The Effect of Investor Attention on the Pricing of Seasoned Equity Offerings

Cristian A. Pinto*

This draft: February, 2015

Abstract

I investigate the role of investor attention on seasoned equity offerings' (SEOs) outcomes. I use an archive of *Thomson Reuters'* news articles and third-party newswires to proxy for investor attention. I find that the volumes of news articles prior to the offerings are positively associated with the offer price discounts of SEOs. Furthermore, the volumes of news articles are negatively associated with the cumulative abnormal returns three days around the SEOs. I conclude that the costs of equity increase with the frequency of news stories prior to SEOs. Overall, the evidence is consistent with the hypothesis that investor attention contributes to the efficiency of the stock market and affects investors' information processing in SEOs.

Keywords: Investor attention, seasoned equity offerings, news analytics.

* Ph.D. Candidate in Finance, A.B. Freeman School of Business, Tulane University, cpintogu@tulane.edu.

1. Introduction

Investors' limited attention is an important concept to understand the behavior of financial markets (e.g., market trends and cycles). Attention is a scarce cognitive resource (Kahneman, 1973), and investors cannot maintain perfect attentiveness to all trading opportunities (Duffie, 2010). A large body of financial literature has already demonstrated how investors' attention constraints affect financial markets (e.g., Merton, 1987; Barber and Odean, 2008; Fang and Peress, 2009; Hirshleifer, Lim, and Teoh, 2011). This previous research has focused primarily on the effect that investors' limited attention has on stock returns and trading volumes. Meanwhile, as scholars pursue this line of inquiries, the role that investor attention has on corporate actions remains largely unexplored.

In this article, I use recent advances in news analytics to examine the effect of investor attention on both the pricing and returns of seasoned equity offerings (SEOs).[1] I provide evidence that investor attention may explain part of observed empirical irregularities in the SEO market. These anomalies include high SEO offer price discounts, negative short-term abnormal returns, and negative long-run stock performance.

Theoretical and empirical papers have provided different explanations for these negative SEO effects. Scholars propose that the explanations for SEO discounts include compensation to investors for uncertainties regarding the value of issuers, price pressure effects, agency problems between underwriters and firms, and underwriters' price practices, among others (e.g., Corwin, 2003). Meanwhile, scholars most frequently cite two explanations for the negative market reaction to SEOs. They point to the adverse selection

[1] Practitioners generally use the term "follow-on" equity offerings.

problem of Myers and Majluf (1984), where rational investors interpret an equity issuance to be management's signal that the stock is overvalued, and they also note the theoretical arguments of Jung, Kim, and Stulz (1996) that suggest that investors react negatively to SEOs because they are concerned about the misuse of the proceeds.

Several studies have also shown that issuers can reduce these negative effects associated with SEOs by using marketing efforts to capture investors' attention and expand their investor base prior to the offerings. To measure the effects that investor attention has on the issuers' short-run demand curves, these studies employ several proxies for investor attention. For example, to measure underwriters' marketing efforts, Gao and Ritter (2010) use the issuing firms' offer method choices (accelerated SEOs or fully marketed SEOs), and Huang and Zhang (2011) use the number of underwriters for the SEOs. Meanwhile, to measure the attention of retail (or individual) investors, Lu, Holzhauer, and Wang (2014) use the pre-issue search frequency tool in Google. Overall, these studies conclude that investor attention and offer price discounts substitute for each other.

In this article, I explore a new measure of investor attention and find contrasting results. To measure investor attention, I calculate the amount of firm-specific news items in a recently developed news analytics product called *Thomson Reuters News Analytics* (TRNA). TRNA is a machine readable service that contains all news that Reuters or the represented companies themselves publish (via newswire services) from January 2003 onwards. The advantage of this dataset is that it contains news articles and press releases that have appeared on the screens of traders; therefore, it may be a better and more direct source of data to proxy for the information arrival rates to professional traders than other news databases. It should also be superior to indirect measures that previous literature has used to measure attention.

I begin my investigation by examining whether investor attention prior to SEOs is significantly associated with SEO discounts (defined as negative returns from the previous day's closing transaction prices to the offer prices). I find that the number of news articles 90 days prior to the SEOs offer dates positively impacts discounting levels. Barber and Odean (2008) argue that individual investors are net buyers of attention-grabbing stocks; thus, individual investor attention results in temporary price pressure. My findings suggest that firms do not fully incorporate this price pressure into their offer prices. To explain this result, I propose a simple model. The model setting assumes that firms need to compensate institutional investors for the large negative market reactions to SEOs investors expect when the firms make the offers public. In my model, institutions act as specialists, and they resell all or a fraction of their allocation of shares to retail investors in the after-market. If retail investors are paying close attention to companies' information prior to the offerings, their reactions will be strongest when firms issue new equity and thereby, firms' managers signal that the stocks are overvalued. Therefore, to entice institutional investors into the market for the SEOs, issuers will have to set low offer prices, resulting in high offer price discounts.

Next, I study the reactions of the market to SEOs and explore how these reactions relate to the degree of investor attention prior to the offerings. Consistent with my investor attention explanation for the pricing of SEOs, I find that the cumulative abnormal returns over the interval of (-1 to +1) days around the issuances are statistically and negatively related to the number of news articles 90 days prior to the offerings. This result indicates that firms with high levels of investor attention that offer new equity experience a large decline in their stock prices at the issuances.

I also examine the long-run stock performance of issuers. Although I find some evidence that the cumulative abnormal returns in the year following the issuances are most negative for stocks associated with the lowest pre-issue firm-specific volumes of news articles, these results appear to be sensitive to the weighting scheme (equal or value-weighted portfolios) I use to calculate average abnormal returns.

I perform several robustness checks of my previous findings. Because a number of unobservable firm characteristics can simultaneously drive both the volume of news articles and SEO outcomes, I use an instrumental variable (IV) approach with two instruments to mitigate endogeneity concerns. The first instrument uses a measure of the degree of distraction of media outlets because some exogenous events in other industries may have shifted overall attention away from the firm that is issuing new equity. More specifically, I measure media distraction as the daily volume of negative news articles in non-related industries, across all 12 Fama-French industries, 90 days prior to the offerings. The second instrument uses an indicator variable for companies in industries that historically have faced high litigation risks. These companies may prefer to minimize information disclosure because regulators might perceive them to be misleading investors, or alternatively these firms may be forthcoming with disclosures to avoid having regulators accuse them of withholding information. Overall, my primary findings remain robust after I use the IV approach to control for endogeneity concerns.

I contribute to the financial literature in the following ways. First, I augment the vast literature on behavioral finance by introducing and testing a firm-specific measure of investor attention by employing a novel database of news articles from a news analytics provider. Second, I contribute to the sparse literature that examines the effects of investor attention in corporate events (e.g., Ahern and Sosyura, 2014; Kempf, Manconi, Spalt 2014; Liu, Sherman, Zhang, 2014). Third, I contribute to the growing literature on the media and its influence in stock prices (e.g., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Fang and Peress, 2009; Peress, Forthcoming). In contrast to previous literature that uses news articles published in major newspapers, I focus on the firm-specific public news that professional traders receive in real time.

I structure the remainder of the paper as follows. Section 2 provides a literature review. Section 3 develops the hypotheses. Section 4 presents the data sets that I use in the empirical analysis. Section 5 describes the econometric methodology and measures for investor attention and control variables, and establishes the key empirical results. The last section contains a summary and concluding remarks.

2. Related Literature

Among the sparse literature on the effects of investor attention on SEO outcomes, the overall conclusion seems to be that investor attention prior to issuances flattens the short-run demand curve for the issuing firm's stock, thereby reducing the adverse effects of SEOs. For instance, Gao and Ritter (2010) use the issuing firms' offer method choices (accelerated SEOs or fully marketed SEOs) to study the effects that underwriting marketing efforts prior to issuances have on the issuers' short-run demand curves. They find that the demand elasticity prior to the offers and the offer sizes are important determinants of the offer method choices. They conclude that marketing effort and offer price discount often substitute for each other.

Huang and Zhang (2011) also support this hypothesis that marketing efforts can lower the offer price discounts by flattening the demand curves of SEOs. These authors find that the number of underwriters of SEOs are negatively related to the offer price discounts, especially when the relative offer sizes are large and the stock return volatilities are high.

Lu et al. (2014) present more direct evidence for the effects of investor attention on SEOs. To proxy for investor attention, they use the user search frequency index from Google Insight for Search (GIS), a service that tracks the search frequency for every Google search engine user on a daily basis. They find that an increase in the pre-issue GIS index change is negatively related to the offer price discount.

The study in this paper appears to be the first work to document the effects that investor attention, measured by the volume of news articles, have on SEO outcomes. One study that takes a similar approach is the Ph.D. dissertation of Sun (2013), who investigates the effects of media coverage on SEOs in the U.K. Sun (2013) finds that the number of news articles and the tone of the news are negatively related to the SEOs' offer price discounts. I differ from Sun (2013) in that my empirical investigation is on a sample of U.S. firms. Also, Sun's (2013) research focuses on news articles that have appeared in major newspapers. In contrast, I sample a Thomson Reuters's database that collects all forms of news that Reuters or the represented firms themselves publish. This dataset presents the news exactly as it has appeared on the screens of traders. Thus, I believe this data represents an improved proxy over newspapers articles because the Thomson Reuters database tracks the arrival rate of firm-specific public information that goes directly to professional traders.

Finally, my empirical results contradict those of Gao and Ritter (2010), Huang and Zhang (2011), and Lu et al. (2014). They find that increased investor attention prior to the SEOs arises out of additional underwriters' marketing efforts, flattens the demand curves of the issuers, and thereby decreases the offer price discounts. In contrast, I find that high levels of pre-SEO investor attention are positively related to the offer price discounts. I hypothesize that this result is consistent with a model where the offer price discounts appear as compensation to institutional investors. These discounts compensate investors for the large negative reactions to the SEOs that they expect when reselling their shares to retail investors that were more attentive to management's signals that the stocks were overvalued. Moreover, for my sample of SEOs, I do not find a significant relationship between the numbers of managing underwriters that authors use to measure marketing efforts and the volume of news articles prior to the offerings.

3. Hypotheses Development

Merton (1987) developed the first theoretical approach to model the role of investor attention in financial markets. In his paper, he proposes a model of capital market equilibrium with incomplete information where an investor obtains information on only a subset of all available securities. By modifying the Sharpe-Lintner-Mossin Capital Asset Pricing Model (CAPM), Merton demonstrates that the return of a stock depends on the proportion of investors who are aware of the stock. For example, a firm with a small investor base will have higher returns than a firm with a large investor base. Merton further demonstrates that if a firm contemplates increasing its scale of investment, then the expected returns that its current investors will demand will increase with the amount of investment, and the magnitude of this increment for investors' required expected returns will be relatively high for firms with small investor bases. As Merton noted, his model provides researchers with characteristics to determine the firm's stock price response to changes in the supply of its shares. Thus, securities of firms with low investor recognition will face significantly downward-sloping demand curves.

We can obtain predictions similar to Merton's (1987) from Duffies' (2010) Inattentive Investment Hypothesis. The underlying assumption of Duffie's (2010) model is that some fraction of investors are inattentive for a number of periods after each trade. This behavior occurs because paying attention to trading opportunities is costly; therefore, a proportion of investors trade only sporadically. The remaining fraction of investors trades in every period, but these investors are risk averse and have only limited capital. Therefore, when an equity supply shocks arrives, for instance a shock that comes from an SEO, only a limited set of investors will be available to absorb it. The smaller the number of available investors, the higher the price concessions that firms that are issuing equity must offer to compensate investors for their immediacy and also reward them for the inventory risk they hold over time until inattentive investors become available and allow them to unwind their positions.

Duffie's (2010) model predicts a price decline on the day a firm issues an SEO (price must decline to provide incentive for available investors to absorb the supply shock). The magnitude of this price drop will be positively related to investors' inattention and their degrees of risk aversion. Furthermore, Duffie's (2010) model predicts that sometime after the offering, the price must reverse and rise to compensate investors who absorbed the initial equity supply shock. This prediction implies that the degree of investors' inattention prior to an SEO will also affect the long-term market reaction to the SEO.

However, both Merton's (1987) and Duffies' (2010) models overlook one role that investor attention plays in the context of SEOs. The issuance of new shares is negative news to investors because they interpret equity issuances as management's signals that the stocks are overvalued (Myers and Majluf, 1984). For instance, Baker and Wurgler's (2002) Equity Market Timing Theory argues that firms issue shares at high prices and repurchase them at low prices with the intentions of exploiting temporary mispricings in the cost of equity, relative to the cost of other forms of capital. In fact, as of this writing, market timing theory is arguably the most prominent theoretical explanation among researchers to account for changes in firms' capital structures. In addition, the theory has received validation from survey evidence that suggests that equity market timing is an important factor that influences corporate capital structure decisions. For instance, a widely cited paper by Graham and Harvey (2001) shows that two-thirds of CFOs admit that timing considerations play an important role in their financing decisions.

