2 x_{t-2} + \cdots . v_{2,t} \quad \text{(A.2)}$$

where r_t is the difference in (log) prices p_t, and x_t is a column vector of trade-related variables: a trade sign indicator, signed trading volume, and signed square root of trading volume to allow for concavity between prices and trades. $v_{1,t}$ and $v_{2,t}$ are zero-mean, serially uncorrelated disturbances from the return equation and the trade equation, respectively. The above VAR can be inverted to obtain its vector moving average (VMA) representation that expresses the variables in terms of contemporaneous and lagged disturbances:

$$r_t = a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \cdots . + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \cdots$$

$$x_t = c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \cdots . + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \cdots$$

(A.3)

To calculate the pricing error, only the return equation in (A.3) is used. The pricing error under the Beveridge and Nelson (1981) identification restriction can be expressed as:

$$s_t = a_0 v_{1,t} + a_1 v_{1,t-1} + \cdots . + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \cdots$$

(A.4)

where $\alpha_j = -\sum_{k=j+1}^{\infty} a_k^*$, $\beta_j = -\sum_{k=j+1}^{\infty} b_k^*$

The variance of the pricing error is then computed as

$$\sigma_{(s)}^2 = \sum_{j=0}^{\infty}[\alpha_{j,}\beta_j]Cov(v)\begin{bmatrix}\alpha_j \\ \beta_j\end{bmatrix}$$

(A.5)

The standard deviation of the pricing error, equal to the square root of $\sigma_{(s)}^2$, is my main measure of efficiency, which I denote SDPE. In the estimation of SDPE, all transactions in TAQ that satisfy the trade and quote filtering criteria (refer to footnote 5) are included. Following Hasbrouck (1993), I exclude overnight returns. I use the Lee and Ready (1991) algorithm to assign trade directions. I assume that trades are reported five seconds late and adjust time stamps for records between 1993 and 1998, but make no time adjustment after this period (Bessembinder, 2003).

Boehmer and Kelly (2009) scale SDPE by the standard deviation of prices to make comparisons across stocks meaningful. However, in my 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.

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Figure 1. The esimated coefficient of IPO dummy for the 35 weeks after the IPO offer date

The Figure plots the estimated coefficient of IPO dummy and the corresponding 95% confidence interval from the following regression: $\boldsymbol{SDPE_i = a_0 + a_1 IPO\ dummy + a_2}\ \mathbf{ln}(\boldsymbol{numtrades}) + \boldsymbol{a_3}\ \mathbf{ln}(\boldsymbol{mktcap}) + \boldsymbol{a_4 NYSE + a_5 NASDAQ} + \sum_{j=1}^{48} \boldsymbol{b_j Industry\ dummy_j} + \sum_{t=1}^{T-1} \boldsymbol{c_t Year\ dummy_t}$ The regression is estimated for each of the 35 weeks (i.e., 5-trading day periods) following the IPO offer date. IPO dummy is equal to 1 for the sample of IPO stocks and 0 for the sample of matched seasoned stocks. The remaining variables in the regression are described in Table 5.

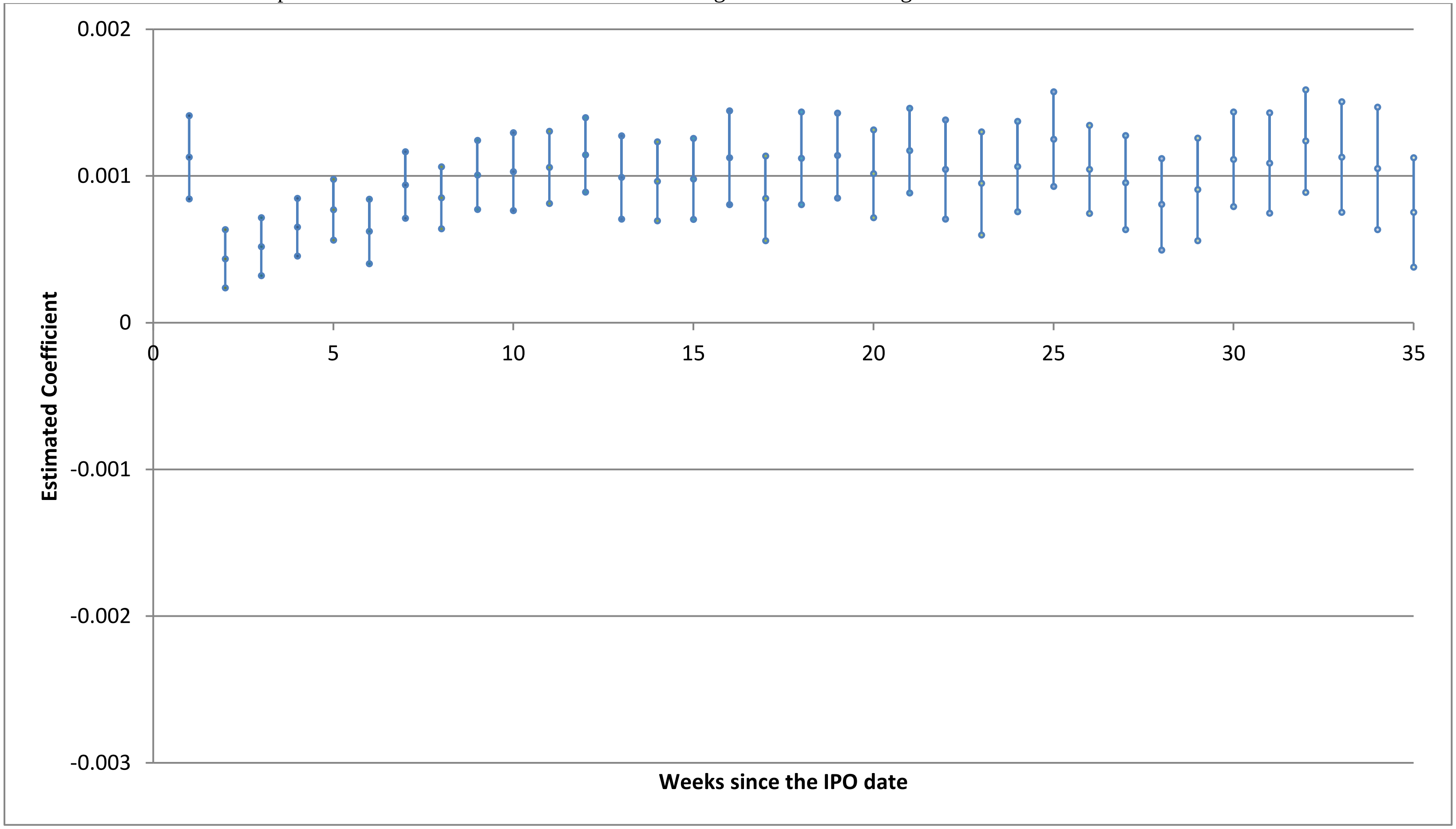

Figure 2. The estimated coefficient of high-rep dummy for IPO stocks for the 35 weeks after the IPO offer date.
The Figure plots the estimated coefficient of high-rep dummy and the corresponding 95% confidence interval from the following regression: $\mathbf{SDPE_i = a_0 + a_1 High\ rep\ dummy + a_2 \ln(numtrades) + a_3 \ln(mktcap) + a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t}$ The regression is estimated for each of the 35 weeks (i.e., 5-trading day periods) following the IPO offer date. High-rep dummy equals 1 if the book underwriter for the IPO has a rank of 8 or above and 0 if the rank is below 8. The book underwriter's reputation rank is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. The remaining variables in the regression are described in Table 6.

