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Order Flow Patterns around Seasoned Equity Offerings and their Implications for Stock Price Movements

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Abstract

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In this study, we employ order imbalance measures to provide evidence that there exists an individual/institutional dichotomy in reactions to seasoned equity offerings (SEOs). The normally positive relation between imbalances and returns disappears for trade number imbalances but remains intact for dollar imbalances following SEOs. Further analysis supports the notion that small individual investors keep buying SEO stocks actively while the returns of these stocks reverse in the post-issue period. It seems to take about two years for individuals to adequately revise their overoptimistic views. Consequently, the SEO portfolios that individual investors buy on net strongly underperform relative to industry/size-matching non-issuer portfolios as well as to SEO portfolios that institutional investors buy on net in the post-issue period.

The issue of stock return underperformance following initial public offerings (IPOs) or seasoned equity offerings (SEOs) has been the focus of several well-known papers [see Ritter (1991), Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), Lee (1997), and Loughran and Ritter (1997)]. Loughran and Ritter (1995) find that companies issuing stock (both IPOs and SEOs) during 1970-1990 significantly underperform relative to nonissuing firms for 5 years after the offerings. This study suggests that managers take advantage of overvaluation in the IPO and SEO markets. Brav and Gompers (1997) raise an issue about IPO underperformance, arguing that the underperformance is not an IPO effect but a characteristic of small, low book-to-market firms. Schultz (2003) shows that if more firms go public after stock prices have risen, event-time analyses are likely to exhibit poor performance of IPO firms, suggesting that the underperformance is not surprising. Gompers and Lerner (2003) document by using a pre-NASDAQ IPO sample that the underperformance of IPOs is sensitive to the method of return measurement.

In the literature on performance after IPOs or SEOs mentioned above, however, the debate has naturally focused on returns or accounting performance, while trading activity around these events has not been examined. As argued in Chordia, Roll, and Subrahmanyam (2002), studies on trading activity are essential to a deeper understanding of economic interactions in financial markets. By exploring the behavior of trading activity measures around corporate events, we can potentially obtain a better understanding of the sources of return dynamics around these events.

Within a broader context, voluminous research has been devoted to understanding the association between stock returns and trading activity [e.g., Karpoff (1987), Gallant, Rossi, Tauchen (1992), Hiemstra and Jones (1994), and Lo and Wang (2000)]. In this literature, trading activity has been mostly proxied by an unsigned activity measure, or volume. However, signed returns are more closely linked to trading activity through a signed measure (order imbalances), rather than an unsigned measure (volume).

Order imbalances have recently caught many researchers' attention as one of the most important variables in explaining exchange rate movements. For example, Evans and Lyons (2002) show that daily DM/$ exchange rate changes are surprisingly well-explained by imbalances, with the R^2 reaching as high as 60% in the regressions. In the context of stock markets, there have been relatively fewer lines of research using order imbalances. Obviously, it is a formidable task to assign hundreds of millions of transactions to either buyer-initiated or seller-initiated categories. For this reason, the scope of the existing literature analyzing order imbalances is limited only to specific agents, a narrow range of stocks, OTC markets, or a short period of time [for various aspects relating to institutional investors, see Kraus and Stoll (1972), Lakonishok, Shleifer, and Vishny (1992), Wermers (1999), and Sias (1997); for studies using 20-30 stocks, see Brown et al. (1997), and Hasbrouck and Seppi (2001); for a study on the NASDAQ, see Griffin et al. (2003); and for analyses over a short periods of time, see Blume, MacKinlay, and Terker (1989), Stoll (2000), and Chan and Fong (2000)]. Only recently have studies investigating aggregate and individual order imbalances using broader and longer series of data appeared. Among them are: Chordia, Roll, and Subrahmanyam (2002), Chordia and Subrahmanyam (2004), and Subrahmanyam (2005).

With regard to corporate events, Lee (1992) investigates order imbalances around earnings announcements for 230 NYSE firms during the 253 trading days of 1988. Interestingly, he finds that individual investors differ from institutional investors in their reactions to the same earnings news. Other than his short-horizon study, however, there appears to be a dearth of literature on how order flows react to corporate events such as initial public offerings, seasoned equity offerings, M&As, earnings announcements, stock splits, repurchases, and so on.

Recently, Chordia, Huh, and Subrahmanyam (2004) analyze cross-sectional aspects of trading activity for NYSE/AMEX and NASDAQ firms using comprehensive datasets over a 40-year period (1963-2002). Their study focuses more on unsigned trading activity (turnover), although the determinants of order imbalances are also discussed. The present study focuses more on signed activity measures and their association with price movements, specifically in relation to a significant corporate event in capital markets: seasoned equity offerings (SEOs). Our primary goal in this study is to shed some light on how order imbalances and returns are characterized around SEOs.[1]

Specifically, we attempt to answer the following questions in this study: What are the typical patterns of order imbalances (OIMBs) around SEOs? Are patterns in the SEO portfolio different from those of a benchmark portfolio? Is there any shift in the OIMB-return relations caused by new equity offerings? If there is, who induces the deviation and why does it occur? Given the return reversal after SEOs, who causes the correction in re-

[1] Butler, Grullon, and Weston (2004) examine liquidity following SEOs, which is presumably related to unsigned volume. While their study offers valuable insights, they do not consider signed order imbalances as a measure of trading activity.

turns in the post-issue period? And, is there any difference in return performance between the SEO portfolios that individual investors aggressively buy and the SEO portfolios that institutions aggressively buy in the post-SEO period?

To our knowledge, this is the first study to investigate patterns of daily/monthly order imbalances around SEOs and their concomitant return implications using a long time-series (1988-2002). There are a few reasons for why there is merit to investigating the order flow-return relation specifically in the context of SEOs. For example, if the relation in this setting is very different from that in a general setting, it could imply the existence of informational asymmetry or behavioral biases among investors. Thus, if high levels of order imbalances are observed immediately *before* any corporate news announcements, this provides evidence of information leakage or insider trading. Similarly, if high levels of imbalances emerge *after* the event, this enables us to gain some insights into how quickly traders adjust to new equilibrium prices. In case of IPOs, however, we cannot examine trading activity before the event. In addition, trading activity after IPOs is affected by the first-time listing issues, for example, a lockup period. SEOs allow us to compare investor reactions before the event with those after the event. Moreover, to minimize dilution effects, managers have greater incentives to time SEOs than to time other corporate events such as stock splits. Stock splits also are likely to be contaminated by liquidity-related issues. For these reasons, SEOs represent an ideal corporate event around which order flow patterns might potentially reveal some interesting features of investor reactions.

Quite aside from the specific context of SEOs, our study has broader implications. Most empirical investigations of corporate events have centered on return behavior surrounding the event, rather than on trading volume. Yet trading activity is obviously an essential feature of financial markets and thus warrants separate examination. Indeed, trading volumes are large in financial markets. For example, the NYSE website indicates that the annual share turnover rate in 2003 on the NYSE was about 99%, amounting to a total volume of about 350 billion shares. Assuming a per share value of $20 and a 50 basis point round-trip cost of transacting, this amounts to a transaction cost of several billion dollars that the investing public paid in 2003. Understanding the patterns in the costly activity of financial market trading is clearly of economic importance. In particular, if signed trading activity patterns around corporate events are uncovered as being at odds with concurrent return patterns, then this potentially has implications for how the economic resources of financial market agents should be optimally allocated to trading activity in firms that experience corporate events *vis-a-vis* similar firms that do not do so.

In this study, we uncover the following features regarding trading activity in the portfolio of stocks experiencing an SEO. We find that the normally positive relation between imbalances and returns disappears for trade number imbalances but remains intact for dollar imbalances following SEOs. Under the plausible assumption that dollar imbalances are likely to be more strongly related to institutional trades than individual trades, our analysis supports the notion that small individual investors keep buying SEO stocks actively while the returns of these stocks reverse in the post-issue period. We also link the imbalance results specifically to changes in institutional holdings of SEO stocks. The results indicate that it is the institutional investors that cause the correction in returns after the offerings. Specifically, the SEO portfolios which individual investors aggressively buy on net strongly underperform relative to industry/market cap-matching non-issuer portfolios as well as to SEO portfolios which institutional investors buy on net in the post-issue period. This evidence indicates that individual investors on average may allocate resources more optimally to trading activity by eschewing SEO stocks.

The remainder of this paper is organized as follows. In the next section, the data, sample selection, and definitions of variables are described. In Section II, we examine the patterns of order flows and other key variables around SEOs. Section III investigates how order imbalances and returns are related around SEOs, providing evidence of a "delinkage" between trade-number imbalances and returns in the post-SEO period. In Section IV, we explore who induces the delinkage (institutions vs. individuals). Section V discusses possible explanations for our results. Section VI summarizes and concludes.

I. Data, Sample Selection, and Definitions

A. Order Imbalance Data

For this study, we use a number of databases. First, order imbalance (OIMBs) data are used for NYSE-listed stocks over the sample period of 15 years (1988-2002).[2] The data are originally estimated by the Lee and Ready (1991) algorithm using transactions data

[2] For details on the OIMB data, see Chordia, Roll, and Subrahmanyam (2002).

from the Institute for the Study of Securities Markets (ISSM) and the NYSE Trades and Automated Quotations (TAQ) databases. Only NYSE stocks are included in the sample. Following Lee and Ready (1991), for the years 1988 to 1998, any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained. Based on feedback from microstructure scholars, who indicated that timing differences in recording trades and quotes have dramatically declined in recent years, this delay rule was not imposed for the last four years (1999-2002). For this period, the quote immediately prior to each transaction (i.e., the quote closest in time to the transaction, with a time stamp of one second or more before the transaction) was retained.

Then the transactions data are signed as follows. If a transaction occurs above the prevailing quote mid-point, it is regarded as buyer-initiated and *vice versa*. If a transaction occurs exactly at the quote mid-point, it is signed using the previous transaction price according to the tick test: buyer-initiated if the sign of the last non-zero price change is positive, and *vice versa*.

Of course, as per the time-honored adage, for every buyer, there is a seller, and *vice versa*. In this regard, it is worth noting that the imbalance database, in general, estimates the sign of orders that demand immediacy and liquidity, i.e., market orders and marketable limit orders. These orders are accommodated by market making agents or liquidity suppliers, who include standing order traders, limit order traders, and specialists.[3] Our implicit postulation is that a financial market agent who has a long investment horizon (e.g., of at least several days) and does not seek to earn rents from *de facto* market making would typically act as a demander of liquidity, and it is the behavior of these types of agents that the imbalance data seeks to capture. We define two order imbalance measures as follows:

NOIMB: A scaled measure of order imbalances in the number of trades. That is, buyer-initiated trades minus seller-initiated trades divided by the sum of the two types of trades. Since this metric counts only the frequency of trades, it ignores the information content of the trade size, leading to the effect of weighting smaller trades more heavily than it would otherwise do. Therefore, NOIMB is more likely to pick up the trading behavior of small traders.

[3]Assuming that specialists maintain on average constant inventories, the excess of buyer-initiated orders over seller-initiated orders is absorbed by standing-order and limit-order traders.

DOIMB: A scaled measure of order imbalances in dollar value, similarly defined as buyer-initiated dollar volume minus seller-initiated dollar volume divided by the sum of the two. This metric measures the information content of the size of trades as well as of the frequency of trades. Thus DOIMB is more likely to reflect the trading behavior of large traders.

Order imbalances are scaled by the total number of trades or by the total dollar volume to eliminate the impact of total unsigned trading activity, since more actively traded stocks in terms of the number of trades or dollar trading volume are likely to have higher order imbalances. By comparing results obtained using the two imbalance measures, we expect to obtain more insights on the differential behavior of small vs. large traders.

B. SEO Data

Before turning to the details of the data on seasoned equity offerings, we describe the salient aspects of the SEO process. The event of an SEO shares many features with that of an IPO. The procedure begins with an announcement by the firm of an intent to issue additional shares, concurrently with the filing of intent with the SEC. The offer price and size are finalized after SEC approval is obtained. Between the initial announcement and the offer date in the U.S., the underwriter gathers indications of investor interest and conducts roadshows, often specifically soliciting attention from large institutional clients. A relevant phenomenon in an SEO is the providing of price support by an underwriter. Rules 10b-6, 10b-7 and 10b-8 of the Securities and Exchange Act of 1934 allow an underwriter to place price bids "for the purpose of pegging, fixing or stabilizing the price of any security" when such stabilization is used to facilitate the success of the offering. Aggarwal (2000) and Cotter, Chen, and Kao (2004) provide evidence of price stabilization in the context of IPOs and SEOs, respectively. Such stabilization takes two forms: the first is to post a stabilizing bid to purchase shares at a price not exceeding the offer price if the share distribution is not complete. The second is to sell more shares to the investors before the issue, effectively taking a short position that is "covered" in the after-market. Flipping of shares (the quick turning around of initial allocations in the secondary market) is not expressly prohibited, but penalties are imposed on "flippers" by imposing monetary penalties on such activities (called "penalty bids"). We discuss the implications of such activities on order imbalances later in the paper.

We extract the SEO data from the SDC Platinum database. In the sample, SEOs conducted by closed-end funds and REITs are excluded.[4] To survive in our sample, SEOs are required to overlap with the OIMB data. Moreover, because the event window at a daily horizon is 120 trading days and that at a monthly horizon is 36 months surrounding the event date,[5] we use only the sample of SEOs issued by NYSE-listed firms over a subset of the 15-year period: i.e., July 1988 - June 2002 for the daily sample, and January 1989 - December 2001 for the monthly sample. For the analysis at a monthly horizon, we initially intended to expunge SEOs issued during the three years at each end of the whole sample period (1988-2002). In that case, however, our sample size at a monthly horizon is significantly reduced. Therefore, SEOs offered during 1989-1990 and 2000-2001 are retained. This means that when the OIMB and other datasets are aligned around the event dates, part of the time series associated with such SEOs are truncated in the monthly event window. SEOs repeated by the same firm within the monthly event window are eliminated to minimize potentially misleading effects on our results.[6]

In the end, 777 SEOs in the daily sample and 586 SEOs in the monthly sample remain, as shown in Panel A of Table 1.[7] In our daily sample, the average amount of gross proceeds (without netting out the underwriter spread) and the mean number of issues from SEOs are $190.23 million and 6.34 million shares, respectively [see Panel B of

[4] In some studies on the return underperformance after IPOs or SEOs, utility companies are excluded on the grounds that the utility industry is heavily regulated and so SEOs by utility firms are not assumed to have typical informational asymmetry problems existent in other operating companies. Since our primary concern is trading activity (order flow patterns) around SEOs, in our sample we retain SEOs conducted by utility companies. The results excluding utility firms are very similar to those including utility firms.