When managers of a firm announce the issue of new equity, investors in the firm realize that they may have been overly optimistic about the fundamental value of the firm and consequently react negatively to the management's announcement. Several papers have provided numerous explanations for the aggregate magnitude of these reactions. In this paper, I propose a behavioral foundation. The literature on behavioral finance proposes that one of the reasons for investors' under or over-reaction to corporate events may be their limited attention in financial markets. Scholars have used this argument most frequently to explain the post-earnings announcement drift effect.

For instance, theoretical models by Hirshleifer, Lim, and Teoh (2011), Peng and Xiong (2006), and Peng (2005) suggest that when investors' attention to a firm is low, they may ignore its earnings announcements, resulting in stock price under-reaction to the earnings news. Following the announcements, prices continues to drift in the direction of the earnings news as investors gradually incorporate the information into prices.

Some empirical support also exists for the under-reaction of stock prices to the announcement of SEOs. In particular, Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) find evidence that the stock prices fall on the announcement date, but then continue to drift in the same direction over the next few years.

This behavioral hypothesis is the focus of my investigation in this study. More specifically, I propose an investor attention explanation for the evidence that SEOs have high offer price discounts, negative short-term abnormal returns, and negative long-run stock price performances. I argue that when investors pay high attention to a company's information, they are likely to acknowledge the issuance of new shares and therefore are able to instantaneously incorporate the negative news into prices. I hypothesize that the offer price discounts will be high for companies with high investor attention and that the negative short-term market reactions to equity issuances will be more pronounced among stocks that receive high investor attention prior to the offerings, while the long-term negative performances will be less pronounced among the same stocks. The following are the primary hypotheses I examine in this study:

Hypothesis 1*: The magnitude of the offer price discount (the cost of equity) is positively related to the degree of investor attention (measured by the volume of firm-specific news articles) prior to the SEO.*

Hypothesis 2*: The magnitude of the negative short-term market reaction to an SEO is positively related to the degree of investor attention prior to the SEO.*

Hypothesis 3*: The magnitude of the negative long-term performance of an SEO is negatively related to the degree of investor attention prior to the SEO.*

In Appendix A, I provide an illustrative simple model that formalizes these hypotheses. The model's setup involves the issuer to allocate the new shares to selected institutional investors (or specialists) who seek to maximize their profits from purchasing and subsequently reselling the new shares to retail investors. These retail investors are attention constrained; thus, a fraction of these retail investors do not fully incorporate into prices the management's signal that the stock is overvalued when a firm issues new equity. The model predicts that if many retail investors are paying close attention to a company's information prior to the offering, their reactions will be strongest when firm's managers signal that the stock is overvalued. The model then predict that the offer price discount will be also a function of the degree of investor attention. If investor attention is high, the offer price discount will be high to compensate specialists for the large negative market reaction to the SEO specialists expect when the firm makes the offer public.

To empirically test these hypotheses, I use the following datasets, econometric methodology, and measures for investor attention and control variables.

4. Data

I start by collecting all company-specific news articles from *Thomson Reuters News Analytics* (TRNA). TRNA is a comprehensive archive that contains all news that Reuters News or the companies themselves (via newswire services such as PR Newswire and Business Wire, among others) publish. Each information release contains the following components: an identifier of the company mentioned in the news (Reuters Instrument Code, or RIC), a time stamp to the millisecond, a relevance indicator that measures how substantive the news is for the company, and a sentiment indicator that shows the tone of the news (more precisely, it indicates the probabilities of the news having a positive, negative, or neutral tone). Sinha (2011), Kyle et al. (2012), Dzielinski and Hasseltoft (2013), and Cahan, Chen, and Nguyen (2013) describe the dataset in detail. For this study, the sample covers all news articles Reuters sent to its clients from January 2003 through December 2012.

I only consider news articles for U.S. common stocks listed in the New York Stock Exchange (NYSE), the American Stock Exchange (Amex), and the Nasdaq National Market (NASDAQ). In total, TRNA contains about 1.9 million news items for the stocks listed on these exchanges from January 2003 to December 2012. The average number of firms the database covered during this period was 3,820.

I follow Kyle et al. (2012) by applying several filters to identify new information. I remove all one-line alert messages that Thomson Reuters usually sends out before important news articles appear in full. I exclude updates and corrections because they simply provide additional detail about original articles. I also exclude news items linked to more than one article in the sample (wrap-up articles), to make sure that this information had not already appeared in the sample; thus, I include only the most “attention-grabbing” news stories.

News articles can mention multiple firms. If a news item is associated with several firms, this news story may be irrelevant for some of them. For example, news articles about small companies often mention large companies simply to provide a context for a general description of the industry in which both companies operate. TRNA assigns a relevance value associated with each pair of news items and firms. This relevance parameter ranges from zero to one, where relevance equals to one if the news item is highly relevant for a particular firm (usually the company's name appears in the headline of the news article), and lower than one, otherwise. In my empirical tests, I include only those articles whose relevance parameters for given firms are greater than 0.35. This figure is the same threshold Kyle et al. (2012) used.

I merge the news dataset with stock prices from the Center of Research in Security Prices (CRSP). I include only common stocks. Thus, I exclude ADRs, REITs, closed-end funds, and primes and scores, i.e., stocks that do not have a CRSP share type code of 10 or 11. I combine CRSP prices with TRNA news articles by using the TICKER associated with each stock. Empirical financial literature typically uses the CUSIP code or PERMNO of a company to merge different databases. However, such variables are not available for the TRNA news database. Instead, TRNA identifies a company by its Reuters Instrument Code (RIC) from which I am able to construct the TICKER of each company.

After imposing these filters, I identify 764,680 news articles from January 2003 to December 2012 on 3,392 companies. Table 1 presents the number of news articles and firms in my sample, categorized by year.

[Table 1 about here]

Next, I collect data on seasoned equity offerings from the Securities Data Corporation (SDC) database. SDC provides information about issue prices, issue sizes, filing dates, and issue dates, among other variables. In line with the earlier literature on SEOs, I apply several filters to the SEO data. I include only offerings listed on the NYSE, the Amex, and the NASDAQ. I remove units, REITs, closed-end funds, and ADRs issuances from the sample. I require that at least part of the SEO issue should be "primary shares” (i.e., I remove 100% secondary issues). Finally, to minimize the effects of small illiquid stocks, the SEO should have an offer price of at least \$3. After imposing these filters, I identify 3,231 SEO issuances from January 2003 to December 2012 by 1,729 companies. After I merge these SEOs with the CRSP dataset, I obtain 2,850 SEOs.

Prior studies (e.g., Safieddine and Wilhelm, 1996; Altinkilic and Hansen, 2003; Ngo and Varela, 2013) show that offer dates that come directly from the SDC database are often incorrect. These errors occur because some offers take place after the trading has closed, but SDC nevertheless assigns that day as the offer date. For example, Safieddine and Wilhelm (1996) find that 18.4 percent of offers between 1980 and 1991 required an offer date correction. Altinkilic and Hansen (2003) find that SDC classified over 50 percent of the offer dates incorrectly from 1980 to 1998. To address this problem, like Safieddine and Wilhelm (1996), I apply a volume-based correction method to identify the accurate offer date. Safieddine and Wilhelm (1996) argue that high trading volumes surge on offer days. Consequently, to correct the offer date, I use the following rule: If the dollar volume on the day following the SDC offer date is (1) more than twice the dollar volume on the SDC offer date and (2) is more than twice the average daily trading dollar volume over the previous 250 trading days, then I designate the day following the SDC offer date to be the correct offer date. After imposing these filters, I modified the issue dates for 1,539 of the total of 2,850 SEOs from January 2003 to December 2012.

To conform to the previous literature and minimize the influence of regulatory issues, I exclude offers by financials (SIC code 6000-6999) and utilities (SIC code 4900-4999). When I exclude these offers, the number of SEOs in my sample shrinks to 1,494 of which 929 are covered by TRNA. For control variables, I retrieve company financial statement items from *COMPUSTAT*, data on analysts' coverage from I/B/E/S, and data on institutional ownership from the Thomson Reuters Institutional Holdings (13F) database.

Table 2 provides descriptive statistics for the final sample of 929 SEOs. Table 3 provides descriptive statistics for the final sample that include news article data, SEO details, and firms' characteristics. An average SEO firm appears in six news articles in the three months prior to the SEO issue date. The average SEO discount is 5.1 percent. For an average SEO proceed of $140.08 million, this discount represents about $7.14 million less in proceeds, a significant cost for issuing new equity. The average cumulative abnormal return for the interval of $(-1, +1)$ days around SEOs is -2.8 percent. For an average issuer's market capitalization of $1,368.87 million (untabulated), these cumulative abnormal returns represent about $38.33 million less in shareholders' wealth.

[Table 2 about here]

[Table 3 about here]

5. Empirical Results

5.1 Investor Attention and SEO Discount

The first analysis examines the effects of investor attention, prior to the issuances, on SEO price discounts in a multivariate setting. The following equation shows the baseline regression for this test:

$$Discount_{it} = \alpha_i + \beta_1 News\ Articles_{it-1} + \beta_2 Tone_{it-1} + \gamma' X_{it-1} + T_t + I_i + \epsilon_{it}, \quad (1)$$

where $Discount_{it}$ is as in equation (2), described below, $News\ Articles_{it}$ is the accumulated volume of news articles for firm i 90 days before the SEO, and $Tone_{it}$ is the aggregate tone of news articles calculated as in equation (3), described below. The vector X_{it-1} contains control variables. I calculate all firm-level control variables on a quarterly basis using the most recent quarter prior to the SEO event. I include in all regressions both year (T_t) and industry (I_i) fixed-effects.

I define the percentage offer price discount as follows:

$$Discount_{it} = \ln\left(\frac{p_{t-1}}{p_{offer}}\right) \times 100, \tag{2}$$

where, p_{offer} is the SEO offer price, and p_{t-1} is the closing price on the day prior to the offer date.

I calculate the aggregate tone of news articles as follows:

$$Tone_{it} = \sum_{k=1}^{N} Prob(Positive)_{itk} - \sum_{k=1}^{N} Prob(Negative)_{itk}. \tag{3}$$

TRNA provides sentiment scores for each company that a news item mentions. The scores show how likely each k news story for firm i is to be positive ($Prob[Positive]$), neutral, or negative ($Prob[Negative]$). TRNA labels each news article as positive, neutral, or negative, according to the highest score probability. The sentiment is at the entity level, so two different companies can have different scores for the same news article.

Control variables: I control for other known determinants of SEO discounts that prior literature has documented. Prior empirical studies have shown that some of the most pervasive determinants of SEO discounts include the level of investor uncertainty about firm value, the size of the offering itself, and underwriters' pricing practices. Consequently, the vector X_{it-1} in equation (1) includes proxies that reflect these key factors. First, I control for stock price uncertainty using the stock volatility for the past 12 months. Many studies show that high return volatility is associated with high levels of discounting (e.g., Corwin, 2003; Duc Ngo and Varela, 2012).

Besides stock price uncertainty, the size of an SEO is also an important determinant of the offer price discount, mainly because large SEOs are difficult to place, but also new shares dilute earnings per shares for current shareholders (Stowell, 2010). Altinkilic and Hansen (2003), and Corwin (2003) control for the effects of the size of the offerings using the ratio of shares offered over the total number of shares outstanding prior to the offerings. I follow these studies and control for the same ratio. I also control for the natural log of the proceeds. I expect positive coefficients for these variables.

Corwin (2003) additionally finds that conventional underwriter pricing practices may have important effects on SEO discounts. To account for these effects, he includes the control variable *Tick*, which is a dummy variable equal to one if the decimal portion of the closing price on the day prior to the offer is less than $ 0.25 and equal to zero otherwise. He also adds the variable, *Ln (price),* and the interaction term, *Ln (price)**Tick,* to his regression model. I also include these variables in my regressions. Based on Corwin (2003), I expect the sign of coefficients on *Ln (price)*Tick* and *Ln (price)* to be negative and positive, respectively.

Altinkilic and Hansen (2003), and Corwin (2003) show that pre-offer price run ups are also significant determinants of discounts. I follow these studies, and I control for the effects of pre-offer price run ups using the market adjusted cumulative abnormal returns over the period of (-60,-2) trading days prior to the offer. Altinkilic and Hansen (2003), and Corwin (2003) also document that NASDAQ issuances are more underpriced than NYSE/Amex issuances. Therefore, I include the indicator variable, *Nasdaq*, that equals to one if the issuer's primary exchange is NASDAQ and equal to zero if the firm's primary exchange is NYSE or AMEX.

Many studies that examine the discount of SEOs argue that underwriters' reputations may affect the magnitude of SEO discounts. Accordingly, I control for the reputation of the lead book runner in the following way. I include an indicator variable, *Reputation*, that equals one if the book runner ranking, according to Professor Jay Ritter's underwriter reputation ranking, equals nine (i.e., most prestigious) and equals zero if the underwriter's ranking is below nine.

