Does Institutional Trading Affect Underwriting*

Amber Anand
Whitman School of Management
Syracuse University

Paul Irvine
Neeley School of Business
Texas Christian University

Tingting Liu
Ivy College of Business
Iowa State University

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Abstract

This paper investigates the impact of institutional trading on SEO lead underwriter choice. We measure the trading intensity of the lead investment bank in several different ways and find that bank trading has a significant effect on underwriter choice. A bank that concentrates its trading in particular stocks has an improved probability of earning the underwriting mandate in those stocks. We also find that the trading intensity of the lead bank has a significant effect on SEO underpricing and the composition of the underwriting syndicate. We attribute these results to the fact that banks that are large and active traders in an issuer's stock have a competitive advantage in accessing the current shareholder base. For smaller banks, we show that even a comparative advantage in trading the issuer's stock produces similar effects.

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Abstract

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1. Introduction

What determines underwriter choice in seasoned equity offerings (SEOs)? While underwriter choice in seasoned offerings has attracted less attention in the literature than initial public offerings (IPOs), there exists mixed evidence on the role of IPO pricing, analyst coverage and prior relationships in the decision.[1] For example, James (1992) suggests that the likelihood of switching underwriters for a secondary issue depends on the time between the IPO and the secondary issue as well as the underwriter's pricing performance in the IPO. In contrast, Krigman, Shaw, and Womack (2001) find little evidence that issuers switch investment banks due to dissatisfaction with underwriter performance at the time of the IPO. Instead, Krigman et al. (2001) attribute the switching of underwriters between the IPO and the SEO to a lack of quality research coverage from the lead underwriter, particularly in issuers whose reputation has improved since the IPO.

Ljungqvist, Marston, and Wilhelm (2006) further investigate the role of analysts and do not find that aggressive analyst behavior influences underwriter choice.[2,3] Rather, they find that the main determinant of lead underwriter choice is the strength of the prior underwriting relationship between the bank and the firm. But the nature of this finding is economically obscure. Why is the strength of the prior underwriting relationship important to underwriter choice? Is it

[1] On the underwriting decision in IPOs, Dunbar (2000) finds that initial overpricing and higher issue-day returns have a negative effect on subsequent underwriting market share. This finding suggests that future issuers avoid banks that leave too much money on the table. Using the position of a bank within underwriting syndicates, Bajo, Chemmanur, Simoyan and Tehranian (2016) propose that the centrality of an investment bank within the network of banks leads to a number of positive post-IPO characteristics including greater institutional investor holdings, higher analyst coverage and improved stock liquidity after the IPO.

[2] Considering that the bulk of the Ljungqvist et al. (2006) sample (1993-2002) predates Regulation FD, which severely restricted analyst ability to participate in underwriter activities, it is unlikely that analysts have any greater scope to influence underwriter choice after the end of their sample period.

[3] Not that analysts' contributions were insignificant to underwriting at this time. Groysberg, Healy and Maber (2011) attribute the considerable bonuses paid to analysts during the internet boom period to corporate finance activity.

the personal relationship between the issuer's executives and the underwriting team? Based on the evidence in Ljungqvist et al. (2006), it is not. The addition of highly-ranked equity underwriting staff or the departure of staff from an investment bank does not significantly affect the likelihood of the bank winning an equity underwriting mandate. This result is consistent with the matching model of Fernando, Gatchev, and Spindt (2005), wherein they propose a series of spot markets in the underwriting decision, where relationships are not particularly important. Although some issuers improve in quality over time and 'graduate' to a higher quality investment bank at the time of their SEO, they contend that issuer quality and underwriter quality is relatively stable, leading to a tendency for issuers to use the same lead underwriter for their IPO and SEO.

We examine whether the strength of trading in an issuer's stock is a component of this relationship. A bank's trading in a stock is reflective of the bank's relationship with the issuer's potential investor base. The potential investor base includes current owners, but also other investors who have previously held the stock or may have latent demand for the stock. In choosing the underwriter for an SEO, the issuer naturally seeks to raise the required funds while minimizing the price impact of the offering. A bank's access to the potential investor base for the stock is likely to help achieve these twin objectives, and raise the bank's chances of receiving the underwriting mandate. These arguments rely on informational frictions in the markets. If these frictions are insignificant, that is when potential investors are easily identifiable and a bank's relationship with an investor is uninformative to the investor about the issue, then trading may not affect the underwriting decision.

We rely on a large sample of institutional trades from 1999-2014 made available by the Abel Noser corporation for our analysis. The data provide two distinct advantages for our analysis over other datasets available to academics: 1) the brokers handling the orders are identified; and

2) the data are focused on institutional traders, who are more important to the share allocation process. We find that investment banks have higher trading market shares in the stocks they underwrite than they do in the average stock. While the larger banks tend to have a higher market share of trading and tend to win more lead underwriting mandates, there is a subtler economic choice driving banks' behavior. We find that not just absolute competitive advantage, but also comparative advantage aids the bank in winning underwriting mandates. That is, when banks specialize in trading in a stock, relative to their own trading in other stocks, they are more likely to be picked as underwriters.

There is limited existing evidence on how concentrated trading activity affects underwriter choice. Krigman et al. (2001) examine trading in 118 Nasdaq firms that switched their SEO lead underwriters from their IPO lead underwriters in the mid-1990's. Their evidence is mixed. While they find that both the IPO lead underwriter and co-lead underwriter have a significant trading presence in the stock prior to the SEO they do not directly investigate the link behind trading and lead underwriting. Instead, concentrating on firms that switch underwriters, they find that new underwriters trade an insignificant amount of monthly volume prior to the SEO. Based on this finding they reject their hypothesis that a new lead underwriter is hired because of their dominant trading position. We expand on Krigman et al. (2001) by examining the role of trading intensity in the choice of SEO underwriter while controlling for a prior IPO lead underwriter relationship and come to a different conclusion: trading intensity is important for SEO lead underwriter choice.

There are several reasons why our results might diverge from Krigman et al. (2001). First, the studies are not directly comparable since Krigman et al. (2001) examine a somewhat different question of what determines underwriting switching, while we pattern our study on Ljungqvist et al. (2006) who examine the more general question of lead underwriter choice. Second, we greatly expand breadth and width of the sample from 118 SEOs in Krigman et al. (2001) to 5,575 SEOs in our study and from 3 years in Krigman et al. (2001) to 15 years in this paper. Finally, we include NYSE firms as well as Nasdaq firms in the sample; because of data restrictions Krigman et al. (2001) could only examine Nasdaq firms.[4] Using a more complete sample, our findings are consistent with the explanation that trading intensity reflects a stronger relationship between the bank and the issuer's shareholder base, a relationship that significantly affects the issuer's lead underwriter choice.

Our analysis also has implications for the nature of the underwriting syndicate. When the lead bank is not a prominent trading intermediary, are they more likely to have a co-lead underwriter to offset this weakness? What is the nature of the equilibrium if they do make these choices? To provide empirical evidence on these questions, we further investigate the choice of hiring a co-lead underwriter. Consistent with our expectation, we find a negative relation between the level of the lead underwriters' trading intensity and the choice of using a co-lead underwriter, indicating that lead underwriters with a lower level of trading in the issuer's stock are more likely to have a co-lead in the underwriting syndicate.

We examine outcomes associated with choosing an underwriter who is a large trader in the stock. We focus on the SEO discount and SEO underpricing as the outcome measures. If there is a benefit to hiring large traders as underwriters, we expect such issues to be associated with smaller discounts and lower underpricing. We measure discounts and underpricing as in Altkinic and Hansen (2003) and find that higher broker trading in the issuer's stock results in a lower discount

[4] We also note that the Nasdaq market makers studied in the Krigman et al. (2001) analysis perform a different function from brokers in our analysis. Market makers trade as principals and provide continuous quotes. Their primary obligation is to the issuer and the exchange. Brokers act as agents for institutional clients in finding liquidity in the market. This difference further complicates the direct comparison of results.

and lower overall SEO underpricing. Since the equilibrium choice of the underwriting syndicate also includes whether to hire a co-lead, this result indicates that hiring a co-lead does not fully replace the ability of the lead underwriter to place the stock with minimal disruption in the stock price.

By using institutional trading data and isolating the data to particular underwriting banks, this paper makes a new contribution to the longstanding corporate finance questions of SEO underwriter choice and SEO issue-day pricing. In doing so, we demonstrate that institutional trading data can invigorate seasoned problems with new approaches and new ideas. Thus, we demonstrate how trading data can make a significant contribution to corporate finance research.

2. Data

2.1 Trading data

We use the Abel-Noser corporation institutional trading data from 1999 through June 2014 to measure brokers' trading activity. Relative to other available data, the Abel Noser data contain broker identifiers associated with each order, and exclusively focus on institutional trades. These advantages are crucial for our analysis but also account for the widespread use of the data in academic studies.[5] These studies include Chemmanur, He and Hu (2009) who examine institutions receiving SEO allocations, and show that institutions obtain larger SEO allocations in stocks with better subsequent performance. Hu, Jo, Wang, and Xie (2018) estimate that Abel-Noser data cover

[5] Gang Hu's Abel Noser data page (http://ganghu.org/an/) lists 56 publications that use Abel Noser data.