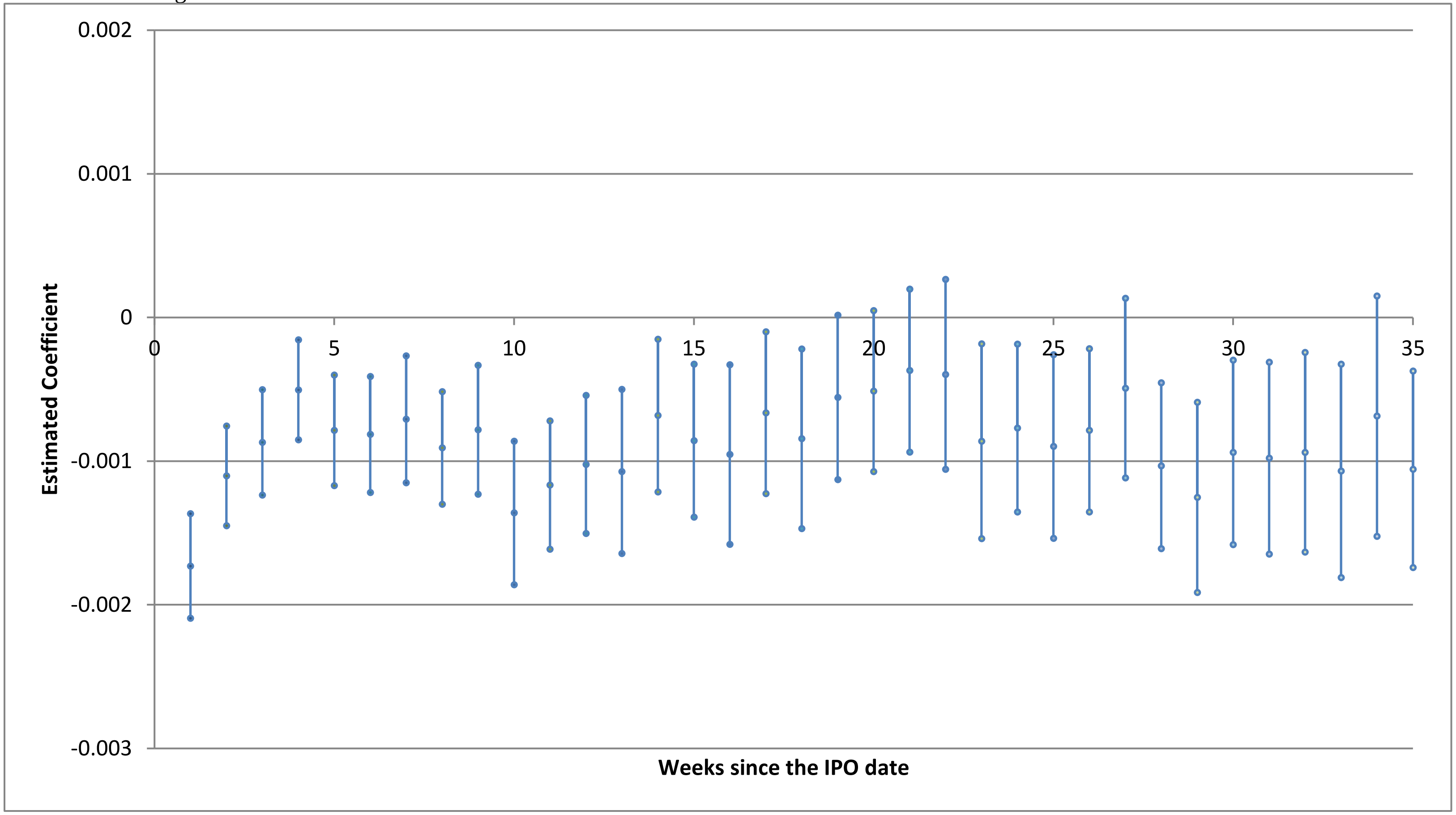

Figure 3. The estimated coefficient of VC back dummy for the 35 weeks after the IPO offer date.
The Figure plots the estimated coefficient of VC back dummy and the corresponding 95% confidence interval from the following regression: $\boldsymbol{SDPE_i = a_0 + a_1 VC\ back\ dummy + a_2} \ln(\boldsymbol{numtrades}) + \boldsymbol{a_3} \ln(\boldsymbol{mktcap}) + \boldsymbol{a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t}$ The regression is estimated for each of the 35 weeks (i.e., 5-trading day periods) following the IPO offer date. VC back dummy is equal to 1 for IPOs backed by VCs and 0 for IPOs not backed by VCs. The remaining variables in the regression are described in Table 6.

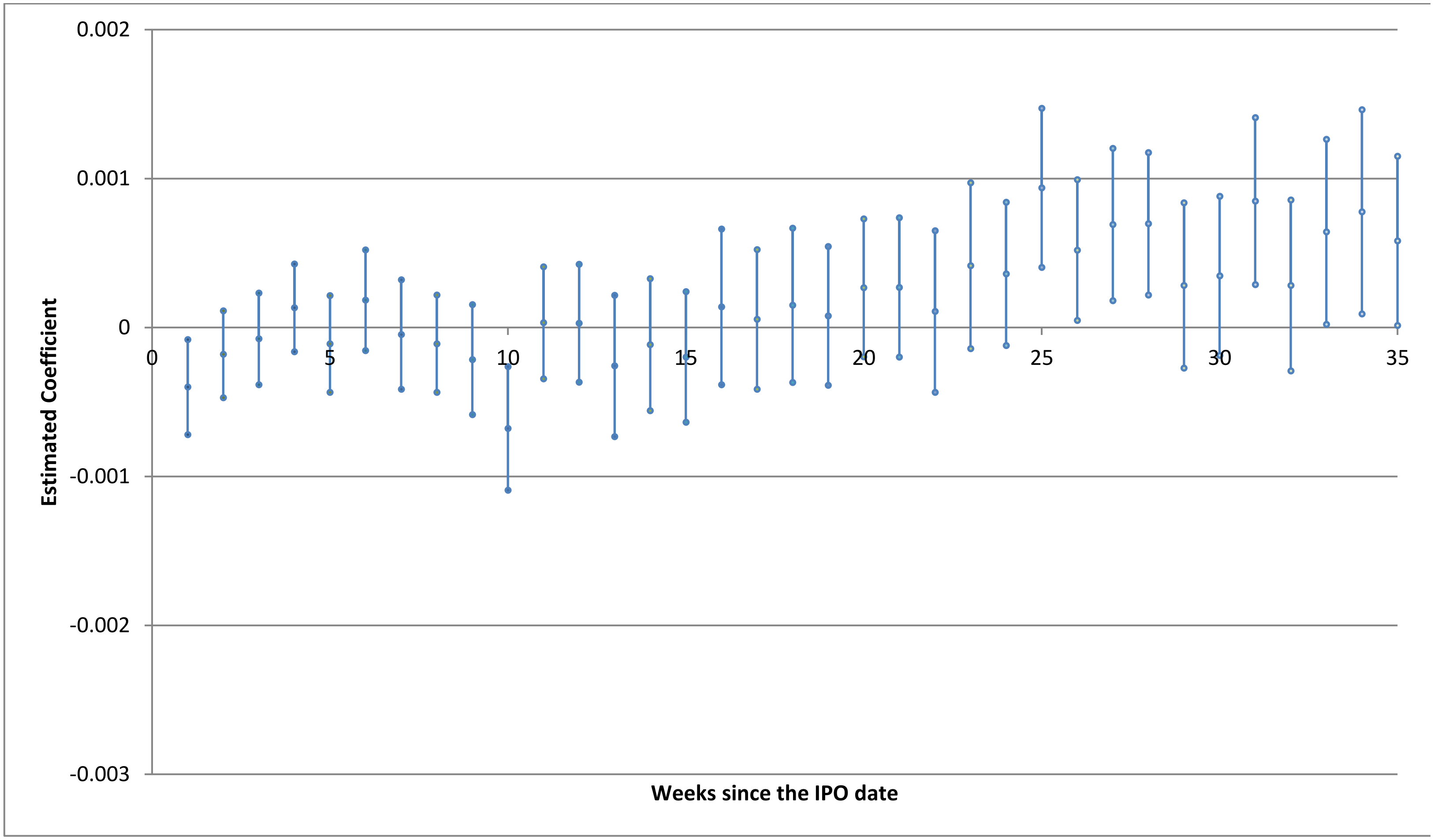

Figure 4. The estimated coefficient of IPOs with large syndicate dummy for the 35 weeks after the IPO offer date.

The Figure plots the estimated coefficient of large syndicate dummy and the corresponding 95% confidence interval from the following regression: $\boldsymbol{SDPE_i = a_0 + a_1 \textbf{large syndicate } dummy + a_2 \ln(numtrades) + a_3 \ln(mktcap) + a_4 NYSE + a_5 NASDAQ + \sum_{j=1}^{48} b_j Industry\ dummy_j + \sum_{t=1}^{T-1} c_t Year\ dummy_t}$ The regression is estimated for each of the 35 weeks (i.e., 5-trading day periods) following the IPO offer date. Large syndicate dummy is equal to 1 if IPOs have more than 3 managers and 0 if IPOs have less than/equal to 3 managers. The remaining variables in the regression are described in Table 6.