Finally, to control for the degree of information asymmetry between firms and investors, I use the number of analysts who are following the firms. Small firms may be hard to value; thus, I also control for firm size (the natural log of market equity).

I "Winsorize" all control variables at the upper and lower one percent levels.[2] This approach is the standard procedure scholars use in the finance literature to minimize the influence of extreme outliers. I also Winsorize *discount* at the upper and lower one percent levels to ensure that extreme values on the dependent variable do not drive the results.

Results: Table 4 reports regression results with robust standard errors for the effects that the total volume of news articles and the aggregate tone of news articles before SEOs have on offer price discounts. The results show that the volume of news articles before SEOs is positively related to price discounts. The coefficient of *News Articles* is 0.0747 and is statistically significant at the five percent level. To put the economic significance of this coefficient in concrete terms, for an average issuer, increasing the number of news stories prior to the SEO by one is associated is associated with a 0.0747 percent increase in the SEO price offer discount, or $104,640 (=$140.08 million*0.00075), with the other variables in the model held constant.

[2] For a discussion and references on the Winsor approach, see Barnett and Lewis (1994).

This result is economically substantial and consistent with the prediction of my first hypothesis. I interpret these results as follows. On the one hand, investor attention prior to an SEO creates temporary price pressures on the issuer's stocks. For instance, Barber and Odean (2008) argue that investors are net buyers of attention-grabbing stocks; thus, investor attention results in temporary price pressures. Figure 1 illustrates these price pressures in the days leading to the SEO issuances. The figure plots the average ratio of the stock price to the closing price on the offering date for SEOs I classify into two portfolios, "low" and "high" investor attention offerings. I form these portfolios by dividing issuers into below and above-median values for the volume of news articles 90 days prior to the offerings. The figure depicts a higher price pressure for issuers with high levels of investor attention than for issuers with low levels of investor attention. The results suggest that firms with high levels of investor attention do not fully incorporate this price pressure into their offer prices.

[Figure 1 about here]

On the other hand, high investor attention implies that many investors are attentive to the overvaluation signals when firms issue new equity. If investors pay high attention to management's signals that the stocks are overvalued, then issuers have to set low offer prices to entice institutional investors into the market for SEOs. Institutional investors will only make profits from reselling the stock to retail investors if the offer price discounts are sufficiently large to compensate them for the large negative market reactions they expect on the day of the SEOs. Therefore, to entice institutional investors into the market for the SEOs, issuers with high levels of investor attention will have to set low offer prices, resulting in high offer price discounts for these firms.

For comprehensiveness, I also control for a number of firm and deal characteristics that appear in the existing literature that may affect SEO discounts. However, variables that other studies have emphasized do not seem to play an important role for this sample of SEOs. In fact, only variables related to the size of SEOs and to financial analysts' coverage are statistically significant with SEO discounting.

[Table 4 about here]

5.2 Robustness Checks

In this section, I conduct a set of robustness tests for my primary findings. First, I use an instrumental variables (IV) approach to address the endogeneity issue relative to the fact that a number of unobservable variables can simultaneously drive both the volume of news articles and SEO offer discounts. Reverse causality is also possible; companies that expect high discounts may attempt to minimize investor attention by generating fewer news articles.

Instruments need to represent events that are likely to affect the volume of firm-specific news articles, but that will not directly affect SEO discounts. I employ two instruments. The first instrument uses a proxy for media distraction. I construct a measure of media distraction based on the daily volume of negative news articles in the 90 days before the SEO issuances. I apply this measure to firms in industries not related to the issuers across all Fama-French 12 industry classifications. I argue that other newsworthy stories may distract media outlets, or they may deliberately choose to cover more attention-grabbing news stories in other industries to increase their readerships. Furthermore, several authors suggest that market participants pay higher attention to negative news than to positive news, and consequently the market's reaction to negative news is significantly larger than its reaction to positive news (e.g., Kothari, Shu, and Wysocki, Forthcoming; Sletten, Forthcoming). These facts support my decision to use the volume of negative news articles over positive or neutral news stories.

The second instrument uses variations in news stories that firms themselves originated. For example, Ahern and Sosyura (Forthcoming) show that firms originate and disseminate information to the media to influence their stock prices during merger and acquisition negotiations when two companies are in the process of determining the stock exchange ratio. Ahern and Sosyura term this strategy as “active media management.” However, several articles have also suggested that companies that face high litigation risk may prefer to minimize information disclosure because regulators may perceive them to be misleading investors. Alternatively, these firms may be more forthcoming with disclosures to avoid having regulators accuse them of withholding information. A large number of studies, starting with Francis, Philbrick, and Schipper (1994), find that the majority of lawsuits are against firms in the biotechnology, computer, electronics, and retail industries. Therefore, I define the indicator variable, *Litigation Risk*, as instrument that equals one for issuers in computer (SIC codes 3570–3577 and 7370–7374), electronics (3600–3674), and retail (5200–5961) industries, and equal zero otherwise. I exclude the biotechnology (SIC Codes 2833–2836) industry because when I include an indicator variable for this industry in the baseline model, the coefficient is positively and statistically significantly associated with the offer price discount (Huang and Zhang, 2011, find a similar result). Thus, the biotechnology industry does not meet the exclusion restriction that is necessary for identification in the IV model. Finally, I make the strong assumption that the aggregate tone of the news articles is exogenous. By including the aggregate tone as an exogenous variable, I improve the relevance of my instruments.

Table 5 reports the results for the instrumental variable approach. Column (1) of Table 5 reports the first-stage results. The result for the F-statistic for weak instruments is 12.98, which surpasses the threshold of ten that Stock, Wright, and Yogo (2002) suggested. Column (2) of Table 5 reports the second-stage results. The coefficient estimate for the prediction of *News Articles* is 0.3922 and statistically significant at the 10 percent level. These results suggest that the positive relationship I reported earlier between the volume of news articles prior to SEO issuances and SEO discounts, although it loses some of its statistical significance, retains the same sign after I control for potential endogeneity problems.

[Table 5 about here]

As an additional robustness check, in unreported results, I evaluate the robustness of my findings when I exclude observations that pertain to the financial crisis, defined as June 2007 to June 2009. The economical and statistical significance of the relationship between the volume of news articles prior to SEO issuances and SEO outcomes remain similar, suggesting that the financial crisis did not drive my primary findings.

Finally, as mentioned before, prior studies (Gao and Ritter, 2010; Huang and Zhang, 2011) have shown that SEO marketing efforts can lower the offer price discounts by flattening the demand curves of SEOs. To contrast my results to those of these studies, I now proceed to estimate the relationship among the marketing effort of an SEO, volume of news articles prior to the issuances, and SEO discounts.

First, I estimate the relationship between the number of news articles prior to an SEO issuance and several proxies for SEO marketing efforts, including the logged number of managing underwriters; the logged number of lead, co-lead, and co-managing underwriters; and the logged number of bookrunners. At the same time, I control for other factors that likely affect the degree of media coverage of a firm. For instance, considering that TRNA is a machine-readable database of news articles that target certain market participants, such as institutional investors and sell-side analysts, I control for the institutional ownership ratio, the total number of institutions holding the stock, and the numbers of analysts who are following the firm. I also include the market capitalization equity (in logarithms), equity market-to-book ratios, return of assets (ROA), total assets (in logarithms), and the cumulative dollar trading volume six months prior to the SEO issuances. Finally, certain industries may possibly receive more media coverage than the others. Accordingly, I include industry dummy variables to capture such industry-specific effects.

Table 6 shows that the coefficients associated with marketing efforts proxies are not statistically different from zero. These results suggest that the pre-offer number of news stories and marketing of the securities, measured by the number of underwriters who are managing the offerings, are proxies for different economic concepts.

[Table 6 about here]

Next, I reexamine the effect of the number of news articles on SEO discounting, but now control for the number of managing underwriters and its interaction with the offer size and stock volatility, as suggested by Huang and Zhang (2011). Specifically, I re-estimate equation (2) with three additional variables: the logged numbers of lead, co-lead, and co-managing underwriters; and two terms for their interactions with the relative offer size and the return volatility. I report regression results in Table 7. Consistent with Huang and Zhang (2011), the number of managing underwriters has a negative and significant coefficient. However, when I include the interaction terms, the coefficient loses its significance. More relevant for this study, after I include the variable suggested by Huang and Zhang (2011), the significance of the coefficient for the number of news articles remains at previous levels.

[Table 7 about here]

5.3 Investor Attention and Short-term Returns around SEOs

In this section, I study how investor attention affects the market reactions to SEOs. To examine the market reactions to the issuances of new equity, I use standard event study methods to estimate the stock price reactions to the issuances (e.g., Brown and Warner, 1985). I compute abnormal returns using the market model. I proxy the market return by the return of the CRSP equally-weighted portfolio (EWRETD in the CRSP database). I base the estimation of normal returns on the time series for the interval of (-250,-5) days before the actual issuances. Finally, I calculate the cumulative abnormal returns (CAR) during the interval of $(-1, +1)$ days around the SEOs. This excess of return is the part of the change in the issuer's stock return that is not correlated with overall market movement in stock returns, and we may assume that it reflects the effect of the SEO.[3]

[3] I focus on the issue dates rather than announcement dates because most SEOs are now shelf registered. In these offerings, the appropriate information event is the issue date, not the filing date that scholars have generally used to proxy for the actual announcement date. Clinton et al. (2014) argue that earlier studies on pre-SEO disclosure (e.g., Marquardt and Wiedman,1998; Lang and Lundholm, 2000) refer to the filing or registration date as the SEO information event date because their samples comprised traditional (non-shelf) offerings. In these offerings, firms conveyed information about the upcoming SEOs on the registration dates, and the issue dates usually occurred soon after registration (Bethel and Krigman, 2008). In contrast, with shelf registrations firms register securities that they reasonably expect to issue over the next two years. For instance, Clinton et al. (2014) find that in over 80 percent of their sample's equity issues filing dates predates

Before I perform the regression analysis, I graphically illustrate the relationship between the volume of news articles prior to the offerings and SEO abnormal returns. Figure 2 plots the daily abnormal returns over a ten-day window around the offer dates for two portfolios, "low" and "high" investor attention, that I form by dividing the SEOs sample into below and above-median values for the volume of news articles 90 days prior to the offerings, respectively. The figure depicts more negative abnormal returns for issuers with high levels of investor attention than for issuers with low levels of investor attention.

[Figure 2 about here]

Next, I use a multivariate setting to examine the effects investor attention prior to the SEO has on the market reaction to the event. I regress the cumulative abnormal returns for the interval of $(-1, +1)$ days around the SEOs on the volume of news articles and on the aggregate tone of news articles before SEOs using the following specification:

$$\widehat{CAR}_{it} = \alpha + \beta_3 News\ Articles_{it-1} + \beta_4 Tone_{it-1} + \gamma' X_{it-1} + T_t + I_i + \epsilon_{t,i}, \quad (4)$$

where $\widehat{CAR}_{it}$ is the cumulative abnormal return for SEO company i, on day t, $News\ Articles_{it-1}$ is the number of news articles 90 days before the SEO, and $Tone_{it-1}$ is the aggregate tone of the news articles 90 days before the SEO.

Control variables: I control for investors' concerns regarding the misuse of the SEO proceeds using Tobin's Q ratios that are a measure of firms' investment opportunities. I expect to see a positive coefficient on this variable. Lucas and McDonald (1990) and Jung et al. (1996) also use firms' past returns as a proxy for the availability of profitable projects.

the issue dates by 257 days on average. Heron and Lie (2002) find that an average of 102 days from the filing dates to the issue dates for shelf offers during the 1980 to 1998 period. Autore et al. (2008) find that, on average, firms conduct shelf offerings 111 days after the filing date during the period 1990 to 2003. Consistent with prior findings, in the sample of SEOs I use in the present study, the time lapse between the filing and issue dates is 272 days.

Accordingly, I control for the abnormal firms' returns from the past 60 days as proxy for this influence. This variable also may stand as a proxy for overvaluation because the market timing literature suggests that firms issue shares when stock prices are high.

I use firm size as a proxy for asymmetric information. Large firms are under great scrutiny by investors and are actively followed by analysts. I include the natural logs of total assets of the firm and of market equity as proxies for firm's size. I expect to see positive coefficients on these variabless. I also control for the number of analysts who are following the companies' stocks, another proxy for asymmetric information.

Finally, Masulis and Korwar (1986) find that the size of the SEO affects offering day returns. Therefore, I control for the ratio of shares offered over shares outstanding and for the natural log of SEO proceeds. I also include firm-level controls and both industry and year fixed-effects.

