Social Media Management: Evidence on Seasoned Equity Offerings

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Abstract

This paper demonstrates that firms actively manage social media to maximise their SEO proceeds by managing liquidity costs and lifting market valuations in the post-SEO period before the expiration of lockup agreements. We find that SEO firms receive more favourable messages on the financial social media platform, StockTwits, around the periods from 62 trading days to 10 trading days prior to the offerings and from 10 trading days subsequent to the offerings to the expiration of lockup agreements, compared to their non-SEO matching controls. Moreover, evidence shows that SEO firms ranking in the top quartile of abnormal pre-SEO bullishness on social media reduce their underpricing by 1.12% on average. We reject a competing hypothesis of investor attention by finding subsequent price reversal and long-run underperformance for SEO firms which undergo active social media management.

Keywords: Social Media; Seasoned Equity Offerings; SEO Underpricing; Textual Analysis; Machine Learning; Investor Sentiment

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1 Introduction

Public firms raise capital through seasoned equity offerings (SEOs). It is well documented that abnormal stock returns of public firms around their SEO announcements are significantly negative (e.g., Masulis & Korwar, 1986). Moreover, SEO offer prices on average have a 3% discount from the most recent closing prices (e.g., Mola & Loughran, 2004). The recent literature on social media and stock prices shows that investor opinions transmitted through online financial social media platforms such as Twitter, StockTwits and SeekingAlpha significantly predict stock returns (see, e.g., Chen, De, Hu & Hwang, 2014; Renault, 2017; Bartov, Faurel, & Mohanram, 2018). Thus, we conjecture that in the age of social media, SEO firms may have strong incentive to actively manage its social media coverage with the attempt to reduce underpricing and increase SEO proceeds. For example, the U.S. Securities and Exchange Commission (SEC) investigated 27 firms and individuals, who were charged for the use of social media to disseminate fraudulent and bullish articles to promote stocks in 2017. This resulted in a payment of up to $3 million in settlement fees, which includes disgorgement and penalty fees, by 17 defendants. In response, the SEC issued an investment alert to investors and warned them of the potential misleading or fraudulent stock recommendations for stock promotion schemes on social media or investment newsletters.

In this study, we fill a gap in the literature by documenting that active social media management around SEOs reduces SEO underpricing. Empirical evidence from literature such as Renault (2017), Giannini, Irvine and Shu (2019), and Cookson and Niessner (2020) show that StockTwits contemporaneously impact stock prices and liquidities. We employ a sample of SEO firms covered by social media on StockTwits to show that SEO firms actively manages its social media coverage and receives more favourable posts during the pre-SEO period to reduce underpricing. Moreover, since lockup agreements restrict corporate insider selling for a pre-determined period (the lockup period) after the offering, we also investigate whether SEO firms try to manage their bullish social media coverage during the post-SEO period before the expiration of lockup agreements. We propose two competing hypotheses to explain social media activities around SEOs: an active social media management hypothesis and an investor attention hypothesis. We employ the Difference-in-Differences (DID) design and use the Propensity Score Matching (PSM) technique to match SEO firms with non-SEO control firms. We document empirical evidence suggesting that compared with matched control firms, SEO firms receive more bullish social media messages around the periods from 62 trading days to 10 trading days prior to the offerings and from 10 trading days subsequent to the offerings to the expiration date of lockup agreements.

Our findings are generally consistent with the active social media management hypothesis. We show that SEO firms that undergo active social media management reduce their SEO underpricing by 1.12%, after controlling for deal characteristics, firm characteristics, year fixed effects and industry fixed effects. Furthermore, SEO firms with active social media management in the lockup periods exhibit higher post-issue stock liquidity (measured by quoted spreads, effective spreads, stock turnover and Amihud (2002) illiquidity ratios) and higher buy-and-hold abnormal returns. Subsequent to the expiry of lockup agreements, results exhibit persistent price reversal and long-run underperformance. Specifically, after sorting SEO firms into quartiles based on their abnormal social media bullishness around the offerings, the mean difference in market-adjusted buy-and-hold-abnormal returns between the bottom and top quartile is 6.07% in the following six months and 29.77% in the following three years after the expiration of SEO lockup agreements. These results suggest that investors in SEO stocks may ultimately pay the price of active social media management by SEO firms.