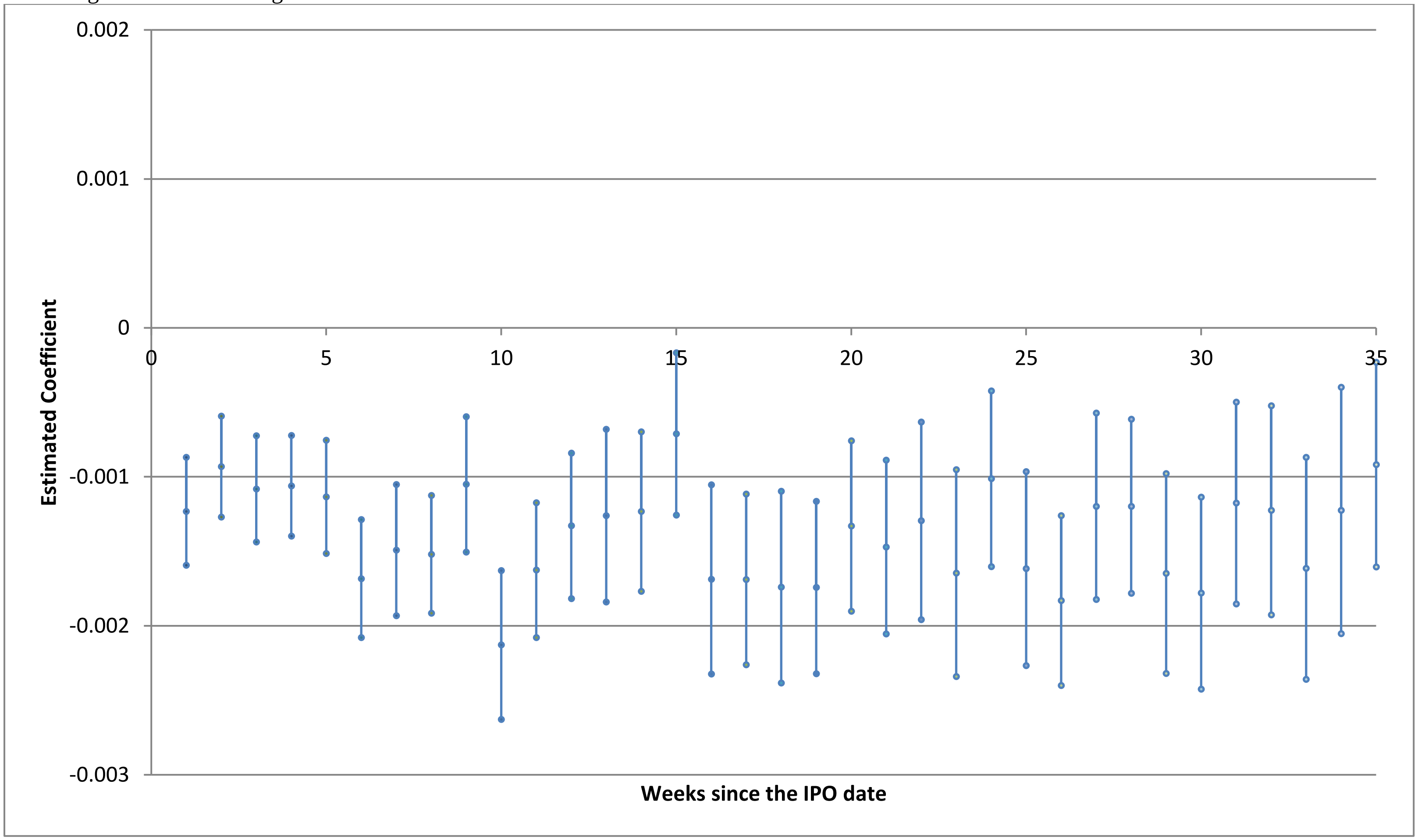

Table 1. Construction of IPO and seasoned stock samples

This table presents the IPO and seasoned stocks sample selection process. The following IPOs are deleted: ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, and IPOs with an offer price below $5 per share. The IPO firm's stock must be included on both the Center for Research in Security Prices (CRSP) and the NYSE Trade and Quote (TAQ) databases and have at least 100 valid trades over the 175 trading days after the IPO. Screens used in defining a valid trade are listed in Table 2. The final sample contains 3,486 IPOs. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases. There are 3,292 seasoned stocks in my sample.

A. IPO sample

	The Number of IPOs
Number of IPOs on SDC between 1993 and 2005	5,918
Less: ADRs, REITs, close-end funds, spinoffs, limited partnerships, previous LBOs, unit offerings, and offer price below $5	1,624
Less: Not found on CRSP	424
Subtotal	3,870
Less: Not found on TAQ	148
Less: Stocks with less than 100 valid trades	236
Final sample	3,486

B. Seasoned stock sample

	The number of matching seasoned stocks
Number of seasoned stocks matched with IPOs	3,870
Less: Not found on TAQ	149
Less: Stocks with less than 100 valid trades	429
Final sample	3,292

Table 2. Descriptive Statistics

This table presents descriptive statistics. Panel A presents variables calculated from TAQ. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). Absolute spread is defined as the dollar difference between the ask and bid. Relative spread is the absolute spread scaled by transaction price. The effective spread is twice the absolute value of the difference between trade price and quote midpoint. Trades and quotes used in the calculation of these variables must meet the criteria used in Boehmer and Kelley (2009). Specifically, I use trades and quotes only during regular market hours between 9:30 am and 4:00 pm and exclude overnight price changes. For trades, I require that TAQ's CORR field is equal to zero, and the COND field is either blank or equal to *, B, E, J, or K. I delete trades with non-positive prices or sizes. I also exclude a trade if its price differs by more than 30% from the previous trade price. I include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. I exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. I require that the difference between bid and ask be less than 25% of the quote midpoint. Trades and the associated quotes that meet these criteria are defined as "valid trades." Panel B presents variables of firm and offering characteristics. Market capitalization for the IPO firm is the closing price of the IPO firm's stock on the first day of trading times the number of shares outstanding on that day. The market capitalizations of seasoned stocks are calculated on the same day. The number of trades is combined number of valid trades during the 175 trading days after the IPO. The book underwriter's reputation rank (UW rank) is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC dummy equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC), and zero otherwise. Syndicate size is the number of lead, co-lead, and co-managers (as defined by SDC). NYSE is equal one if the IPO is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if the IPO is listed on NASDAQ, and zero otherwise. AMEX equals one if the IPO is listed on AMEX, and zero otherwise. Bubble equals one for IPO offer dates between September 1998 and August 2000, and zero otherwise. The last column provides the p-value from a t-test of difference of means for IPO and seasoned stocks, assuming either equal or unequal variances based on an equality of variance test. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed above. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

	IPO stocks				Seasoned stocks				IPO –Seasoned stock
	Mean	Std. dev.	Median	No. of Obs.	Mean	Std. dev.	Median	No. of Obs.	Difference in means
Panel A: TAQ variables									
SDPE	0.0076	0.0092	0.0054	3,486	0.0062	0.0078	0.0039	3,292	0.0013 (<.0001)
Absolute spread	0.3062	0.1719	0.2659	3,486	0.2598	0.2610	0.2058	3,292	0.0464 (<.0001)
Relative spread	0.0249	0.0203	0.0189	3,486	0.0231	0.0215	0.0166	3,292	0.0017 (0.0007)
Effective spread	0.2627	0.9119	0.2198	3,486	0.2098	1.2181	0.1450	3,292	0.0529 (0.042)
Panel B: Firm characteristics									
Market capitalization (in $ million)	472.976	1,297.577	171.390	3,486	481.028	1,232.300	179.161	3,292	-8.052 (0.7936)
The number of trades	27,775	70,355	7,218	3,486	33,391	125,904	6315.50	3,292	-5616.400 (0.021)
UW rank	7.270	2.240	8.000	3,486					
VC dummy	0.442	0.497	0.000	3,486					
Syndicate size	2.877	1.769	3.000	3,486					
NYSE	0.137	0.344	0.000	3,486	0.264	0.441	0.000	3,292	0.1272 (<.0001)
NASDAQ	0.843	0.364	1.000	3,486	0.656	0.475	1.000	3,292	-0.1864 (<.0001)
AMEX	0.020	0.141	0.000	3,486	0.080	0.270	0.000	3,292	0.0592 (<.0001)
Bubble	0.213	0.409	0.000	3,486	0.2211	0.4151	0.000	3,292	0.008 (0.4244)

Table 3. Panel A. IPO stocks by years, industry, and SDPE.
This table provides the annual number of IPOs, yearly average offer price of IPO firms, average book underwriter's rank (UW rank), the average percentage of IPOs backed by venture capitalists, the average size of the managing syndicate, yearly average standard deviation pricing error (SDPE) for IPOs, annual number of seasoned stocks, yearly SDPE for seasoned stocks, and p-value from the test of mean difference between IPOs and seasoned stocks' SDPE. In panel A, I show the breakdown of IPO stocks by year of the offering. In panel B, I sort the sample by Fama-French 49 industry and show the top 10 and bottom 10 in terms of number of IPOs. In panel C, I sort the sample by Fama-French 49 industry and show the top 10 and bottom 10 in terms of SDPE. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). The book underwriter's reputation rank (UW rank) is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC dummy equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC), and zero otherwise. Syndicate size is the number of lead, co-lead, and co-managers (as defined by SDC). The last column provides the p-value from a t-test of difference of means for SDPE for IPO and seasoned stocks, assuming either equal or unequal variances based on an equality of variance test. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades in during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

Year	# IPOs	Offer price ($)	UW rank	VC dummy	Syndicate size	IPO SDPE	# of SS	SS SDPE	p-value
1993	241	12.79	6.972	0.386	2.213	0.0154	193	0.0101	0.0079
1994	317	10.85	6.462	0.369	1.972	0.0116	272	0.0110	0.5379
1995	406	12.30	6.905	0.438	2.241	0.0106	379	0.0093	0.0150
1996	597	12.12	6.967	0.395	2.400	0.0104	571	0.0088	0.0006
1997	400	12.19	6.951	0.310	2.500	0.0064	386	0.0061	0.4233
1998	255	12.32	7.095	0.290	2.693	0.0055	239	0.0062	0.1167
1999	426	14.78	7.973	0.608	3.444	0.0045	426	0.0032	<0.0001
2000	328	14.67	8.211	0.707	3.646	0.0052	323	0.0031	<0.0001
2001	68	13.73	8.104	0.559	4.000	0.0026	67	0.0025	0.6296
2002	60	14.61	8.084	0.350	4.317	0.0023	55	0.0023	0.9959
2003	62	14.82	7.840	0.419	3.903	0.0016	60	0.0015	0.5013
2004	167	13.81	7.779	0.533	4.383	0.0018	163	0.0013	0.0007
2005	159	14.53	7.875	0.327	4.295	0.0016	158	0.0016	0.7715
Total	3,486	12.97	7.299	0.441	2.875	0.0076	3,292	0.0062	(<.0001)

Table 3 – continued

Table 3. Panel B. The top 10 and bottom 10 industries by number of IPOs.