Results: Table 8 shows the results when I regress the cumulative abnormal returns over the three days around the offer date, $CAR(-1,1)$, on the proxies for investor attention and the control variables. Column (2) of Table 8 shows that the coefficient for *News Articles* is -0.1104 and statistically significant at the five percent level. The result is also economically significant: increasing the number of news articles by one is associated with a loss of 0.11 percent in pre-issue firm value, or $1.51 million (=$1,368.87*0.0011), with the other variables in the model held constant. This result is consistent with the prediction of my second hypothesis. If investors pay high attention to the overvaluation signals, the market negative reaction will be most pronounced to the equity offerings. Furthermore, the negative market reaction will be strongest because many investors will react to the concerns related to potential problems of agency, free cash flow, or overinvesting the proceeds from the issuances. The results are also consistent with Fang and Peress' (2009) liquidity (or impediments-to-trade) hypothesis where stocks of companies that lack media coverage may be difficult to trade. This hypothesis implies that if investor attention is high, many traders are able to sell their stocks during SEOs, resulting in large price declines on the day of SEOs' issuance dates.

Column (3) of Table 8 shows that the tone of news articles also plays an important role in the returns around issuances. I find that the tone of the news articles prior to an SEO positively impacts the abnormal returns around SEOs. This result suggests that a negative sentiment about a firm before an SEO will negatively affect the market reaction to the issuance. The result is consistent with the findings of Tetlock et al. (2008) that show that the fraction of negative words in firm-specific news stories can forecast low firm earnings, and that negative words in news stories about firms' fundamentals are particularly useful predictors of future earnings and returns.

[Table 8 about here]

5.4 Investor Attention and Long-term Returns following SEOs

A number of studies find that after issuing SEOs, firms underperform in the long-run (e.g., Ritter, 2003; Loughran and Ritter, 1995). In this section, I investigate the relationship between investor attention prior to the SEOs and the long-run stock price performances of SEOs.

To examine the long-run performance of the offerings, I calculate long-term stock returns over different horizons for issuers classified into two categories according to their volume of news stories prior to the offerings. Tables 9 shows the long-term stock price returns for issuers with high volumes of news articles 90 days prior to the offerings ("high") and issuers with low volumes of news articles 90 days prior to the offerings ("low"). To adjust for expected returns, I use multiple approaches. First, I calculate portfolio-matched buy-and-hold abnormal returns (BHARs) for three, six, and 12 months after the offering dates. Second, I compute cumulative abnormal returns (CARs), which are similar to BHARs, but involve summing returns rather than compounding (multiplying).[4] Finally, I use the calendar-time regression approach advocated by Fama (1998). In all instances, I show the results for both equally-weighted (EW) and value-weighted (VW) "high" and "low" portfolios.

To obtain the BHARs, I calculate monthly compounded returns over the different horizons and then subtract the compounded returns of a benchmark portfolio over the same periods. The benchmark portfolio I use corresponds to the value-weighted size/book-to market (BM) portfolio proposed by Fama and French (1993). To obtain the adjusted returns, I match each firm to one of the 25 corresponding size/BM portfolios at the beginning of the offer quarter, using the size/BM breakpoints from Professor Kenneth French's website. Panel A of Table 9 summarizes the BHAR results. I find some evidence that the "low" news articles portfolio overperforms the "high" news articles portfolio at the three-month interval with a difference in cumulative returns of 2.95 percent for the EW and VW bases. At the 12-month interval, the returns pattern reverses with the "high" issuers overperforming the "low" issuers by 5.18 percent on a VW basis. However, this difference is statistically insignificant. Overall, while the BHAR analysis offers some evidence that issuers with high volumes of news articles prior to the issuances have higher long-term performances than issuers with low volumes of news articles, the results appear

[4] To compute CARs and BHARs, I modify the SAS code in the Internet Appendix of Bhojraj, Hribar, Picconi, and McInnis (2009), available at http://www.afajof.org/details/page/3626901/Supplements.html.

to be sensitive to the weighting scheme (equal- versus value-weighted portfolios) that I use to calculate average abnormal returns.

Fama (1998) and Mitchell and Stafford (2000) advocate using cumulative abnormal returns (CARs) instead of BHARs because BHARs can magnify first periods abnormal returns as a result of compounding. Moreover, summations behave better statistically than compounded returns (e.g., compounding returns may produce extreme skewness) and lead to fewer inference problems (Barber and Lyon, 1997). Therefore, I also calculate long-term CARs. To calculate issuers' CARs, I use the same portfolio matching procedure described above for benchmark returns and calculate both EW and VW returns in a similar fashion. Panel B of Table 9 reports the results. As with the BHARs approach, the results are inconclusive. For instance, I find some evidence of performance differences on a short-term basis. However, at the 12-month horizon, differences between the "high" and "low" portfolios are statistically equal to zero for both EW and VW CARs.

Next, I calculate long-run abnormal returns using a calendar-time approach. Fama (1998), Mitchell and Stafford (2000), and Brav, Geczy, and Gompers (2000), among others, recommend applying the calendar month portfolio approach to mitigate the problems of correlation of returns across events when calculating the expected returns in long-term abnormal returns. This approach is as follows: for both the "high" and "low" attention portfolios, for every month from January 2003 to December 2012, I form equal-weighted and value-weighted portfolios of firms that had issued SEOs in the preceding 12 month, and that belong to the specific attention portfolio. Then, I regress the calendar time returns for these portfolios on the following Carhart (1997) four-factor model:

$$R_{pt} - R_{ft} = \alpha + \beta(R_{pt} - R_{ft}) + sSMB_t + hHML_t + mUMD_t + \epsilon_{p,t}, \qquad (5)$$

where R_{pt} is the monthly return on an equal weighted calendar-time portfolio, R_{ft} is the one-month T-bill return, R_{mt} is the return on the CRSP equally-weighted market index, SMB_t is the average return on portfolios of small stocks minus the average return of portfolios of large stocks, HML_t is the average return on value (high market-to-book ratio) stocks minus the average return on growth (low market-to-book ratio) stocks, and UMD_t is the average return on portfolios of high momentum stocks minus the average return on portfolios of low momentum stocks (factors data is from Professor Kenneth French's website). The estimates of the intercept terms (*alphas*) of the factor regressions are the measures of abnormal returns. The intercepts provide the monthly abnormal returns on the calendar-time portfolios. The null hypothesis is that *alpha* is not significantly different from zero. I interpret a significant negative *alpha* as a negative average abnormal return for the portfolio.

Panel C of Table 9 presents the post-issue abnormal stock price performances from (+1, +12) months for the two portfolios that I classify by the total volume of news articles prior to the issuances. I find some evidence of a negative relationship between pre-issue firm-specific volumes of news articles and post-issue abnormal returns that is consistent with the investor attention view of my third hypothesis. Specifically, when I use the equally-weighted (EW) and value-weighted (VW) model, respectively, issuing firms in the "low" portfolio have significantly negative average post-issue abnormal returns: -0.49 percent per month (-5.88 percent after one year) and -0.02 percent per month (-0.24 percent after one year). However, only the results for the EW are significant. I find that issuing firms in the "high" portfolio also have significantly negative average post-issue abnormal returns, but they are lower than the returns of the "low" portfolio: -0.40 percent per month

(-4.8 percent after one year) and -0.21 percent per month (-2.52 percent after one year) for the equally-weighted and value-weighted models, respectively. Only the results for the EW are significant. Overall, these results partially support my hypothesis that the negative long-term performances of SEOs are negatively related to the degree of investor attention prior to the SEOs. But again, the results appear to be sensitive to the weighting scheme I use to calculate average abnormal returns. I may argue, however, that the lack of a clear long-run price reversal for the "high" portfolio supports my hypothesis that an increase in individual investor attention before an offering helps promote efficient stock price reactions to SEOs.

[Table 9 about here]

6. Summary and Concluding Remarks

In this article, I have shown how investor attention affects seasoned equity offerings' outcomes. To proxy for investor attention, I use the volume of news articles in the *Thomson Reuters News Analytics* database, a comprehensive archive of stories that covers thousands of companies in the U.S.

Merton (1987) provides a theoretical framework in which investor attention can affect asset prices. A large body of empirical evidence confirms Merton's model's predictions that investor attention is positively related to assets returns. The empirical literature has used different proxies to measure investor attention: extreme returns, trading volume, advertising expenses, Google searches, and news articles and headlines. Empirical literature has also suggested that the content and tone of news articles is significantly related to stock prices. For instance, Tetlock et al. (2008) show that negative words, in particular, predict companies' earnings and stocks returns. Meanwhile, the effects that investor attention and news articles have on corporate actions remains largely unexplored.

In the context of seasoned equity offerings, my results contradict some of the prior empirical findings regarding the effects of investor attention on SEOs. In particular, using the volume of news articles prior to SEOs, I find that investor attention is positively and significantly related to firms' SEO price discounts and negatively and significantly associated with cumulative abnormal returns around issuances. Previous authors have used the offer method choice, number of underwriters, and users search frequencies in Google to proxy for investor attention; they find the opposite relationships. However, I believe the variable I use in this study may represent a better proxy for the attention of professional traders than other variables that appear in the literature.

I conduct a set of robustness tests for my primary findings. I address the confounding effects that can simultaneously drive both the volume of news articles prior to SEOs and SEO discounts; these confounding effects may affect my findings. To partially alleviate this concern, I use an instrumental variables approach. The instruments I employ are the degree of media distraction (measured by the number of negative news articles in non-related industries) and litigation risks (firms in computers, electronics, and retail industries). These instruments represent events that are likely to affect the volume of firm-specific news articles, but that will have no direct effects on SEO discounts. After these robustness tests, my results still hold. Nevertheless, other instruments may be more appropriate. For instance, a potential instrumental variable candidate is the presence of board members with mass media experience (Gurun, 2014). I will leave these additional robustness checks for future research.

Despite some endogeneity concerns, this study identifies another role that investor attention plays in financial markets. More importantly, this study illuminates how the degree of investor attention can significantly affect SEO outcomes. The results in this paper are interesting and suggest some avenues for future research. For instance, if managers recognize the reported relationships, they may be motivated to attempt to manipulate investor attention when their firms are in the market for seasoned equity offerings. That motivation will be one focus of my investigations in future research.

List of References

Aggarwal, R. (2003). Allocation of Initial Public Offerings and Flipping Activity, *Journal of Financial Economics* 68, 111–135.

Ahern, K. R. and D. Sosyura. (2014). Who Writes the News? Corporate Press Releases during Merger Negotiations, *The Journal of Finance* 69, 241-291.

Altinkili, O. and R. Hansen. (2003), "Discounting and Underpricing in Seasoned Equity Offers", *Journal of Financial Economic* 69, 285-323.

Autore, D. and T. Kovacs. (2014). Investor Recognition and Seasoned Equity Offer, *Journal of Corporate Finance* 25, 216-233

Baker. M. and J. Wurgler. (2000). The Equity Share in New Issues and Aggregate Stock Returns, *The Journal of Finance* 55, 2219-2257.

Baker. M. and J. Wurgler. (2002). Market Timing and Capital Structure, *The Journal of Finance* 57, 3-28.

Baker. M. and J. Wurgler. (2013). Behavioral Corporate Finance: An Updated Survey, *Chapter 5* of the *Handbook of the Economics of Finance*, Volume 2, Part A, 357–424

Barber, B. and T. Odean. (2008). All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *The Review of Financial Studies* 21, 785–818.

Barberis, N., A. Shleifer, and R. Vishny. (1998). A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Barnett, V. and Lewis, T. (1994). Outliers in Statistical Data, John Wiley & Sons, Chichester.

Bhattacharya, U., N. Ray Galpin, and X. Yu. (2009). The Role of the Media in the Internet IPO Bubble, *Journal of Financial and Quantitative Analysis* 44, 657–682.

Brav, A., C. Geczy, and P. Gompers. (2000). Is the Abnormal Return Following Equity Issues Anomalous? *Journal of Financial Economics* 56, 209-249.

Brown, S. and J. Warner. (1985). Using Daily Stocks Returns The case of Event Studies, *Journal of Financial Economics* 14, 3-31.

Buehlmaier, M. (2012). The Role of Media in Takeover: Theory and Evidence, working paper, University of Hong Kong.

Cahan, S., C. Chen, and N.H. Nguyen. (2013). Media Sentiment, Investor Sentiment, and Stock Price Sensitivity to Earnings, working paper.

Chemmanur, T., and A. Yan. (2009). Advertising, Attention, and Stock Returns, working paper, Boston College and Fordham University.

Chemmanur, T., S. He, and G. Hu. (2009). The Role of Institutional Investors in Seasoned Equity Offerings, *Journal of Financial Economics* 94, 384-411.

Clinton, S., J. White, and T. Woidtke. (2014). Differences in the Information Environment Prior to Seasoned Equity Offerings under Relaxed Disclosure Regulation, DERA Working Paper 2013-05.

Cook, D. O., R. Kieschnick, and R. A. Van Ness. (2006). On the Marketing of IPOs, *Journal of Financial Economics* 82, 35–61.

Corwin, S. (2003). The Determinants of Underpricing for Seasoned Equity Offers, *The Journal of Finance* 58, 2249–2279.

Da, Z., J. Engelberg, and P. Gao. (2011). In Search of Attention, *The Journal of Finance* 66, 1461–1499.

DeAngelo, H., L. DeAngelo, and R. Stulz. (2010). Seasoned Equity Offerings, Market Timing, and the Corporate Lifecycle, *Journal of Financial Economics* 95, 275-295.