Additionally, using data from the Ravenpack database, we do not find evidence supporting active media management in traditional media sources such as news or press releases, which suggests that in the age of social media, SEO firms are more likely to use social media rather than traditional media to influence SEO offer pricing. We demonstrate that SEO firms with smaller size, lower institutional ownership, lower market-to-book ratios, higher idiosyncratic volatility, or higher analyst dispersion, reveal higher levels of active social media management around the offerings.

Our paper contributes to two strands of literature. First, we contribute to the literature that investigates the role of social media in financial markets. The literature documents significant influences of social media on stock price (e.g., Chen et al., 2014) and trading volume (e.g., Giannini et al, 2019; Cookson & Niessner, 2020). We contribute to this literature by showing that firms may actively manage their social media coverage to influence their SEO outcomes. Second, we contribute to the strand of corporate finance literature on SEOs. The literature documents that firms manage their pre-SEO earnings (e.g., Teoh, Welch & Wong, 1998; Kim & Park, 2005) or increase their pre-SEO investor recognition (Autore & Kovacs, 2014) to reduce the degree of underpricing. We show that social media is another important channel where issuing firms manage their floatation costs. In particular, we find that SEO firms with high information asymmetry tend to undergo more active social media management. An implication from the findings is that market regulators may need to monitor social media activity of SEO firms more closely, especially those fund-raising firms with high levels of information asymmetry.

The rest of the paper proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and empirical methodology. Section 4 discusses the main findings. Section 5 reports the robustness results. Section 6 concludes. A variable definition table (Table A1) and additional empirical results are provided in the Appendix.

2 Literature Review and Hypothesis Development

2.1 Literature review

Literature portrays the primary role of media in financial market as a key channel of financial information, which consequently shapes market participants' expectations and leads to investment decisions and economic outcomes (e.g., Busse & Green, 2002; Tetlock, Saar-Tsechansky & Macskassy, 2008; Liu & McConnell, 2013). A related strand of literature investigates the influence of corporate active media management on stock price during major corporate events. Building on the research of

Bushee and Miller (2012) on investor relation (IR) firms, Solomon (2012) states that IR firms could spin their clients' news around non-earnings press release by creating more positive media coverage relative to the negative coverage, which consequently leads to higher announcement returns. Ahern and Sosyura (2014) highlight the active media management of acquiring firms in fixed-ratio stock mergers and find the increasing number of firm-initiated news and subsequent build-up of acquirers' stock prices before the fixed-ratio is determined during the negotiation period.

The internet era brought about the wide accessibility of online social media to the masses. As such, researchers have since exhibited increasing interests in whether financial social media plays a similar role in the transmission of information as traditional news media channels. Evidence suggests that online messages exhibits significant predictive power on stock returns and trading volumes across various social media platforms including Yahoo! Finance and Raging Bull (Antweiler & Frank. 2004), SeekingAlpha (Chen et al, 2014), HotCopper (Leung & Ton, 2015), StockTwits (e.g., Renault, 2017; . Giannini et al., 2019; Cooksoon and Niessner, 2020) and Twitter (Bartov et al, 2018). Among which, we employ social media from StockTwits given its large user base covering a wide spectrum of user characteristics such as their investment strategies, details of their professional background, and their level of financial sophistication. Cookson and Niessner (2020) use the features of self-reported user information, such as experience and investment approaches on StockTwits to construct several measures of disagreements including overall disagreement among users and cross-/ within-group disagreements among investor groups identified by users' investment approaches. They show that disagreement is positively correlated with the abnormal trading volume in the same day for each stock and the disagreement from earnings week to one week after earnings is associated with the contemporaneous spike of abnormal trading volume. Cookson, Engelberg and Mullins (2020) employs textual analysis techniques to identify partisanship amongst StockTwit users and show that partisan disagreement on the social media platform could explain about 30% of the increase in stock turnover during the COVID-19 pandemic.

Jung, Naughton, Tahoun and Wang (2018) discover that high litigation risk firms strategically disseminate quarterly earnings announcements via Twitter. Specifically, those firms tend to post fewer tweets of “bad” earnings announcements, and the likelihood of strategic dissemination is positively related to their levels of social media audience and negatively related to the levels of investor sophistication. Our paper aims to fill the research gap by investigating the active social media management by firms during specific corporate events such as SEOs.