Industries (FF #)	# IPOs	IPO SDPE	Offer Prc ($)	UW rank	VC dummy	Syndicate size
Softw (36)	634	0.0075	13.033	7.533	0.642	2.869
BusSv (34)	369	0.0060	13.061	7.584	0.509	3.000
Chips (36)	197	0.0064	12.890	7.874	0.614	3.188
Telcm (32)	180	0.0066	14.923	8.007	0.489	3.436
Rtail (43)	172	0.0077	13.122	7.158	0.395	2.661
Drugs (13)	163	0.0074	11.117	7.302	0.785	2.918
Whlsl (42)	150	0.0097	11.942	6.468	0.213	2.436
Medeq (12)	128	0.0087	11.709	7.345	0.727	2.630
ElcEq (22)	128	0.0084	13.104	7.228	0.570	2.641
Fin (48)	111	0.0049	16.095	7.262	0.081	3.200
Average of top 10	236	0.0076	12.767	7.388	0.549	2.864
Ships (25)	8	0.0060	14.500	7.501	0.125	2.625
Boxes (24)	8	0.0060	12.906	7.501	0.125	2.750
Fabpr (40)	8	0.0094	10.125	7.126	0.125	2.500
Mines (2)	7	0.0023	15.036	9.001	0.000	4.429
Aero (24)	6	0.0062	12.083	7.334	0.167	2.667
Agriculture (1)	4	0.0055	10.750	7.001	0.500	3.000
Smoke (5)	4	0.0059	10.563	5.251	0.250	2.250
Coal (29)	3	0.0010	18.667	9.001	0.000	5.667
Guns (26)	3	0.0018	15.500	8.334	0.000	4.000
Gold (27)	1	0.0135	12.000	9.001	1.000	3.000
Average of bottom 10	5	0.0055	13.284	7.823	0.208	3.262

Table 3. Panel C. The top 10 and bottom 10 industries by SDPE.

Industries	IPO SDPE	# IPOs	Offer Prc($)	UW rank	VC dummy	Syndicate size
Paper (39)	0.0176	15	11.6167	5.8010	0.4667	2.1333
Rubbr (15)	0.0171	13	9.5769	6.3856	0.0000	1.8462
Hlth (11)	0.0124	87	11.6190	7.2424	0.5632	2.5814
Beer (4)	0.0122	10	12.6000	6.2010	0.5000	2.0000
Other (49)	0.0108	12	11.1458	7.0010	0.2500	2.1667
Toys (6)	0.0107	29	10.7328	5.9665	0.0690	2.1379
Mach (21)	0.0099	57	12.8487	7.1940	0.2807	2.4912
Meals (44)	0.0098	80	11.3125	6.3510	0.1500	2.4750
Whlsl (42)	0.0097	150	11.9421	6.4677	0.2133	2.4362
FunEntertainment (7)	0.0096	62	12.3871	6.0494	0.2097	2.6935
Average of top 10	0.0120	52	11.5782	6.4660	0.2703	2.2961
Food (2)	0.0068	23	12.1500	6.3488	0.2174	2.7391
Telcm (32)	0.0066	180	14.9230	8.0066	0.4889	3.4358
Chips (37)	0.0064	197	12.8896	7.8741	0.6142	3.1878
BusSv (34)	0.0060	369	13.0605	7.5837	0.5095	3.0000
Insur (46)	0.0058	72	15.7910	7.5566	0.1389	4.0845
Steel (19)	0.0054	29	14.3190	7.9665	0.1379	2.6897
Fin (48)	0.0049	111	16.0946	7.2623	0.0811	3.2000
Oil (30)	0.0047	60	15.1167	7.7510	0.2333	3.2667
Unknown	0.0046	37	13.3196	7.1361	0.2703	3.4595
Util (31)	0.0031	13	17.2115	7.7702	0.1538	4.0769
Average of bottom 10	0.0054	109	14.4875	7.5256	0.2845	3.3140

Table 4. Correlation matrix for IPOs and seasoned stocks

This table presents correlation matrixes for IPO variables and seasoned stock variables. The sample of 3,486 IPOs and the sample of 3,292 seasoned stocks are from January 1993 through December 2005. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). 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 shares outstanding times the closing price on the first trading day of the IPO. The book underwriter's reputation rank (UW rank) is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC dummy equals one if the firm received financing from venture capitalists prior to the IPO (as defined by SDC), and zero otherwise. Syndicate size is the number of lead, co-lead, and co-managers (as defined by SDC). NASDAQ equals one if the stock is listed on NASDAQ, and zero otherwise. NYSE equals one if the stock is listed on the New York Stock Exchange, and zero otherwise. AMEX equals one if the stock is listed on the American Stock Exchange, and zero otherwise. P-values are reported in parentheses. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades in during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

Panel A: Correlation Matrix (IPOs)

	SDPE	Ln(numtrades)	Ln(mktcap)	UW rank	VC dummy	Syndicate size	NYSE	NASDAQ	AMEX
SDPE		-0.482	-0.449	-0.399	-0.051	-0.304	-0.262	0.267	-0.048
		(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.004)
Ln(numtrades)			0.740	0.472	0.250	0.462	0.095	-0.043	-0.120
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)
Ln(mktcap)				0.669	0.192	0.528	0.332	-0.250	-0.165
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
UW rank					0.253	0.404	0.266	-0.186	-0.167
					(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
VC dummy						0.065	-0.247	0.259	-0.067
						(0.000)	(0.000)	(0.000)	(0.000)
Syndicate size							0.333	-0.287	-0.068
							(0.000)	(0.000)	(0.000)
NYSE								-0.922	-0.057
								(0.000)	(0.001)
NASDAQ									-0.334
									(0.000)
AMEX									

Panel B: Correlation Matrix (Seasoned stocks)

	SDPE	Ln(numtrades)	Ln(mktcap)	NYSE	NASDAQ	AMEX
SDPE		-0.435	-0.536	-0.306	0.302	-0.032
		(0.000)	(0.000)	(0.000)	(0.000)	(0.011)
Ln(numtrades)			0.618	0.045	0.078	-0.212
			(0.000)	(0.000)	(0.000)	(0.000)
Ln(mktcap)				0.308	-0.183	-0.180
				(0.000)	(0.000)	(0.000)
NYSE					-0.828	-0.176
					(0.000)	(0.000)
NASDAQ						-0.406
						(0.000)
AMEX						

Table 5. Cross-sectional regression of standard deviation of pricing error (SDPE)

The dependent variable is SDPE. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). IPO dummy equals 1 for IPO stocks and 0 for seasoned stocks. Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date. (In the last column, I use the number of trades during the first 5 trading days.) Ln (mktcap) is the natural log of shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if the stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if the stock is listed on NASDAQ, and zero otherwise. Year dummy corresponds to the year of IPO offer date for both IPOs and matching seasoned stocks. Industry dummy is dummy variable for each Fama-French 49 industries. Column (1) – (3) are cross-sectional regressions encompassing the whole sample period (175 trading days) while column (4) is a cross-sectional regression for the first week (i.e., 5-trading days) since the IPO offer date. P-values are reported in parentheses. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades in during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

	(1)	(2)	(3)	(4)
Intercept	0.0062	0.0346	0.0368	0.0268
	(<.0001)	(<0.0001)	(<0.0001)	(<0.0001)
IPO dummy	0.0013	0.0006	0.0005	0.0011
	(<.0001)	(0.0013)	(0.0035)	(<0.0001)
ln(numtrades)		-0.0016	-0.0011	-0.0005
		(<0.0001)	(<0.0001)	(<0.0001)
ln(mktcap)		-0.0016	-0.0017	-0.0016
		(<0.0001)	(<0.0001)	(<0.0001)
NYSE		0.0019	0.0020	-0.0004
		(<0.0001)	(<0.0001)	(0.2174)
NASDAQ		0.0063	0.0060	0.0021
		(<0.0001)	(<0.0001)	(<0.0001)
Year dummies				
1994			-0.0022	0.0027
			(<0.0001)	(<0.0001)
1995			-0.0022	0.0035
			(<0.0001)	(<0.0001)
1996			-0.0026	0.0028
			(<0.0001)	(<0.0001)
1997			-0.0051	0.0003
			(<0.0001)	(0.4757)
1998			-0.0050	-0.0012
			(<0.0001)	(0.0207)
1999			-0.0042	0.0006
			(<0.0001)	(0.1963)
2000			-0.0029	0.0007
			(<0.0001)	(0.1766)
2001			-0.0044	-0.0010
			(<0.0001)	(0.0941)
2002			-0.0051	-0.0015
			(<0.0001)	(0.0108)
2003			-0.0059	-0.0018
			(<0.0001)	(0.0014)
2004			-0.0061	-0.0024
			(<0.0001)	(<0.0001)

2005			-0.0059	-0.0024
			(<0.0001)	(<0.0001)
Industry dummies	No	No	Yes	Yes
Adj. R2	0.0059	0.3530	0.3566	0.5439
No. of Obs.	6,778	6,778	6,778	4982

Table 6. Cross-sectional regression of standard deviation of pricing error (SDPE) including dummies for financial intermediaries (Underwriter rank, VC-backing, Syndicate size).