DellaVigna, S. and J. Pollet. (2009). Investor Inattention, Firm reaction, and Friday Earnings Announcements, *The Journal of Finance* 64, 709–749.

DellaVigna, S. and E. Kaplan. (2007). The Fox News Effect: Media Bias and Voting, *The Quarterly Journal of Economics* 122, 1187–1234.

Demers, E. and C. Vega. (2011). Linguistic Tone in Earnings Press Releases: News or Noise? working paper.

Demiralp, I, R. D'Mello, F. Schlingemann, and V. Subramaniam. (2011). Are There Monitoring Benefits to Institutional Ownership? Evidence from Seasoned Equity Offerings, *Journal of Corporate Finance* 17, 1340–1359.

Deng , X., E. Hrnjic, and S.E. Ong. (2012). Investor Sentiment and Seasoned Equity Offerings, working paper, National University of Singapore.

Dzielinski, M, and H. Hasseltoft. (2013). Why Do Investors Disagree? The Role of a Dispersed News Flow, working paper,

Duffie, D. (2010). Presidential Address: Asset Price Dynamics with Slow-Moving Capital, *The Journal of Financ*e 65, 1237–1267.

Engelberg, J., and C. A. Parsons. (2011). The Causal Impact of Media in Financial Markets, *The Journal of Finance* 66, 67–97.

Fang, L. and J. Peress. (2009). Media Coverage and the Cross-Section of Stock Returns, *The Journal of Finance* 4, 2023–2052.

Gao, X. and J. Ritter. (2010). The Marketing of Seasoned Equity Offerings, *Journal of Financial Economics* 97, 33-52.

Graham, J., and C. Harvey. (2001). The Theory and Practice of Corporate Finance: Evidence from the Field, *Journal of Financial Economics* 60, 187-243.

Griffin, J., N. Hirschey, and P. Kelly. (2011). How Important is the Financial Media in Global Markets? *The Review of Financial Studies* 24, 3941–3992.

Gurun, U. (2014). Price of Publicity, working paper, University of Texas at Dallas.

Henry, T. and J. Koski. (2010). Short Selling around Seasoned Equity Offerings, *Review of Financial Studies* 23, 4389-4418.

Hirshleifer, D., S. Lim, and S. Teoh. (2009). Driven to Distraction: Extraneous Events and Underreaction to Earnings News, *The Journal of Finance* 64, 2289-325.

Hirshleifer, D., S. Lim, and S. Teoh. (2011). Limited Investor Attention and Stock Market Misreactions to Accounting Information, *Review of Asset Pricing Studies* 1, 35-73.

Huang, R. and D. Zhang. (2011), The Marketing Role of Managing Underwriters in Seasoned Equity Offerings, *Journal of Financial and Quantitative Analysis* 46, 141-170.

Jung, K., Y-C. Kim, and R. Stulz. (1996). Timing, Investment Opportunities, Managerial Discretion, and the Security Issue Decision, *Journal of Financial Economics* 42, 159-185.

Kahneman, D. (1973). Attention and Effort, Prentice-Hall, Englewood Cliffs, New Jersey.

Kempf, E., A. Manconi, and O. Spalt (2014). Distracted Shareholders and Corporate Actions, Working paper.

King, M. and D. Segal. (2009). The Long-Term Effects of Cross-Listing, Investor Recognition, and Ownership Structure on Valuation, *Review of Financial Studies* 22, 2393-2421.

Kothari, S., S. Shu, and P. Wysocki. (Forthcoming). Do Managers Withhold Bad News? *Journal of Accounting Research* forthcoming.

Kyle, A., A. Obizhaeva, N. Sinha, and T. Tuzun. (2012). News Articles and the Invariance Hypothesis, working paper.

Lang, M. and R. Lundholm. (2000). Voluntary Disclosure and Equity Offerings: Reducing Information Asymmetry or Hyping the Stock? *Contemporary Accounting Research* 17, 623-662.

Lee, C, A. Shleifer, and R. Thaler. (1991). Investor Sentiment and the Closed-End Fund Puzzle, *The Journal of Finance* 46, 75-109.

Lehavy, R. and R. Sloan. (2008). Investor Recognition and Stock Returns, *Review of Accounting Studies* 13, 327–361.

Liu, L., A. Sherman, and Y. Zhang. (2014). The Long-Run Role of the Media: Evidence from Initial Public Offerings, *Management Science* 60, 1945-1964

Ljungqvist, A., V. Nanda, and R. Singh. (2006). Hot Markets, Investor Sentiment, and IPO Pricing, *Journal of Business* 79, 1667-1702.

Loughran, T. and J. Ritter. (1995). The New Issue Puzzle, *Journal of Finance* 52, 23-51.

Lu, X., H. Holzhauer, J. Wang (2014). Attention: A Better Way to Measure SEO Marketing Impact, *Journal of Trading* 9, 64-75.

Lucas, D. and R. McDonald. (1990). Equity Issues and Stock Price Dynamics. Journal of Finance, 45(4), 1019–1043.

Masulis, R., and A. Korwar. (1986). Seasoned Equity Offerings: An empirical investigation. *Journal of Financial Economics,* 15, 31-60.

Merton, R. C. (1987). A Simple Model for Capital Market Equilibrium with Incomplete Information, *The Journal of Finance* 42, 483–510.

Mitchell, M. and E. Stafford. (2000), Managerial Decisions and Long-term Stock Price Performance, *Journal of Business* 73, 287-329.

Myers, S. and N. Majluf. (1984). Corporate Financing and Investment Decisions when Firms Have Information that Investors do not Have, *Journal of Financial Economics* 13, 187-221.

Ngo A. D. and O. Varela, (2012). Earnings Smoothing and the Underpricing of Seasoned Equity Offerings, *Managerial Finance* 38, 833 – 859.

Peng, L. (2005). Learning with Information Capacity Constraints, *Journal of Financial and Quantitative Analysis* 40, 307–329.

Peng, L. and W. Xiong. (2006). Investor Attention, Overconfidence and Category Learning, *Journal of Financial Economics* 80, 563–602.

Peress, J. (Forthcoming). The Media and the Diffusion of Information in Financial Markets: Evidence from Newspaper Strikes, Forthcoming in the *Journal of Finance*

Ritter, J. (2003). Investment Banking and Securities Issuances, *Chapter 5 of the Handbook of the Economics of Finance*, Edited by G.M. Constantinides, M. Harris and R. Stulz, 253-304.

Safieddine, A. and W. Wilhelm. (1996), "An Empirical Investigation of Short-Selling Activity Prior to Seasoned Equity Offerings", *Journal of Finance* 51, 729-749.

Sletten, E. (Forthcoming). The Effect of Stock Price on Discretionary Disclosure, *Review of Accounting Studies* forthcoming.

Shleifer, A. (2000). Inefficient Markets: An Introduction to Behavioral Finance, Oxford University Press, Oxford.

Shleifer, A. and R. Vishny. (1997). The Limits of Arbitrage, *The Journal of Finance* 52, 35-55.

Sinha, N. (2011). News Articles and Momentum, working paper.

Solomon, D. (2012). Selective Publicity and Stock Prices, *The Journal of Finance* 67, 599–638.

Spiess, D. and J. Affleck-Graves. (1995). Underperformance in Long-Run Returns Following Seasoned Equity Offerings, *Journal of Financial Economics* 38, 1123-45.

Stowell, D. (2010). Investment Banks, Hedge Funds and Private Equity: A New Paradigm. Elsevier, Academic Press.

Sun, J. (2013). Research on Capital Structure and Financing Decision: Evidence from the UK, unpublished Ph.D. dissertation, Durham University Business School.

Tetlock, P. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market, *The Journal of Finance* 62, 1139-1168

Tetlock, P., M. Saar-Tsechansky, and S. Macskassy. (2008). More than Words: Quantifying Language to Measure Firms' Fundamentals, *The Journal of Finance* 63, 1437-1467.

Appendix A: The Model

In this section, I develop a simple model of the pricing of SEOs that incorporates investor attention. Similar to Ljungqvist, Nanda, and Singh's (2006) model for the underpricing of IPOs, in my setup, the issuer allocates the new shares to selected institutional investors (or specialists) who seek to maximize their profits from purchasing and subsequently reselling the new shares to retail investors.

[1] Because paying attention to a large amount of information is costly, a fraction of these retail investors are not fully attentive to all publicly available information. Consequently, they do not immediately fully incorporate into prices the managements' signals that the stocks are overvalued when firms have decided to issue new equity. The magnitude of the negative reactions to the SEO issuances will depend on the fraction of inattentive retail investors.

I develop the model in a framework that contain the following characteristics:

1. Firms need to issue new equity to undertake a project. The project is durable (i.e., the firm must not need to undertake it immediately);
2. Managers must be better informed than outside investors about the value of the assets in place and the value of the new project;
3. Investors will pay attention only to a subset of the available stocks, and that subset will differ across investors;
4. Degree of investor attention will vary over time; and,

[1] Two papers have investigated institutional investors stock flipping activities (selling of allocated shares shortly after an offering). In the context of IPOs, Aggarwal (2003) reports that institutional investors sell about 26 percent of shares allocated to them within two days of the IPO. Meanwhile, in the context of SEOs, Chemmanur, He, and Hu (2009) find that institutional investors sell only 3.2 percent of the shares allocated to them in the first two days after the issuance. However, they report that this figure increases to 26 percent within the first three months following the offerings.

5. High investor attention will lessen limits to arbitrage (stock illiquidity).

In the model, managers weigh the cost of issuing equity, which is a function of investor attention, against the value of new projects. The aim of the model is to determine the relationship between the cost of the issue (the offer price discount and price drop at the issuance date) and the degree of investor attention prior to the offering.

The model consists of three periods.

- Date 1: The firm decides to issue equity because the stock is overvalued. Managers believe that the current stock price, P_1, is higher than the firm's assets' fundamental values warrant. The firm engages an investment bank underwriting syndicate, with one or more lead bookrunners and a number of co-managers. The lead bookrunner will conduct road shows with a selected number of institutional investors, assess the investors' demands, and build order books. The firm and its investment bankers will determine the appropriate size, Q_2^*, and the appropriate offer price, P_o^*, based on the expected investor demand. The group of underwriters will then allocate the shares to the institutional investors.
- Date 2: The firm announces the SEOs to the public, new shares begin trading, and price P_2 is observed.
- Date 3: The firm is sold at true value, V_T.

Three types of agents participate in this economy: firms (and their underwriters [2]), specialists (or institutional investors), and retail investors.

[2] I will ignore agency problems between firms and underwriters.

1. Firms

The firm care about two things: the proceeds it can make by issuing Q_2 new shares and the value of already outstanding shares of the firm at date 3 (terminal date). Because the firm's project is durable, managers will wait to undertake the project when they perceive the shares of the company are overvalued.

The objective function of the firm is

$$\max_{Q_2, P_o} V_k = P_o Q_2 + V_T Q_1, \tag{A1}$$

where Q_2 is the number of share sold in the offerings, Q_1 is the number of shares held by current stockholders, P_0 is the offer price, and V_T is the terminal (true) payoff of the security.

2. Specialists

Specialists hold assets initially when they are issued and subsequently liquidate the shares in the retail market. Specialists have limited capital available and have alternative investments with an expected return of r. As for retail investors, for specialists, attending to information is also costly. The cost of attending to the issuer's information is c. To simplify the algebra, I set r and c equal to zero.

Also for simplification, I assume that this economy has only one specialist (a monopoly). The specialist's problem is similar to that of the issuer. In equilibrium, the specialist will invest in SEOs only if he does not expect to lose as a consequence. Therefore, if the SEO offer price is P_o, then the specialist's participation constraint is

$$-P_o Q_2 + Q_2 E[P_2] \geq c + r = 0. \tag{A2}$$

The first term of equation (A2) is the cost of buying all the shares in the SEO. The second term represents the cash flow the specialist receives from reselling the shares to retail investors at date 2. The price at which the specialist can resell the shares, P_2, will be a function of the degree of the retail investors' attention to the SEO (overvaluation) signal.

3. Retail investors

To incorporate the effect of investor attention in my model, I borrow key elements from Hirshleifer, Lim, and Teoh's (2011) model on investor attention and stock market misreactions to accounting information. I base this part of my model entirely on their study.

I assume this economy has two types of retail investors: investors who are fully attentive to all date 2 available information and investors with limited attention who ignore date 2 public information (the SEO). Both types of investors update their beliefs as Bayesian rational players. I represent the preferences of investors by a mean-variance utility function, defined as

$$u^i(\cdot) = E^i\left[C_3^i\right] - \frac{\gamma}{2} var^i\left(C_3^i\right), \tag{A3}$$

where C_3^i is the terminal consumption for investor type i, and γ is the parameter of risk aversion.