[5] In this study, the event date is the issue date as recorded in the SDC Platinum database, which is also the same as the offer date, as opposed to the announcement date or filing date of an SEO.

[6] We excluded the repeated SEOs according to the following criteria. Among SEOs repeated within 6 months (at the daily horizon) and those repeated within 3 years (at the monthly horizon), we first exclude an SEO that is secondary (SECON: both primary and secondary offerings). If they are all primary SEOs (PRIM: pure primary offerings), we exclude a smaller SEO based on the number of shares newly issued. The number of deleted SEOs by this rule is 26 at the daily horizon, and 191 at the monthly horizon.

[7] In the monthly sample, 191 repeated SEOs were deleted from the total 777 SEOs. Note also that the numbers of observations used in various computations are smaller than the total number of SEOs (daily 777, and monthly 586) because of missing values in the datasets as well as the truncation in the monthly event window.

In Panel A of Table 1, PRIM means pure primary offerings: that is, equity offerings through new issuance only. SECON means pure secondary offerings (offerings of shares previously issued and sold by current shareholders) or both primary and second offerings together. For details, see Mini Manual (interrim edition) issued by Securities Data Company (SDC).

Table 1]. The mean size of SEOs defined by the ratio of proceeds to the market value at day -1 (SSEO1) is 15.34% and that defined by a ratio of new issues to the total number of shares outstanding at day -1 (SSEO2) is 15.92%. Panel C in the table also shows that equity offerings are from a broad range of industries, with SEOs issued by manufacturing (40.54%), transportation, communication, electric, gas, and sanitary services (17.37%), and finance, insurance, and real estate (13.38%) being the ones most frequently observed in our sample. Looking at the samples in more detail by 2-digit SIC code, we find that the majority of SEOs are from the industry such as electric, gas, and sanitary services (105 firms), oil and gas extraction (56 firms), electronic/electrical equipment and components (49 firms), chemicals and allied products (45 firms), and industrial/commercial machinery and computer equipment (44 firms).

C. Other Data

In addition to the two databases above, we use the CRSP daily and monthly files to obtain turnover (TURN), returns (RET), split- and stock dividend-adjusted prices (ADJP),[8] and market values (MV: price times the number of shares outstanding). The book-to-market ratio (BTM) is constructed by dividing the book value by the market value, where the book value is the sum of common equity, deferred tax, and investment tax credit from the CRSP/Compustat Merged (CCM) file. The institutional ownership (IO) data comes from Standard & Poor's. This IO variable is available for 1980-2001, but only on an annual basis.[9]

II. Patterns of Order Flow, Turnover, and Price Movements around SEOs

We match the datasets of the chosen variables (i.e., NOIMB, DOIMB, RET, TURN, ADJP, MV, IO, and NOANA) with the SEO dataset using company identification numbers as well as the offer dates. The process of assigning the values of those variables to

[8]To calculate the split- and stock dividend-adjusted price (ADJP) from the CRSP database, price (PRC) is divided by CFACPR (cumulative factor to adjust price).

[9]To examine whether the analyst coverage of SEO firms is different from that of non-issuer firms, we also use the number of analysts following a firm (NOANA). NOANA is extracted from the I/B/E/S database, available through Wharton Research Data Services (WRDS).

our SEO sample firms is as follows.

For each SEO firm, its values of each variable at daily or monthly levels are aligned around the offer (issue) date of the SEO over the two event windows of 241 trading days and 73 months.[10] Having assigned the values of each variable around the offer dates for the issuer firms (SEO portfolio), we then form a benchmark portfolio based on two firm characteristics for comparison purposes. That is, for each firm in the SEO portfolio, all of the non-issuer (NYSE-listed) firms from the same industry as the SEO firm by 2-digit SIC code are first singled out. Among these non-issuer firms from the same industry, we then select one firm with similar size (market value, MV) as of December prior to the offer date and match it with the SEO firm. Given that we often cannot find a non-issuer with exactly the same MV in matching, we choose a firm with an MV closest to but slightly *higher* than that of the issuer. As indicated, for a firm to be eligible as an SIC/MV-matching firm, first it should not offer equity issues within the event window *and* second, should have the OIMB data available over the event window. If a non-issuer candidate as an SIC/MV-matching firm with a slightly higher MV does not happen to have the OIMB data, then a firm with the closest but slightly lower MV is chosen.[11] Once the SIC/MV-matching firms are selected, then their own values for the above key variables (NOIMB, DOIMB, RET, TURN, ADJP, MV, IO, and NOANA) are obtained from relevant databases at daily and monthly levels. For all the firms in the SIC/MV-matching portfolio, these values of each variable are again aligned around the offer date of the matched SEO firm.

We first plot the daily time series of returns and order imbalances in Figure 1, panel A, which suggests that both imbalance measures generally are above zero; NOIMB remains much higher after day 30 than DOIMB. Further, in the period day 0 to day 7, the SEO firms experience extensive seller-initiated trades, which may be due to flipping of shares

[10] That is, the daily event window includes 120 trading days before and after the offer date, and the monthly window includes 36 months before and after the event month. The reason that we use two types of event windows is the following. First, we wish to take a close look at the patterns of trading activity in a high frequency setting on the occasion of the corporate events (SEOs). Therefore, an interval of 120 trading days (equivalent to about 6 months) around the event is adopted. Second, return performance associated with SEOs is of interest, and most existing literature examines it at 3-5 year horizons. Thus, we choose 36 months (3 years) before and after the event for comparison purposes with existing results.

[11] The MV matching process follows Loughran and Ritter (1995). We also applied the same process to form a benchmark portfolio based on the industry and book-to-market ratio, measured as of December prior to the year of the SEO (SIC/BTM-matching), and the results were broadly similar using this alternative benchmark.

obtained in the initial allocation. In particular, NOIMB and DOIMB at day 1 are -15.17% and -9.51%, respectively.[12] Boehmer and Fishe (BF) (2002) indicate that underwriters sell more shares than the original amount and cover the resultant short position in the secondary market in order to provide price support. This may help explain the general rise in DOIMB for the first twenty days or so following the SEO. An interesting fact is that returns (RET) are highest on days 1-2. This spike in returns on days 1-2 for SEO firms may be due to underwriters' price-support by directly placing stabilizing bids in the aftermarket. The findings of BF and that of Aggarwal (2000) in the context of IPOs indicate, however, that price support activities of the preceding type last only about two to four weeks following the SEO, so that such activities are distinct from our conclusions about the long-run relation between imbalance and returns.

We provide the descriptive statistics of our sample firms by (sub)periods in Table 2. For brevity, we restrict our discussion of descriptive statistics to the monthly horizon. To obtain the mean values of each variable in this table, the time-series averages over an interval are first computed for individual firms. Then the equally-weighted mean values of the averages across all the sample SEOs are calculated for each interval. The average monthly return (RET) in the pre-event period is 2.35%, but that in the post-event period is only 0.59%. This fact is consistent with the extant literature on the return outperformance before SEOs and underperformance after the issuance. As shown in Figure 1(B), average monthly NOIMB starts to rise from month -8, remaining at its peak near 6% for a long time (month 3 to month 13) *after* the event, and with the exception of 2 middle months, hovering around 2% until month 28. Table 2 as well as Figure 1(B) contrasts the monthly average return before the event (2.35%) with that after the event (0.59%). Table 2 also indicates that monthly turnover (TURN) significantly increases to 9.51% on average after new equity offerings, which compares to the monthly average turnover of 5.5% for the 1,186 NYSE/AMEX firms over the sample period (1984-2001) as documented by Chordia, Huh, and Subrahmanyam (2004).[13]

Next, to facilitate our understanding of order imbalance differentials between the two groups, the SEO portfolio's abnormal order imbalances (ANOIMB, ADOIMB) relative to those of the non-issuers are computed by subtracting imbalances of the SIC/MV-matching

[12] Conversations with Alexander Cruz at Thomson Financial confirmed that the shares of new offerings start to trade on the exchange market from the next business day (day 1) after the offer date.

[13] Chordia, Huh, and Subrahmanyam (2004) show that the monthly average turnover in the sample of 1,820 firms is 6.0% for the period of 1983-2002. For details, see Panel A of Table 1 in the paper.

group from those of the SEO group. The results are presented in Figure 2. As can be seen in Figure 2(A), daily abnormal trade-number imbalances, ANOIMB, of the SEO firms are generally positive (except for the daily interval [0, 18]), while abnormal dollar imbalances, ADOIMB, oscillate around the x-axis after the issuances. At a monthly horizon, the levels of ANOIMB in Figure 2(B) are far from the x-axis from month -6 on (except for month 0). For monthly ADOIMB shown in Figure 2(B), the levels are well above zero in the monthly interval $[-11, -2]$. However, the levels in the post-event period show no discernible bias and oscillate around the x-axis. The figures suggest that in the post-event period the behavior of DOIMB, unlike that of NOIMB, is similar in the two comparison portfolios.

So far we have gauged the differences in variables of interest for the two portfolios by graphs and descriptive statistics alone. We now formally investigate how imbalances and other variables of SEO firms are statistically different from those of nonissuer firms. Given our two comparison groups where firms in an SEO portfolio are all one-to-one matched in pairs with nonissuer firms based on the 2-digit SIC code and firm size (MV), we can conduct a paired sample t-test to examine pairwise differences in order imbalances (NOIMB and DOIMB) as well as in other variables (RET and TURN). Let the difference between the two paired values in a variable be $d_i = v_i^{SIC/MV} - v_i^{SEO}$, where v_i^{SEO} is a value of firm i from the SEO portfolio and $v_i^{SIC/MV}$ a value of an SIC/MV-matching firm paired with firm i. Then we want to test the null hypothesis, H_0: $E(d_i) = 0$, against the alternative hypothesis, H_1: $E(d_i) \neq 0$.

Tables 3 presents the results for monthly horizons (the ones for the daily horizons are omitted for conciseness). Panels A and B contain the cross-sectional averages of our key variables by subperiod for the SEO and SIC/MV-matching portfolios, respectively. To obtain mean values in an interval, the relevant variables are first averaged in the time-series, then in the cross-section.[14] Since the characteristics in the days or months immediately before and after the event are of special interest, two single-month values are computed in the subperiods immediately around the event month. Panel C presents statistics for the paired sample t-test.

Panel C shows that for NOIMB, H_0 can be strongly rejected at the 5% significance

[14] We adopt our method of averaging across firms, then across time for two reasons. First, this procedure enables us to avoid issues related to event date clustering. Second, models to calculate abnormal imbalance are not well-established enough for us to do a reliable event study.

level from month -16 to month 24 for NOIMB (except for month 1). We also see that the distribution of monthly DOIMB for the SEO portfolio is significantly different at 1% from that for the SIC/MV-matching portfolio in interval $[-8, 0]$. For this monthly DOIMB, however, H_0 cannot be rejected even at 10% from month 2 on. This, in turn, suggests that the distribution of DOIMB for the SEO portfolio over the post-issue period is close to that for the SIC/MV-matching portfolio.

Panel C in Table 3 also demonstrates that the differences in turnover (TURN) between the SEO group and the control group are statistically significant in the vast majority of cases. Turnover in SEO firms is higher than that of the matching firms even before the issuance, which is possibly indicative of increased investor interest that accompanies the price runup. For returns (RET), point estimates in Panels A and B suggest that the SEO firms consistently outperform over the pre-event period but underperform over the post-event period at a monthly horizon. The t-statistics in Panel C confirm that the return underperformance in the post-SEO period is statistically significant from month 5 on in our total sample, similarly to the results from certain subsamples as we will see later.

III. Order Imbalances and Price Pressure

Do order imbalances cause price pressure that has a direct effect on returns on the occasion of equity offerings? Does a high positive level of a current order imbalance translate to a high rate of a current stock return in both the time series and the cross section around SEOs? Modern finance theories suggest that price movements are tightly associated with order imbalances. For example, Kyle's (1985) model relates price changes to order flows. Dynamic inventory models of Ho and Stoll (1981) and Spiegel and Subrahmanyam (1995) also explore how market makers facing competition accommodate buying and selling pressure from outside investors. Empirically, Blume, MacKinlay, and Terker (1989) use intradaily dollar-volume imbalances for NYSE stocks to document that there is a strong relation between order imbalances and returns during the 2-day period of the 1987 market crash. In a more general setting, recent studies [viz. Chordia, Roll, and Subrahmanyam (2002), Chordia and Subrahmanyam (2004)] document that order imbalances are significantly positively associated with contemporaneous returns.

However, our observations in the previous section lead us to raise a question whether OIMBs really drive returns in the specific setting of SEOs. As described in Section II, Figures 1(A) and 1(B) suggest that the relation between order imbalances and returns is weakened or turns negative around the offer date. In this section, we examine the time-series relation between the two variables around the occasion of equity offerings.

A. Correlation Coefficients

We first compute correlation coefficients between returns and OIMBs by (sub)period both for the SEO firms and for the SIC/MV-matching firms. The results are shown in Table 4. Over the whole period at a daily horizon, Panel A shows that DOIMB for the SEO firms is positively correlated (46%) with returns, but NOIMB is negatively correlated (-13%) with the same. Over the pre-event period ($[-120, -1]$), the correlation coefficients of both NOIMB and DOIMB for the SEO firms are positive and statistically significant. In contrast, in the post-SEO period ([1, 120]), NOIMB for the SEO firms is significantly negatively correlated (-32%) with return, while DOIMB is positively correlated with this quantity.

These features of the SEO firms are in sharp contrast with those for the control group. As shown in the right-hand part of Panel A, the correlation coefficients in the SIC/MV-matching group are all positive and consistent at 22%-40% over the whole event window, without showing any dramatic fluctuation or sign reversal by subperiod for both NOIMB and DOIMB.