The dependent variable is SDPE. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). High-rep dummy equals 1 if the book underwriter for the IPO has a rank of 8 or above and 0 if the rank is below 8. The book underwriter's reputation rank is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). Ln (numtrades) is the natural log of the number of valid trades over the 175 trading days after the IPO offer date in columns (1)-(4) and during the first 5 trading days in columns (5)-(7). Ln (mktcap) is the natural log of shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if the stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if the stock is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO offer date. Industry dummy is dummy variable for each Fama-French 49 industries. Only IPO stocks are included to test the role of financial intermediaries on efficiency in this table. Column (1) – (4) are cross-sectional regressions encompassing the whole sample period (175 trading days) while column (5)-(7) is cross-sectional regression for the first week since the IPO offer date. P-values are reported in parentheses. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.0311	0.0346	0.0327	0.0304	0.0222	0.0251	0.0234
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
High-rep dummy	-0.0019			-0.0013	-0.0017		
	(<0.0001)			(0.0004)	(<0.0001)		
VC-back dummy		-0.0004		0.0001		-0.0004	
		(0.2267)		(0.8267)		(0.0145)	
Large syndicate dummy			-0.0034	-0.0030			-0.0012
			(<0.0001)	(<0.0001)			(<0.0001)
Ln(numtrades)	-0.0015	-0.0016	-0.0015	-0.0015	-0.0005	-0.0007	-0.0006
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Ln(mktcap)	-0.0010	-0.0013	-0.0010	-0.0008	-0.0011	-0.0013	-0.0012
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
NYSE	0.0035	0.0032	0.0033	0.0035	-0.0001	-0.0006	-0.0003
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.7955)	(0.3237)	(0.6243)
NASDAQ	0.0073	0.0074	0.0074	0.0074	0.0035	0.0035	0.0035
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Year dummies							
1994	-0.0034	-0.0034	-0.0034	-0.0035	0.0024	0.0023	0.0022
	(0.0244)	(0.0277)	(0.0222)	(0.0229)	(0.0003)	(0.0006)	(0.0011)
1995	-0.0030	-0.0029	-0.0027	-0.0028	0.0037	0.0036	0.0036
	(0.0390)	(0.0474)	(0.0546)	(0.0556)	(<0.0001)	(<0.0001)	(<0.0001)
1996	-0.0032	-0.0032	-0.0030	-0.0031	0.0028	0.0027	0.0027
	(0.0207)	(0.0245)	(0.0295)	(0.0324)	(<0.0001)	(<0.0001)	(<0.0001)
1997	-0.0060	-0.0058	-0.0056	-0.0058	-0.0002	-0.0002	-0.0001
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.7581)	(0.7542)	(0.8507)
1998	-0.0059	-0.0058	-0.0057	-0.0059	-0.0020	-0.0020	-0.0019
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0015)	(0.0019)	(0.0044)
1999	-0.0043	-0.0039	-0.0040	-0.0042	0.0004	0.0007	0.0009
	(0.0002)	(0.0006)	(0.0002)	(0.0003)	(0.5005)	(0.2890)	(0.1534)
2000	-0.0030	-0.0025	-0.0027	-0.0031	0.0001	0.0005	0.0008
	(0.0102)	(0.0278)	(0.0109)	(0.0085)	(0.8573)	(0.4595)	(0.2408)
2001	-0.0054	-0.0049	-0.0050	-0.0053	-0.0019	-0.0016	-0.0013
	(<0.0001)	(0.0003)	(<0.0001)	(<0.0001)	(0.0119)	(0.0392)	(0.0901)
2002	-0.0058	-0.0055	-0.0055	-0.0058	-0.0020	-0.0018	-0.0015
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0114)	(0.0192)	(0.0511)
2003	-0.0068	-0.0064	-0.0065	-0.0068	-0.0028	-0.0025	-0.0022
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0003)	(0.0012)	(0.0051)
2004	-0.0069	-0.0064	-0.0064	-0.0067	-0.0033	-0.0030	-0.0026
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

2005	-0.0065	-0.0062	-0.0065	-0.0067	-0.0030	-0.0029	-0.0026
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.3344	0.3288	0.3407	0.3430	0.5564	0.5445	0.5502
No. of Obs	3486	3486	3486	3486	3068	3068	3068

Table 7. Logistic regression of delisting probability.

The dependent variable is equal to 1 if the stock delists due to poor performance (i.e., CRSP delist code = 500, 510-591) within 5 years of the IPO offer date, 0 otherwise. IPO dummy equals 1 for IPO stocks and 0 for seasoned stocks. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). High-rep dummy equals 1 if IPO stocks have underwriter's rank 8 or above and 0 if IPO stocks have underwriter's rank below 8. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if IPO or seasoned stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if IPO or seasoned stock is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO date of both IPOs and matching seasoned stocks. Industry dummy is dummy variable for each Fama-French 49 industries. Column (1) – (4) include both IPO and seasoned stocks while column (5) – (8) include only IPO stocks. P-values are reported in parentheses. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades in during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-2.145	-2.2732	-2.4991	2.2647	-0.1530	0.9439	0.5524	-0.2999
	(<.0001)	(<.0001)	(<.0001)	(0.0005)	(0.8880)	(0.3739)	(0.6033)	(0.7835)
IPO dummy	0.4678		0.4221	0.4051				
	(<.0001)		(<.0001)	(<0.0001)				
SDPE		49.7710	48.3425	49.231	47.829	51.270	43.681	41.938
		(<.0001)	(<.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
High-rep dummy					-0.5679			-0.4830
					(<0.0001)			(0.0006)
VC-back dummy						-0.0674		0.0501
						(0.5691)		(0.6806)
Large syndicate dummy							-0.6516	-0.5365
							(<0.0001)	(0.0005)
Ln(numtrades)				0.3802	0.1971	0.1736	0.1813	0.1992
				(<0.0001)	(0.0025)	(0.0076)	(0.0052)	(0.0023)
Ln(mktcap)				-0.6985	-0.4138	-0.5221	-0.4539	-0.3752
				(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
NYSE				0.0153	-0.7580	-0.8467	-0.8196	-0.7458
				(0.9436)	(0.0571)	(0.0335)	(0.0404)	(0.0644)
NASDAQ				-0.1386	-0.2473	-0.2263	-0.1907	-0.2090
				(0.4695)	(0.4425)	(0.4822)	(0.5575)	(0.5199)
Year dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
-2 log likelihood	5245.11	5137.28	5104.61	4611.89	2572.25	2590.01	2572.13	2590
No. of Obs	6,778	6,778	6,778	6,778	3490	3490	3490	3490

Table 8. Panel A. Cross-sectional regression of various efficiency measures comparing the efficiency of IPOs and seasoned stocks.

This table presents the regression results from the same regression model as in table 5 column (3) except for using various efficiency proxies. SDPE is the standard deviation of pricing error based on the Hasbrouck (1993). |AR30| is absolute value of the thirty-minute quote midpoint returns autocorrelation. |1-VR(30,60)| represents the variance ratio and equals the absolute value of the sixty-minute quote midpoint return variance divided by twice the variance of the thirty-minute quote midpoint return minus one. STVOL is the quote midpoint return volatility over the thirty-minute interval. PD is price delay (Hou and Moskowitz, 2005) calculating the average delay with which information is impounded into stock prices by first regressing stock returns for each firm on contemporaneous (restricted model) and four lagged weekly market returns (unrestricted model) as follows. 1- (R2restricted / R2unrestricted). IPO dummy equals one if stocks are IPO, and zero if stocks are seasoned 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if IPO or seasoned stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if IPO or seasoned stock is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO date of both IPOs and matching seasoned stocks. Industry dummy is dummy variable for each Fama-French 49 industries. P-values are reported in parentheses. The sample size in each column varies because the values for some of the efficiency proxies could not be calculated for some observations. All models include year and industry dummies. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades in during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

	SDPE	|AR30|	|1 − VR(30,60)|	STVOL	PD
Intercept	0.0368	0.3826	0.6821	0.0548	1.3853
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
IPO dummy	0.0005	0.0012	0.0210	0.0035	0.0165
	(0.0035)	(0.7215)	(0.0065)	(<0.0001)	(0.0343)
Ln(numtrades)	-0.0011	-.0391	-.0724	0.0004	-.0435
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0534)	(<0.0001)
Ln(mktcap)	-0.0017	0.0066	0.0157	-.0036	-.0448
	(<0.0001)	(0.0008)	(0.0005)	(<0.0001)	(<0.0001)
NYSE	0.0020	0.0434	0.0669	0.0009	-.0030
	(<0.0001)	(<0.0001)	(0.0007)	(0.4272)	(0.8815)
NASDAQ	0.0060	0.0505	0.1853	0.0048	0.0397
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0313)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.3566	0.2120	0.2235	0.1154	0.1512
No. of Obs	6778	6547	6572	6763	6765

Table 8. Panel B. Cross-sectional regression of various efficiency measures including financial intermediaries variables (Underwriter rank, VC-backing, Syndicate size)

This table presents the regression results from the same regression model as in table 6 column (4) except for using various efficiency proxies. SDPE is the standard deviation of pricing error based on the Hasbrouck (1993). |AR30| is absolute value of the thirty-minute quote midpoint returns autocorrelation. |1-VR(30,60)| represents the variance ratio and equals the absolute value of the sixty-minute quote midpoint return variance divided by twice the variance of the thirty-minute quote midpoint return minus one. STVOL is the quote midpoint return volatility over the thirty-minute interval. PD is price delay (Hou and Moskowitz, 2005) calculating the average delay with which information is impounded into stock prices by first regressing stock returns for each firm on contemporaneous (restricted model) and four lagged weekly market returns (unrestricted model) as follows. 1- (R2restricted / R2unrestricted). IPO dummy equals one if stocks are IPO, and zero if stocks are seasoned stocks. High-rep dummy equals 1 if IPO stocks have underwriter's rank 8 or above and 0 if IPO stocks have underwriter's rank below 8. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if IPO is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if IPO is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO date of both IPOs. Industry dummy is dummy variable for each Fama-French 49 industries. Only IPO stocks are included to test the role of financial intermediaries on efficiency in this table. P-values are reported in parentheses. The sample size in each column varies because the values for some of the efficiency proxies could not be calculated for some observations. All models include year and industry dummies. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2.