12% of total CRSP volume over their sample period and reach as high as 15% during the 1999-2005 period.[6] The total amount of trading is considerable, as outlined in Table 1.

As mentioned above, the data include broker codes associated with each trade. In addition, Abel Noser provides a translation file which maps broker codes to broker names. In certain cases, broker codes are unresolvable, most often because the broker code is unknown or missing. Overall, broker-identified data constitutes over 286.8 million trades. This data represents 78.4% of the total trades in the data set, 80.8% of the share volume, and 80.7% of the dollar value traded.[7] We can identify an average of 630 different brokers in each quarter, though this number generally tends to decline in recent years from a high of 839 in 2006-07 to a low of 496 in 2014. Table 1 reports yearly aggregate trading statistics for the full sample of institutional trades and for the sample where we can identify the broker that executed the trade. Trade characteristics such as average trade size and average dollar volume per trade are comparable across the full sample and the identified broker subsample.

At least part of the decline in the number of active brokers in the data set comes from a growing trend of industry consolidation. This consolidation is discussed in Ljungqvist et al. (2006) and poses a considerable challenge to identifying continuing entities in our data set. We identify a total of 106 mergers between the banks in our Abel-Noser data set. However, only a limited number of these are relevant to our empirical tests since we follow Ljungqvist et al. (2006) and restrict our final data set to a limited set of investment banks likely to be in competition for

[6] Hu et al. (2018) note that their estimate is markedly higher than the estimate in Puckett and Yan (2011) who estimate that the trades included in the Abel-Noser data constitute 8% of CRSP volume for 1999-2005.

[7] The vast majority of these unknown codes have a single broker code that indicates the broker is unknown, but these trades represent a considerable fraction of the data set. Further, the amount of unknown broker transactions varies considerably over time, from a low of 6.59% in 2000 to a high of 49.63% in the second quarter of 2011.

underwriting mandates. In these cases, after the date of the merger, all relevant trading in the purchased institution is rolled into the trading of the acquirer.

It is also notable that there are multiple broker codes in the data set that refer to the same business enterprise. For example over the 1999-2014 period ABN Amro has as many as six different broker codes associated with the bank. This diverse trading is consolidated into a single parent company so that total bank trading can be accurately measured. After consolidation, we calculate monthly trading for each parent bank and the market share of every parent bank in each stock-month. This gives us a history of how active the investment bank is in the trading of each company in the data set.

Finally, while the data have the advantage of isolating institutional trading which is likely to be more important from an allocation perspective, we recognize that the data are limited to Abel Noser clients. Similar to other studies using the data, we assume that these clients are representative of overall institutional trading.

2.2 Secondary offering data

We gather offering data from the SDC database for the 1999-2014 period. There are several restrictions we put on the sample. First, the issue must be a secondary offering and not an IPO so that the relevant trading in the company's shares can be calculated prior to the secondary offering. Second, the issue must be made in the U.S. public market and third, the issuing company must be listed on the NYSE, AMEX or Nasdaq exchanges. We primarily impose the latter two restrictions to center our issuing sample on stocks likely to appear in the US institutional Abel-Noser data sample.

Given these restrictions, we find a total of 6,940 secondary issues during the 1999-2014 period and report this total in Panel A of Table 2. We also record the total number of brokers recorded in the database each year. In Panel B, We examine the aggregate issue activity for the 30 most active domestic public-market SEO investment banks from 1999-2014. We find that the lead underwriter business is concentrated; the Top 30 brokers lead 5,575 offerings, comprising 80.33% of the total sample. As in Ljungqvist et al. (2006), we concentrate on these most important banks as reasonable competitors, who are much more likely to win an SEO lead underwriter mandate than the other banks in our data set.

Even these successful firms are not immune to consolidation, and the turmoil of 2008 caused a particularly high number of mergers with this group of lead underwriters. There are a total of 8 mergers that cause firms to disappear from our lead underwriter sample beginning with the acquisition of Donaldson, Lufkin, Jenrette by Credit Suisse First Boston in October of 2000 through the acquisition of Keefe, Bruyette, Woods by Stifel in February, 2013.[8] We treat these eight firms as separate competitors prior to the date of the merger and consolidated with the acquiring firm after that date.

Panel B of Table 2 shows that the most active issuer in the data set is Merrill Lynch/Bank of America who is the lead underwriter for 676 secondary offerings or 9.74% of the total number of issues. The 30th ranked broker is William Blair who is the lead underwriter for 33 issues or 0.48% of the total. Overall, the top five firms account for 49.7% of SEOs.

All of the Top 30 brokers were standalone entities at some point in the sample, even if they subsequently merge into another firm. As such, all thirty are present in the Abel Noser trading data

[8] See Appendix Table A1 for a relevant list of broker mergers in our sample.

at some time in the 1999-2014 period and thus, have their trading activity recorded. Panel B of Table 2 also reports each broker's volume rank by share volume in the Abel Noser data and their percentage of total trading by volume within the data set. Lead underwriting is more concentrated than the trading business. The top five institutional brokers are responsible for 28.0% of trading volume. One reason the trading business is less concentrated is due to the fact that certain large brokers, such as ITG group, Liquidnet, Instinet and Fidelity, do not have an underwriting business.

2.3 Other data sources

Since prior studies (Fang, 2005; Ljungqvist et al., 2006) document that previous business relationships play an important role in obtaining underwriting contracts, we construct three variables to capture prior business relations between issuers and underwriters. Following Fang (2005), we construct an indicator variable (*Prior bond lead*) that equals one if the lead underwriter of the issuer has served as bond lead underwriter in the 5-year period prior to the SEO, and zero otherwise. We construct a second indicator variable (*Prior M&A advisor*) that equals one if the lead underwriter has served as a financial advisor in mergers and acquisitions transactions in the 5-year period prior to the SEO, and zero otherwise. Finally, we construct an indicator variable (*Prior IPO lead*) that equals one if the firm used the same SEO lead underwriter for its IPO issuance, and zero otherwise. We obtain bond issuance and financial advisor information from SDC for the period 1994-2014.[9]

To measure broker's reputation, we classify brokers into either the "reputable" or "less reputable" group based on the market share ranking in Thomson Reuters annual league tables

[9] We do not restrict IPO issuance to be within the 5-year period prior to the SEO.

during our sample period.[10] Following Fang (2005), we classify the top eight banks as "reputable" and the rest as "less reputable."[11] We also obtain the information on whether a given bank provides research coverage during the year prior to the SEO issue month. Bank identity is obtained from the I/B/E/S Detail History file and is manually matched to the top 30 banks from our data set. For each bank and for each SEO issue, we create an indicator variable, *coverage*, which equals one if the bank has at least one analyst providing earnings forecast during the 12 month period prior to the issue date, and zero otherwise.

2.4 Method

2.4.1 Estimation of the lead underwriter choice

The basic structure of our estimation method follows Ljungqvist et al. (2006) where bank *j's* likelihood of earning firm *i's* underwriting mandate at time *t* is estimated from probit model:

$$\Pr(bank\ k\ leads\ firm\ i's\ SEO\ at\ time\ t) = f(trading\ intensity, X_K) \tag{1}$$

where X_K is a matrix of explanatory variables. The matrix is built in such a way that for every SEO, the dependent variable equals one for the lead underwriter, and zero for the remaining brokers among the Top 30. For each SEO every investment bank in the Top 30 that still exists as a separate company at the time of the offer is represented in X_K.

Trading intensity is our variable of interest. In addition, we include control variables, X_K, following those in Fang (2005) and Ljungqvist et al. (2006) to capture the prior business relation

[10] The classic reference for league tables was *Investment Dealer Digest*. Unfortunately, this excellent source appears to be no longer in operation. We obtain our league tables from Thomson Reuters Eikon database.
[11] The top eight banks are Merrill/BOFA, Goldman Sachs, Morgan Stanley, Citi, CSFB, JP Morgan, UBS Warburg, and Lehman Brothers. Barclays is also classified as a top 8 broker after its merger with Lehman Brothers in September 2008.

between an issuer and a bank as well as a bank's reputation. These control variables include *Prior bond lead*, *Prior IPO lead*, *Prior M&A advisor*, *Reputable broker,* and *Analyst coverage,* and are defined in Section 2.3.

2.4.2 Measuring trading intensity

Broker-specific trading is not often studied, probably due to limited data availability, but there are several exceptions. Aitken, Garvey, and Swan (1995) discuss how brokers may be willing to take short-run trading losses in order to facilitate trade with their long-term clients. Aitken et al. (1995) is the first paper to outline how long-term relationships might operate in the institutional trading business. Irvine (2000) uses Canadian brokerage data to determine whether analyst coverage is associated with higher broker market share of trading. Jackson (2005) uses Australian broker data to measure the tradeoff between reputation and optimism in analysts' forecasts. Di Maggio, Franzoni, Kermani and Sommavilla (2017) examine bank networks for the largest banks in the Abel-Noser data. They find that banks centrally located within the trading network are important to the diffusion of information, particularly after they execute informed trades. Grullon, Underwood, and Weston (2014) find comovement among the network of firms that use the same lead underwriter. Comerton-Forde, Fernandez. Frino and Oetomo (2005) and Anand, Irvine, Puckett, and Venkataraman (2009) both focus on differential ability across brokers in execution quality for their clients.