Given that most existing literature examines return performance following IPOs/SEOs in the mid- to long-term, we are more interested in the OIMB-return relations at a longer horizon. At the monthly horizon in Panel B of Table 4, for the SEO firms, the correlation coefficients in the pre-event period ($[-36, -1]$) are much larger (90% for NOIMB and 87% for DOIMB) than those in Panel A. In the post-event period ([1, 36]), however, NOIMB is again negatively correlated (-26%) with returns, while the coefficient of DOIMB is positive (43%) and statistically significant at 1%. Unreported results by subperiod show that the correlation coefficients of NOIMB in intervals [1, 18] and [19, 36] are -14% and -31%, respectively, while the values for DOIMB are 73% and 11%, respectively. This suggests that there is a reversal in the normally positive relation between trade-number imbalances (NOIMB) and returns in the post-issue period. For SIC/MV-matching nonissuers in Panel B, the coefficients remain positive in both the pre- and post-event periods.

B. Time-series Regressions

To explore return-imbalance relations more precisely, we consider time-series regressions in the next step. We propose a candidate estimation including a scaled volume measure (turnover) as a control variable in the following equation:

$$RET_t = \varphi_0 + \varphi_1 OIMB_t + \varphi_2 TURN_t + \varepsilon_{t.} \quad (1)$$

The above specification is potentially problematic, because of the possibility of the endogeneity bias in Equation (1) for order imbalances as well as for turnover. Thus, for both of our issuer and non-issuer samples, we perform the regression-based Hausman test for endogeneity. In most subperiods, the joint null hypothesis of no endogeneity could not be rejected, suggesting that OLS is a reasonable choice *vis-a-vis* two-stage least squares (2SLS) regressions.[15] Therefore, we simply employ OLS regressions of returns on concurrent order imbalances (each of NOIMB and DOIMB) and turnover by subperiod as in Equation (1).

Table 5 contains the results. As Panel A of this table demonstrates, daily returns in the SIC/MV-matching portfolio are strongly positively related to both NOIMB and DOIMB in the pre-event period as well as in the post-event period at the 5% significance level (daily intervals $[-120, -1]$ and [1, 120]). However, this is not the case for the SEO portfolio in the left-hand part of Panel A. The coefficient of NOIMB is positive and significant at 1% in the pre-event period. But its sign reverses in the post-event period (interval [1, 120]), with the coefficient being statistically significant at 10%. For DOIMB, the relation is rather similar to that of the non-issuer group. The coefficient of DOIMB is positive in both the pre- and post-event periods, and furthermore, it is significant at the 1% level in the post-SEO period.

For the longer horizon in Panel B, the features observed in Panel A are retained. In the case of SEO firms, the coefficient of NOIMB is positive and statistically significant

[15]In the equation $RET_t = \varphi_0 + \varphi_1 OIMB_t + \varphi_2 TURN_t + u_t$, the endogeneity of OIMB and TURN can be tested as follows. Under an assumption that OIMB and TURN are endogenous, we fit OIMB and TURN by OLS using the instruments as in $Y_t = \delta_0 + \delta_1 RET_{t-1} + \delta_2 TURN_{t-1} + \delta_3 LN(ADJP)_{t-1} + v_t$, where Y_t is either $OIMB_t$ or $TURN_t$. Given the fitted values ($\widehat{OIMB}_t$, $\widehat{TURN}_t$) and the two series of estimated residuals ($\widehat{v}_{1t}$, $\widehat{v}_{2t}$), the regression-based Hausman test involves testing the joint null hypothesis $H_0 : \rho_1 = \rho_2 = 0$ where ρ_1 and ρ_2 are coefficients in the linear projection of u_t on $\widehat{v}_{1t}$ and $\widehat{v}_{2t}$, i.e., $u_t = \rho_1 \widehat{v}_{1t} + \rho_2 \widehat{v}_{2t} + e_t$. We can easily test H_0 in the equation $RET_t = \varphi_0 + \varphi_1 OIMB_t + \varphi_2 TURN_t + \rho_1 \widehat{v}_{1t} + \rho_2 \widehat{v}_{2t} + e_t$ by OLS and its F-statistic computed using the sums of squared residuals from the unrestricted vs. restricted regressions. In most subperiods, we cannot reject the joint null hypothesis. For details, see Wooldridge (2002).

at the 1% level in the pre-event period, while NOIMB is negatively related to returns after the offerings (interval $[-36, -1]$ vs. [1,36]). However, the coefficients of DOIMB are consistently positive and statistically significant at 1% in both the pre- and post-event periods, without being affected by the event of equity offerings (compare the results for intervals $[-36, 36]$, $[-36, -1]$, and [1, 36]). For the control group, we do not see any contrast across the pre- and post-SEO periods in both NOIMB and DOIMB.

In unreported analyses, we also include NOIMB and DOIMB together as explanatory variables within the same regression. While this regression is subject to potential multicollinearity between the two imbalance measures, we find that for the post-SEO period, the coefficient of NOIMB remains negative and marginally significant for the SEO sample firms, but positive and significant at 5% for the control groups. The coefficients of DOIMB, however, is positive for both groups in the post-issue period: strongly significant for the SEO groups and marginally significant for the control groups. Overall, this supports the notion that DOIMB is the driver of stock price movements, but also suggests that NOIMB and the stock price move in opposite directions after the SEO.

Based on the above analyses, our major findings can be summarized as follows. The most notable characteristic in the time series is that the relation between NOIMB and returns in the SEO portfolio is indeed "delinked" in the post-SEO period, in the sense that while NOIMB and returns are strongly positively related in a more general setting with a broad sample, the positive relation disappears or turns negative in the post-SEO setting. However, DOIMB is consistently positively related to returns regardless of new equity offerings. In most cases for the SIC/MV-matching control groups, we do not observe such a contrast between NOIMB and DOIMB.

IV. Who Induces the Delinkage?

Questions still waiting to be addressed are the following: Why does the delinkage occur only in trade-number imbalances but not in dollar-volume imbalances in the post-SEO period? Why are the reactions of small traders different from those of large traders? Who keeps trading SEO stocks aggressively in the post-issue period while those stocks perform poorly? Who causes the correction in the returns of SEO stocks in the post-issue period? Are some investor groups superior to other investor groups in designing trading strategies for SEO stocks around the equity offerings? Considering that we are primarily concerned with the above issues in the longer term, we limit the discussion in this section to the monthly horizon results only.

It appears reasonable to suppose that small traders, represented in NOIMB, consist of individual investors and large traders are mostly institutional investors, as represented in DOIMB (see Griffin, Harris, and Topaloglu, 2003, and Chakravarty, 2001).[16] This postulation, however, is not without a little ambiguity; e.g., Chan and Lakonishok (1995) and Keim and Madhavan (1995) document that institutional investors sometimes split their orders across several days. Given that institutional ownership data are available, we investigate the extent to which NOIMB and DOIMB capture the trading activity of individual and institutional investors, respectively. In so doing, we also investigate whether the trading strategies of institutional investors around SEOs dominate those of individual investors around these events.[17]

A. One-Way Sorting

We form two different SEO portfolios from the total 586 SEOs by comparing the yearly levels of institutional ownership (IO) as follows:

P1: A portfolio of SEO firms whose institutional ownership decreases after year 0. P1 is imputed to be the SEO portfolio that *individual* investors buy on net after year 0.

[16] To provide a rudimentary algebraic justification for this mapping from individuals/institutions to our imbalance measures, suppose m_b individuals buy and m_s individuals sell. Let the corresponding numbers for institutions be n_b and n_s. Define $m \equiv m_b - m_s$ and $n \equiv n_b - n_s$. Further, let individuals and institutions trade in lots of size K_1 and K_2, respectively, with $K_1 < K_2$. Then $NOIMB = m+n$, whereas $DOIMB = mK_1P + nK_2P$, where P is the price per share. Letting σ_x^2 denote var(x), and $K \equiv K_2/K_1$, it can easily be shown that $\{\text{corr}(NOIMB, m)\}^2 = \sigma_m^2/(\sigma_m^2 + \sigma_n^2) > \{\text{corr}(DOIMB, m)\}^2 = \sigma_m^2/(\sigma_m^2 + K^2\sigma_n^2)$ (assuming independence of the random variables for simplicity). Similarly $\{\text{corr}(NOIMB, n)\}^2 = \sigma_n^2/(\sigma_m^2+\sigma_n^2) < \{\text{corr}(DOIMB, n)\}^2 = \sigma_n^2/\left(K^{-2}\sigma_m^2 + \sigma_n^2\right)$. This provides a simple analytical framework for our conceptual linkages of $NOIMB$ and $DOIMB$ with individual and institutional net buying activity, respectively.

[17] From an analytical standpoint, a question may naturally arise as to what type of framework is consistent with the market not responding to NOIMB in equilibrium within the post-SEO period. We allude here to models where market makers respond differently to orders of different sizes (e.g., Easley and O'Hara, 1987). Sophisticated market makers may desist from responding strongly to small (likely retail) orders in the post-SEO period because they may be cognizant of extrapolative individual investor behavior in SEO stocks due to overconfidence and/or naïveté (as we discuss later in Section V). The process of price adjustment in the period following security issuances may therefore be more reliant on DOIMB as well as public information flows, rather than NOIMB (see Daniel, Hirshleifer, and Subrahmanyam, 1998, and Foster and Viswanathan, 1993 for models where public information flows are material in price formation).

P2: A portfolio of SEO firms whose institutional ownership increases after year 0. Thus, P2 is the SEO portfolio that *institutional* investors buy on net after year 0.

For comparison purposes, two SIC/MV-matching portfolios corresponding to P1 and P2 are also constructed from the total sample of SIC/MV-matching firms. We call them P1_M and P2_M, respectively. If NOIMB (DOIMB) adequately represents the activities of individual (institutional) investors, we expect the levels of this variable to be high in P1 (P2), relative to the SIC/MV-matching group.

Let IO_t denote institutional ownership in year t since the SEO. In constructing P1 and P2, we consider 4 choices: 1) $IO_0 > IO_1$ vs. $IO_0 < IO_1$, 2) $IO_0 > IO_1 > IO_2$ vs. $IO_0 < IO_1 < IO_2$, 3) $IO_0 > IO_2$ vs. $IO_0 < IO_2$, and 4) $IO_0 > IO_3$ vs. $IO_0 < IO_3$. Among them, we adopt choice 3), in part, for the following reason. IO_0 is the level of institutional ownership at the end of year 0, by which on average 6 months have already passed since the offerings, because SEOs can be conducted from January to December of the event year (year 0). So, by comparing IO_0 and IO_2, in effect, we are comparing the level of IO at month 6 with that of IO at month 30. As we see in Figure 1(B), NOIMB and ANOIMB continue to be high until month 28. Moreover, considering that SEO firms usually do not underperform during the first 6 months after the offerings [Loughran and Ritter (1995)], many institutional investors may buy SEO stocks up to month 6. Therefore, it is reasonable to compare IO_0 and IO_2 for our purpose.[18] As per choice 3), the sample size is 174 SEOs for P1 and 290 SEOs for P2.

The results are presented in Tables 6-8 and Figures 3 and 4. First, we examine the level changes in IO and NOANA for P1 and P2 in Figures 3(A) and 3(B). By construction, IO decreases in P1 at year 2 relative to year 0, while it increases in P2. Notice that IO in P1 starts to rise from year -1, showing a substantive increase at year 0. This indicates that institutional investors in P1 starts to buy SEO stocks earlier (than they do so in P2) and sell after year 0.[19]

Next, we examine the features of our key variables for P1 and P2 in Table 6. The most noticeable characteristic after month 0 is the level of NOIMB in P1 and P2. An unreported figure shows that NOIMB of P1 in interval [2, 18] rises beyond 10% at month

[18] Choice 2) would arguably be better, but the sample size is too small for this case. Although we adopt choice 3), the results from other choices are very similar.

[19] The behavior of NOANA shows no large difference between P1 and P2.

9.[20] In Panel A of Table 6, the average level of NOIMB in this interval is 8.02%, which is obviously far above the level of its control group (P1_M) as indicated by the t-statistic in Panel A. This means that indeed NOIMB reflects well the trading activity of individual investors, because P1 represents the portfolio that individuals are imputed to buy on net during years 1 and 2 following the offerings.

We now check how the two imbalance measures behave within P2. Since institutions buy while individuals sell on net in P2, we expect that NOIMB will be low but DOIMB will be relatively higher in P2 than in P1. The latter is not exactly the case.[21] However, Panel B of Table 6 demonstrate that the levels of NOIMB in P2 are much lower than in P1 after the offerings. Specifically, NOIMB in P2 over interval [2, 18] is only 2.90%, which compares to 8.02% in P1. But these levels are still higher than those of the control group (P2_M) as implied by the t-statistics. One explanation is that NOIMB of P2 also reflects partly the trading activity of *institutional* investors who split their orders to reduce the price impact. Even though SEO stocks generally underperform after the offerings, it is possible that institutions buy some SEO stocks after the offerings for informational or liquidity reasons. For example, Gibson, Safieddine, and Sonti (2003) document that SEO firms experiencing the greatest increase in institutional ownership around the offer date outperform their benchmark portfolios in the year following the issue relative to those experiencing the greatest decrease.

To check the imbalance pattern differences relative to the benchmarks, the abnormal OIMBs for P1 and P2 are plotted in Figure 4. This figure graphically contrasts the differential behavior of NOIMB and DOIMB in the post-issue period. The abnormal trade-number imbalance (ANOIMB) in P1 [see Figure 4(A)] is extremely high in interval [1, 18], while ANOIMB in P2 [see Figure 4(B)] is around 2%. This high level of ANOIMB in P1 (aggressive buying orders for SEO stocks from individual investors) is not justified by return performance of the portfolio over the post-issue period. For instance, in Panel A of Table 6, compare the average return of -0.61% for P1 with that of 1.34% for P1_M over the interval [2, 18]. The t-statistic (6.63) strongly suggests that P1 underperforms its benchmark portfolio, P1_M, in this period. In contrast to ANOIMB, the abnormal dollar-volume imbalances (ADOIMB) in Figure 4 tend to oscillate around zero in both P1

[20]Recall that in the total sample, the highest level of NOIMB after the offerings is about 6.1% [see Figure 1(B)].