	SDPE	|AR30|	|1 – VR(30,60)|	STVOL	PD
Intercept	0.0304	0.368	0.8592	0.0460	1.3732
	(<0.0001)	(<.0001)	(<.0001)	(<.0001)	(<0.0001)
High-rep dummy	-0.0013	-0.0063	-0.0044	-0.0009	-0.0237
	(0.0004)	(0.3230)	(0.8032)	(0.017)	(0.0653)
VC-back dummy	0.0001	-0.0084	0.0210	0.0007	-0.0125
	(0.8267)	(0.098)	(0.1222)	(0.4009)	(0.2575)
Large syndicate dummy	-0.0030	-0.0204	-0.0554	-0.0063	-0.0499
	(<0.0001)	(0.0133)	(0.0365)	(0.0072)	(0.0020)
Ln(numtrades)	-0.0015	-0.0379	-0.0827	-0.0005	-0.0682
	(<0.0001)	(<.0001)	(<.0001)	(0.2945)	(<0.0001)
Ln(mktcap)	-0.0008	0.0104	0.0217	-0.0014	-0.0198
	(<0.0001)	(0.0004)	(0.007)	(0.0001)	(0.0032)
NYSE	0.0035	0.0376	0.0573	-0.0015	-0.0013
	(<0.0001)	(0.0129)	(0.0406)	(0.3319)	(0.9728)
NASDAQ	0.0074	0.0565	0.1818	0.0030	0.0642
	(<0.0001)	(<.0001)	(<.0001)	(0.0285)	(0.0574)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.3430	0.2489	0.2532	0.1175	0.2166
No. of Obs	3486	3347	3367	3475	3484

Table 8. Panel C. Logistic regression of delisting probability on various efficiency measures with IPO dummy.
This table presents the regression results from the same regression models as in table 7 column (4) except for using various efficiency proxies. The dependent variable is equal to 1 if the stock delists due to poor performance (i.e., CRSP delist code = 500, 510-591) within 5 years of the IPO offer date, 0 otherwise. Each column shows the same logistic regression except for using different efficiency proxies. SDPE is the standard deviation of pricing error based on the Hasbrouck (1993). |AR30| is absolute value of the thirty-minute quote midpoint returns autocorrelation. |1-VR(30,60)| represents the variance ratio and equals the absolute value of the sixty-minute quote midpoint return variance divided by twice the variance of the thirty-minute quote midpoint return minus one. STVOL is the quote midpoint return volatility over the thirty-minute interval. PD is price delay (Hou and Moskowitz, 2005) calculating the average delay with which information is impounded into stock prices by first regressing stock returns for each firm on contemporaneous (restricted model) and four lagged weekly market returns (unrestricted model) as follows. 1-(R2restricted / R2unrestricted). IPO dummy equals one if stocks are IPO, and zero if stocks are seasoned 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if IPO or seasoned stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if IPO or seasoned stock is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO date of both IPOs. Industry dummy is dummy variable for each Fama-French 49 industries. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Matching seasoned stocks are selected based on four criteria: (1) Seasoned stocks must have been trading on CRSP for at least three years before the IPO date. (2) They must be in the same Fama-French 49 industry as the IPO firm. (3) The price of seasoned stock is within 15% of the IPO stock's closing price on the first day of trading. (4) Of the set of possible seasoned stocks from the first three criteria, I select the one seasoned stock with the closest market capitalization to the market capitalization of IPO stock as measured at the close of the IPO stock's first day of trading. As with the IPO stocks, the sample of seasoned stocks must be included on both the CRSP and TAQ databases and have at least 100 valid trades in during the first 175 trading days after the same offer date as the IPO. There are 3,292 seasoned stocks in my sample.

	SDPE	|AR30|	|1 − VR(30,60)|	STVOL	PD
Intercept	2.2647	4.0342	4.1205	3.4288	3.5176
	(0.0005)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Efficiency proxies	49.2310	0.6783	0.7640	15.6051	0.6154
	(<.0001)	(0.0176)	(0.0417)	(<.0001)	(<.0001)
IPO dummy	0.4051	0.3797	0.4044	0.3560	0.4072
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Ln(numtrades)	0.3802	0.3409	0.3227	0.3119	0.3390
	(<.0001)	(0.0305)	(<.0001)	(<.0001)	(<.0001)
Ln(mktcap)	-0.6985	-0.7933	-0.7849	-0.7379	-0.7658
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
NYSE	0.0153	0.0757	0.0981	0.1188	0.1236
	(0.9436)	(0.7248)	(0.6472)	(0.5810)	(0.5641)
NASDAQ	-0.1386	0.1440	0.1477	0.1113	0.1638
	(0.4695)	(0.4422)	(0.4288)	(0.5528)	(0.3783)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
-2 log likelihood	4611	4533	4683	4647	4661
No. of Obs	6778	6547	6572	6763	6765

Table 8. Panel D. Logistic regression of delisting probability on various efficiency measures with only IPO stocks and financial intermediaries

This table presents the regression results from the same regression models as in table 7 column (8) except for using various efficiency proxies. The dependent variable is equal to 1 if the stock delists due to poor performance (i.e., CRSP delist code = 500, 510-591) within 5 years of the IPO offer date, 0 otherwise. Each column shows the same logistic regression except for using different efficiency proxies. SDPE is the standard deviation of pricing error based on the Hasbrouck (1993). |AR30| is absolute value of the thirty-minute quote midpoint returns autocorrelation. |1-VR(30,60)| represents the variance ratio and equals the absolute value of the sixty-minute quote midpoint return variance divided by twice the variance of the thirty-minute quote midpoint return minus one. STVOL is the quote midpoint return volatility over the thirty-minute interval. PD is price delay (Hou and Moskowitz, 2005) calculating the average delay with which information is impounded into stock prices by first regressing stock returns for each firm on contemporaneous (restricted model) and four lagged weekly market returns (unrestricted model) as follows. 1- (R2restricted / R2unrestricted). High-rep dummy equals 1 if IPO stocks have underwriter's rank 8 or above and 0 if IPO stocks have underwriter's rank below 8. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if IPO or seasoned stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if IPO or seasoned stock is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO date of both IPOs and matching seasoned stocks. Industry dummy is dummy variable for each Fama-French 49 industries. I include only IPO stocks in this table because financial intermediaries belong to only IPO stocks. P-values are reported in parentheses. The sample size in each column varies because the values for some of the efficiency proxies could not be calculated for some observations. All models include year and industry dummies.

	SDPE	|AR30|	|1 – VR(30,60)|	STVOL	PD
Intercept	-0.2999	0.8970	1.0467	0.8510	0.4648
	(0.7835)	(0.4039)	(0.3294)	(0.4242)	(0.6649)
Efficiency proxies	41.938	0.2629	0.1160	6.3421	0.5210
	(<.0001)	(0.5047)	(0.0993)	(0.1877)	(0.0064)
High-rep dummy	-0.4830	-0.5165	-0.5052	-0.5062	-0.5105
	(0.0006)	(0.0002)	(0.0003)	(0.0003)	(0.0002)
VC-back dummy	0.0501	0.0944	0.0830	0.0491	0.0674
	(0.6806)	(0.4453)	(0.4991)	(0.6860)	(0.5774)
Large syndicate dummy	-0.5365	-0.7304	-0.7038	-0.6003	-0.6299
	(0.0005)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Ln(numtrades)	0.1992	0.1463	0.1379	0.1383	0.1666
	(0.0023)	(0.0305)	(0.0387)	(0.0302)	(0.010)
Ln(mktcap)	-0.3752	-0.4169	-0.4192	-0.4111	-0.4026
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
NYSE	-0.7458	-0.6122	-0.6167	-0.5951	-0.6263
	(0.0644)	(0.1286)	(0.1246)	(0.1380)	(0.1173)
NASDAQ	-0.2090	0.0760	0.0882	0.0927	0.0837
	(0.5199)	(0.8113)	(0.7811)	(0.7693)	(0.7902)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes
-2 log likelihood	2560	2472	2503	2569	2576
No. of Obs	3486	3347	3367	3475	3484

Table 9. Panel A. Logit model to explain the characteristics of IPOs underwritten by prestigious underwriters.
This table shows maximum likelihood estimate of the logit model to explain the characteristics to distinguish IPOs with prestigious underwriters from IPOs with non-prestigious underwriters. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Initial return is the percent difference between the closing price on the first trading day and the offer price. Prcupdate is the percentage difference between the midpoint of preliminary price range and the final offer price. 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 shares outstanding times the closing price on the first trading day of the IPO. Age is the number of years since the firm was founded at the time of IPO. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). P-values are reported in parentheses. The likelihood ratio statistic measures the joint significance of the model.

$$\mathrm{High-rep\ dummy_i} = \mathrm{a_0} + \mathrm{a_1 initial\ return} + \mathrm{a_2 prcupdate} + \mathrm{a_3}\ln(\mathrm{numtrades}) + \mathrm{a_4}\ln(\mathrm{mktcap}) + \mathrm{a_5 age} + \mathrm{a_6 VCback\ dummy} + \mathrm{a_7 large\ syndicate\ dummy}$$

Intercept	-18.30
	(<0.0001)
Initial return	-0.9171
	(<0.0001)
Prcupdate	1.3383
	(0.0002)
Ln(numtrades)	-0.1531
	(0.0010)
Ln(mktcap)	1.5978
	(<0.0001)
age	0.0066
	(0.0213)
VC-back dummy	0.8187
	(<0.0001)
Large syndicate dummy	0.3550
	(<0.0001)
-2 log likelihood	2708.211
No. of Obs	3,486

Table 9. Panel B. Logit model to explain the characteristics of IPOs with large syndicate size.