Irvine (2000), Krigman et al. (2001), and Jackson (2005) are examples of the relatively few papers that specifically look at investment bank market share in particular stocks. The availability of brokers' identifiers in the Australian and Canadian markets facilitated the ability to track the buying and selling brokers involved in each trade. Unfortunately, the ability to track broker trading across the entire market is no longer readily available to researchers who have Canadian and

Australian trading data.[12] In both Irvine (2000) and Jackson (2005), the focus is on analyst coverage rather than underwriting, and Krigman et al. (2001) is limited in scope. Therefore the existing literature provides little guidance on how to measure investment bank specific trading in our context. To do so we begin by measuring the trading intensity of a particular underwriting bank using three variants of the investment bank's market share (by volume) in the issuer's stock. The first variant is a direct market share of trading in the stock of issuer *i*:

$$\text{Trading intensity} = \frac{b_{i,k,t-1}}{\sum b_{i,t-1}} \quad (2)$$

where $b_{i,k,t-1}$ represent bank *k's* trading in the stock of issuer *i* at time *t* - 1, where the year of issue is year *t*. Thus *Trading intensity* is measured by the market share of trading for bank *k* for issuer *i*. We follow Krigman et al. (2001) and calculate all of our trading intensity measures using data beginning 12 months prior to the issuing date.

Yet it is immediately apparent from Panel B of Table 2 that there is a correlation between the scale of the bank's overall trading and the number of SEOs issues led by the bank. Large brokers tend to underwrite more issues and trade greater volumes. To control for differences in scale across banks, we calculate two relative trading intensity measures as follows:

$$\textit{Relative trading intensity1} = \textit{trading intensity}_{i,k,t-1} - \frac{1}{N}\sum \textit{trading intensity}_{j,k,t-1} \quad (3)$$

and:

$$\textit{Relative trading intensity2} = \frac{\textit{trading intensity}_{i,k,t-1}}{\frac{1}{N}\sum \textit{trading intensity}_{j,k,t-1}} \quad (4)$$

where j represents all stocks that bank *k* trades in the calendar year prior to the issue date of

[12] Comerton-Forde, Putnins and Tang (2011) documents the increasing use of broker anonymity.

firm *i's* SEO. *Relative trading intensity* thus represents the market share of bank *k* in issuer *i's* stock relative to their average *Trading intensity* or market share across all stocks that they can trade.

It is difficult to hypothesize about which of these measures best captures the importance of trading on the likelihood of winning a lead underwriting mandate. It is apparent from Table 2 that the number of issues is highly correlated with average bank market share (0.88). The ability of large banks to win mandates due to their size suggests that if trading matters for underwriting, then *Trading intensity*, which captures the competitive trading advantage held by the bank, should be important to winning the underwriting mandate. As an absolute measure, *Trading intensity* reflects the absolute size of a bank's access to the shareholder base in a particular stock.

The argument that relative trading intensity matters for underwriting is more subtle and better reflects the underlying economics. All brokers are in competition for institutional clients and their commission-driven trading business. They must make strategic decisions about what syndicates they participate in, and whether to compete for the offering of a particular firm (Fernando et al. 2005). In unreported results we find that the smallest 14 brokers, those below the Ljungqvist et al. (2006) cutoff level of the top 16, almost never have an absolute competitive advantage in the trading of the issuer.[13] Their only strategic response is to concentrate their corporate finance and trading activities in particular stocks to potentially gain a *comparative* advantage with some issuers. If banks do concentrate their trading in particular stocks relative to their average level of trading activity does that mean

[13] For robustness purposes, we test whether our empirical results hold for the top 16 investment banks, replicating the sample of banks in Ljungqvist el al. (2006). We find similar coefficients and significance levels in this subset of the data.

that they have put particular strategic emphasis on such stocks in an attempt to win more underwriting mandates? It is this potential comparative advantage that our relative trading measures attempt to capture. In our empirical tests, we investigate the explanatory power of both *Trading intensity* and *Relative trading intensity* on winning underwriting mandates.

2.4.3 Measuring SEO discounting and underpricing

We further investigate whether trade intensity has a significant impact on issue outcomes. We follow Altinkilic and Hansen (2003) and measure outcomes through underpricing, discounting, and the issue-day return as follows,

$$\frac{p_1}{p_0} = [\frac{p_{-1}}{p_0}] \times [\frac{p_1}{p_{-1}}] \tag{5}$$

where p_1 is the issue-day's closing price, p_0 is the offer price, and p_{-1} is the prior day's closing price. The ratio of p_1/ p_0 measures underpricing, the ratio of p_{-1}/ p_0 measures discounting and the ratio of p_1/ p_{-1} measures issue day return. We follow Altinkilic and Hansen (2003) and take logarithms and show that underpricing is the sum of discounting and the issue-day return.

$$U = D + R \tag{6}$$

where U denotes underpricing, D denotes discounting and R denotes issue day return.[14] Lower values of underpricing and discounting reflect better outcomes for issuers.

3. Results

3.1. Trading intensity and lead underwriting

Table 3 presents univariate statistics on our trading intensity measures in the 12 months preceding the SEO. In presenting these statistics we consider only the trading of the Top 30

[14] We notice that some firms have stock dividends or splits on the issue date or prior date, causing the unadjusted closing prices an unreliable input for measuring returns or discounting. In these cases, we use the CRSP Cumulative Factor to adjust prices then calculate the variables of interest.

brokers SEO-underwriting banks because they are only competing with each other for the trading mandate; trading through all other banks is irrelevant for SEO underwriter choice. Therefore, we find that the average Top 30 market share in the SEO sample is a comparatively high 6.1%. Yet the market share of lead underwriters, defined as *Trading Intensity* in Equation (2) is considerably higher at 15.0%. This is the first indication that trading intensity could be important for underwriter choice.

Given these averages, the mean of *Relative trading intensity1*, which just represents the difference between a bank's market share in the issues where they are chosen as lead underwriter and their market share in issues where they are not chosen, is 8.9%. *Relative trading intensity2* is a more complete control for bank size, it represents the ratio of a bank's trading in the issues where the bank acts as the lead underwriter relative to their market share in all other issues in the sample. The mean of *Relative trading intensity2* is 4.25, indicating that the average bank does considerably more trading in lead underwritten SEOs than they do in other stocks. In the year before the SEO, banks of all sizes exhibit a concentration of trading in stocks that they are eventually chosen to underwrite. Both measures of relative trading intensity reject the null that there is no difference in broker market share between issues they lead and issues they do not lead.

Figure 1 plots the average level of lead underwriter market share in the seasoned offering from 12 months prior to the issue to 12 months after the issue. For comparison purposes it also plots the average market share of Top 30 brokers who do not lead the underwriting syndicate. The figure shows that lead underwriters, on average, trade approximately 10% more of the issue's trading volume than non-lead underwriters. This trading advantage exists both before and after the issue date. The other notable feature in

Figure 1 is the spike in lead broker market share around the issue date. This increase in lead broker trading is to be expected around the time that the lead allocates the issue to investors, but it also serves as indirect evidence of Chemmanur et al.'s (2009) contention that the Abel Noser trading data can be effectively used to determine SEO share allocations.

3.2. Trading intensity and lead underwriter choice

We explore the relation between trading intensity and lead underwriter choice more rigorously in Table 4 which presents the results from our base probit model of lead underwriter choice. Each regression contains a block of 30 observations for each SEO, as in Ljungqvist et al. (2006). Each of the 30 observations contains information on the independent variables for each of the Top 30 investment banks. The dependent variable equals one for the lead underwriter and zero for the remaining banks. Our total sample of 147,167 observations is comparable to the 142,132 observations in Ljungqvist et al. (2006).[15] We report marginal effects instead of coefficients. Thus, the reported coefficients represent the change in the probability per unit change in the relevant explanatory variables at the mean; for indicator variables, the coefficient represents the change in the probability associated with moving the indicator from zero to one.

The primary variables of interest in these regressions are the measures of trading intensity. However, we also control for the reputation of the investment bank and the past underwriting and advising relationships between the bank and the issuer. Higher trading intensity or higher relative intensity in the issuer's stock significantly increases the probability of the bank earning the lead underwriting mandate.

[15] Matrices of 30 banks multiplied by 5,575 observations should total 167,250. However, when a bank is purchased or merges with another bank, we drop that bank from the sample as they are no longer an independent underwriting competitor. This accounts for the sample size.

Reputable brokers are also more likely to win the underwriting mandate. Although this fact is evident in Table 2 Panel B, the regression analysis allows us not only to control for other important variables, but can be used to reveal some of the subtler nature of the relation. For instance, in Appendix Table A2 we substitute the Top 5 trading ranks of the underwriting bank's market share for the continuous variable *Trading Intensity*. We find monotonically increasing coefficients from rank five to rank one. Specifically, the Model (1) results suggest that having the highest market share in the issuer's stock increases the probability of winning the lead underwriting mandate by 10.3% while Model (5) results suggest that being among top 5 traders in the issuer's stock increases the winning probability by 4.6%. These results suggest that the higher the bank's rank in the trading of the issuer, the more trading intensity matters for underwriter choice. We also note that past underwriting, IPO and advisory relationships also help the bank to win the underwriting mandate. So trading intensity does not completely explain the importance of these past relationships for underwriter choice.