[21]We re-examine this issue by way of two-way sorts in the next subsection.

and P2. Also note in Panel B of Table 6 that P2 outperforms P2_M at least in interval [2, 18] after the equity offerings.

In the next step, we compute correlation coefficients and regress returns on OIMBs in order to examine the delinkage discussed in the previous section. As can be seen in Table 7, the delinkage between returns and NOIMB in P1 is prominent in the post-issue period (negative 19%), while it does not emerge in P2 (positive 21%)[22] or in the two benchmark portfolios. These features generally obtain in the regression results as well, even after controlling for turnover (see Table 8).

To summarize, we find that the delinkage between NOIMB and returns in the post-issue period is observed only in the SEO portfolio which individual investors buy on net (P1). Another notable point is that the SEO portfolio which individual investors buy aggressively (P1) underperforms its SIC/MV-matching non-issuer portfolio (P1_M) as well as the SEO portfolio which institutional investors buy on net (P2) in the post-issue period. In addition, stocks in the SEO portfolio which individual investors buy aggressively (P1) are more actively traded even before the issuances than their SIC/MV-matching firms are. Overall, the results accord with the notion in the previous section that individuals' trading activity in certain SEOs leads to a delinkage between NOIMB and returns.

B. Two-Way Sorting

One concern in the above experiment is that sorting by IO only may not capture properly the different aspects of individuals and institutions manifested in the two OIMB measures. For example, in the post-event period, DOIMB is not higher in P2 relative to P1. Therefore, we experiment again by forming two portfolios using two firm characteristics. We first sort the total SEO sample by firm size (MV) as of month 0 in ascending order, and split the SEO firms into two groups. The rationale is that if institutional investors prefer to trade large stocks, sorting in this manner can potentially enable us to separate out more efficiently the effect of individual/institutional investors on our OIMB measures. Then, two sub-portfolios are constructed, one from the small-sized group and the other from the larger-sized group, by comparing IO as follows:

P3: A portfolio of small-sized SEO firms whose institutional ownership decreases after

[22] Recall here that P2 is a portfolio of SEO firms, not of industry/size-matching firms.

year 0. Thus, P3 is the *smaller* SEO stocks that *individual* investors buy on net after year 0.

P4: A portfolio of large-sized SEO firms whose institutional ownership increases after year 0. That is, P4 is the *larger* SEO stocks that *institutional* investors buy on net after year 0.

For comparison, two SIC/MV-matching portfolios corresponding to P3 and P4 are also constructed. Let us call them P3_M and P4_M, respectively.[23] As expected, there are large differences in the levels of IO and NOANA between P3 and P4 after sorting this way. Figures 3(C)-3(D) show that P3 consists of stocks with much lower IO and fewer NOANA than P4. As of year −3, the IO levels are 41.79% and 49.81% in P3 and P4, respectively, and the levels become 42.58% and 64.86% at year 2.[24]

The behavior of our key variables are qualitatively very similar to those from the one-way sorted results. Therefore, we briefly discuss only some salient aspects in this subsection. By sorting this way, unreported figures show that the overall DOIMB levels are indeed higher than the NOIMB levels in P4 in the post-issue period, capturing the buying activities of institutions more efficiently. Table 9 presents the analog of Table 7 for the two-way sorts. We note that returns on P3 in the post-SEO period are consistently lower than those in P3_M and P4. In particular, the small-sized SEO firm portfolio which individual investors buy on net (P3) strongly underperforms its benchmark portfolio (P3_M) in intervals [2, 18] and [19, 36] as the test statistics indicate. To compare the returns of P3 and P4 in the post-issue period, we also conduct a t-test for the hypothesis that the return of P4 exceeds that of P3, finding the test statistics of 2.45, 6.17, and 1.99 for month 1, interval [2, 18], and interval [19, 36], respectively. This suggests that P3 significantly underperforms relative to the large-sized SEO portfolio which institutions buy on net (P4) in interval [1, 36]. Notice in particular from Table 9 that the average return on P3 in [2, 18] is negative (−0.85%), whereas that on P4 in the corresponding interval is as high as 1.08%. We observe that unlike P3, P4 marginally underperforms its SIC/MV-matching portfolio (P4_M) only in interval [19, 36] over the post-issue period. NOIMB is also generally higher for P3 in comparison to P3_M in the post-issue period

[23] We form four subportfolios for the SEO sample, but present results for two of these only, for brevity and because the central phenomena of interest (the high positive NOIMB in the post-SEO period and the return-NOIMB disconnect) are more strongly evident in these portfolios.

[24] The NOANA levels are also 7.69 vs. 18.66 at year −3, while they are 7.83 vs. 19.53 at year 2.

but a similar behavior does not obtain for P4 *vis-a-vis* P4_M. Unreported regression results analogous to Table 8 again confirm that the NOIMB-return delinkage in the post-issue period is a phenomenon that is more prominent in the small-sized SEO firm portfolio which individual investors buy on net (P3).

A potential issue with regard to the interpretation of the results is that the formation criteria used for the control samples could somehow mimick changes in institutional holdings within the SEO samples. To preclude this possibility, we present the annual levels and their changes in institutional ownership (IO) for all of our sample portfolios (SEO firms, P1-P4, and their control counterparts, P1_M-P4_M) as well as the t-test results in Table 10. It can be seen from Panel A that while the SEO samples show significant changes in IO around SEOs (especially between year 0 and year 2), the control samples do not. Indeed, Panel B exhibits that the null hypothesis of no change in IO between year 0 and year 2 cannot be rejected for the control groups, but can be rejected for every SEO group. In Panel C, the changes in IO between year 0 and year 2 (dIO) for the SEO samples are also statistically different from those for the non-SEO control samples. This indicates that the construction procedure for the control samples does not mimick the IO pattern of the SEO samples.

V. Discussion

The pecking order theory [Myers (1984)] posits that firms issue equity as a last resort because of information asymmetry between insiders and investors. Managers are reluctant to issue equity when they believe their shares are undervalued, while investors often interpret an equity issue as an indication that managers believe the firm's stock is overvalued. This situation in turn leads to the negative stock market reaction when the equity offering is announced. Therefore, asymmetric information models suggest that when an equity offering is announced, the market will revalue the stock so that it is no longer overvalued or undervalued. That is, there should be no underperformance in the post-issue period. However, the empirical evidence suggests that when the offering is *announced*, the market does not fully revalue the stock, and thus the stock is still substantially overvalued when the new equity is *issued*, resulting in negative abnormal returns for several years following the issuance. This has been a puzzle in the capital markets, triggering voluminous studies trying to explain the phenomenon or to ascertain the truth of underperformance.

In our paper, we go beyond the extant return analyses around SEOs and document that the relation between NOIMB and returns gets delinked on the occasion of SEOs, while DOIMB does not show such a delinkage. Why does this occur? In the previous section, we have explored the roles of NOIMB and DOIMB as proxies for individual and institutional trading activities. We also observe that the NOIMB-return delinkage and the high level of ANOIMB are conspicuous in the SEO portfolios that individual investors buy on net in the post-issue period.[25] It follows from these facts that the two groups of investors differ in their reactions to the same corporate event. Institutional investors' abnormal trading behavior picked up by DOIMB disappears soon after the offerings [see Figure 4(B)], and the delinkage does not occur in DOIMB. However, individual investors' abnormal trading behavior picked up by NOIMB continues to be high throughout the post-issue period [Figure 4(A)]. All these features are predominant in our total SEO sample as well [Figure 2(B)]: the delinkage is strong in NOIMB, but is weak or non-existent in DOIMB.[26] The evidence thus suggests that there exists heterogeneous behavior between individual and institutional investors. Why do individual investors appear to keep trading the SEO stocks in a manner tilted toward the buy side for about 2 years during which the stocks tend to perform poorly?

A. DOIMB and Institutional Investors

First, we consider why institutional investors' trading behavior represented by DOIMB does not show abnormal buying after the equity offerings. A possible explanation is their informational advantage stemming from competition, cost efficiency, and better access to information sources [Hand (1990)]. There is evidence that some institutional investors trade based on superior information about forthcoming earnings, although such trading

[25] A concern here may be that SEOs are more common for firms with certain patterns of institutional ownership and we potentially may be picking up patterns in ownership rather than the impact of SEOs. To address this, we run alternative regressions controlling for the pre-event institutional ownership as an additional explanatory variable, and find that the results are substantively unaltered. These regressions are available from the authors.

[26] We note that there may be some noise involved in directly mapping IO to OIMB because IO is available only at annual intervals, and there is also some noise involved in signing OIMB. Nonetheless, we calculated the grand correlations between dIO and annual NOIMB as well as DOIMB (calculated as the average of monthly OIMBs), where dIO is the annual change in institutional ownership. The correlations are as follows: corr(dIO, NOIMB)=-0.048 and corr(dIO, DOIMB)=$+0.044$ for the full sample. For the SEO (control) firm groups the correlations are respectively -0.075 and $+0.013$ (-0.047 and $+0.052$). All correlations but the 0.013 are statistically different from zero.

may not be widespread. Ali et al. (2002) document that the change in institutional ownership of a firm during a calendar quarter is positively associated with the three-day abnormal returns at the time of the subsequent announcement of the company's quarterly earnings. They report that changes in ownership by independent investment advisors, investment companies, and insurance companies are positively associated with subsequent earnings announcement returns, while those by internally managed pension funds, educational funds, and private foundations are not. This is because the former institutions face greater competition for clients, which creates pressure to improve returns by actively seeking information in the short run.

Institutional investors may also have enjoyed superior access to information from companies until the adoption of SEC Regulation FD in October 2000.[27] Evidence suggests that at least before the enactment of this regulation, institutional investors and analysts had opportunities to obtain private information regarding future earnings through a selective disclosure process such as conference calls or meetings open only to analysts/institutional investors, and private communications/interviews with company executive officials [see Hutchins (1994) and Berenbeim (1994)].

Overall, it is reasonable to propose that large sophisticated institutional investors indeed trade on superior information, discount adequately the stock price for possible earnings management as well as analysts' overoptimism, and promptly sell short overvalued SEO stocks with lower transaction costs. This, together with the price-setting activities of the market-making sector, drives the market prices of issuers to appropriate levels very rapidly after the SEO takes place. Therefore, DOIMB, reflecting the trading activity of larger institutional investors, does not show a delinkage with returns in the post-SEO period.

B. NOIMB and Individual Investors

Why is the NOIMB-return delinkage more prominent in the portfolios that individual investors buy on net after SEOs? More specifically, we discuss why small individual investors keep trading the SEO stocks in a manner tilted toward the buy side in the post-issue period while such stocks tend to underperform.

[27] Regulation FD requires that when a firm intentionally discloses material information, it should do so publicly, but not selectively. The disclosure may be in the form of an 8-K filing with the SEC, a press release, or a public statement.

The most probable explanation appears to be the cognitive biases of small individual investors. For example, in the framework of Daniel, Hirshleifer, and Subrahmanyam (1998), investors are susceptible to psychological/behavioral biases: overconfidence and biased self-attribution. The model implies that investors overreact to private information signals and underreact to public information. Possibly, overconfident individual investors invest in SEO stocks based on a private opinion, which, in part, reflects the good performance of SEO stocks in the pre-issue period. If they receive confirming public information, their overconfidence grows, which leads them to buy more aggressively. However, when they receive disconfirming public information (in this case, the announcements of SEOs), their confidence falls only modestly. Thus, they are sluggish in adjusting to the market response, continuing to buy SEO stocks for a considerable period after the offerings.

Lakonishok, Shleifer, and Vishny (1994) show that "value" stocks exhibit abnormally higher returns than "glamour" stocks, and suggest that extrapolation by investors may cause glamour stocks to become overvalued. Note from Figure 1(B) that the price run-up and return outperformance of SEO firms in the pre-issue period begins from around month -16. This price run-up can occur because managers are more likely to issue new stock when the price level is high. The second reason is that managers may manage earnings before offering new issues in order to boost the stock price.[28] Moreover, to keep the market price from dropping below the offer price, analysts affiliated with underwriting banks may try to make earnings projections look favorable. Consequently, stock prices of firms considering issuing new shares are likely to rise for a certain period of time before the event. Small, and possibly naïve, investors may observe this good return performance in the pre-event period and tend to extrapolate this trend, trading more aggressively than is justified by subsequent return performance of such stocks.

To sum up, market participants do not appear to be homogeneous in their reactions to seasoned equity offerings. Given that NOIMB and DOIMB appear to at least partially capture the net buying activities of individual and institutional investors, respectively, the evidence supports the notion that large institutions (together with the market-making sector) cause the return correction following SEOs. Our results accord with the notion that individual investors are tardy in adjusting their beliefs about future earnings potential of

[28]Teoh, Welch, and Wong (1997), and Rangan (1997) report that firms making more aggressive use of discretionary accruals to inflate earnings have the worst subsequent return underperformance after equity offerings. Of course, other issuers simply issue equity after observing a stock price run-up without intentionally attempting to manipulate. See Lee (1997).

the issuers, systematically lagging behind the market response. It appears to take about two years before small investors adequately revise their views.

VI. Conclusion

The literature on financial markets has traditionally centered on explaining asset prices, while trading activity has not attracted its due attention. In conformance with this observation, the literature on securities offerings (IPOs or SEOs) has also focused on return performance after issuance, without emphasis on the trading activity around those corporate events. Trading activity, however, can potentially shed additional light on the cause of the predictable return patterns following equity issues.

Many researchers have recently explored the association between stock returns and trading activity. In most such studies, trading activity has been proxied by an unsigned activity measure, or volume. Signed order flows, however, may be a stronger driver of returns. Thus, this study investigates patterns of two signed trading activity measures (order imbalances in trade numbers, NOIMB, and in dollars, DOIMB) and their implications for price movements surrounding the SEOs for NYSE-listed firms over the 15-year period (July 1988-June 2002). The results indicate that the abnormal trade-number imbalances (ANOIMB) continue to remain high for about 2 years after the SEOs, while the abnormal dollar-volume imbalances (ADOIMB) disappear soon after the offerings. Most importantly, we uncover that the relation between NOIMB and returns is delinked in the post-SEO period. This NOIMB-return delinkage in the post-issue period is a phenomenon that is conspicuous in the SEO portfolios which individual investors buy on net. The delinkage does not occur in the SEO portfolios which experience net purchases by institutional investors. We also do not observe it in most cases for the SIC/MV-matching benchmark portfolios.