I assume that investor's initial wealth endowment is W, and that retail investors can trade the stock at price P_2. As before, let V_T denote the terminal (true) payoff of the security, which will be revealed to all retail investors at date 3. If I denote the type i investor's cost of attending to the public information (the SEO) of a firm as k^i, and denote as h^i the holdings of the stock by investor type i, then the consumption at date 3 of an investor type i is

$$C_3^i = W - k^i + h^i(V_T - P_2). \tag{A4}$$

The investor's portfolio choice problem is then

$$\max_{h^i} u^i = E[\,W - k^i + h^i(V_T - P_2)] - \frac{\gamma}{2} var^i\left(W - k^i + h^i(V_T - P_2)\right)$$
$$\Leftrightarrow \max_{h^i} h^i\big(E^i[V_T] - P_2\big) - \frac{\gamma}{2} var^i\big(h^i P_2\big). \tag{A5}$$

The first order condition (FOC) for a solution to the portfolio problem yields

$$\frac{\partial}{\partial h^i} = \frac{\partial}{\partial h^i}\left\{h^i\big(E^i[V_T] - P_2\big) - \frac{\gamma}{2} {h^i}^2 var^i(P_2)\right\} = 0$$

$$\Rightarrow E^i[V_T] - P_2 - \gamma h^i var^i(P_2) = 0$$

$$\Rightarrow {h^i}^* = \frac{E^i[V_T] - P_2}{\gamma\, var^i(P_2)}. \tag{A6}$$

Letting α^i denote the fraction of investor type i, the stock price at date 2, P_2, is determine by the market clearing condition

$$\sum_i \alpha^i\, h^i = Q_2. \tag{A7}$$

Substituting h^i from (A6) in (A7), solving for P_2, and assuming that only the expectation term depends on i, but the variances are independent of i (i.e., $var^i(V_T) = var(V_T)$), yields

$$P_2 = \sum_i \alpha^i E^i[V_T] - \gamma var(V_T) Q_2. \tag{A8}$$

Finally, suppose that at date 2, fraction α^u of investors ignore the overvaluation signal (the SEO) and adhere to their prior beliefs. Then, by equation (A8), I obtain the following

$$P_2 = \alpha^u E[V_T] + (1 - \alpha^u) E[V_T|SEO] - \gamma var(V_T) Q_2, \tag{A9}$$

where $E[V_T] = P_1$ is the price just before the SEO, and $E[V_T|SEO] = V_T$. I assume $P_1 > P_2 \geq V_T$, i.e., the firm is overvalued at date 1. Thus, the price at date 2 will depend on the fraction α^u of investors who ignore management's signal that the stock at date 1 was overvalued and who adhere to their prior beliefs. The other fraction fully takes into account management's signal and values the stock at V_T. Although this demand curve for retail investor is downward sloping (the slope is given by $-\gamma var[V_T]$), the main driver of the stock price in this model is the fraction of inattentive retail investors, α^u.

The following proposition characterizes the dynamics of the price change from date 1 to date 2 and formalizes the second hypothesis in this essay.

Proposition 1. *The negative immediate price reaction to the SEO announcement will be high if the fraction of investors who are inattentive to company information is also high.*

Proof. According to equation (A9),

$$\begin{aligned} P_2 - P_1 &= (\alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO] - \gamma var(V_T)Q_2) \\ &\quad -(E[V_T] - \gamma var(V_T)Q_2) \\ &= (1-\alpha^u)(E[V_T|SEO] - E[V_T]) < 0. \end{aligned} \tag{A10}$$

Because the firm is overvalued, $E[V_T|SEO] < E[V_T]$.

■

4. The issuer's objective function

I assume that the issuer does not need a particular level of financing. Then, the issuer's problem is to maximize the profit from selling the SEO shares. The issuer solves

$$\begin{gathered} \max_{P_0, Q_2} V_k = P_o Q_2 + V_T Q_1 \\ s.t.\ -P_o Q_2 + Q_2 E[P_2] \geq 0, \end{gathered} \tag{A11}$$

I can now derive the issuer's optimal offer price and prove the following proposition that formalizes the first hypothesis in this essay.

Proposition 2. *The SEO offer price (discount) will be high (low) when the fraction of investors who are inattentive to company information is high, where*

$$P_o^* = \frac{\alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO]}{2}, \tag{A13}$$

which is increasing with α^u.

Proof. First, I define the Lagrangean of problem (A12):

$$\mathcal{L}(\lambda, P_o, Q_2) = P_o Q_2 + V_T Q_1$$
$$- \lambda[P_o Q_2 - Q_2\{\alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO] - \gamma var(V_T)Q_2\}]$$

and obtain the necessary Kuhn-Tucker conditions

$$\frac{\partial \mathcal{L}}{\partial P_o} = P_o Q_2 - \lambda Q_2 = 0 \quad \Rightarrow \lambda = 1.$$ [3]

$$\frac{\partial \mathcal{L}}{\partial Q_2} = P_o - \lambda[P_o - \alpha^u E[V_T] - (1-\alpha^u)E[V_T|SEO] + 2\gamma var(V_T)Q_2] = 0$$

$$\Rightarrow \lambda = \frac{P_o}{P_o - \alpha^u E[V_T] - (1-\alpha^u)E[V_T|SEO] + 2\gamma var(V_T)Q_2}$$

Substituting $\lambda = 1$, I can write the issuer's optimal offer size

$$\Rightarrow Q_2^* = \frac{\alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO]}{2\gamma var(V_T)}.$$

From the last Kuhn-Tucker condition, I have that

$$\frac{\partial \mathcal{L}}{\partial \lambda} = -P_o Q_2 + Q_2\{\alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO] - \gamma var(V_T)Q_2\} = 0.$$

[3] This proves that the participation constraint will always be binding. If the constraint were slack. Then, the issuer can increase P_o without bounds and at the same time increase his proceeds, while always keeping the specialist willing to participate. Thus, no solution exists to the optimization problem (in fact, no parameter in the model needs to be maximized). (See Ljungqvist, Nanda and Singh's (2006) for a similar proof).

Substituting Q_2^* into the last condition, I have the issuer's optimal offer price

$$P_o^* = \alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO] - \gamma var(V_T)Q_2^*$$

$$= \frac{\alpha^u E[V_T] + (1-\alpha^u)E[V_T|SEO]}{2}.$$

Finally, taking the partial derivative of P_o^* with respect to α^u, I have

$$\frac{\partial P_o^*}{\partial \alpha^u} = \frac{E[V_T] - E[V_T|SEO]}{2} > 0.$$

This expression is positive because the firm is overvalued, i.e., $E[V_T|SEO] < E[V_T]$.

∴ The offer price is increasing with α^u.

■

Appendix B: Variable definition

Variable Name	Definition
Discount	Negative return (in percentage) from the offering previous day's closing transaction price to the offer price.
CAR (-1,1)	Cumulative abnormal return over the three-day event window around the offer date. The market-adjusted cumulative abnormal return is calculated from market model regressions for each issuing firm and is subtracted from returns of the firm. The market model estimation window starts 250 trading days before the offering and ends five trading days before the offering. Firms that have no returns for at least 30 trading days are dropped.
News Articles (-90,-1)	Accumulated volume of news articles for the issuer firm 90 days prior to the SEO.
Tone (-90,-1)	Aggregate tone of news articles for the issuer firm 90 days prior to the SEO calculated as: $\sum_{k=1}^{T} Prob(Positive)_{itk} - \sum_{k=1}^{T} Prob(Negative)_{itk}$, where $Prob[Positive]$ and $Prob[Negative]$ are scores that show how likely each news story is to be positive and negative, respectively.
Media Distraction	Accumulated volume of negative news articles for companies classified in industries different from the industry of the issuer in the 90 days prior to the SEO, across all Fama-French 12 industry classifications.
Litigation Risk	Dummy variable that equals one for issuers in the computer (SIC Codes 3570–3577 and 7370–7374), electronics (3600–3674), and retail (5200–5961) industries, and zero otherwise.
Tick<1/4	Dummy variable that equals to one if the decimal portion of the closing price on the day prior to the offer is less than $ 0.25, and zero otherwise.
Nasdaq	Dummy variable that equals to one if the issuer's primary exchange is NASDAQ, and zero if NYSE or AMEX are the firm's primary exchanges.
Underwriter Reputation	Dummy variable that equals one if the book runner ranking, according to Jay Ritter's underwriter reputation ranking, equals nine (i.e., most prestigious) and zero if the underwriter's ranking is below nine.
Cash to Assets	Cash and Short-Term Investments / Total Assets.
Market-to-Book Ratio	Market Equity / Book Value of Equity, where Market Equity=Price* Common Shares Outstanding, and Book Equity= Stockholders Equity + Deferred Taxes + Investment Tax Credit - Preferred Stock.
Return Past 12 Months	Stock Return of Last 12 Months of Fiscal Period.
Stock Volatility	Total Stock Return Volatility in the Last 24 Months.
Leverage	(Debt in Current Liabilities + Long-Term Debt) / Total Assets.
ROA	Income Before Extraordinary Items / Total Assets.
CAPEX to Assets	Capital Expenditures / Total Assets.
Tobin's Q	(Total Assets + Market Equity – Book Value of Equity) / Total Assets.
Age	Years since IPO.

Figure 1. ***Average price dynamics around SEOs with low and high investor attention.***

This figure plots the average ratio of the stock price to the closing price on the offering date for SEOs I classify into two portfolios, “low” and “high” investor attention, that I form by dividing the SEOs sample into below and above-median values for the volume of news articles 90 days prior to the offerings, respectively. The plotted line (+) shows the average ratio for “low” investor attention offerings. The plotted line (▲) shows the average ratio for “high” investor attention offerings. The sample period is 2003-2012. The sample consists of all NYSE/AMEX/NASDAQ stocks covered by Thomson Reuters News Analytics.

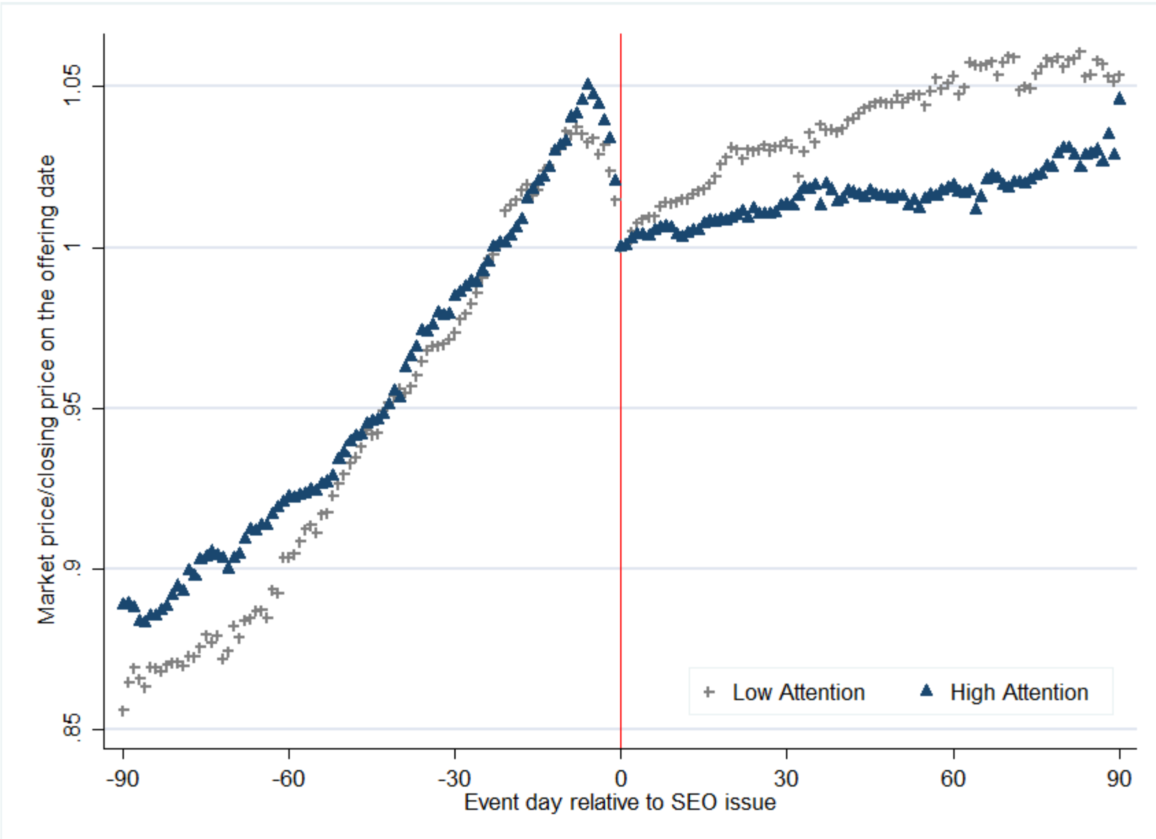

Figure 2. ***Issuers' daily abnormal returns around SEOs with low and high investor attention.***

This figure plots the average daily abnormal returns over a ten-day window around the offer dates for two portfolios, "low" and "high" investor attention, that I form by dividing the SEOs sample into below and above-median values for the volume of news articles 90 days prior to the offerings, respectively. I compute abnormal returns using the market model. I proxy the market return by the return of the CRSP equally-weighted portfolio. I base the estimation of normal returns on the time series for the interval of (-250,-5) days before the actual issuances. The sample period is 2003-2012. The sample consists of all NYSE/AMEX/NASDAQ stocks covered by Thomson Reuters News Analytics.