Finally we note that the coefficients of all three measures of prior relationships between the bank and the issuer are positive and statistically significant. These results suggest that trading intensity does not completely subsume the importance of past relationships.[16]

3.2.1 Trading intensity, lead underwriting and analyst coverage

The next two tables expand on the probit regression in Table 4. Table 5 examines the question

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[16] The inclusion of the trading intensity variables does lower the coefficients on past relationships. For example, the coefficient of the relation variable, *Prior IPO lead*, is 0.205 without including trading intensity variables. The magnitude of this coefficient is reduced by about half if the trading intensity variables are included as additional explanatory variables. This result indicates that one of the reasons past relationships were important in Ljungqvist et al. (2006) is that these variables captured a component of the trading relationship between the bank and the issuer.

of how trading intensity interacts with analyst coverage in winning SEO underwriting mandates. Krigman et al. (2001) find that lead underwriter research coverage is a significant determinant of firms that switch underwriters from their IPO to their SEO. Ljungqvist et al. (2006) also find that analyst status and experience influence lead underwriter choice. Given these results, we investigate whether coverage is a substitute or a complement to trading intensity as a determinant of underwriter choice. Since analyst coverage helps to determine SEO lead brokers, it could be that coverage serves as a strategic substitute for firms that do not trade a particularly large fraction of the issuer's stock. Conversely, coverage combined with higher trading intensity could reflect a strong commitment on the part of the bank towards the ongoing liquidity of the issuer's stock. This particularly strong commitment could be rewarded by being chosen as the lead underwriter for the SEO.

We examine this question by first adding a coverage dummy variable to the Table 4 regressions. The variable is set equal to 1 if the broker provides coverage of the issuer's stock. We then interact each measure of trading intensity with the coverage dummy variable. If the coefficient on the interaction term is negative, then coverage acts as a substitute for trading activity. If the coefficient on the interaction term is positive, then coverage acts as a complement to trading activity in the ability of the bank to win the SEO underwriting mandate.

In Table 5, we find that coverage alone does increase the probability of a bank being chosen as the lead underwriter. Given the existing evidence, this result is expected. To directly examine the substitute/complement question we examine the coefficients of the interaction term and find that these coefficients are significantly positive for both *Trading intensity* and *Relative trading intensity 1*. However, the interactive coefficient is insignificant for *Relative trading intensity 2* (Column 3). We conclude that analyst coverage seems to generally work in tandem with trading intensity to help the bank win underwriting mandates, though the strength of the complementarity relation is dependent on the trading measure we use.

3.2.2 Trading intensity, lead underwriting and broker reputation

Another important determinant of lead underwriter choice is bank reputation as outlined in Megginson and Weiss (1991), Krigman et al. (2001) and Fernando et al. (2005). For bank reputation we conduct a similar experiment to that in Table 5. First we control for whether the bank has a high reputation, as determined by the bank's ranking in historical equity underwriting league tables. Then we interact the reputation dummy variable, set to 1 if the broker is in the top eight broker's historically, with all three of our trading intensity measures. The sign of the coefficient on the interaction term determines if bank reputation is a substitute or complement to trading activity in the issuer's choice of lead underwriter.

Columns (1) and (2) of Table 6 report that the coefficients on the interaction term between broker reputation and trading intensity are negative and significant. Using either *Trading intensity* or *Relative trading intensity 1* as regressors, we would conclude that reputation is a substitute for trading intensity, and given the relative size of the interaction coefficients, an incomplete substitute. [17] However, in Column (3) we use *Relative trading intensity 2* as the independent variable, and report a significantly positive coefficient on the interaction term. Since all reputable firms are relatively large banks, the interaction effect reported is not attributable to the fact Trading Intensity 2 better controls for bank size and that under this measure smaller banks are relatively more important. Given these mixed

[17] The sum of the two coefficients is positive and statistically significant at the 1% level.

results we are unable to definitively state that reputation is an effective substitute for trading intensity in the competition for lead underwriter status.

3.3 Trading intensity and SEO pricing

Our main hypothesis that a bank's trading intensity in a particular stock increases the probability of winning underwriting mandates presumes that a bank that trades a high percentage of an issuer's trading volume has a competitive advantage in winning lead underwriting mandates. But we also determine that brokers that trade particular stocks with greater intensity than they trade other stocks have a comparative advantage in winning underwriting mandates. Both the absolute advantage and the comparative advantage hypotheses are based on the conjecture that a bank with high trading intensity or high relative trading intensity has better access to the firm's potential shareholders. Since the current shareholders have already demonstrated an interest in the stock, it could be possible that the broker's advantage in accessing a greater percentage of the shareholder base provides liquidity to the issue thus improving the pricing of the secondary offering.

We test the effect of our three measures of trading intensity by examining SEO underpricing as well as its components outlined by Altkinic and Hansen (2003), where the amount of SEO underpricing is the total of the SEO discount and the issuing-day return (Equations (5) and (6)). We hypothesize that if trading intensity gives the lead investment bank an advantage in accessing potential shareholders, then trading intensity should be negatively related to SEO underpricing and the amount of the SEO discount.

Table 7 presents summary statistics for the discount, the issue-day return and the total underpricing for the SEOs in our sample. We also separate issuers by listing exchange since Altkinic and Hansen (2003) report that Nasdaq listings suffered larger underpricing than

NYSE issues. We find that mean underpricing in our sample averages 2.5% and that the Nasdaq average (3.4%) is larger than the NYSE sample average (1.7%). These averages are quite close to those reported for 1990-1997 SEOs in Altkinic and Hansen (2003) who find 3.01% underpricing for Nasdaq issues and 1.78% underpricing for NYSE issues.[18] Although mean underpricing is similar to Altkinic and Hansen (2003) its components, discounting and issue-day return are larger in magnitude in our sample. The mean discount is 4.3%, while the mean first day return is -1.9%.

Table 8 presents a regression analysis of SEO underpricing, discounting and issue-day returns that includes all three measures of trading intensity. For each measure we regress the SEO discount, the issue-day return and the total underpricing on trading intensity and a set of control variables that have been documented to significantly impact SEO underpricing. Jegadeesh et al. (1993) and Beatty and Welch (1996) report that the inverse of the offer price has a significant effect on underpricing.[19] Stock return volatility has also been found to be positively related to underpricing (Barry et al., 1990; Barry et al., 1991; Jegadeesh et al., 1993). Further, Megginson and Weiss (1991), Dunbar (1995), Booth and Chua (1996), Carter et al. (1998) find that broker reputation has a positive effect on underpricing. Finally, Altkinic and Hansen (2003) report that relatively large offers have greater discounting. We thus include the amount of the offer, relative size of the offer (the ratio of the total proceeds to the market capitalization 5 days prior to the issue date), the reputation of the broker, the inverse of stock price, idiosyncratic volatility and an indicator variable for an SEO that is

[18] Underpricing in Altkinic and Hansen (2003) is larger than that reported by several studies in the 1980s. They note an increasing trend in the fraction of offers that are discounted throughout the 1990s.
[19] Jegadeesh et al. (1993) and Beatty and Welch (1996) report that underpricing is higher for lower priced stocks. We follow Altinkilic and Hansen (2003) and use the inverse of the market price prior to the issue date because the offer price is endogenous.

listed on Nasdaq as control variables.

We find that both absolute and relative trading intensity results in significantly smaller SEO underpricing and discounting, and has no significant effect on the issue-date return. This result shows that the lead underwriter's trading intensity in the issue has a significant effect on SEO pricing.[20]

Particularly notable for the issuers and their investment banks is that the decision to concentrate in particular stocks to obtain a comparative advantage in the trading of particular issuers also has a significant effect on the discount and the level of underpricing. Relative trading intensity, in particular Relative trading intensity 2, which represents specialization largely independent from the scale of the bank's gross trading activity, also has a significantly negative affect on underpricing and the level of the discount. This result shows that smaller brokers, who have little chance of dominating the overall level of trading in a security, can still provide value to the issuer by making the strategic decision to concentrate their corporate finance and trading activities in particular firms.

This result also has the potential to explain why issuers do not always choose the largest and most reputable investment banks to underwrite their offering. The potential issuer may be just another client to a Goldman Sachs or Morgan Stanley, but a relatively important client to a smaller investment bank. The results in Table 8 show that choosing an underwriter who specializes in a particular issuer, even if they are not a large bank, can have pricing benefits for the issuer.

[20] Appendix Tables A3 and A4 report the SEO discount and underpricing regressions using the bank's trading rank instead of the continuous trading intensity measure. Appendix Table A4 reports a monotonic increase in the absolute size of the coefficients as trading rank increases. These results suggest that the more important the trading relationship between the bank and the issuer, the better the SEO pricing.

3.4 Trading intensity and the underwriting syndicate

The evidence we present on the SEO pricing effects of trading intensity raises the question of why every issuer doesn't choose the investment bank with the highest level of trading activity in their stock, or at least the highest level of relative trading intensity. The results in Tables 4-6 show that trading intensity is a measure of importance in the lead underwriter decision. However, these probit regressions, at best, explain only about 20% of the underwriter choice decision. Clearly there is considerable variation in underwriter choice across issuers that is unrelated to trading intensity. Although over 50% of all issuers hire a lead underwriter that is among their top four traders, some issuers seem to ignore the importance of trading intensity. Why isn't the equilibrium in this market that all issuers choose the bank that most heavily trades their shares?