The above findings suggest that there is heterogeneity across individual and institutional investors in their reactions to the equity offerings. By way of our empirical tests, we infer that small traders are well represented by individual investors and large traders by institutional investors. Thus, the evidence supports the notion that individuals indulge in buying SEO stocks while their returns reverse in the post-issue period. This finding is intriguing from the perspective of investor rationality.[29] It takes about two years before small investors adequately revise their beliefs. Consequently, the SEO portfolios which individual investors aggressively buy on net strongly underperform the SIC/MV-matching benchmark portfolios as well as the SEO portfolios which institutional investors buy on net in the post-issue period.

A key contribution of this study is to provide evidence pointing to the notion that non-institutional investors induce anomalous order flow patterns (the NOIMB-return delinkage) in SEO stocks. Our analysis of the link between trading activity and return patterns also sheds light on the important economic question of how investors should allocate costly resources to trading activity. We suggest that the buying activity in SEO stocks that we document is not likely earn super-normal returns.

However, the sample of this study is constrained by the availability of OIMB data. Thus, the analysis is based on a restricted sample of stocks compared with the studies on the post-issue underperformance of IPOs or SEOs. The difficulties of obtaining broader and longer OIMB data preclude us from doing a larger sample study. In this sense, some caution is warranted in drawing a general conclusion from our results. Our hope is that this work can act as a catalyst, leading to more fruitful research in this area. In particular, an order flow analysis with a broader sample of SEOs conducted by AMEX- and NASDAQ-listed firms could shed further light on this debate.

[29] While the insightful papers of Brav and Heaton (2002) and Lewellen and Shanken (2003) rationalize pricing anomalies in a setting with learning and structural uncertainty, they do not explore the trading activity-return relation.

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Table 1
Sample of SEOs

Panel A shows the sample of SEOs by year. The sample period is from July 1988 to June 2002 at a daily horizon, and January 1989 to December 2001 at a monthly horizon. The definitions in Panel A are: *PRIM*: pure primary offerings; *SECON*: both primary and secondary offerings together; *#SEOs*: the total number of SEOs (PRIM + SECON). Panel B contains summary statistics for the SEO sample (777 SEOs). The definitions of items in Panel B are: *Proceeds*: the amount of proceeds from SEOs in million US dollars; *#Issues*: the number of issues in SEOs in million shares; *SSEO1*: size of SEO defined as {Proceeds/market value at day(-1)}*100; *SSEO2*: size of SEO defined as {#Issues/shares outstanding at day(–1)}*100; *MV(t-1)*: price*shares outstanding as of the year-end prior to the SEO in billion US dollars. Panel C breaks down the sample (daily) by industry and 2-digit SIC code. The value in each parenthesis in the second column of Panel C indicates the number of sample SEOs from the industry defined by the corresponding 2-digit SIC code.

Panel A: SEO Sample by Year

	Daily Horizon			Monthly Horizon		
Year	PRIM	SECON	#SEOs	PRIM	SECON	#SEOs
Jul-Dec 1988	4	3	7	-	-	-
1989	15	5	20	15	4	19
1990	17	5	22	11	5	16
1991	50	20	70	37	17	54
1992	52	27	79	46	22	68
1993	52	34	86	43	24	67
1994	33	31	64	28	24	52
1995	25	24	49	22	14	36
1996	35	34	69	34	34	68
1997	21	34	55	19	29	48
1998	21	26	47	22	26	48
1999	30	24	54	20	17	37
2000	20	15	35	13	8	21
2001	35	28	63	29	23	52
Jan-Jun 2002	43	14	57	-	-	-
Total	453	324	**777**	339	247	**586**

Panel B: Summary Statistics for SEOs

Variable	MEAN	STD	MIN	MAX
Proceeds ($mill)	190.23	276.16	2.10	2599.80
#Issues (mill shares)	6.34	9.28	0.18	136.83
SSEO1 (%)	15.34	16.65	0.27	282.98
SSEO2 (%)	15.92	14.71	0.24	174.30
MV(t-1) ($bill)	3.52	9.79	0.01	187.76

Panel C: Industry Breakdown for SEO Sample			
Industry	**2-Digit SIC Code (#SEOs)**	**Industry Total SEOs**	**%**
Mining, Oil/Gas Extraction	10 (6), 12 (1), 13 (56)[a]	63	8.11
Construction	15 (2), 16 (5), 17 (2)	9	1.16
Manufacturing	20 (10), 22 (7), 23 (15), 24 (2), 25 (2), 26 (11), 27 (19), 28 (45)[b], 29 (8), 30 (7), 31 (1), 32 (10), 33 (24), 34 (21), 35 (44)[c], 36 (49)[d], 37 (22), 38 (12), 39 (6)	315	40.54
Transportation, Communication, Electric, Gas, Sanitary Services	40 (2), 42 (2), 44 (5,), 45 (8,), 47 (1), 48 (12), 49 (105)[e]	135	17.37
Wholesale	50 (12), 51 (14)	26	3.35
Retail	52 (1), 53 (9), 54 (9), 55 (7), 56 (3), 57 (5), 59 (15)	49	6.31
Finance, Insurance, Real Estate	60 (14), 61 (13), 62 (9), 63 (30), 64 (4), 65 (5), 67 (29)	104	13.38
Services	70 (10), 72 (4), 73 (28), 75 (2), 78 (4), 79 (4), 80 (12), 83 (1), 87 (11)	76	9.78
Total		**777**	**100.00**

[a] Oil and gas extraction.
[b] Chemicals and allied products.
[c] Industrial/commercial machinery and computer equipment.
[d] Electronic/electrical equipment and components, except computer equipment.
[e] Electric, gas, and sanitary services.

Table 2
Descriptive Statistics of Key Variables for the SEO firms

This table exhibits the descriptive statistics of key variables for the monthly SEO sample over the event windows. To obtain the mean values of each variable in this table, the time-series averages over an interval are first computed for individual firms, and then the equally-weighted mean values of the averages across all the sample SEOs are calculated for each interval. The definitions of variables are: trade-number order imbalances *(NOIMB)*, dollar-volume imbalances *(DOIMB)*, returns *(RET)*, turnover *(TURN)*, split- and stock dividend-adjusted prices *(ADJP)*, and market values *(MV)*. *Period [a, b]* means an interval from month *a* to month *b* relative to the event month. The number of samples at a monthly horizon is 586 SEOs over the sample period from January 1989 to December 2001.

	Whole Period [-36, 36]		Pre-event Period [-36, -1]		Event Month [month 0]		Next Month [month 1]		Post-event Period [1, 36]	
Variable	MEAN	STD	MEAN	STD	MEAN	STD	MEAN	STD	MEAN	STD
NOIMB (%)	2.36	14.77	1.09	15.81	-3.06	16.10	2.65	14.42	3.78	13.69
DOIMB (%)	1.84	18.98	1.74	21.19	-1.69	19.06	3.10	16.85	2.04	16.78
RET (%)	1.46	12.29	2.35	11.99	1.19	11.10	1.90	11.26	0.59	12.63
TURN (%)	8.50	8.91	7.28	7.93	16.17	12.45	10.67	15.01	9.51	9.80
ADJP ($)	20.08	14.87	17.13	13.28	23.21	14.97	23.57	15.49	22.96	16.46
MV ($bill)	3.03	9.49	2.30	6.75	3.15	9.70	3.26	10.05	3.77	12.22

Table 3

The Paired Sample T-Test: Comparison of the SEO-Firm Portfolio with the SIC/MV-matching Benchmark Portfolio around SEOs

This table shows how the characteristics of the issuers (SEO firms) at monthly horizons are different from those of the non-issuers (2-digit SIC code & size-matching firms) in trade-number order imbalances *(NOIMB)*, dollar-volume imbalances *(DOIMB)*, turnover *(TURN)*, and returns *(RET)* around SEOs. Panel A contains the cross-sectional means in each period for the SEO firm portfolio, while Panel B does the same for the SIC/MV-matching portfolio. To compute the statistics of the paired sample t-test in Panel C, the time series of each variable is first averaged over the interval to obtain the average value for each SEO firm so that we can compare the mean of these average values with the mean of the corresponding average values of SIC/MV-matching firms in the interval. The values in each interval in Panels A and B are the mean values of the averages across the individual firms in the corresponding interval. Interval *[a, b]* means a period from month *a* to month *b* relative to the event month. The total number of SEO firms at a monthly horizon is 586. *N* is the number of observations used in the paired sample t-test. In this test, the null hypothesis is H_0: $\mu^{SIC/MV} - \mu^{SEO} = 0$, where $\mu^{SIC/MV}$ is the mean value of the SIC/MV-matching firms and μ^{SEO} is that of the SEO firms.

Item	[-36, -25]	[-24, -17]	[-16, -9]	[-8, -5]	[-4, -1]	-2	-1	0	1	2	[1, 4]	[5, 8]	[9, 16]	[17, 24]	[25, 36]
Panel A: Means for SEO Firms															
NOIMB (%)	-0.031	0.895	1.486	2.427	4.614	4.624	3.573	-3.061	2.648	4.785	4.824	5.594	5.338	3.350	1.738
DOIMB (%)	-0.013	0.428	2.586	3.713	6.066	5.946	6.105	-1.690	3.101	2.544	2.485	1.924	1.961	2.104	1.824
TURN (%)	7.252	7.246	7.747	7.371	8.210	8.693	7.881	16.172	10.672	10.624	10.225	9.591	9.741	9.245	9.642
RET (%)	1.459	1.369	2.689	4.080	5.146	5.945	2.894	1.185	1.900	0.294	0.804	0.441	0.440	0.563	0.937
Panel B: Means for Non-issuer SIC/MV-matching Firms															
Item	[-36, -25]	[-24, -17]	[-16, -9]	[-8, -5]	[-4, -1]	-2	-1	0	1	2	[1, 4]	[5, 8]	[9, 16]	[17, 24]	[25, 36]
NOIMB (%)	-0.130	0.206	0.011	0.155	1.274	0.585	1.593	1.757	1.392	2.286	1.301	1.374	1.600	1.189	1.064
DOIMB (%)	0.000	0.913	1.832	1.683	1.575	1.555	1.137	2.894	2.082	3.201	2.253	2.106	2.248	2.299	1.948
TURN (%)	6.764	6.694	6.502	6.401	6.735	6.815	6.635	6.549	6.482	7.004	6.787	6.888	7.186	7.879	8.076
RET (%)	1.451	*1.213*	1.524	1.891	2.203	2.384	1.939	1.893	0.925	0.845	0.908	1.266	0.953	1.234	1.305
Panel C: T-statistics for the Paired-Sample T Test															
Item	[-36, -25]	[-24, -17]	[-16, -9]	[-8, -5]	[-4, -1]	-2	-1	0	1	2	[1, 4]	[5, 8]	[9, 16]	[17, 24]	[25, 36]
NOIMB	*-0.16*	*-1.49*	*-2.36*	*-3.34*	*-5.32*	*-5.33*	*-2.34*	*5.50*	*-1.49*	*-2.97*	*-5.45*	*-6.83*	*-6.91*	*-3.82*	*-1.85*
DOIMB	*0.53*	*0.01*	*-0.51*	*-2.74*	*-6.82*	*-4.21*	*-4.81*	*4.19*	*-1.50*	*0.79*	*-0.39*	*0.33*	*0.14*	*0.41*	*0.04*
TURN	*-2.04*	*-1.88*	*-3.67*	*-3.35*	*-3.24*	*-2.47*	*-3.20*	*-17.51*	*-6.28*	*-2.86*	*-5.15*	*-7.72*	*-7.51*	*-4.46*	*-4.65*
RET	*-0.53*	*-0.89*	*-5.25*	*-7.16*	*-9.22*	*-5.40*	*-1.71*	*1.31*	*-1.70*	*0.96*	*0.38*	*2.61*	*2.09*	*2.31*	*1.98*
N	411	456	488	511	553	541	548	547	549	550	561	567	568	526	472

Table 4

Time-Series Correlation Coefficients between Returns and Order Imbalances around SEOs

This table shows correlation coefficients between the two time series of returns and order imbalances at both daily and monthly horizons. The time series are obtained by cross-sectionally averaging (equal-weighted) the returns and order imbalances of the component stocks for each portfolio over the event window. Panel A contains the results of the SEO-firm portfolio and its SIC/MV-matching portfolio at a daily horizon., while Panel B does the same at a monthly horizon. *Interval [a, b]* means a period from day (month) *a* to day (month) *b* relative to the event date (month). *NOIMB* stands for trade number order imbalances and *DOIMB* for dollar volume imbalances. The number of SEO firms is 777 for Panel A and 586 for Panel B. Under the null hypothesis of zero correlation, asymptotic standard error of the correlation coefficient is $1/\sqrt{N}$, where N is the number of observations (trading days or months) used in computing the correlation coefficients.

Panel A: Daily Horizon

	SEO Firms		SIC/MV-Matching Firms	
Interval	Correlation with NOIMB	Correlation with DOIMB	Correlation with NOIMB	Correlation with DOIMB
[-120, 120]	-0.13	0.46	0.22	0.26
[-120, -1]	0.29	0.18	0.22	0.23
[1, 120]	-0.32	0.18	0.40	0.36

Panel B: Monthly Horizon

	SEO Firms		SIC/MV-Matching Firms	
Interval	Correlation with NOIMB	Correlation with DOIMB	Correlation with NOIMB	Correlation with DOIMB
[-36, 36]	-0.08	0.58	0.31	0.19
[-36, -1]	0.90	0.87	0.46	0.40
[1, 36]	-0.26	0.43	0.38	0.24

Table 5
Time-Series Regressions of Returns on Order Imbalances around SEOs

This table shows the results of time-series regressions of returns on order imbalances and turnover for daily and monthly data as in $RET_t = \varphi_0 + \varphi_1 OIMB_t + \varphi_2 TURN_t + \varepsilon_t$. The time series are obtained by cross-sectionally averaging (equal-weighted) the returns (RET), order imbalances (OIMB), and turnover (TURN) of the component stocks for each portfolio over the event window. Panel A contains the results for the SEO-firm portfolio and its SIC/MV-matching portfolio for the daily horizon. Panel B does the same for the monthly horizon. *Interval [a, b]* means a period from day (month) *a* to day (month) *b* relative to the event date (month). *Const* is an intercept. *NOIMB* stands for trade number order imbalances and *DOIMB* for dollar volume imbalances. The values in the upper row for each interval are coefficients estimated from the regressions over the interval. The values italicized in the lower row of each interval are t-statistics. Coefficients significantly different from zero at the significance levels of 1% , 5%, and 10% are indicated by ***, **, and *, respectively. The number of SEO firms is 777 for Panel A and 586 for Panel B.