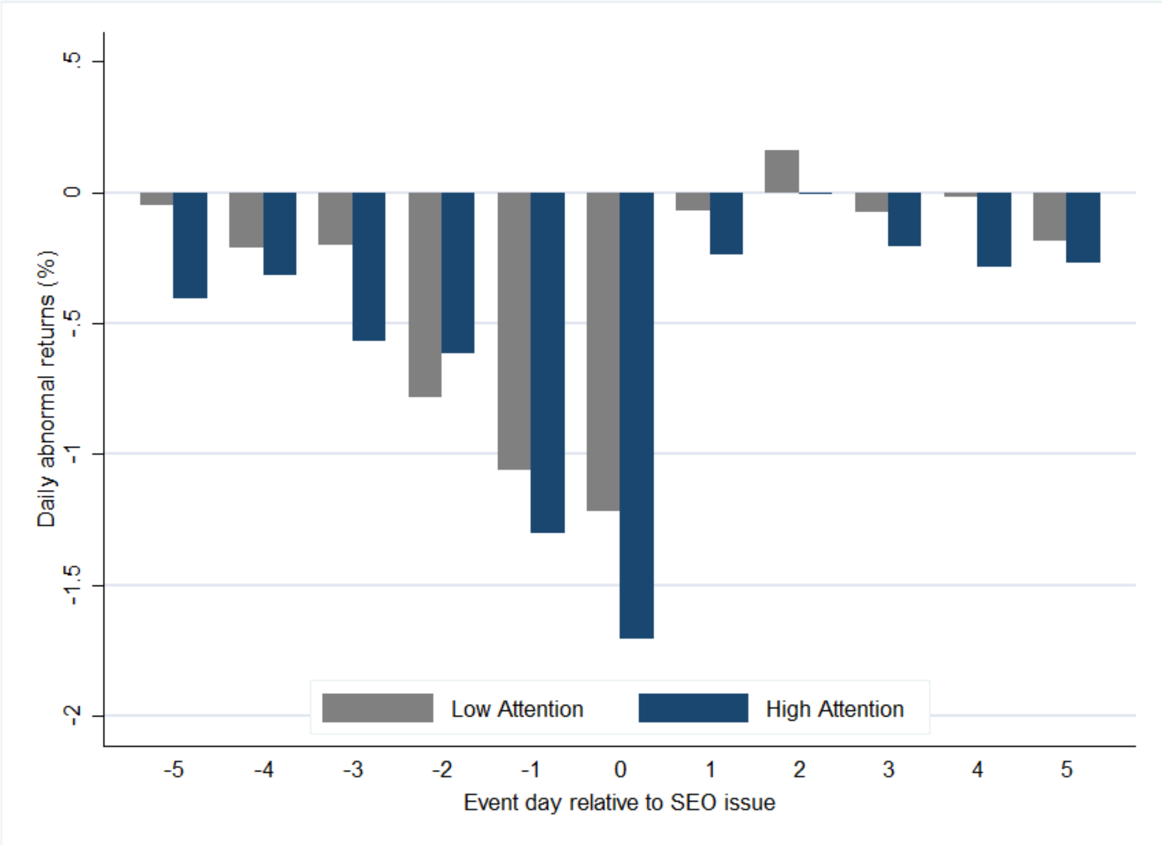

Table 1. **Summary statistics for the sample of Thomson Reuters news articles**

This table presents the number of news articles and firms, categorized by year, in the Thomson Reuters News Analytics for firms in my sample of seasoned equity offerings (SEOs). I only consider news articles for U.S. common stocks listed in the New York Stock Exchange (NYSE), the American Stock Exchange (Amex), and the Nasdaq National Market (NASDAQ). I apply several other filters to the news data. I describe these filters in Section 4.

Year	***Total Number of News Articles***	***Positive Articles***	***Negative Articles***	***Neutral Articles***	***Firms Covered***
2003	46,927	24,285	13,328	9,314	1,846
2004	43,702	24,005	10,243	9,454	1,918
2005	45,240	26,503	8,753	9,984	2,048
2006	56,466	32,497	11,399	12,570	2,200
2007	74,526	37,445	16,672	20,409	2,364
2008	106,383	48,474	27,752	30,157	2,539
2009	80,079	38,348	23,521	18,210	2,626
2010	89,327	46,687	23,201	19,439	2,709
2011	111,024	58,634	30,056	22,334	2,880
2012	111,006	58,379	32,738	19,889	3,048
All	764,680	395,257	197,663	171,760	3,392

Table 2. **Summary statistics for seasoned equity offerings**

This table presents descriptive statistics for the sample of seasoned equity offerings (SEOs) I use in this study. The sample period is January 2003 to December 2012. SEO data is from the SDC Platinum database. I apply several filters to the data. I describe these filters in Section 4. I define *discount* as the ratio of the closing price on the day before the offering to the offer price (in logarithm). *CAR(-1,1)* are the cumulative abnormal returns for the interval of $(-1, +1)$ days around the SEOs. I compute abnormal returns using the market model. I Winsorize *discount* and *CAR(-1,1)* at the upper and lower one percent levels.

	Full SEO Sample				**Sample with TRNA Data**			
Year	Number of SEOs	Proceeds ($ Million)	Discounting	CAR (-1,1)	Number of SEOs	Proceeds ($ Million)	Discounting	CAR (-1,1)
2003	154	122.45	3.93%	-0.74%	91	124.79	3.57%	-0.25%
2004	179	141.89	3.40%	-1.24%	85	149.73	3.18%	-1.08%
2005	150	123.15	3.79%	-1.63%	69	126.88	3.27%	-1.97%
2006	149	131.06	4.24%	-1.21%	83	166.73	4.05%	-1.13%
2007	152	169.14	3.48%	-1.72%	86	183.72	3.01%	-0.80%
2008	81	403.67	4.23%	-3.92%	56	247.05	3.95%	-2.88%
2009	219	144.39	7.87%	-5.39%	155	156.54	7.93%	-5.75%
2010	156	96.67	6.41%	-4.15%	110	98.38	6.37%	-3.76%
2011	126	121.65	5.85%	-2.80%	99	130.14	5.67%	-2.85%
2012	128	100.48	5.85%	-4.80%	95	93.99	6.01%	-4.88%
	1494				929			

Table 3. **Summary statistics for key variables**

This table reports descriptive statistics for the dependent and independent variables I use in this study. I collect news articles from Thomson Reuters News Analytics for the period January 2003 to December 2012. I take data on firms' characteristics from COMPUSTAT. I collect data on seasoned equity offerings (SEOs) from SDC Platinum database. The table presents the number of observations, mean, min, max, standard deviation, skewness, and kurtosis. I define these variables in Appendix B.

	N	***Mean***	***Min***	***Max***	***SD***	***Skewness***	***Kurtosis***
TRNA							
News Articles (-90,-1)	929	6.05	0.00	45.00	7.37	2.54	11.83
Tone (-90,-1)	929	1.05	-2.65	9.76	2.04	1.65	6.89
SEO characteristics:							
Discount	927	0.051	-0.047	0.293	0.058	1.810	6.998
CAR(-1,1)	917	-0.028	-0.273	0.165	0.084	-0.359	3.459
Proceeds ($ Million)	929	140.08	4.00	1375.00	200.88	3.91	21.00
Firms Characteristics:							
Ln(Market Equity)	891	6.276	2.213	10.727	1.246	0.460	3.680
Ln(Assets)	893	5.725	1.999	10.060	1.730	0.407	2.646
Leverage	871	0.255	0.000	1.482	0.283	1.703	6.842
ROA	882	-0.209	-1.752	0.377	0.398	-1.732	5.967
CAPEX to Assets	891	4.750	-12.862	49.094	9.594	2.284	9.762
Tobin's q	891	3.426	0.697	15.621	2.873	2.001	7.617
Cash to Assets	893	0.344	0.000	0.974	0.331	0.622	1.880
Market-to-Book Ratio	818	5.988	0.321	49.689	7.499	3.380	17.249
Return Past 12 Months	761	0.574	-0.836	4.798	1.040	1.728	6.674
Stock Volatility 24 Months	687	0.198	0.063	0.749	0.113	2.285	10.319
Institutional Ownership Ratio	929	0.582	0.000	1.133	0.283	-0.184	2.119
Ln(1+Number of Analysts)	929	1.814	0.000	3.332	0.748	-0.702	3.191
Age (Since IPO)	893	12.375	0.000	42.000	9.514	1.158	3.604

Table 4. **OLS regressions of offer price discounts**

This table presents the parameter estimates for the following model:

$$Discount_{it} = \alpha_i + \beta_1 News\ Articles_{it-1} + \beta_2 Tone_{it-1} + \gamma' X_{it-1} + T_t + I_i + \epsilon_{it},$$

where $Discount_{it}$ is define as the ratio of the closing price on the day before the offering to the offer price (in logarithms), $News\ Articles_{it-1}$ is the accumulated volume of news articles for firm i 90 days before the SEO, $Tone_{it-1}$ is the aggregate tone of news articles calculated as in equation (3). The vector X_{it-1} contains control variables. Firm-level control variables are calculated on a quarterly basis. I define control variables in Appendix B. I also include Fama-French 49 industries fixed-effects and year fixed-effects. Robust standard errors are in parentheses. *, **, and *** indicate the coefficient is significantly different from zero at the 10%, 5%, and 1% significant level, respectively.

	(1)	*(2)*	*(3)*
News of Articles (-90,-1)		**0.0747****	**0.0767****
		(0.0309)	(0.0378)
Tone (-90,-1)			**-0.0138**
			(0.1154)
Controls:			
Ln(Market Equity)	0.7643*	0.6320	0.6351
	(0.4472)	(0.4428)	(0.4411)
Stock Volatility	-1.5434	-3.7588	-3.8536
	(18.3270)	(17.8138)	(18.0034)
Shares Offered / Shares Outstanding	3.0933**	3.1825**	3.1777**
	(1.4618)	(1.4297)	(1.4328)
CAR (-60,-2)	1.0510	1.0404	1.0491
	(0.8661)	(0.8595)	(0.8683)
Tick<1/4	3.0315	2.3797	2.3970
	(3.3420)	(3.4128)	(3.4232)
Ln(Price)	-0.0924	-0.2173	-0.2102
	(0.9780)	(1.0125)	(1.0124)
Tick<1/4*Ln(Price)	-1.1481	-0.9394	-0.9453
	(0.9714)	(1.0103)	(1.0137)
Nasdaq	0.6697	0.6675	0.6715
	(0.5198)	(0.5171)	(0.5190)
Underwriter Reputation	-0.4610	-0.4883	-0.4924
	(0.3898)	(0.3872)	(0.3900)
Ln(SEO Proceeds)	-1.1474**	-1.1257**	-1.1267**
	(0.5501)	(0.5492)	(0.5484)
Ln(1+Analysts)	-1.1071**	-1.2417***	-1.2439***
	(0.4299)	(0.4382)	(0.4372)
Year fixed-effects + intercept	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes
N	807	807	807
Adjusted R2	0.1905	0.1961	0.1896

Table 5. **Instrumental variable regressions of offer price discounts**

This table reports regression results of an instrumental variable approach. In the first stage, I predict the accumulated volume of news articles during 90 days before the SEO for each issuer using the following two instrumental variables: *Media distraction* and *litigation risk*. The instrument *Media distraction* is the accumulated volume of negative news articles 90 days before the SEO for companies classified across all Fama-French 12 industries that are different from the industry of the issuer. The instrument *Litigation risk* is a binary variable that equals one if the issuer is in the computer, electronics, or retail industry; and equals zero otherwise. In the second stage I regress, SEO *discount*, defined as the ratio of the closing price on the day before the offer to the offer price (in logarithms), on the predicted number of news articles and control variable. I calculate firm-level control variables on a quarterly basis. I define control variables in Appendix B. I also include year fixed-effects. Robust standard errors are in parentheses. *, **, and *** indicate the coefficient is significantly different from zero at the 10%, 5%, and 1% significant level, respectively.