We can think of several possible answers to this question. First, investment banks trade thousands of different firms every day and they may not be aware of the trading market share information or its importance in the underpricing of SEO issues. Even if the bank's trading desk is aware of the market share information, barriers to information transfer within the bank could result in the failure of the trading desk to transfer this information to the corporate finance department. Still another barrier to information transfer exists between banks and issuing firms, and the corporate finance department may not be able to convince potential issuers of the importance of trading intensity in the underwriting process.

Secondly, we show that analyst coverage is an important determinant of lead underwriter choice. It could be that the issuer overrates the importance of coverage relative to the importance of trading intensity when choosing an investment bank. Similarly, we show that reputation acts as a partial substitute for trading intensity in the choice of lead underwriter. Again, the issuer could overweight the importance of investment bank reputation, relative to the importance of trading intensity, in their lead underwriter decision. Finally, the inclusion of trading intensity in Tables 4-6 does not completely subsume the significance of past corporate finance relationships, so there is still an unexplained element of the past relationship that explains underwriter choice.

Most of these reasons are driven by the lack of complete knowledge of the importance of trading intensity on underwriter choice and SEO pricing. Alternatively, we next examine a market response hypothesis that could answer the question of why the market equilibrium does not depend solely on trading intensity. Specifically, the lead underwriter has a choice in how to compose the underwriting syndicate by choosing to work with a co-lead underwriter. The choice of a co-lead underwriter would expand the issuer's access to its potential shareholder base and allow the syndicate to compete against a lead underwriter with a higher trading intensity in their stock.

We examine the question of market-based response by determining whether trading intensity or relative trading intensity has a significant effect on whether underwriting syndicate includes a co-lead underwriter. We hypothesize from the perspective of an investment bank that does not have the highest market share of the potential issuer's trading. To compete for the underwriting mandate the investment bank could strategically choose to add a co-lead underwriter. Adding a co-lead would increase the access of the SEO shares to the pool of potential shareholders, accomplishing much the same thing for the issuer as choosing the investment bank with the highest trading intensity.

However, adding a co-lead underwriter reduces the lead bank's revenues from the offering, since all else equal they will have to share the allocation and the associated revenues with another lead underwriter. We hypothesize that a potential lead underwriter would be more likely to make this choice when they have lower trading intensity and therefore adding a co-lead would give the issuer access to a larger percentage of its potential shareholder base and improve the bank's chances of winning the lead underwriter mandate.

In Table 9 we examine the effect of trading intensity on the choice of whether to hire a co-lead underwriter by regressing a co-lead dummy variable on all three measures of trading intensity and a number of controls that could potentially determine the presence of a co-lead in the underwriting syndicate. The controls include the *Amount* of the offer, since a larger offering requires more effort to place the shares without a considerable price discount. We also include the *Relative size* of the offer as a percentage of the firm's market capitalization 5 days prior to the offering for the same general reason that we include *Amount*, a dummy for broker reputation, the inverse of the stock price, a Nasdaq dummy variable for issuers listed on the Nasdaq and the idiosyncratic volatility of the firm.

The results in Table 9 show that conditional on our control variables, the lower the lead broker's trading intensity or relative trading intensity the more likely they are to hire a co-lead underwriter for the offering. This result suggests a competitive response for a broker who does not have a particularly high level of trading intensity in the potential issuer's stock. The investment bank can successfully compete for the lead underwriting mandate by adding a co-lead underwriter to the offering syndicate.

4. Conclusion

This paper examines the effect of institutional trading on the likelihood of an investment bank winning an SEO lead underwriting mandate. We construct a measure of each bank's market share in the stock of the issuer for 12 months prior to the issue date and find that higher absolute market share the investment bank possesses, the higher the likelihood of winning the lead underwriting mandate. Since large investment banks tend to dominate both trading and underwriting, we control for scale by calculating two measures of relative trading intensity. These measures aim to isolate the effect of a bank's strategic decision to concentrate their trading and underwriting activities in a particular potential issuer. We find that both measures of trading intensity have a significant effect on winning the underwriting mandate. Both absolute trading advantage and comparative trading advantage help the investment bank win the lead underwriting mandate. We attribute these results to the fact that banks that concentrate their trading in particular stocks have a competitive advantage in accessing the pool of current shareholders, a natural target for placing SEO allocations.

We find that lead underwriter's trading intensity and relative trading intensity have important effects on SEO pricing, a fact not previously recognized in the literature on seasoned equity offerings. Our measures of investment bank trading are significantly negatively related to SEO underpricing and total SEO discount. A higher absolute level of trading in the issuer's stock and a bank's relative concentration in the issuer's stock both produce a significantly lower level of stock underpricing on the issue date and a significantly lower SEO discount.

The degree of trading concentration of the lead underwriter in the issuer's stock also has significant implications for the investment bank's strategic decisions and for the composition of the underwriting syndicate. We show that analyst coverage acts as a complementary factor to trading intensity in winning underwriting mandates, and that bank reputation acts as a substitute for trading intensity. These results can aid the investment banks' decisions on where to focus their limited resources. Finally, we examine the question of why all issuers do not seek out banks that trade heavily in their stock. We outline several potential factors and empirically test the hypothesis that banks with a weaker trading presence in the issuer's stock might compensate by hiring a co-lead underwriter to increase the breadth of the offering. Since hiring a co-lead dilutes the profits of the lead underwriter, banks must foresee a greater chance of capturing the underwriting mandate when deciding whether to add a co-lead manager. Empirically, we find that banks are significantly more likely to add a co-lead manager to the issue as their trading intensity in the issuer's stock declines. This finding not only demonstrates that lead underwriter trading affects the composition of the underwriting syndicate, but demonstrates one way in which the underwriting market responds to institutional trading.

Along with the results in Chemmanur, He and Hu, (2009), our analysis shows that researchers can effectively use institutional trading data to increase our understanding of fundamental questions in corporate finance. Since this paper establishes the importance of trading intensity in SEO pricing, and both Grullon et al. (2014) and Chemmanur et al. (2016) identify the importance of bank network centrality, one fruitful direction for future research is to examine whether centrality in the trading market (Di Maggio et al. 2017) is also important for SEO pricing.

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Figure 1
Trading activity around SEO issuance: Lead versus non-lead brokers

This figure plots the trading activities for the lead broker and non-lead brokers from month -12 before the secondary issues through month +12 after the issue month, where the issue month is month 0. For each stock *j* in each month *t*, for broker *i*, trading percent is the ratio of trading volume by broker *i* divided by the total trading volume by all brokers in that month ($Pct_{j,i,t} = Volume_{j,i,t}/\sum Volume_{j,t}$). The sample period is from 1999 to June 2014.

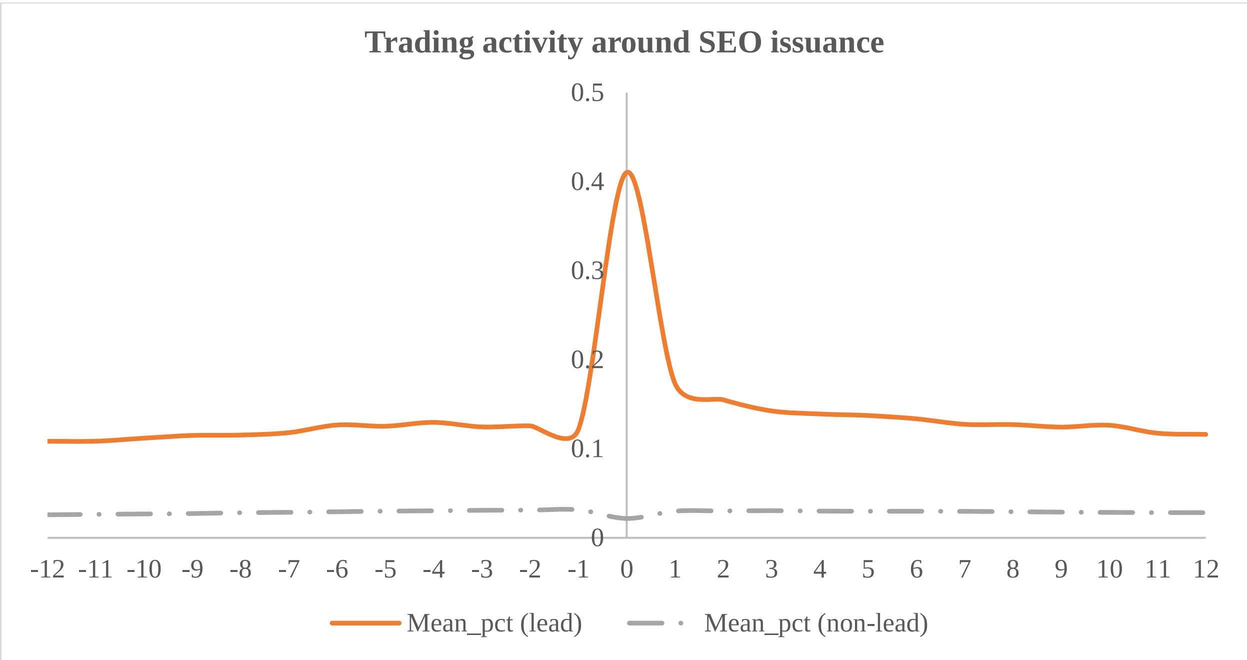

Table 1
Trading Activities for the Full Sample and Identified Broker Sample

This table presents trading activities for the full sample and identified broker sample over time. The identified broker sample includes all brokers that could be identified and assigned trades. Yearly broker totals are in Panel A of Table 2. Our sample period is from 1999 to June 2014.