Panel A: Daily Horizon Regressions

	SEO Firms						SIC/MV-Matching Firms					
	On NOIMB			On DOIMB			On NOIMB			On DOIMB		
Interval	Const	NOIMB	TURN	Const	DOIMB	TURN	Const	NOIMB	TURN	Const	DOIMB	TURN
[-120, 120]	0.3132 ***	-0.0245 ***	-0.1761 ***	-0.0470	0.0352 ***	0.0728 **	0.3866 ***	0.0218 ***	-1.0104 ***	0.2852 **	0.0184 ***	-0.7359 **
	7.20	*-4.11*	*-3.96*	*-1.56*	*8.04*	*2.09*	*3.39*	*3.98*	*-2.99*	*2.51*	*4.27*	*-2.23*
[-120, -1]	0.4895 ***	0.0438 ***	-1.1230 **	0.4907 **	0.0198 **	-0.9647 **	0.0950	0.0192 **	-0.0228	-0.0088	0.0151 **	0.2642
	2.59	*3.75*	*-2.35*	*2.51*	*2.35*	*-1.97*	*0.64*	*2.42*	*-0.05*	*-0.06*	*2.55*	*0.61*
[1, 120]	0.0788 *	-0.0099 *	0.0262	-0.1112 ***	0.0278 ***	0.1706 ***	0.3228 *	0.0314 ***	-0.9867 **	0.2937 *	0.0229 ***	-0.8926 *
	1.69	*-1.79*	*0.62*	*-4.17*	*5.16*	*5.87*	*1.95*	*4.82*	*-2.07*	*1.73*	*4.23*	*-1.84*

Panel B: Monthly Horizon Regressions

	SEO Firms						SIC/MV-Matching Firms					
	On NOIMB			On DOIMB			On NOIMB			On DOIMB		
Interval	Const	NOIMB	TURN	Const	DOIMB	TURN	Const	NOIMB	TURN	Const	DOIMB	TURN
[-36, 36]	4.5620 ***	0.0479	-0.3780 ***	3.8829 ***	0.4903 ***	-0.3909 ***	3.1770 ***	0.1140 *	-0.2740 **	2.8903 ***	0.0950	-0.2359 **
	4.94	*0.61*	*-3.33*	*5.64*	*7.28*	*-4.92*	*3.75*	*1.82*	*-2.20*	*3.66*	*1.59*	*-2.02*
[-36, -1]	-0.8595	0.7764 ***	0.3237	-3.6902	0.4532 ***	0.7205 *	1.6442	0.3589 ***	-0.0237	-2.5651	0.2601 ***	0.5858
	-0.31	*7.17*	*0.82*	*-1.34*	*6.39*	*1.85*	*0.58*	*2.98*	*-0.06*	*-0.84*	*2.86*	*1.27*
[1, 36]	-0.6125	-0.1073 *	0.1687	1.4067	0.4606 ***	-0.1849	-1.2419	0.3151 ***	0.2586 **	-0.8164	0.1983 *	0.2192
	-0.28	*-1.72*	*0.71*	*0.67*	*2.86*	*-0.80*	*-1.23*	*2.68*	*1.97*	*-0.75*	*1.89*	*1.56*

Table 6

One-Way Sorting: Comparison of the SEO Portfolio that Individual Investors Buy on Net with the SEO Portfolio that Institutional Investors Buy on Net in Period Year 1-Year 2 (Monthly)

This table presents how the SEO portfolio that individual investors buy on net (Panel A) compares to the portfolio that institutional investors buy on net (Panel B) from year 1 to year 2 after the offerings in trade number order imbalances *(NOIMB)*, dollar volume imbalances *(DOIMB)*, turnover *(TURN)*, and returns *(RET)*. It also shows how the characteristics of the issuers (SEO firms) are different from those of the non-issuers (SIC/MV-matching firms). To form an SEO portfolio (P1) for Panel A, the SEO firms whose institutional ownership at year 2 is less than that at year 0 are selected from the total 586 SEO firms. For portfolio P2 in Panel B, the SEO firms whose institutional ownership at year 2 is greater than that at year 0 are selected from the total sample. The number of SEO firms is 174 in Panel A and 290 in Panel B. The upper part contains the cross-sectional means in each interval for the SEO firm portfolios (P1 and P2), while the central part does the same for the SIC/MV-matching portfolios (P1_M and P2_M). The mean values reported in the upper and middle part are computed as in Table 3 in the process of conducting the paired sample t-test using the time-series averages over the interval for individual firms. The lower part exhibits *t*-statistics for the paired sample t-test so that portfolios P1 and P2 can be compared with their SIC/MV-matching portfolios P1_M and P2_M, respectively. Interval *[a, b]* means a period from month *a* to month *b* relative to the event month. *N* is the number of observations used in the paired sample t-test.

	Panel A: For SEO Portfolio Individuals Buy on Net in Year 1-Year 2								**Panel B: For SEO Portfolio Institutions Buy on Net in Year 1-Year 2**							
	Means for SEO Firms (**P1**)								Means for SEO Firms (**P2**)							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB (%)	1.093	2.317	4.202	3.740	-1.309	5.555	8.020	2.352	-0.849	0.781	3.175	2.165	-4.924	0.534	2.896	1.934
DOIMB (%)	0.856	3.178	6.077	6.197	0.203	3.099	2.503	1.979	-1.138	1.501	3.683	5.165	-3.867	3.111	0.772	1.553
TURN (%)	7.252	8.170	7.955	8.101	16.941	10.932	10.102	9.760	6.400	6.657	6.300	6.333	13.768	8.332	7.325	8.056
RET (%)	1.676	2.498	5.093	3.246	2.592	0.959	-0.608	-0.329	1.268	2.451	4.446	2.275	1.103	3.030	1.440	0.944
	Means for Non-issuer SIC/MV-matching Firms (**P1_M**)								Means for Non-issuer SIC/MV-matching Firms (**P2_M**)							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB (%)	0.918	0.725	0.023	0.875	1.872	2.264	0.803	0.309	-0.716	0.251	0.720	1.642	1.321	0.950	0.531	0.675
DOIMB (%)	0.628	1.957	0.678	-0.075	2.942	2.079	1.752	1.901	0.016	1.236	1.542	1.231	1.476	2.207	0.838	1.074
TURN (%)	6.718	5.952	6.294	6.793	6.732	6.621	6.857	8.080	6.275	6.400	6.038	6.040	6.194	5.821	6.454	7.015
RET (%)	1.639	*1.620*	1.668	0.637	1.898	0.784	1.343	1.204	1.543	1.548	2.191	2.105	1.259	1.146	1.024	0.978
	T-statistics for the Paired-Sample T Test								T-statistics for the Paired-Sample T Test							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB	*-0.14*	*-1.61*	*-4.16*	*-1.84*	*2.29*	*-1.98*	*-8.10*	*-2.46*	*0.41*	*-1.00*	*-2.83*	*-0.53*	*4.35*	*0.12*	*-3.71*	*-1.93*
DOIMB	*-0.68*	*-0.89*	*-5.24*	*-3.25*	*1.47*	*-0.33*	*-1.03*	*-0.45*	*1.57*	*-0.39*	*-2.21*	*-2.69*	*3.09*	*-1.09*	*0.07*	*-1.00*
TURN	*-1.97*	*-3.63*	*-3.35*	*-1.98*	*-10.43*	*-5.41*	*-5.71*	*-2.82*	*-0.69*	*-0.79*	*-0.63*	*-0.60*	*-13.18*	*-5.58*	*-2.57*	*-2.79*
RET	*-0.52*	*-2.24*	*-7.87*	*-2.18*	*-0.78*	*-0.02*	*6.63*	*3.94*	*1.12*	*-3.40*	*-8.07*	*-0.10*	*0.49*	*-2.59*	*-2.00*	*0.03*
N	136	152	164	164	164	163	172	162	222	245	273	270	269	270	283	272

Table 7
One-Way Sorting: Time-Series Correlation Coefficients between Returns and Order Imbalances for the SEO Portfolio that Individual Investors Buy on Net and for the SEO Portfolio that Institutional Investors Buy on Net in Period Year 1-Year 2 (Monthly)

This table shows correlation coefficients between the two time series of returns and order imbalances for monthly data. The time series are obtained by cross-sectionally averaging (equal-weighted) the returns and order imbalances of the component stocks for each portfolio over the event window. Panel A contains the results for the SEO-firm portfolio that individual investors buy on net in period year 1-year 2 (P1), while Panel B does the same for the SEO portfolio that institutional investors buy on net (P2). Panels A and B also include the results for the corresponding SIC/MV-matching portfolios (P1_M and P2_M). The number of SEO firms is 174 in Panel A and 290 in Panel B. *Interval [a, b]* means a period from month *a* to month *b* relative to the event month. *NOIMB* stands for trade number order imbalances and *DOIMB* for dollar volume imbalances. Under the null hypothesis of zero correlation, asymptotic standard error of the correlation coefficient is $1/\sqrt{N}$, where N is the number of observations (months).

	Panel A: SEO Portfolio Individuals Buy		**Panel B: SEO Portfolio Institutions Buy**	
Interval	Correlation with NOIMB	Correlation with DOIMB	Correlation with NOIMB	Correlation with DOIMB
	P1: SEO Firms		**P2**: SEO Firms	
[-36, 36]	-0.25	0.51	0.23	0.56
[-36, -1]	0.81	0.75	0.83	0.78
[1, 36]	-0.19	0.47	0.21	0.34
	P1_M: SIC/MV-matching Firms		**P2_M**: SIC/MV-matching Firms	
[-36, 36]	0.21	0.19	0.28	0.13
[-36, -1]	0.25	0.34	0.40	0.40
[1, 36]	0.27	0.28	0.36	0.29

Table 8

One-Way Sorting: Time-Series Regressions of Returns on Order Imbalances for the SEO Portfolio that Individual Investors Buy on Net and for the SEO Portfolio that Institutional Investors Buy on Net in Period Year 1-Year 2 (Monthly)

This table shows the results of time-series regressions of returns on order imbalances and turnover for monthly data as in $RET_t = \varphi_0 + \varphi_1 OIMB_t + \varphi_2 TURN_t + \varepsilon_t$. The time series are obtained by cross-sectionally averaging (equal-weighted) the returns (RET), order imbalances (OIMB), and turnover (TURN) of the component stocks for each portfolio over the event window. Panel A contains the results for the SEO-firm portfolio that individual investors buy on net in period year 1-year 2 (P1), while Panel B does the same for the SEO portfolio that institutional investors buy on net (P2). Panels A and B also include the results for the corresponding SIC/MV-matching portfolios (P1_M and P2_M). The number of SEO firms is 174 in Panel A and 290 in Panel B. *Interval [a, b]* means a period from month *a* to month *b* relative to the event month. *Const* is an intercept. *NOIMB* stands for trade number order imbalances and *DOIMB* for dollar volume imbalances. The values in the upper row for each interval are coefficients estimated from the regressions over the interval. The values italicized in the lower row of each interval are t-statistics. Coefficients significantly different from zero at the significance levels of 1% , 5%, and 10% are indicated by ***, **, and *, respectively.

	Panel A: SEO Portfolio Individuals Buy on Net						**Panel B: SEO Portfolio Institutions Buy on Net**					
	P1: SEO Firms						**P2**: SEO Firms					
	On NOIMB			On DOIMB			On NOIMB			On DOIMB		
Interval	Const	NOIMB	TURN	Const	DOIMB	TURN	Const	NOIMB	TURN	Const	DOIMB	TURN
[-36, 36]	5.1920 ***	-0.0624	-0.4443 ***	4.7466 ***	0.5384 ***	-0.5621 ***	3.3883 ***	0.1657 **	-0.2668 **	3.0257 ***	0.3345 ***	-0.2268 **
	4.00	*-0.71*	*-2.80*	*4.66*	*6.18*	*-4.92*	*4.06*	*2.31*	*-2.28*	*4.24*	*5.81*	*-2.29*
[-36, -1]	-6.9542 ***	0.5895 ***	1.1544 ***	-8.2274 ***	0.2771 ***	1.3805 ***	3.0266	0.6503 ***	-0.1563	2.0157	0.4335 ***	-0.0180
	-2.82	*4.31*	*3.23*	*-3.08*	*3.25*	*3.62*	*1.05*	*8.33*	*-0.34*	*0.63*	*7.02*	*-0.04*
[1, 36]	3.0743	-0.0421	-0.3320	3.6792	0.5325 ***	-0.5372 *	-0.5761	0.2189 *	0.1709	2.2899	0.2874 **	-0.1814
	0.92	*-0.74*	*-0.96*	*1.32*	*3.46*	*-1.90*	*-0.28*	*1.93*	*0.69*	*1.19*	*2.14*	*-0.70*
	P1_M: SIC/MV-matching Firms						**P2_M**: SIC/MV-matching Firms					
	On NOIMB			On DOIMB			On NOIMB			On DOIMB		
Interval	Const	NOIMB	TURN	Const	DOIMB	TURN	Const	NOIMB	TURN	Const	DOIMB	TURN
[-36, 36]	2.3914 **	0.1785 *	-0.1741	3.0927 ***	0.1570 **	-0.2919 *	4.4040 ***	0.1381 *	-0.4761 **	4.5857 ***	0.1056 *	-0.5181 ***
	2.50	*1.85*	*-1.24*	*3.14*	*2.29*	*-1.95*	*3.62*	*1.69*	*-2.50*	*3.91*	*1.77*	*-2.82*
[-36, -1]	0.0591	0.1919 *	0.2154	-1.1198	0.1915 **	0.3952	3.2022	0.2279 **	-0.2339	2.7318	0.2030 **	-0.1868
	0.02	*1.88*	*0.55*	*-0.47*	*2.25*	*1.05*	*1.10*	*2.48*	*-0.50*	*0.93*	*2.45*	*-0.40*
[1, 36]	1.0905	0.2471 *	-0.0163	2.3146	0.2493 *	-0.2328	0.4206	0.2037 **	0.0600	0.8193	0.1166 *	0.0084
	0.63	*1.91*	*-0.07*	*1.39*	*1.92*	*-0.97*	*0.39*	*2.20*	*0.37*	*0.73*	*1.71*	*0.05*