This table shows maximum likelihood estimate of the logit model to explain the characteristics to distinguish IPOs with a large syndicate size from IPOs with a small syndicate size. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. Initial return is the percent difference between the closing price on the first trading day and the offer price. Prcupdate is the percentage difference between the midpoint of preliminary price range and the final offer price. 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 shares outstanding times the closing price on the first trading day of the IPO. Age is the number of years since the firm was founded at the time of IPO. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. High-rep dummy equals 1 if IPO stocks have underwriter's rank 8 or above and 0 if IPO stocks have underwriter's rank below 8. P-values are reported in parentheses. The likelihood ratio statistic measures the joint significance of the model.

$$\text{Large Syndicate dummy}_i = a_0 + a_1\text{initial return} + a_2\text{prcupdate} + a_3\ln(\text{numtrades}) + a_4\ln(\text{mktcap}) + a_5\text{age} + a_6\text{VCback dummy} + a_7\text{Highrep dummy}$$

Intercept	-12.89
	(<0.0001)
Initial return	-0.5950
	(0.0249)
prcupdate	2.2433
	(<0.0001)
Ln(numtrades)	0.3107
	(<0.0001)
Ln(mktcap)	0.9905
	(<0.0001)
age	0.0025
	(0.5277)
VC-backdummy	0.5024
	(0.0009)
High-rep dummy	1.5264
	(<0.0001)
-2 log likelihood	2679.342
No. of Obs	3,486

Table 10: The effect of financial intermediaries on the efficiency after controlling for selection bias.
This table presents regression results of the effect of financial intermediaries on the efficiency controlling for selection bias. The dependent variable is SDPE. SDPE is the standard deviation of pricing error based on Hasbrouck (1993). High-rep dummy equals 1 if the book underwriter for the IPO has a rank of 8 or above and 0 if the rank is below 8. The book underwriter's reputation rank is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if the stock is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if the stock is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO offer date. Industry dummy is dummy variable for each Fama-French 49 industries. Only IPO stocks are included to test the role of financial intermediaries on efficiency in this Table. Column (1) – (2) are cross-sectional regressions of the effect of underwriter reputation on the efficiency after controlling for selection bias while column (3)-(4) is cross-sectional regression of the effect of syndicate size on efficiency after controlling for selection bias . The sample in column (1) and (2) consists of 2,232 IPO with prestigious underwriter and matching 4,464 IPOs with non-prestigious underwriters. The sample in column (3) and (4) consists of 2,842 IPOs with large syndicate size and matching 5,684 IPOs with small-syndicate size. P-values with White (1980) heteroscedastic-consistent standard errors are in parenthesis.

	(1)	(2)	(3)	(4)
Intercept	0.0190	0.0202	0.0277	0.0317
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
High-rep dummy	-0.0003	-0.0003		
	(0.0011)	(0.0009)		
Large syndicate dummy			-0.0005	-0.0005
			(0.0108)	(0.0113)
Ln(numtrades)	-0.0013	-0.0014	-0.0013	-0.0017
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Ln(mktcap)	-0.0002	-0.0001	-0.0011	-0.0010
	(0.0100)	(0.0395)	(<0.0001)	(<0.0001)
NYSE	0.0005	0.0008	0.0016	0.0024
	(0.1773)	(0.0513)	(0.0058)	(0.0017)
NASDAQ	0.0055	0.0053	0.0063	0.0064
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Year dummies				
1994	-0.0017	-0.0016	-0.0009	-0.0015
	(0.0003)	(0.0007)	(0.0638)	(0.0158)
1995	-0.0015	-0.0015	-0.0001	-0.0007
	(<0.0001)	(<0.0001)	(0.8878)	(0.3035)
1996	-0.0022	-0.0022	-0.0017	-0.0023
	(<0.0001)	(<0.0001)	(0.0003)	(0.0003)
1997	-0.0046	-0.0046	-0.0031	-0.0035
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
1998	-0.0046	-0.0046	-0.0019	-0.0032
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
1999	-0.0040	-0.0040	-0.0023	-0.0020
	(<0.0001)	(<0.0001)	(<0.0001)	(0.0002)
2000	-0.0018	-0.0019	-0.0008	-0.0008
	(<0.0001)	(<0.0001)	(0.0449)	(0.1265)
2001	-0.0052	-0.0055	-0.0032	-0.0032
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
2002	-0.0060	-0.0069	-0.0035	-0.0031
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
2003	-0.0073	-0.0072	-0.0044	-0.0043
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
2004	-0.0068	-0.0068	-0.0047	-0.0046
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
2005	-0.0065	-0.0064	-0.0059	-0.0061
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Industry dummies	No	Yes	No	Yes
Adj. R2	0.5615	0.5801	0.4094	0.4875
No. of Obs	6696	6696	8526	8526

Table 11. Cross-Sectional regression of price support for IPO stocks on the standard deviation of pricing error
This table shows the regressions of the price support for IPO stocks from January 1993 to December 2005. The dependent variable is SDPE. SDPE is the standard deviation of pricing error based on the Hasbrouck (1993). Following Lewellen (2006), price support is a dummy variable that is equal to 1 if the IPO closes the first trading day at the offer price (stabilized) and is equal to 0 if it closes below the offer (not stabilized). High-rep dummy equals 1 if IPO stocks have underwriter's rank 8 or above and 0 if IPO stocks have underwriter's rank below 8. The book underwriter's reputation rank is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC-back dummy equals 1 if IPOs are financed by VCs, otherwise 0. Large syndicate dummy equal one if IPO have 3 lead, co-lead, and co-managers or above, otherwise 0 (less than 3). 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 shares outstanding times the closing price on the first trading day of the IPO. NYSE is equal one if IPO is listed on the New York Stock Exchange, and zero otherwise. NASDAQ equals one if IPO is listed on NASDAQ, and zero otherwise. Year dummy correspond to the year of IPO date of both IPOs. Industry dummy is dummy variable for each Fama-French 49 industries. I include only IPO stocks in this table because price support is provided to only IPO stocks. The sample consists of only 756 of the 3,486 IPOs during the period 1993-2005 because 2,730 IPOs with closing prices on the first day of trading above the offer price are excluded from the analysis. The sample of 3,486 IPO from the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed above. P-values are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.0078	0.0130	0.0370	0.0313	0.0361
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Price support	0.0022	0.0023	0.0020	0.0003	0.0008
	(0.0458)	(0.0309)	(0.0544)	(0.8048)	(0.4363)
High-rep dummy		-0.0057	-0.0017	-0.0020	-0.0027
		(<0.0001)	(0.2153)	(0.1208)	(0.0506)
VC-back dummy		0.0010	-0.0002	0.0003	-0.0008
		(0.3724)	(0.8270)	(0.7724)	(0.5042)
Large Syndicate dummy		-0.0026	-0.0002	0.0006	-0.0004
			(0.9004)	(0.7021)	(0.8125)
NYSE			0.0059	0.0043	0.0065
			(0.0697)	(0.1742)	(0.0506)
NASDAQ			0.0095	0.0095	0.0099
			(0.0007)	(0.0004)	(0.0003)
Ln(mktcap)			-0.0031	-0.0001	-0.0008
			(<0.0001)	(0.8856)	(0.2896)
Ln(numtrades)				-0.0035	-0.0021
				(<0.0001)	(0.0006)
				0.0313	0.0361
Year dummies	No	No	No	No	Yes
Industry dummies	No	No	No	No	Yes
Adj. R2	0.0040	0.0495	0.1059	0.1700	0.1970
No. of Obs	756	756	756	756	756

Table 12. One-way classification of post-issue performance by the standard deviation of pricing error (SDPE).
This table presents abnormal return (alphas) of SDPE-sorted portfolios. It also reports abnormal return for the hedged portfolio that is long the lowest SDPE portfolio and short the highest SDPE portfolio with different factor models. The alphas' t-statistics are reported in parentheses. T-statistics are White (1980) heteroskedasticity consistent. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. I calculate long-run abnormal returns by using the intercept (the alpha) of the following Fama French three-factor or Carhart (1997) four-factor regressions,

$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t$------ Fama French 3 factor model
$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t + uUMD_t$------ Carhart 4 factor model

where $r_{p,t}$ is IPO calendar-time portfolio return at month t. I include IPO firms in the portfolio starting from the next month after the IPO date, and ending on the 9th months (about 175 trading days) after the month of IPO date in panel A. In panel B, I examine the abnormal return beyond my sample periods up to four years since the IPO date. The alphas and t-statistics associated with the alphas from a portfolio that is long the lowest SDPE portfolio (Q1) and short the highest SDPE portfolio (Q4) are presented in the bottom row of each panel.

Panel A: Abnormal returns of portfolio sorted by SDPE during 9 months (175 trading days) with various models since the IPO date

Different models	EW 3-Factor	VW 3-Factor	EW 4-factor	VW 4-factor
SDPE				
Q1 (most efficient)	1.56%	1.07	1.27%	0.88%
t-statistics	(3.73)	(2.15)	(3.36)	(1.85)
Q2	1.47%	0.96%	1.21%	0.71%
t-statistics	(2.75)	(1.55)	(2.36)	(1.18)
Q3	-0.16%	-1.49%	-0.11%	-1.42%
t-statistics	(-0.30)	(-2.63)	(-0.21)	(-2.59)
Q4 (least efficient)	-2.91%	-3.09%	-2.72%	-2.80%
t-statistics	(-5.64)	(-4.39)	(-5.33)	(-4.09)
Q4 – Q1	4.54%	4.12%	4.13%	3.71%
t-statistics	(7.32)	(5.31)	(5.31)	(5.14)

Panel B: Sorted by SDPDE and different time horizons with equal-weighted 4-factor model.

Different duration	Year 2	Year 3	Year 4
SPDE			
Q1 (most efficient)	0.64%	0.52%	0.39%
t-statistics	(2.31)	(2.19)	(1.84)
Q2	0.54%	0.89%	0.74%
t-statistics	(1.68)	(3.14)	(2.91)
Q3	-0.35%	0.32%	0.61%
t-statistics	(-0.76)	(0.73)	(1.44)
Q4 (least efficient)	-1.03%	-0.18%	-0.40%
t-statistics	(-2.19)	(-0.37)	(-0.87)
Q4 – Q1	2.02%	0.89%	0.86%
t-statistics	(4.90)	(2.33)	(1.82)

Table 13. Two-way classifications of postissue performance by standard deviation of pricing error (SDPE) and financial intermediaries' variables.