	Full Sample					Identified Broker Sample				
Year	Total Trades (Millions)	Total Shares (billions)	Total Value ($billions)	Average Trade Size	Average $ Volume	Total Trades (Millions)	Total Shares (billions)	Total Value ($billions)	Average Trade Size	Average $ Volume
1999	5.6	50.7	2,252	8,981	398,695	5.2	46.1	2,048	9,005	400,498
2000	8.4	78.1	3,466	9,283	411,497	7.6	67.9	2,999	8,921	393,878
2001	9.9	110.4	3,303	11,194	334,944	8.7	93.4	2,763	10,757	318,014
2002	12.8	142.9	3,398	11,153	265,179	10.8	122.2	2,907	11,243	267,315
2003	15.3	121.7	2,959	7,653	193,491	13.8	107.3	2,601	7,744	187,683
2004	23.1	166.9	4,737	7,201	204,295	14.9	112.8	3,184	7,588	213,566
2005	23.7	141.6	4,375	5,365	184,322	20.0	112.0	3,479	5,601	173,990
2006	37.8	145.6	4,728	3,849	125,066	33.4	113.2	3,689	3,390	110,491
2007	46.31	146.3	5,282	3,157	114,051	40.0	103.8	3,743	2,598	93,675
2008	35.1	163.9	4,754	4,672	135,536	27.1	116.9	3,329	4,300	122,434
2009	28.6	140.8	3,062	4,921	106,980	21.2	114.8	2,517	5,416	118,731
2010	30.0	103.7	2,998	3,457	99,905	17.8	87.2	2,514	4,912	141,628
2011	27.0	83.7	2,701	3,100	100,070	16.2	74.2	2,364	4,574	145,063
2012	28.1	86.6	2,887	3,084	102,862	22.6	77.9	2,580	3,451	114,178
2013	22.4	80.4	3,096	3,589	138,242	18.1	71.2	2,728	3,922	150,386
2014	11.7	43.7	1,615	3,741	138,275	9.0	38.5	1,408	4,265	156,098
Total	365.81	1807	55613	5,900	190,838	286.8	1459.4	44853	6,105	194,227

Table 2
Sample Distribution of Secondary Issues and Summary Statistics

This table presents the distribution of a total of 6,940 secondary issues from 1999 to 2014. Panel A reports secondary issues by year and the total number of brokers trading in a each year. Panel B presents summary statistics for the aggregate issue activity for the Top 30 brokers. The last two columns of Panel B reports each broker's volume rank by share volume in the Abel Noser data and their percentage of total trading by volume within the data set.

Panel A: Secondary issues by year

Year	Number of Issues	Number of Brokers
1999	382	705
2000	358	723
2001	363	777
2002	341	821
2003	427	810
2004	498	782
2005	383	836
2006	427	839
2007	353	839
2008	228	675
2009	536	589
2010	490	583
2011	426	547
2012	513	623
2013	632	573
2014	583	496
Total	6,940	

Panel B: Summary statistics for the Top 30 underwriting brokers

Lead Broker	Issues	Percent of Total Issues	Broker Volume Rank	Trading Market Share
Merrill/BOFA	676	9.74	7	4.16
Goldman Sachs	567	8.17	2	6.45
Citi	562	8.10	4	4.96
Morgan Stanley	517	7.45	1	6.50
CSFB	451	6.50	3	5.92
JP Morgan	428	6.17	8	3.94
UBS Warburg	303	4.37	9	3.92
Lehman	270	3.89	13	2.22
Barclays	209	3.01	14	2.02
Deutsche Alex Brown	573	2.71	11	2.74
Jefferies	165	2.38	16	1.69
BOFA	115	1.66	6	4.65
Bear	106	1.53	18	1.53
Raymond James	100	1.44	35	0.46
Wells Fargo	94	1.35	34	0.50
FBR Capital	75	1.08	44	0.31
CIBC World	74	1.07	26	0.82
Piper Jaffray	74	1.07	30	0.74
Wachovia	70	1.01	55	0.24
RBC Capital	65	0.94	52	0.26
Cowen	59	0.85	21	1.09
Keefe Bruyette	59	0.85	49	0.27
Needham	55	0.79	70	0.14
Baird	51	0.78	32	0.65
Stifel	48	0.69	37	0.41
AG Edwards	43	0.62	65	0.16
Sandler O’Neil	41	0.59	112	0.07
Thomas Weisel	39	0.56	33	0.53
DLJ	35	0.50	51	0.27
William Blair	33	0.48	46	0.30
Total	5,575	80.33		57.92

Table 3
Broker Trading Intensity: Univariate Analysis

This table presents univariate analysis for the lead underwriter trading intensity using three alternative measures: *trading intensity*, *relative trading intensity1,* and *relative trading intensity2*. The lead underwriter trading activity is measured from month -12 to month -1 prior to the issue month, where month 0 is the issue month. *Average market share* is the average market share for each lead underwriter across all stocks. *Trading intensity* is the lead underwriter's market share of trading in the stock of the issuer. *Relative trading intensity1* is the difference between *trading intensity* and *average market share. Relative trading intensity2* is the ratio of *trading intensity* to the *average market share.* Our sample period is from 1999 to June 2014.

Variable	Mean	Median	25th Pctl	75th Pctl	Std Dev	t Value	N
Average market share	0.061	0.063	0.037	0.085	0.033	n/a	5,575
Trading intensity	0.150	0.077	0.020	0.194	0.194	n/a	5,575
Relative trading intensity1	0.089	0.011	-0.024	0.125	0.194	34.31	5,575
Relative trading intensity2	4.250	1.199	0.369	3.228	13.124	24.18	5,575

Table 4
Broker Trading Intensity and Lead Underwriter Choice

This table estimates the probability that a particular broker is chosen to lead the secondary issues using a probit regression model. *Marginal effects* are reported instead of coefficients. The dependent variable is an indicator variable that equals one if a broker is a lead underwriter, and zero otherwise. The main independent variables are *trading intensity*, *relative trading intensity1*, and *relative trading intensity2*, measured during the period of month -12 to month -1, where month 0 is the issue month. *Trading intensity* is the market share of trading in the stock of the issuer. *Relative trading intensity1* is the difference between *trading intensity* and *average trading intensity*. *Relative trading intensity2* is the ratio of *trading intensity* to the *average trading intensity*. *Reputable broker* is an indicator variable that equals 1 if a broker's market share rank is in the top 8, and zero otherwise. *Prior bond lead* is an indicator variable that equals 1 if a broker served as the issuer's lead bonder underwriter in the 5 years prior to the issue date, and zero otherwise. *Prior IPO lead* is an indicator variable that equals 1 if a broker served as the issuer's lead IPO underwriter, and zero otherwise. *Prior M&A advisor* is an indicator variable that equals 1 if a broker served as the issuer's financial advisor in mergers and acquisitions deals in the 5 years prior to the issue date, and zero otherwise. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)
Dependent variable	Lead underwriter dummy		
Trading intensity	0.127***		
	(0.004)		
Relative trading intensity1		0.130***	
		(0.004)	
Relative trading intensity2			0.006***
			(0.000)
Reputable broker	0.048***	0.061***	0.063***
	(0.001)	(0.001)	(0.001)
Prior bond lead	0.030***	0.030***	0.028***
	(0.007)	(0.008)	(0.007)
Prior IPO lead	0.123***	0.123***	0.109***
	(0.013)	(0.013)	(0.012)
Prior M&A advisor	0.144***	0.144***	0.127***
	(0.014)	(0.014)	(0.013)
Observations	147,167	147,167	147,167
Pseudo R2	0.174	0.172	0.177

Table 5
Trading Intensity, Research Coverage, and Lead Underwriter Choice

This table estimates the probability that a particular broker is chosen to lead the secondary issues using a probit regression model. *Marginal effects* are reported instead of coefficients. The dependent variable is an indicator variable that equals one if a broker is a lead underwriter, and zero otherwise. The main independent variables are *trading intensity, relative trading intensity1 (Rintensity1), relative trading intensity2 (Rintensity2),* and interaction terms between each intensity measure and an indicator variable, *Coverage*, which equals one if a broker provides research coverage in the year prior to the issue month, and zero otherwise. *Trading intensity* is the market share of trading in the stock of the issuer. *Relative trading intensity1* is the difference between *trading intensity* and *average trading intensity*. *Relative trading intensity2* is the ratio of *trading intensity* to the *average trading intensity*. *Reputable broker* is an indicator variable that equals 1 if a broker's market share rank is in the top 8, and zero otherwise. *Prior bond lead* is an indicator variable that equals 1 if a broker served as the issuer's lead bonder underwriter in the 5 years prior to the issue date, and zero otherwise. *Prior IPO lead* is an indicator variable that equals 1 if a broker served as the issuer's lead IPO underwriter, and zero otherwise. *Prior M&A advisor* is an indicator variable that equals 1 if a broker served as the issuer's financial advisor in mergers and acquisitions deals in the 5 years prior to the issue date, and zero otherwise. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)
Dependent variable	Lead underwriter dummy		
Trading intensity	0.090***		
	(0.004)		
Trading intensity × Coverage	0.040***		
	(0.006)		
Relative trading intensity1		0.088***	
		(0.004)	
Rintensity1 × Coverage		0.044***	
		(0.006)	
Relative trading intensity2			0.005***
			(0.000)
Rintensity2 × Coverage			0.000
			(0.000)
Coverage	0.042***	0.048***	0.045***
	(0.002)	(0.002)	(0.003)
Reputable broker	0.041***	0.051***	0.053***
	(0.001)	(0.001)	(0.001)
Prior bond lead	0.018***	0.018***	0.016***
	(0.006)	(0.006)	(0.006)
Prior IPO lead	0.071***	0.071***	0.071***
	(0.010)	(0.010)	(0.010)
Prior M&A advisor	0.102***	0.102***	0.091***
	(0.012)	(0.012)	(0.011)
Observations	147,167	147,167	147,167
Pseudo R2	0.210	0.209	0.207