Table 9

Two-Way Sorting: Comparison of the Small-sized SEO Portfolio that Individual Investors Buy on Net with the Large-sized SEO Portfolio that Institutional Investors Buy on Net in Period Year 1-Year 2 (Monthly)

This table presents how the small-sized SEO portfolio that individual investors buy on net (Panel A) compares to the large-sized SEO portfolio that institutional investors buy on net (Panel B) from year 1 to year 2 after the offerings in trade number order imbalances *(NOIMB)*, dollar volume imbalances *(DOIMB)*, turnover *(TURN)*, and returns *(RET)*. It also shows how the characteristics of the issuers (SEO firms) are different from those of the non-issuers (SIC/MV-matching firms). The 586 SEO firms are first sorted by the market value of month 0 in ascending order and split into the two groups. Then the SEO firms whose institutional ownership at year 2 is less than that at year 0 are selected from the smaller-sized group to form a portfolio (P3) for Panel A. For portfolio P4 in Panel B, the SEO firms whose institutional ownership at year 2 is greater than that at year 0 are selected from the larger-sized group. The number of SEO firms is 138 in Panel A and 136 in Panel B. The upper part contains the cross-sectional means in each interval for the SEO firm portfolios (P3 and P4), while the central part does the same for the SIC/MV-matching portfolios (P3_M and P4_M). The mean values reported in the upper and middle part are computed as in Table 3 in the process of conducting the paired sample t-test using the time-series averages over the interval for individual firms. The lower part exhibits *t*-statistics for the paired sample t-test so that P3 and P4 can be compared with P3_M and P4_M, respectively. Interval *[a, b]* means a period from month *a* to month *b* relative to the event month. *N* is the number of observations used in the paired sample t-test.

	Panel A: For Small-sized SEO Portfolio Individuals Buy in Year 1-Year 2							
	Means for SEO Firms (**P3**)							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB (%)	-0.443	-0.950	2.898	3.413	-4.077	3.531	6.790	0.772
DOIMB (%)	-2.639	-1.554	1.755	4.296	-5.214	0.447	0.165	-0.541
TURN (%)	8.268	8.040	8.193	8.489	18.996	14.372	10.896	9.805
RET (%)	0.712	2.423	6.104	2.982	-1.334	-0.363	-0.851	0.006
	Means for Non-issuer SIC/MV-matching Firms (**P3_M**)							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB (%)	-1.976	-2.420	-2.028	-0.400	0.935	-1.117	0.211	-1.968
DOIMB (%)	-2.628	-1.720	-1.267	-3.447	1.605	-2.187	-0.086	-2.292
TURN (%)	7.185	5.841	6.093	6.691	6.510	6.162	6.550	7.691
RET (%)	0.932	*1.059*	2.092	0.763	3.496	0.910	1.094	1.851
	T-statistics for the Paired-Sample T Test							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB	*-1.00*	*-1.14*	*-4.02*	*-1.94*	*2.73*	*-2.16*	*-6.48*	*-2.01*
DOIMB	*0.50*	*-0.05*	*-2.36*	*-2.80*	*2.85*	*-0.70*	*-0.23*	*-1.31*
TURN	*-1.95*	*-2.70*	*-3.34*	*-2.18*	*-11.15*	*-3.63*	*-5.72*	*-3.55*
RET	*0.13*	*-2.45*	*-6.13*	*-1.36*	*3.61*	*1.15*	*5.22*	*2.77*
N*	97	111	126	125	128	125	134	102

	Panel B: For Large-sized SEO Portfolio Institutions Buy in Year 1-Year 2							
	Means for SEO Firms (**P4**)							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB (%)	0.645	2.018	4.788	3.849	-1.463	1.053	3.270	1.852
DOIMB (%)	2.859	4.419	5.085	6.211	0.214	6.854	3.684	3.995
TURN (%)	5.977	6.726	6.162	5.898	11.816	7.289	7.180	8.276
RET (%)	1.308	2.926	3.990	2.901	3.451	2.003	1.084	0.911
	Means for Non-issuer SIC/MV-matching Firms (**P4_M**)							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB (%)	1.374	1.348	2.022	1.829	2.977	3.659	2.622	2.387
DOIMB (%)	3.003	4.106	3.808	1.609	3.136	6.529	3.523	4.853
TURN (%)	6.691	7.051	6.857	6.520	6.849	6.719	7.051	7.744
RET (%)	1.887	1.785	2.385	2.317	1.392	3.004	1.250	1.622
	T-statistics for the Paired-Sample T Test							
Item	[-36, -19]	[-18, -9]	[-8, -2]	-1	0	1	[2, 18]	[19, 36]
NOIMB	*0.48*	*-0.37*	*-2.15*	*-1.14*	*2.83*	*1.60*	*-0.67*	*0.55*
DOIMB	*0.20*	*-0.15*	*-0.85*	*-2.67*	*1.81*	*-0.49*	*-0.18*	*1.18*
TURN	*1.18*	*0.16*	*1.46*	*1.30*	*-7.24*	*-2.07*	*-1.78*	*-1.84*
RET	*2.71*	*-2.95*	*-4.54*	*-0.59*	*-1.59*	*1.06*	*0.57*	*1.75*
N*	108	117	129	125	124	124	134	130

Table 10

Annual Levels and Changes in Institutional Ownership and Analysts around SEOs for SEO Groups and Non-issuer Groups

Panel A documents the annual average levels of institutional ownership (IO) and the number of analysts (NOANA) around SEOs for the SEO groups (portfolios P1 - P4) and non-issuer control groups (portfolios P1_M - P4_M) considered in Section IV. Panel B tests whether the change in IO between year 0 and year 2 (dIO) for each portfolio is different from zero, while Panel C presents the results of paired sample t-tests whether the change in IO between year 0 and year 2 of an SEO group is different from that of a corresponding non-issuer control group. *dIO* in Panel B means the IO level in year 2 less the IO level in year 0 ($dIO = IO_2 - IO_0$). *dIO difference* in Panel C means dIO of an SIV/MV-matching firm minus dIO of an SEO firm. The definitions of P1 - P4 and P1_M - P4_M are the same as described in Tables 6 and 9.

Panel A: Annual Levels in IO and NOANA around SEO

	SEO Firms						SIC/MV-Matching Firms					
year	-3	-2	-1	0	1	2	-3	-2	-1	0	1	2
	P1						P1_M					
IO (%)	46.42	46.73	49.35	60.62	56.80	49.42	52.64	53.35	52.68	53.93	53.83	53.09
NOANA	14.03	13.44	12.79	14.14	15.07	14.89	15.22	14.44	14.12	14.55	13.95	13.98
	P2						P2_M					
IO (%)	42.04	42.87	42.89	50.00	58.21	61.88	50.30	51.05	51.28	53.21	53.29	53.99
NOANA	13.49	12.74	12.24	13.27	14.00	14.80	13.05	12.88	12.86	12.93	13.32	13.43
	P3						P3_M					
IO (%)	41.80	40.15	39.98	55.49	51.66	42.58	49.38	47.43	47.94	49.34	49.23	48.07
NOANA	7.69	7.37	6.52	8.14	8.36	7.83	8.39	8.32	7.63	7.40	6.98	7.48
	P4						P4_M					
IO (%)	49.81	49.29	49.22	55.32	61.88	64.86	60.15	60.25	60.97	61.95	62.90	62.23
NOANA	18.66	17.56	16.84	18.22	18.81	19.53	18.01	18.03	17.50	17.80	18.45	18.88

Panel B: T-Test for Null Hypothesis H0: $\mu_{dIO} = 0$

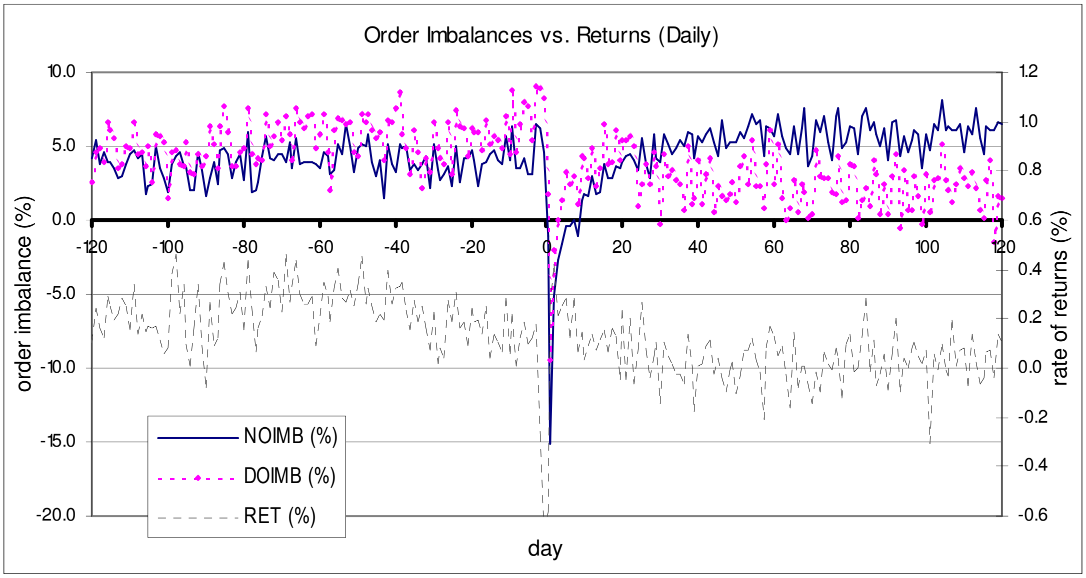
item	P1	P1_M	P2	P2_M	P3	P3_M	P4	P4_M
mean of dIO	-11.1947	-0.8326	11.8862	0.7825	-12.9183	-1.2727	9.5433	0.2877
t	*-10.10*	*-0.10*	*17.45*	*1.38*	*-7.10*	*-0.25*	*12.11*	*0.92*

Panel C: Paired Sample T-Test for Null Hypothesis H0: $\mu_{dIO}^{SIC/MV} - \mu_{dIO}^{SEO} = 0$

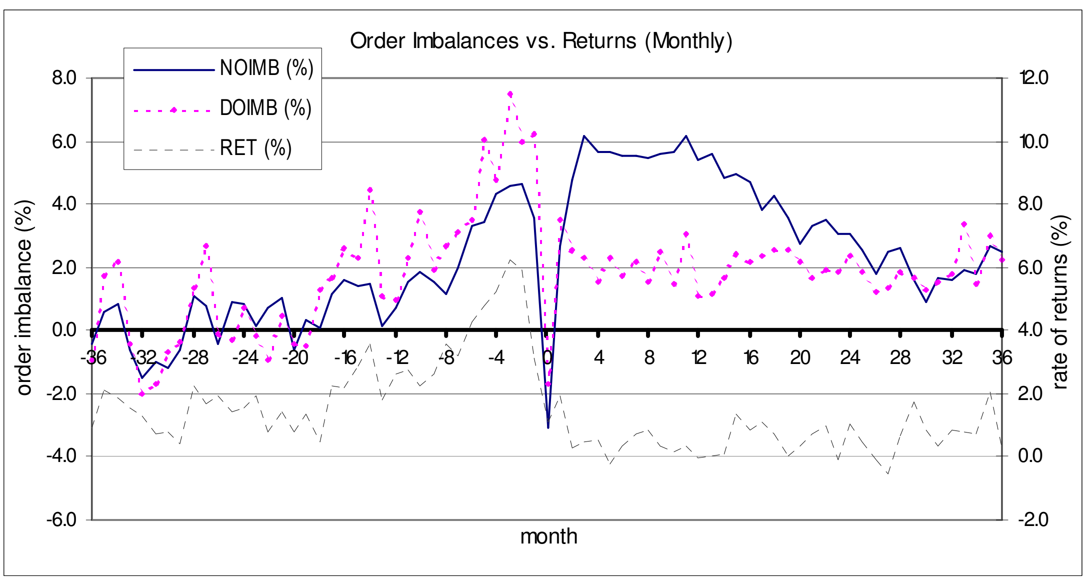
item	P1 vs. P1_M	P2 vs. P2_M	P3 vs. P3_M	P4 vs. P4_M
mean of dIO differences	12.0306	-11.4539	12.2174	-9.2398
t	*6.10*	*-9.31*	*5.34*	*-5.74*

Figure 1
Order Imbalances vs. Returns around SEOs

The following graphs plot the values of our key variables around the event date or month for the SEO firm portfolios at a daily horizon in Figure 1(A) and at a monthly horizon in Figure 1(B) over the event windows. The definitions of variables are: trade number order imbalances *(NOIMB)*, dollar volume imbalances *(DOIMB)*, and returns *(RET)*. The numbers of sample firms are 777 at a daily horizon and 586 at a monthly horizon. The sample periods are from July 1988 to June 2002 at a daily horizon, and January 1989 to December 2001 at a monthly horizon.