This table presents abnormal return (alphas) of two-way sorts based on the SDPE and financial intermediary variables. It also reports abnormal return for the hedged portfolio that is long the lowest SDPE portfolio and short the highest SDPE portfolio holding financial intermediaries effects constant based on the value weighted four-factor model. The alphas' t-statistics are reported in parentheses. T-statistics are White (1980) heteroskedasticity consistent. High-rep includes IPOs with underwriter's rank 8 or above and low-rep for IPOs between 1 and 7. The book underwriter's reputation rank is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC-back includes IPOs backed by VC and otherwise they are non-VC-back IPOs. Large syndicate (SYN2) includes IPOs with more than 3 lead, co-lead, and co-manager or above and small syndicate (SYN1) for IPOs less than 3. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. I calculate long-run abnormal returns by using the intercept (the alpha) of the following value-weighted Carhart (1997) four-factor regressions,

$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t + uUMD_t$ ------ Carhart 4 factor model

where $r_{p,t}$ is IPO calendar-time portfolio return at month t. I include IPO firms in the portfolio starting from the next month after the IPO date, and ending on the 9th months (about 175 trading days) after the month of IPO date in panel A. The alphas and t-statistics associated with the alphas from a portfolio that is long the low SDPE portfolio and short the high SDPE portfolio is presented in the last column of each panel. The alphas and t-statistics associated with the alphas from a portfolio that is long the High-rep (VC-Back) [SYN2] portfolio and short the Low-rep (Non-VC-Back) [SYN1] portfolio is presented in the bottom row of panel A (B) [C]. The winner group is the low SDPE/high-rep (VC-Back) [SYN2] group while the loser group is the high SDPE/low-rep (Non-VC-Back) [SYN1] group in panel A (B) [C].

Panel A. Abnormal returns of portfolio sorted by SDPE and underwriter's rank during 9 months (175 trading days) since the IPO date.

1. Holding period = 9 months			
	Low SDPE	**High SDPE**	**Low - High SDPE**
High-rep	1.12% (1.82)	-1.80% (-2.96)	**2.94%***(3.98)**
Low-rep	-0.03% (-0.03)	-2.08% (-3.40)	**1.91% (1.51)**
Highrep-Lowrep	**1.29% (0.95)**	**0.29% (0.44)**	**3.47***(4.60), winner/loser**

Panel B. Abnormal returns of portfolio sorted by SDPE and VC-backing during 9 months (175 trading days) with valued weighted four factor model since the IPO date.

1. Holding period = 9 months			
	Low SDPE	**High SDPE**	**Low - High SDPE**
VC-Back	1.4% (1.96)	-1.74% (-2.54)	**3.26%*** (4.09)**
Non-VC-Back	0.78% (2.08)	-1.28% (-2.15)	**2.68%*** (3.82)**
VCback – NVCback	**0.76% (1.03)**	**-0.46% (-0.75)**	**2.81%***(3.43), winner/loser**

Panel C. Abnormal returns of portfolio sorted by SDPE and syndicate size during 9 months (175 trading days) with valued weighted four factor model since the IPO date.

1. Holding period = 9 months (175 trading days)			
	Low SDPE	**High SDPE**	**Low - High SDPE**
SYN2 (large)	1.38% (2.18)	-2.11% (-3.19)	**3.35%***(4.83)**
SYN1 (small)	-0.24% (-0.22)	-2.94% (-3.51)	**2.82%**(2.41)**

SYN2 – SYN1	0.26% (0.19)	0.94% (0.97)	4.49%***(4.56), winner/loser

Table 14. One and two-way classifications of out-of-sample postissue performance
This table shows one-way and two-way classification of out-of-the sample postissue performance using time periods after my sample periods (175 trading days). One-way classification (Panel A) reports abnormal return (alphas) of standard deviation of pricing error (SDPE)-sorted portfolios during out-of-the sample periods. It also reports abnormal return for the hedged portfolio that is long the lowest SDPE portfolio and short the highest SDPE portfolio with different factor models during out-of-the sample periods. My out-of-sample periods start one month after my in-sample-period (175 trading days) and lasts another nine months. Two-way classifications (Panel B) report abnormal return (alphas) of two-way sorts based on the SDPE and financial intermediary variables during out-of-the sample periods. It also reports abnormal return for the hedged portfolio that is long the lowest SDPE portfolio and short the highest SDPE portfolio holding financial intermediaries effects constant based on the value weighted four-factor model. The alphas' t-statistics are reported in parentheses. T-statistics are White (1980) heteroskedacticity consistent. SPDE is the standard deviation of pricing error based on Hasbrouck (1993). High-rep includes IPOs with underwriter's rank 8 or above and low-rep for IPOs between 1 and 7. The book underwriter's reputation rank is from Loughran and Ritter (2004) [http://bear.warrington.ufl.edu/ritter/rank.htm] and is on a 0 – 9 scale, with 9 being the highest rank. VC-back includes IPOs backed by VC and otherwise they are non-VC-back IPOs. Large syndicate includes IPOs with more than 3 lead, co-lead, and co-manager or above and small syndicate for IPOs less than 3. The sample consists of 3,486 IPO during the period 1993-2005 and is identified through Thomson's SDC new issue database. 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 during the first 175 trading days after the IPO are excluded from my IPO sample. Screens used in defining a valid trade are listed in Table 2. I calculate long-run abnormal returns for one-way classification by using the intercept (the alpha) of the following both equal and value-weighted Fama French three-factor or Carhart (1997) four-factor regressions. For two-way classifications, I report long-run abnormal returns by using the intercept of only following value-weighted four-factor regression,

$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t$------ Fama French 3 factor model
$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t + uUMD_t$ ------ Carhart 4 factor model

where $r_{p,t}$ is IPO calendar-time portfolio return at month t. I include IPO firms in the portfolio starting from the next month after my sample period (175 trading days), and ending on the 19th months (10th to 19th months after the IPO date).

Panel A: Out-of-the sample test (One-way sort). Abnormal returns of portfolio sorted by SDPE during 9 months (175 trading days) starting from 10th month following the offer month to 19th months with various models. The alphas and t-statistics associated with the alphas from a portfolio that is long the lowest SDPE portfolio (Q1) and short the highest SDPE portfolio (Q4) are presented in the bottom row of each panel.

Different models	EW 3-Factor	VW 3-Factor	EW 4-factor	VW 4-factor
SPDE				
Q1 (most efficient)	-0.02%	0.03%	0.30%	-0.07%
t-statistics	(-0.04)	(0.07)	(0.92)	(-0.17)
Q2	-0.63%	-0.48%	-0.02%	-0.27%
t-statistics	(-1.31)	(-1.04)	(-0.05)	(-0.56)
Q3	-1.33%	-0.91%	-0.75%	-0.56%
t-statistics	(-2.88)	(-1.87)	(-1.81)	(-1.09)
Q4 (least efficient)	-0.57%	-1.37%	-0.02%	-0.95%
t-statistics	(-0.91)	(-2.26)	(0.04)	(-1.54)
Q4 – Q1	0.44%	1.29%	0.18%	0.73%
t-statistics	(0.76)	(1.81)	(0.29)	(1.00)

Panel B: Out-of-the sample test. (Two-way sort). The alphas and t-statistics associated with the alphas from a portfolio that is long the low SDPE portfolio and short the high SDPE portfolio is presented in the last column of each panel. The alphas and t-statistics associated with the alphas from a portfolio that is long the High-rep (VC-Back) [SYN2] portfolio and short the Low-rep (Non-VC-Back) [SYN1] portfolio is presented in the bottom row of panel 1 (2) [3]. The winner group is the low SDPE/high-rep (VC-Back) [SYN2] group while the loser group is the high SDPE/low-rep (Non-VC-Back) [SYN1] group in panel 1 (2) [3].

1. Two way sorts based on SDPE and underwriter's reputation

1. Holding period = 5 to 14 months (175 trading days since the IPO date)			
	Low SDPE	**High SDPE**	**Low - High SDPE**
High-rep	0.50% (0.91)	-1.15% (-2.07)	1.22%*(1.87)
Low-rep	-2.21% (-2.34)	-1.61% (-2.60)	-0.78% (-0.71)
Highrep-Lowrep	-3.30%*** (-2.83)	0.67% (1.23)	2.06***(2.88), winner/loser

2. Two way sorts based on SDPE and VC-backing

1. Holding period = 9 months			
	Low SDPE	**High SDPE**	**Low - High SDPE**
VC-Back	1.17% (1.73)	-1.28% (-2.49)	2.33%***(3.38)
Non-VC-Back	-0.62% (-1.58)	-1.12% (-1.45)	0.45% (0.55)
VCback – Non-VCback	-1.83%**(-2.74)	0.37% (0.56)	2.26**(2.40)

3. Two way sorts based on SDPE and Syndicate size

1. Holding period = 5 to 14 months (175 trading days since the IPO date)			
	Low SDPE	**High SDPE**	**Low - High SDPE**
SYN2 (large)	0.51% (0.92)	-1.39% (-2.49)	1.47%**(2.24)
SYN1 (small)	-1.99% (-2.17)	-1.34% (-2.18)	-0.71% (-0.69)
SYN2 – SYN1	-3.03%***(-2.78)	0.16%(0.29)	1.79%**(2.53)