Table 6
Trading Intensity, Broker Reputation, and Lead Underwriter Choice

This table estimates the probability that a particular broker is chosen to lead the secondary issues using a probit regression model. *Marginal effects* are reported instead of coefficients. The dependent variable is an indicator variable that equals one if a broker is a lead underwriter, and zero otherwise. The main independent variables are *trading intensity, relative trading intensity1 (Rintensity1), relative trading intensity2 (Rintensity2),* and interaction terms between each intensity measure and an indicator variable, *Reputable*, which equals one if a broker is classified as reputable, and zero otherwise. *Trading intensity* is the market share of trading in the stock of the issuer. *Relative trading intensity1* is the difference between *trading intensity* and *average trading intensity*. *Relative trading intensity2* is the ratio of *trading intensity* to the *average trading intensity*. *Reputable broker* is an indicator variable that equals 1 if a broker's market share rank is in the top 8, and zero otherwise. *Prior bond lead* is an indicator variable that equals 1 if a broker served as the issuer's lead bonder underwriter in the 5 years prior to the issue date, and zero otherwise. *Prior IPO lead* is an indicator variable that equals 1 if a broker served as the issuer's lead IPO underwriter, and zero otherwise. *Prior M&A advisor* is an indicator variable that equals 1 if a broker served as the issuer's financial advisor in mergers and acquisitions deals in the 5 years prior to the issue date, and zero otherwise. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)
Dependent variable		Lead underwriter dummy	
Trading intensity	0.160***		
	(0.005)		
Trading intensity×Reputable	-0.060***		
	(0.006)		
Relative trading intensity1		0.163***	
		(0.005)	
Rintensity1×Reputable		-0.058***	
		(0.006)	
Relative trading intensity2			0.006***
			(0.000)
Rintensity2×Reputable			0.001***
			(0.000)
Reputable broker	0.055***	0.063***	0.059***
	(0.002)	(0.001)	(0.002)
Prior bond lead	0.029***	0.029***	0.028***
	(0.007)	(0.007)	(0.007)
Prior IPO lead	0.116***	0.117***	0.109***
	(0.012)	(0.012)	(0.012)
Prior M&A advisor	0.138***	0.139***	0.129***
	(0.014)	(0.014)	(0.013)
Observations	147,167	147,167	147,167
Pseudo R2	0.177	0.175	0.178

Table 7
Summary Statistics: SEO Discounting and Underpricing

This table presents summary statistics for underpricing, discounting, and issue-day returns for our sample firms and by exchange listing. *Underpricing* is the logarithm of the ratio of the issue-day's closing price to the offer price. *Discounting* is the logarithm of the ratio of the pre-issue-day's closing price to the offer price. *Issue-day return* is the logarithm of the ratio of the issue-day's closing price to the pre-issue-day's closing price. The last three rows report the mean and medium difference for underpricing, discounting, and issue-day returns between Nasdaq and NYSE issuers. The column "t-test" reports the two-tail t-statistics of two-sample t-tests comparing the means of Nasdaq and NYSE issuers. The column "Wilcoxon test" reports the two-tail p-values of the two-sample Wilcoxon Rank-sum tests comparing Nasdaq and NYSE issuers. Sample period is from 1999 to 2014.

Variable	Mean	Median	25th Pctl	75th Pctl	Std Dev	t Value	N
Discounting	0.043	0.033	0.012	0.062	0.059	54.48	5,568
Issue day return	-0.019	-0.015	-0.042	0.007	0.052	-26.96	5,568
Underpricing	0.025	0.016	0.001	0.037	0.044	41.55	5,568
Nasdaq issuer							
Variable	Mean	Median	25th Pctl	75th Pctl	Std Dev	t Value	N
Discounting	0.053	0.041	0.013	0.080	0.074	35.32	2,413
Issue day return	-0.020	-0.016	-0.049	0.014	0.064	-15.08	2,413
Underpricing	0.034	0.023	0.004	0.051	0.056	29.18	2,413
NYSE issuer							
Variable	Mean	Median	25th Pctl	75th Pctl	Std Dev	t Value	N
Discounting	0.035	0.029	0.011	0.050	0.043	44.7	3,010
Issue day return	-0.018	-0.014	-0.037	0.005	0.040	-24.39	3,010
Underpricing	0.017	0.012	0.000	0.028	0.029	32.69	3,010

Nasdaq-NYSE

Variable	Mean difference	*t*-test	Median difference	Rank test
Discounting	0.018	10.52	0.041	0.00
Issue day return	-0.002	1.14	-0.016	0.57
Underpricing	0.016	12.76	0.023	0.00

Table 8
Broker Trading Intensity and SEO Underpricing

This table reports regression analysis of discounting, issue-day return, and underpricing on broker trading intensity. The dependent variables are D (discounting), R (issue-day return), and U (underpricing). *Underpricing* is the logarithm of the ratio of the issue-day's closing price to the offer price. *Discounting* is the logarithm of the ratio of the pre-issue-day's closing price to the offer price. *Issue-day return* is the logarithm of the ratio of the issue-day's closing price to the pre-issue-day's closing price. The main independent variables are *trading intensity*, *relative trading intensity1*, and *relative trading intensity2*, measured during the period of month -12 to month -1, where month 0 is the issue month. *Trading intensity* is the market share of trading in the stock of the issuer. *Relative trading intensity1* is the difference between *trading intensity* and *average trading intensity*. *Relative trading intensity2* is the ratio of *trading intensity* to the *average trading intensity*. *Amount* is the logarithm of the gross proceeds. *Relative size* is the ratio of the total proceeds to the market capitalization 5 days prior to the issue date. *Reputable broker* is an indicator variable that equals one if a broker's market share rank is in the top 8, and zero otherwise. *1/stock price* is the inverse of stock price prior to the issue date. *Nasdaq* is an indicator variable that equals one if the stock is listed on Nasdaq, and zero otherwise. *Idio. Vol.* is idiosyncratic volatility, which is the standard deviation of the residuals obtained in a Fama and French three factor regression implemented using daily returns in the year prior to the issue date. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014. D, R, and U are in percent.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Var.	D	R	U	D	R	U	D	R	U
Intercept	2.275***	-1.237***	1.316***	2.256***	-1.237***	1.296***	2.448***	-1.376***	1.325***
	(0.400)	(0.319)	(0.314)	(0.399)	(0.319)	(0.313)	(0.409)	(0.324)	(0.324)
Trading intensity	-1.617***	0.429	-1.223***						
	(0.319)	(0.310)	(0.218)						
Relative trading intensity1				-1.776***	0.584*	-1.224***			
				(0.322)	(0.312)	(0.220)			
Relative trading intensity2							-0.038***	0.023***	-0.012**
							(0.007)	(0.007)	(0.005)
Amount	-0.065	0.081	-0.034	-0.070	0.082	-0.038	-0.083	0.089	-0.044
	(0.072)	(0.059)	(0.053)	(0.072)	(0.059)	(0.053)	(0.073)	(0.059)	(0.054)
Relative size	1.293**	-0.014	1.646***	1.326**	-0.034	1.659***	1.353**	-0.102	1.598***
	(0.526)	(0.447)	(0.378)	(0.525)	(0.447)	(0.379)	(0.534)	(0.448)	(0.386)
Reputable broker	-0.159	-0.350***	-0.499***	-0.234*	-0.325**	-0.551***	-0.365**	-0.224	-0.563***
	(0.137)	(0.135)	(0.097)	(0.138)	(0.136)	(0.099)	(0.145)	(0.141)	(0.104)
1/stock price	8.476***	-2.773***	4.325**	8.404***	-2.706***	4.320**	8.660***	-2.655***	4.682**
	(1.938)	(0.978)	(1.860)	(1.927)	(0.976)	(1.859)	(1.963)	(0.972)	(1.903)
Nasdaq	0.163	0.405***	0.553***	0.170	0.399***	0.555***	0.146	0.397***	0.523***
	(0.141)	(0.137)	(0.095)	(0.141)	(0.137)	(0.095)	(0.141)	(0.137)	(0.095)
Idio. Vol.	0.604***	-0.252***	0.343***	0.607***	-0.255***	0.342***	0.587***	-0.253***	0.323***
	(0.046)	(0.040)	(0.031)	(0.046)	(0.040)	(0.031)	(0.045)	(0.040)	(0.030)
Observations	5,384	5,384	5,384	5,384	5,384	5,384	5,384	5,384	5,384
R-squared	0.136	0.020	0.147	0.138	0.021	0.147	0.136	0.022	0.141