	First Stage: Number of Articles (1)	***Second Stage: Discount (2)***
News Articles (-90,-1) (instrumented)		**0.3922***
		(0.2182)
Tone (-90,-1)	1.5411***	-0.4946
		(0.3425)
Instruments:		
Media Distraction	**-1.0651****	
	(0.4189)	
Litigation Risk	**-1.8566*****	
	(0.3951)	
Controls:		
Ln(Market Equity)	1.1116**	0.2983
	(0.4309)	(0.5110)
Stock Volatility	40.1251**	-11.7426
	(16.9457)	(17.2294)
Shares Offered / Shares Outstanding	-0.0376	2.7873**
	(1.6653)	(1.2894)
CAR (-60,-2)	-0.6972	1.0498
	(1.0229)	(0.8942)
Tick<1/4	5.6166	-0.4147
	(3.9404)	(3.9368)
Ln(Price)	0.7079	-0.7136
	(1.5203)	(1.2145)
Tick<1/4*Ln(Price)	-1.7611	-0.0195
	(1.5072)	(1.2783)
Nasdaq	-0.4594	1.0226**
	(0.4811)	(0.4483)
Underwriter Reputation	0.7051*	-0.7845*
	(0.3922)	(0.4175)
Ln(SEO Proceeds)	0.0796	-1.3834**
	(0.4881)	(0.5375)
Ln(1+Analysts)	1.5762***	-1.3269**
	(0.3593)	(0.5417)
Year fixed-effects + intercept	Yes	Yes
Industry fixed-effects	No	No
N	807	807
Adjusted R2	0.3843	0.1234
F(2,738)	12.979	-

Table 6. **News coverage and managing underwriters**

This table presents the parameter estimates for the following panel-data model:

$$News\ Articles_{it} = \alpha_i + \beta_1\ Ln(Managers_{it}) + \gamma' X_{it-1} + T_t + I_i + \epsilon_{it},$$

where $News\ Articles_{it}$ equals the total number of news articles during 90 days before the SEO, and $\ln(Managers_{it})$ represents proxies for the underwriters' efforts in marketing the securities. I use three proxies for SEO marketing efforts: the logged number of managing underwriters; the number of lead, co-lead, and co-managing underwriters; and the number of bookrunners. The vector X_{it-1} contains control variables. I also control for both year and firm fixed-effects. Robust standard errors are in parentheses. *, **, and *** indicate the coefficient is significantly different from zero at the 10%, 5%, and 1% significant level, respectively.

	(1)	***(2)***	***(3)***
Ln (1+Number of Lead Managers)	**-1.3028**		
	(1.0653)		
Ln (1+Number of Managers and Co-managers)		**-0.6117**	
		(0.5513)	
Ln (1+Number of Bookrunners)			**-1.7775**
			(1.2583)
Controls:			
Ln(Market Equity)	-0.0732	-0.0618	-0.0332
	(0.5305)	(0.5174)	(0.5327)
Ln(assets)	0.9954**	0.9441**	1.0242**
	(0.4086)	(0.4083)	(0.4093)
Market-to-Book Ratio	-0.0047	-0.0066	-0.0068
	(0.0342)	(0.0338)	(0.0345)
ROA	-1.4321**	-1.3567**	-1.4453**
	(0.6806)	(0.6892)	(0.6842)
Institutional Ownership Ratio	-2.4829*	-2.4489*	-2.4791*
	(1.2803)	(1.2793)	(1.2770)
Ln(1+ Number of Institutional Owners)	2.1205***	2.1417***	2.0913***
	(0.5117)	(0.5161)	(0.5090)
Ln (1+Number of Analysts)	1.3894***	1.4110***	1.3973***
	(0.4802)	(0.4827)	(0.4803)
Ln (1+ Volume Past 6 Months)	0.9616***	0.9780***	0.9768***
	(0.2563)	(0.2545)	(0.2545)
Firm Fixed-effects + intercept	Yes	Yes	Yes
Year Fixed-effects	Yes	Yes	Yes
N	794	794	794
Adjusted R2	0.2271	0.2266	0.2282

Table 7. **News articles, managing underwriters, and offer price discounts**

This table presents the parameter estimates for the following model:

$$Discount_{it} = \alpha_i + \beta_1 \ln(News\ Articles_{it-1}) + \beta_2 Ln(Managers_{it-1}) + \gamma' X_{it-1} + T_t + I_i + \epsilon_{it},$$

where $discount_{it}$ is define as the ratio of the closing price on the day before the offer to the offer price (in logarithms), $\ln(News\ Articles_{it-1})$ is the logarithm of one plus the accumulated volume of news articles during 90 days before the SEO for firm i, and $\ln(Managers_{it})$ represents proxies for the underwriters' efforts in marketing the securities. To proxies for SEO marketing efforts, I include three variables: the logged numbers of lead, co-lead, and co-managing underwriters; and two terms for their interactions with the relative offer size, and the return volatility. The vector X_{it-1} contains control variables. I calculate firm-level control variables on a quarterly basis. I define control variables in Appendix B. I also include Fama-French 49 industries fixed-effects and year fixed-effects. Robust standard errors are in parentheses. *, **, and *** indicate the coefficient is significantly different from zero at the 10%, 5%, and 1% significant level, respectively.

	(1)	*(2)*	*(3)*	*(4)*
Ln(1+News Articles (-90,-1))			**0.5267****	**0.4725****
			(0.2091)	(0.2069)
Ln (1+Number of Managers and Co-managers)	**-1.2906*****	**0.4405**	**-1.2303*****	**0.4231**
	(0.4073)	(0.6998)	(0.4060)	(0.6993)
Ln (1+Number of Managers and Co-managers)*Relative Size		**-5.1742***		**-4.5871**
		(2.9885)		(2.9433)
Ln (1+Number of Managers and Co-managers)*Volatility		**-26.9549**		**-27.3902**
				(17.4457)
Controls:				
Ln(Market Equity)	0.6349	0.5604	0.5546	0.4901
	(0.4465)	(0.4307)	(0.4403)	(0.4269)
Stock Volatility	-1.9960	27.6928	-2.7225	27.6669
	(17.5618)	(30.7590)	(16.9261)	(30.3200)
Shares Offered / Shares Outstanding	3.1749**	10.4116**	3.4309**	9.8091**
	(1.4638)	(4.8778)	(1.4490)	(4.7604)
CAR (-60,-2)	0.9330	0.8942	0.9082	0.8748
	(0.8673)	(0.8541)	(0.8664)	(0.8540)
Tick<1/4	2.4367	2.2204	1.9658	1.8124
	(3.3400)	(3.2538)	(3.3959)	(3.3275)
Ln(Price)	-0.2822	-0.2498	-0.3492	-0.3144
	(0.9898)	(0.9644)	(1.0151)	(0.9962)
Tick<1/4*Ln(Price)	-0.9407	-0.9028	-0.7983	-0.7791
	(0.9834)	(0.9655)	(1.0095)	(0.9981)
Nasdaq	0.6246	0.6722	0.5524	0.6118
	(0.5113)	(0.5061)	(0.5063)	(0.5016)
Underwriter Reputation	-0.4620	-0.4120	-0.4572	-0.4081
	(0.3901)	(0.3904)	(0.3869)	(0.3878)
Ln(SEO Proceeds)	-0.6828	-0.6659	-0.6556	-0.6367
	(0.5815)	(0.5692)	(0.5843)	(0.5726)
Ln(1+Analysts)	-1.0925**	-1.0712**	-1.2965***	-1.2587***
	(0.4231)	(0.4165)	(0.4369)	(0.4312)
Year fixed-effects + intercept	Yes	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes	Yes
N	803	803	803	803
Adjusted R2	0.1992	0.2082	0.2053	0.2128

Table 8. **OLS regressions of SEO cumulative abnormal returns around offer dates**

This table presents the parameter estimates for the following model:

$$\widehat{CAR}(-1,+1)_{it}^{k} = \alpha + \beta_3 News\ Articles_{it} + \beta_4 Tone_{it} + \gamma' X_{t-1,i} + \delta_t + \lambda_i + \epsilon_{t,i},$$

where $\widehat{CAR}(-1,+1)_{it}^{k}$is the cumulated abnormal return for company i, SEO k, three days around the offer, $News\ Articles_{it-1}$ is the number of news articles 90 days before the SEO, $Tone_{it-1}$ is the aggregate tone of the news articles 90 days before the SEO. The vector X_{it-1} contains control variables. I calculate firm-level control variables on a quarterly basis using the most recent quarter prior to the SEO event. I define control variables in Appendix B. I also include Fama-French 49 industries fixed-effects and year fixed-effects. Robust standard errors are in parentheses. *, **, and *** indicate the coefficient is significantly different from zero at the 10%, 5%, and 1% significant level, respectively.

	(1)	*(2)*	*(3)*
News Articles (-90,-1)		**-0.1104****	**-0.1568*****
		(0.0470)	(0.0535)
Tone (-90,-1)			**0.3075***
			(0.1700)
Controls:			
Tobin's Q	-0.2640	-0.2394	-0.2501
	(0.2255)	(0.2263)	(0.2260)
Cash to Assets	-4.0980**	-3.9371**	-3.9824**
	(1.8079)	(1.8191)	(1.8155)
Leverage	-3.7969	-4.1616*	-3.9092*
	(2.3450)	(2.3651)	(2.3593)
Ln(Assets)	-1.2969*	-1.0913	-1.2148*
	(0.7237)	(0.7422)	(0.7334)
Ln(Market Equity)	0.9686	0.9725	0.9581
	(0.8061)	(0.8062)	(0.8083)
Shares Offers / Shares Outstanding	-0.4237	-0.4676	-0.4534
	(1.5834)	(1.5478)	(1.5674)
CAR (-60,-2)	-0.1039	-0.0464	-0.1481
	(1.2808)	(1.2589)	(1.2781)
Ln(1+Analysts)	1.0442*	1.1920*	1.1166*
	(0.6250)	(0.6280)	(0.6286)
Ln(SEO Proceeds)	0.4672	0.4007	0.4431
	(0.5814)	(0.5804)	(0.5790)
Year fixed-effects + intercept	Yes	Yes	Yes
Industry fixed-effects	Yes	Yes	Yes
N	785	785	785
Adjusted R2	0.0578	0.0635	0.0579

Table 9. **Long-term performance for firms with SEOs**

This table reports long-term stock returns over different horizons for issuers classified into two categories according to their volume of news stories 90 days prior to the offerings. Panel A presents average compounded buy-and-hold abnormal returns (BHARs) for firms with low numbers of news articles 90 days prior to the issuances ("low") and firms with high numbers of news articles 90 days prior to the issuances ("high"). Returns are compounded three, six, and 12 months after the issuances of new equity. I assign firms to one of 25 matching book-to-market/size portfolios using the quintile breakpoints from Ken French's website. I calculate BHARs by first compounding returns for each firm and then subtracting the compounded return on a matching BM/ME portfolio. I report both equal-weighted (EW) and value-weighted (VW) average returns. For VW returns, I construct the weights using the firm's ME at the beginning of the issue quarter, scaled by the level of the CRSP VW index at that date. Panel B presents cumulative abnormal returns (CARs) for "low" and "high" portfolios. The CARs are similar to the BHARs, but I subtract the matching portfolio return each month and then sum returns over the cumulating window. Panel C reports calendar-time factor regression results of portfolios consisting of firms that issue equity in the prior year and belong the "low" and "high" portfolios. Every month from January 2003 to December 2012, I form equally-weighted portfolios of firms that issued seasoned equity in the past year and belong to either the "high" or "low" portfolio. The dependent variable is the excess return of the portfolio over one-month T-bill rate. I use the Carhart (1997) four-factor model as the factor model, and measure portfolio underperformance as the intercept (*alpha*) from the factor regressions. *, **, and *** indicate the coefficient is significantly different from zero at the 10%, 5%, and 1% significant level, respectively.

Panel A: Buy-and-Hold Abnormal Returns (BHARs)			
		Equal-Weighted	Value-Weighted
Month	Attention	**BHARs (%)**	**BHARs (%)**
3	Low	**2.168***	**1.326**
	High	**-0.789**	**-1.624**
	Difference	**2.958***	**2.95***
6	Low	**1.49**	**-3.498****
	High	**1.345**	**0.008**
	Difference	**0.145**	**-3.506**
12	Low	**0.759**	**-0.618**
	High	**-0.091**	**4.561***
	Difference	**0.849**	**-5.179**

Panel B: Cumulative Abnormal Returns (CARs)			
		Equal-Weighted	Value-Weighted
Month	Attention	**BHARs (%)**	**BHARs (%)**
3	Low	**2.271****	**1.033**
	High	**-0.809**	**-2.133***
	Difference	**3.079***	**3.166***
6	Low	**1.675**	**-3.083****
	High	**1.219**	**-0.326**
	Difference	**0.456**	**-2.757**
12	Low	**3.051**	**1.33**
	High	**1.659**	**4.562****
	Difference	**1.392**	**-3.232**

Panel C: Calendar-Times Regressions (Months 1 through 12)			
		Low Attention	High Attention
	Factor	Estimate	Estimate
Equal-Weighted	**Alpha (%)**	**-0.49****	**-0.4***
	MKT	1.291***	1.341***
	SMB	0.074	0.288**
	HML	-0.2*	-0.169*
	MOM	0.321***	0.095
	Adj. R2	0.792	0.826
Value-Weighted	**Alpha (%)**	**-0.02**	**0.21**
	MKT	1.326***	1.358***
	SMB	0.231***	0.652***
	HML	-0.614	-0.208*
	MOM	0.212	0.176
	Adj. R2	0.591	0.689