Generally, firms prefer issuing new equities when current stock price is overvalued. Literature also reveals several key determinants in SEO timing such as short-term need for cash (DeAngelo, DeAngelo & Stulz, 2010), liquidity risks (Lin & Wu, 2013), executive compensation (Brisker, Autore, Colak & Peterson, 2014) and institutional ownership (Altı & Sulaeman, 2012; Hovakimian & Hu, 2016). Literature documents that SEO underpricing of new shares are offered at 2-3% discount from the pre-issue offering price (e.g., Corwin, 2003; Mola & Loughran, 2004). SEO underpricing is shown to be negatively associated with the pre-offer institutional purchase (Chemmanur, He and Hu, 2009), the reputation of leading underwriters (Mola & Loughran, 2004; Jeon & Ligon, 2011), the number of managing underwriters (Huang & Zhang, 2011) and the number of analyst coverage (Bowen, Chen & Cheng, 2008), since the marketing effect of underwriters would both flatten and shift the demand curve upwards and pre-issue analyst coverage mitigates potential information asymmetry between SEO firms and outside investors. Specifically, Autore and Kovacs (2014) argue that SEO underwriting costs are positively related to the investor recognition proxied by the number of analysts following and SEO firms have the incentive to push up valuations prior offerings through an increase in investor recognition. Moreover, the post-issue underperformance in stock returns is shown to be more pronounced in SEO firms with a greater increase in investor attention.

Further, researchers document certain types of abnormal activities of issuing firms or their underwriters prior to SEOs with attempts to maximise SEO proceeds. Teoh et al. (1998) show that SEO firms strategically raise earnings through discretionary accruals prior to SEO issue while the firms with higher levels of earnings management exhibit inferior post-issue long-run performance in stock price and net income. This “greedy SEO issuer” hypothesis is supported by literature which shows that SEO firms exhibiting more aggressive recognition of accruals (Kim & Park, 2005) and real activities manipulation before SEOs (Kothari, Mizik & Roychowdhury, 2016) both result in lower degrees of SEO underpricing.

Karpoff, Lee and Masulis (2013) study the use of SEO lockup agreement, a legal contract to prevent corporate insiders from selling stocks for a pre-determined period after SEO. The duration of most of lockup agreements from 1996 to 2006 ranges from 1 to 180 days and it is positively associated with the level of issuer information asymmetry, and negatively associated with underwriting costs and underpricing. Additionally, negative cumulative abnormal returns are documented around the expiration of lockup agreements, while the early release of lockup agreements by underwriters implying the favourable firm-specific information yields the 3-day abnormal returns of 0.8% centred at the early release date.

2.2 Hypothesis Development

As discussed earlier, firms are shown to actively manage traditional media coverage and sentiments to influence their valuation during important corporate events such as mergers and acquisitions (Ahern & Sosyura, 2014) and non-earnings press release (Solomon, 2012). Moreover, firms prefer to time the market and issue new equities when stocks are overvalued (e.g., DeAngelo et al., 2010) and face less liquidity risks (Lin & Wu, 2013) to maximise capital raising proceeds. SEO firms are found to pay greater underwriting costs to drive up their valuation pre-SEO by increasing investor recognition (Autore & Kovacs, 2014). Given that social median activities are shown to influence stock price and trading volume (Renault, 2017; Giannini et al, 2019; Cookson & Niessner, 2020), we conjecture that in the age of social media, SEO firms would have the incentive to increase their positive social media coverage before SEOs to reduce SEO underpricing.

SEO lockup agreements are frequently used to restrict post-SEO corporate insider selling and to mitigate information asymmetry between issuing firms and outside investors (Karpoff et al., 2013). Therefore, SEO firms are incentivised to manipulate stock liquidity and ramp up stock prices to facilitate post-lockup sales, manage liquidity costs and maximise the sale value of issued stocks after the expiration of SEO lockup agreement.

As such, we formalise our active social media management hypothesis as follows,

H1 (Active Social Media Management): SEO firms undergo active social media management (in terms of both coverage and bullish sentiment) before SEOs and during lockup periods, which lead to lower underpricing in offerings and greater stock returns and liquidity during lockup periods. Importantly, there will be a long-run return reversal as a result of active social media management.

Alternatively, firms would announce their SEO plans before the issue date of an SEO, which brings about an increase in investor attention and recognition for the SEO firms. This is expected to lead to higher levels of social media activity, lower SEO underpricing, greater post-issue stock returns and liquidity and, importantly, the absence of long-run reversals. These results are consistent with the explanation of capital market equilibrium with incomplete information in Merton (1987). Hence, we formalise the alternative hypothesis as follows,

H2 (Investor Attention): An increase in investor attention and recognition for SEO firms around the SEOs lead to greater social media coverage (but not necessarily more bullish sentiment), lower underpricing in offerings and greater stock returns and liquidity during lockup periods due to the increased investor recognition. Importantly, there should be no long-run return reversal.