Table 9
The Choice of Having a Co-lead Underwriter

This table estimates the probability that a lead underwriter uses a co-lead in the underwriting syndicate in the secondary issues using a probit regression model. *Marginal effects* are reported instead of coefficients. The dependent variable is an indicator variable that equals one if a co-lead underwriter is used, and zero otherwise. The main independent variables are *trading intensity*, *relative trading intensity1,* and *relative trading intensity2,* measured during the period of month -12 to month -1, where month 0 is the issue month. *Trading intensity* is the market share of trading in the stock of the issuer. *Relative trading intensity1* is the difference between *trading intensity* and *average trading intensity*. *Relative trading intensity2* is the ratio of *trading intensity* to the *average trading intensity*. All control variables are defined in the heading of Table 8. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)
Dependent variable	Co-lead underwriter dummy		
Trading intensity	-0.138***		
	(0.042)		
Relative trading intensity1		-0.189***	
		(0.043)	
Relative trading intensity2			-0.007***
			(0.001)
Amount	0.146***	0.146***	0.144***
	(0.011)	(0.011)	(0.011)
Relative size	0.339***	0.347***	0.362***
	(0.063)	(0.063)	(0.063)
Reputable broker	0.015	0.007	-0.018
	(0.020)	(0.020)	(0.020)
1/stock price	0.271**	0.252**	0.250**
	(0.115)	(0.114)	(0.115)
Nasdaq	-0.030	-0.028	-0.028
	(0.020)	(0.020)	(0.020)
Idio. Vol.	-0.034***	-0.034***	-0.035***
	(0.006)	(0.006)	(0.006)
Observations	5,384	5,384	5,384
Pseudo R2	0.084	0.086	0.089

Appendix Table A1
List the relevant mergers in our data base

This table lists the relevant broker mergers during our sample period.

Merger completion date	Acquirer name	Target name
10/3/2000	CSFB	DLJ
10/1/2007	Wells Fargo	AG Edwards
5/30/2008	JP Morgan	Bear Stearns
9/22/2008	Barclays	Lehman Brothers
12/31/2008	Wells Fargo	Wachovia
1/1/2009	Bank of America	Merrill Lynch
4/25/2010	Stifel Financial	Thomas Weisel
2/15/2013	Stifel Financial	Keefe, Bruyette & Woods

Appendix Table A2
Trading Intensity and Lead Underwriter Choice: Using ranks

This table is similar to Table 4 expect that the main independent variables are indicator variables instead of continuous variables used in Table 4. *Marginal effects* are reported instead of coefficients. The dependent variable is an indicator variable that equals one if a broker is a lead underwriter, and zero otherwise. The main independent variables are *Trading intensity (Top1)*, *Trading intensity (Top2)*, *Trading intensity (Top3)*, *Trading intensity (Top4)*, and *Trading intensity (Top5)*. *Trading intensity (Top1)* is an indicator variable that equals one if a broker has the highest market share among all 30 brokers, and zero otherwise. *Trading intensity (Top2)* is an indicator variable that equals one if a broker is among the top two brokers based on the rank of the market share among all 30 brokers, and zero otherwise. *Trading intensity (Top3)*, *Trading intensity (Top4)*, and *Trading intensity (Top5)* are defined similarly to *Trading intensity (Top2)*. All other control variables are defined in the heading of Table 4. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)	(4)	(5)
Dependent variable			Lead underwriter dummy		
Trading intensity (Top1)	0.103***				
	(0.005)				
Trading intensity (Top2)		0.075***			
		(0.003)			
Trading intensity (Top3)			0.060***		
			(0.003)		
Trading intensity (Top4)				0.051***	
				(0.002)	
Trading intensity (Top5)					0.046***
					(0.002)
Reputable broker	0.056***	0.051***	0.048***	0.045***	0.042***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Prior bond lead	0.028***	0.027***	0.027***	0.027***	0.028***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Prior IPO lead	0.154***	0.147***	0.151***	0.153***	0.156***
	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)
Prior M&A advisor	0.151***	0.142***	0.142***	0.143***	0.141***
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	147,167	147,167	147,167	147,167	147,167
Pseudo R2	0.156	0.162	0.161	0.158	0.157

Appendix Table A3
Trading Intensity and SEO Discounting: Using ranks

This table is similar to Table 8 expect that the main independent variables are indicator variables instead of continuous variables used in Table 8. The dependent variable is *Discounting*, measured as the logarithm of the ratio of the pre-issue-day's closing price to the offer price. The main independent variables are *Trading intensity (Top1), Trading intensity (Top2), Trading intensity (Top3), Trading intensity (Top4),* and *Trading intensity (Top5). Trading intensity (Top1)* is an indicator variable that equals one if a broker has the highest market share among all 30 brokers, and zero otherwise. *Trading intensity (Top2)* is an indicator variable that equals one if a broker is among the top two brokers based on the rank of the market share among all 30 brokers, and zero otherwise. *Trading intensity (Top3), Trading intensity (Top4),* and *Trading intensity (Top5)* are defined similarly to *Trading intensity (Top2).* All other control variables are defined in the heading of Table 8. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)	(4)	(5)
Dependent Var.			Discounting		
Intercept	2.180***	2.220***	2.237***	2.244***	2.257***
	(0.405)	(0.406)	(0.408)	(0.408)	(0.408)
Trading intensity (Top1)	-0.552***				
	(0.134)				
Trading intensity (Top2)		-0.502***			
		(0.117)			
Trading intensity (Top3)			-0.433***		
			(0.112)		
Trading intensity (Top4)				-0.432***	
				(0.111)	
Trading intensity (Top5)					-0.436***
					(0.111)
Amount	-0.062	-0.060	-0.060	-0.057	-0.055
	(0.073)	(0.073)	(0.073)	(0.074)	(0.074)
Relative size	1.224**	1.187**	1.165**	1.160**	1.151**
	(0.535)	(0.536)	(0.536)	(0.537)	(0.537)
Reputable broker	-0.159	-0.156	-0.147	-0.135	-0.122
	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
1/stock price	9.086***	9.078***	9.107***	9.113***	9.108***
	(2.009)	(2.011)	(2.016)	(2.019)	(2.020)
Nasdaq	0.148	0.147	0.141	0.142	0.139
	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)
Idio. Vol.	0.591***	0.593***	0.590***	0.591***	0.591***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Observations	5,384	5,384	5,384	5,384	5,384
R-squared	0.136	0.136	0.136	0.136	0.136

Appendix Table A4
Trading Intensity and SEO Underpricing: Using ranks

This table is similar to Table 8 expect that the main independent variables are indicator variables instead of continuous variables used in Table 8. The dependent variable is *Underpricing*, measured as the logarithm of the ratio of the issue-day's closing price to the offer price. The main independent variables are *Trading intensity (Top1)*, *Trading intensity (Top2)*, *Trading intensity (Top3)*, *Trading intensity (Top4)*, and *Trading intensity (Top5)*. *Trading intensity (Top1)* is an indicator variable that equals one if a broker has the highest market share among all 30 brokers, and zero otherwise. *Trading intensity (Top2)* is an indicator variable that equals one if a broker is among the top two brokers based on the rank of the market share among all 30 brokers, and zero otherwise. *Trading intensity (Top3)*, *Trading intensity (Top4)*, and *Trading intensity (Top5)* are defined similarly to *Trading intensity (Top2)*. All other control variables are defined in the heading of Table 8. ***, **, and * indicate significance at the 1, 5, and 10 percent level, respectively. Robust standard errors (reported in parentheses) are clustered at the issuer level. Sample period is from 1999 to June 2014.

	(1)	(2)	(3)	(4)	(5)
Dependent Var.			Underpricing		
Intercept	1.262***	1.286***	1.303***	1.297***	1.292***
	(0.319)	(0.320)	(0.322)	(0.322)	(0.323)
Trading intensity (Top1)	-0.372***				
	(0.090)				
Trading intensity (Top2)		-0.316***			
		(0.076)			
Trading intensity (Top3)			-0.302***		
			(0.075)		
Trading intensity (Top4)				-0.260***	
				(0.074)	
Trading intensity (Top5)					-0.211***
					(0.074)
Amount	-0.035	-0.034	-0.033	-0.033	-0.034
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
Relative size	1.582***	1.556***	1.542***	1.539***	1.535***
	(0.384)	(0.385)	(0.384)	(0.385)	(0.385)
Reputable broker	-0.507***	-0.505***	-0.499***	-0.492***	-0.489***
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
1/stock price	4.704**	4.714**	4.711**	4.744**	4.776**
	(1.917)	(1.920)	(1.920)	(1.925)	(1.931)
Nasdaq	0.541***	0.539***	0.538***	0.535***	0.530***
	(0.096)	(0.096)	(0.096)	(0.096)	(0.096)
Idio. Vol.	0.329***	0.330***	0.329***	0.328***	0.327***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Observations	5,384	5,384	5,384	5,384	5,384
R-squared	0.144	0.144	0.144	0.143	0.142