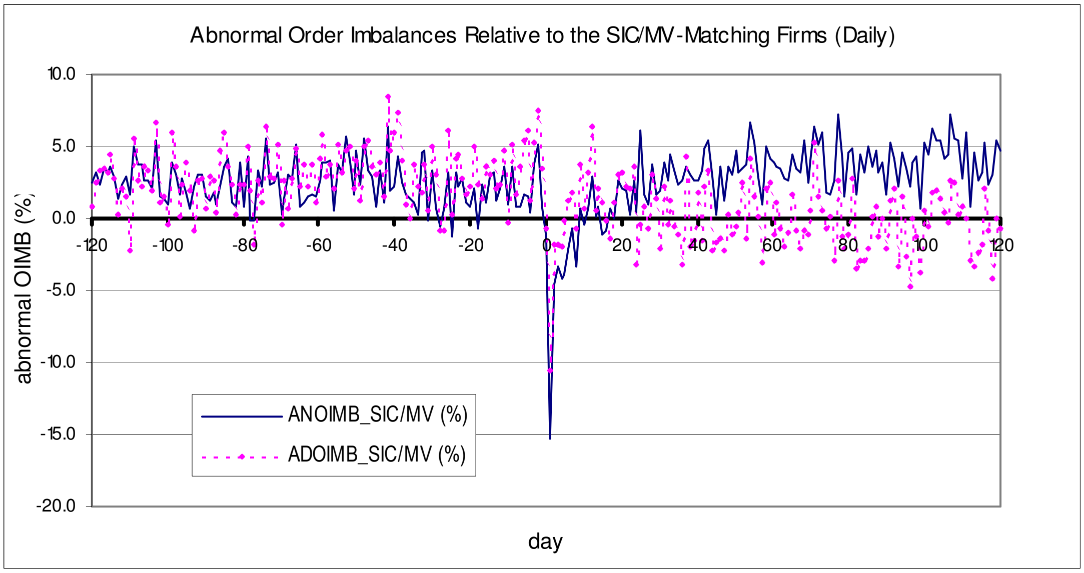
(A) Daily



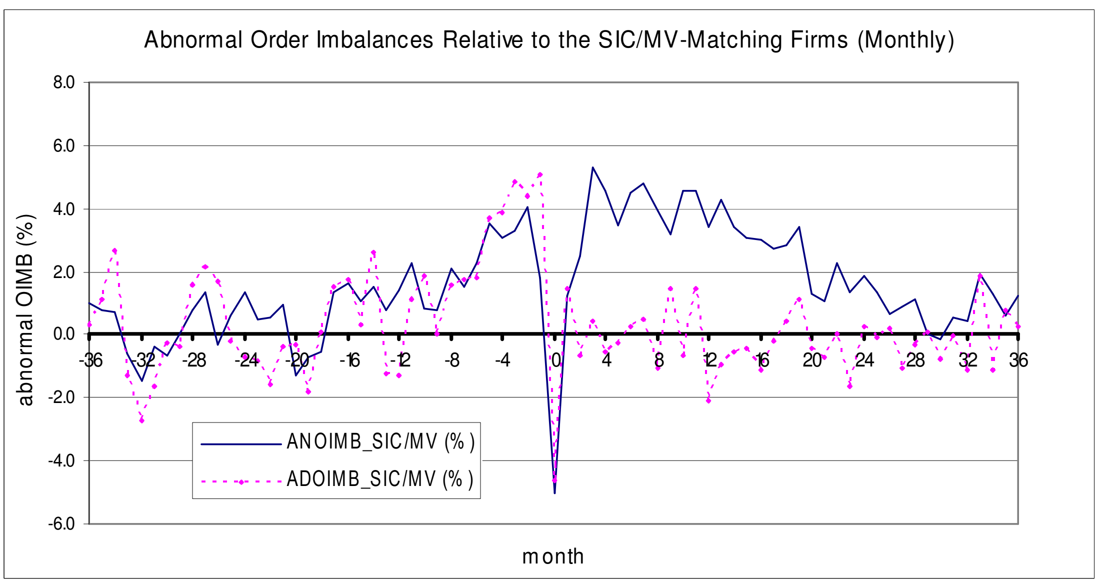
(B) Monthly

Figure 2
Abnormal Order Imbalances Relative to the SIC/MV-matching Benchmark Portfolios

The following graphs plot the values of abnormal trade-number order imbalances (ANOIMB) and abnormal dollar-value imbalances (ADOIMB) around the event date or month for the SEO firm portfolios at a daily horizon in Figure 7(A) and at a monthly horizon in Figure 7(B) over the event windows. ANOIMB are computed by subtracting the trade-number order imbalances (NOIMB) of the SIC/MV-matching benchmark portfolio from those of the SEO portfolio for each horizon. Similarly, DNOIMB are computed by subtracting the dollar-value order imbalances (DOIMB) of the SIC/MV-matching benchmark portfolio from those of the SEO portfolio for each horizon. The numbers of sample firms are 777 at a daily horizon and 586 at a monthly horizon. The sample periods are from July 1988 to June 2002 at a daily horizon, and January 1989 to December 2001 at a monthly horizon.



(A) Daily Abnormal Order Imbalances

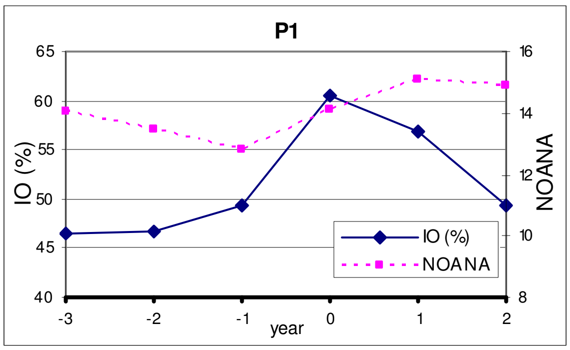


(B) Monthly Abnormal Order Imbalances

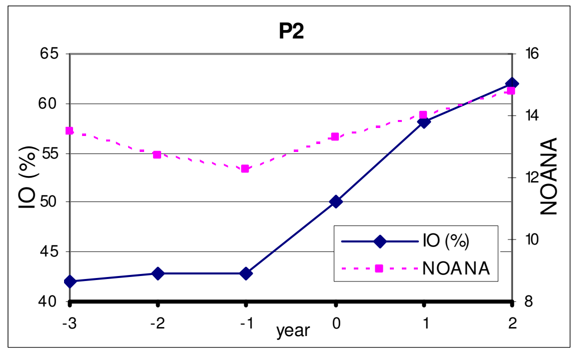
Figure 3
Institutional Ownership and the Number of Analysts for Portfolios P1-P4 (Yearly)

Figure (A) plots the values of institutional ownership (IO) and the number of analysts (NOANA) for the SEO portfolio that individual investors buy on net in Year 1-Year 2 (P1), and Figure (B) does the same for the SEO portfolio that institutional investors buy on net in Year 1-Year 2 (P2). Figure (C) plots IO and NOANA for the small-sized SEO portfolio that individual investors buy on net in Year 1-Year 2 (P3), and Figure (D) does the same for the large-sized SEO portfolio that institutional investors buy on net in Year 1-Year 2 (P4). IO (a solid, diamond-noded line) is measured on the left-hand scale (in %), while NOANA (a dotted, square-noded line) is measured on the right-hand scale. The numbers of observations are 174 for P1, 290 for P2, 138 for P3, and 136 for P4.

1) One-Way Sorted Portfolios

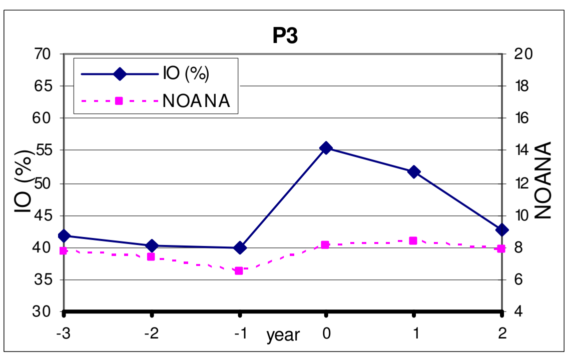


(A) **P1**: SEO Portfolio that Individuals Buy in Year 1-Year 2

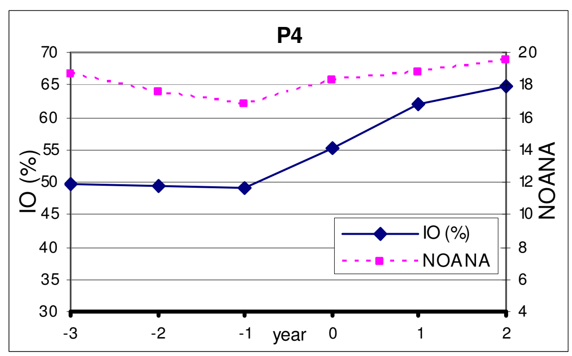


(B) **P2**: SEO Portfolio that Institutions Buy in Year 1-Year 2

2) Two-Way Sorted Portfolios



(C) **P3**: Small-Sized SEO Portfolio that Individuals Buy in Year 1-Year 2

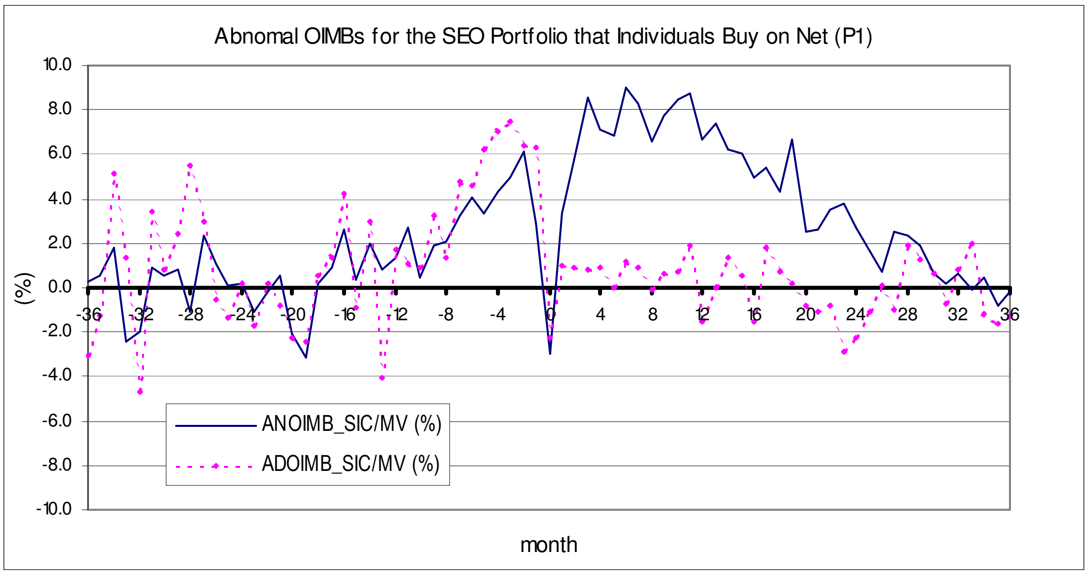


(D) **P4**: Large-Sized SEO Portfolio that Institutions Buy in Year 1-Year 2

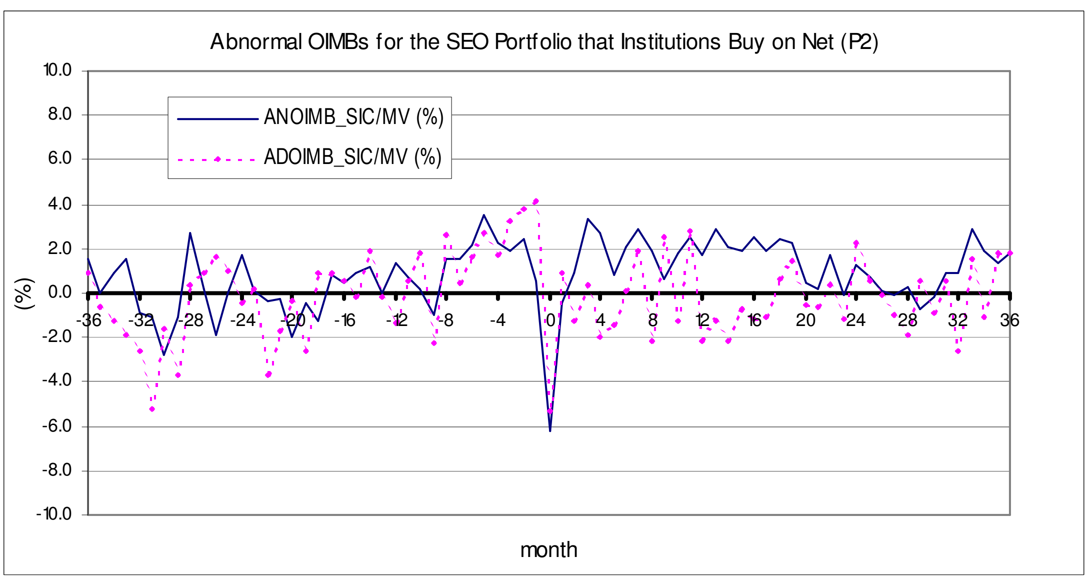
Figure 4

One-Way Sorting: Abnormal Order Imbalances for the SEO Portfolio Individual Investors Buy on Net and for the SEO Portfolio Institutional Investors Buy on Net in Period Year 1–Year 2

The following graphs plot the values of abnormal trade-number order imbalances (ANOIMB) and abnormal dollar-value imbalances (ADOIMB) around the event month for the two SEO firm portfolios sorted by institutional ownership. To form portfolio P1 for Figure A1(A), the SEO firms whose institutional ownership at year 2 is less than that at year 0 are selected from the total 586 SEO firms. To form portfolio P2 for Figure A1(B), the SEO firms whose institutional ownership at year 2 is greater than that at year 0 are selected from the total sample. Also the two corresponding SIC/MV-matching portfolios (P1_M and P2_M) are constructed using the total SIC/MV-matching sample firms. ANOIMB are then computed by subtracting the trade-number order imbalances (NOIMB) of the SIC/MV-matching benchmark portfolio from those of the SEO portfolio. Similarly, DNOIMB are computed by subtracting the dollar-value order imbalances (DOIMB) of the SIC/MV-matching benchmark portfolio from those of the SEO portfolio. The numbers of SEO firms are 174 in P1 and 290 in P2.



(A) Abnormal OIMBs for the SEO Portfolio that Individual Investors Buy on Net in Year 1-Year2 (**P1**)



(B) Abnormal OIMBs for the SEO Portfolio that Institutional Investors Buy on Net in Year 1-Year2 (**P2**)