3 Data and Methodology

We employ completed U.S. SEO cases documented in the SDC Platinum database from 2010 to 2015. We then filter the sample with the following criteria similar to Corwin (2003): (1) we exclude the offers issued by non-US firms and close-end funds according to the Center for Research in Security Prices (CRSP) share codes; (2) we exclude pure secondary offers; (3) we exclude the offers with offer prices lower than $3.00 or over $400.00; (4) the offer should be issued by either NYSE- or Nasdaq-listed firm; (5) the offer should be issued by a firm with trading information on CRSP for at least 252 trading days prior to the SEO; and, (6) we exclude subsequent offers for the same issuing firms within 252 trading days. Moreover, in order to analyse firm's coverage on both traditional and social media platforms, we require the SEO firms to have been covered on both StockTwits and Ravenpack for at least 252 trading days prior to the offer. Consistent with previous SEO studies (e.g. Corwin, 2003; Karpoff et al., 2013), we use the same approach to adjust for the fact that some of the offerings start after the close time of stock exchanges. Specifically, if the daily trading volume on the SDC issue date is less than the half of the trading volume on the following trading day, the issue date is adjusted to the following trading day.

Panel A of Table 1 reports the summary statistics for 666 SEO firms. Firms issue seasoned equity offers with the average offer price of $28.20, which on average are 16.7% of the market equity prior to their SEOs. Sample SEO firms experience the underpricing of 4.43% on average. 430 offers are issued by firms listed in Nasdaq and remaining 236 offers are issued by NYSE-listed firms. Panel B of Table 1shows the descriptive statistics for main variables used for the within-SEO-firm analyses.

[Insert Table 1]

Then, we apply the PSM technique to construct a non-SEO control group. Similar to the treatment group, non-SEO firms should have trading data, traditional media coverage and social media coverage for at least 252 days. We use a logit model to estimate the probabilities of conducting an SEO in each year based on firm-level controls and controlling for year fixed effects and industry fixed effects (by two-digit SIC codes). Then we set the maximum difference between matched scores equal to 1% and match the SEO firms with their nearest non-SEO counterparts without replacement by year and industry.

The validity of the PSM process is shown in Table 2. Panel A suggests that there is no statistical difference in firm-level controls including natural logarithm of total assets, debt ratio, return on assets and natural logarithm of net sales between the treatment and control groups after matching. Panel B reveals the logit regression statistics for pre- and post-match samples respectively. We show that those four controls are no longer statistically significant in explaining the probability of conducting an SEO, meanwhile the pseudo-R^2 drops from 10.8% in pre-match sample to only 0.2% in post-match sample.

[Insert Table 2]

We then collect the following information: (1) user ID, (2) stock ticker, (3) time stamp, (4) the message content, (5) the self-reported sentiment (bullish/bearish) from StockTwits covering the entire sample period. Similar with Cookson and Niessners (2020), we adjust the real posting date according to trading days and hours[1]. For instance, the messages posted after 4 pm in day *t* would be assigned to day *t+1* and the messages posted on weekends or holidays are assigned to next trading day. We use Synthetic Minority Over-sampling Technique (SMOTE) (Chawla, Bowyer, Hall & Kegelmeyer, 2002) and machine-learning algorithms to identify the sentiments of messages without self-reported sentiments. Specifically, we first use the SMOTE to solve the problem of unbalanced dataset of posts with self-reported sentiments. Then, we use the outcome as the training set for Naïve Bayesian algorithm, similar to Antweiler and Frank (2004) and Leung and Ton (2015), to identify the sentiments of posts without self-reported sentiments. Finally, we estimate the bullishness measure at firm-day level, expressed in equation (1). $n_{bull,i,t}$ and $n_{bear,i,t}$ represent the numbers of bullish and bearish posts in StockTwits on firm *i* at day *t*. This measure has the advantage of capturing two dimensions, overall sentiment and daily coverage, of social media activities. Firms with higher level of social media management are expected to exhibit higher bullishness on StockTwits.

$$Bullishness\ (i,t) = \frac{n_{bull,i,t} - n_{bear,i,t}}{n_{bull,i,t} + n_{bear,i,t}} * Ln\left(1 + n_{bull,i,t} + n_{bear,i,t}\right) \tag{1}$$

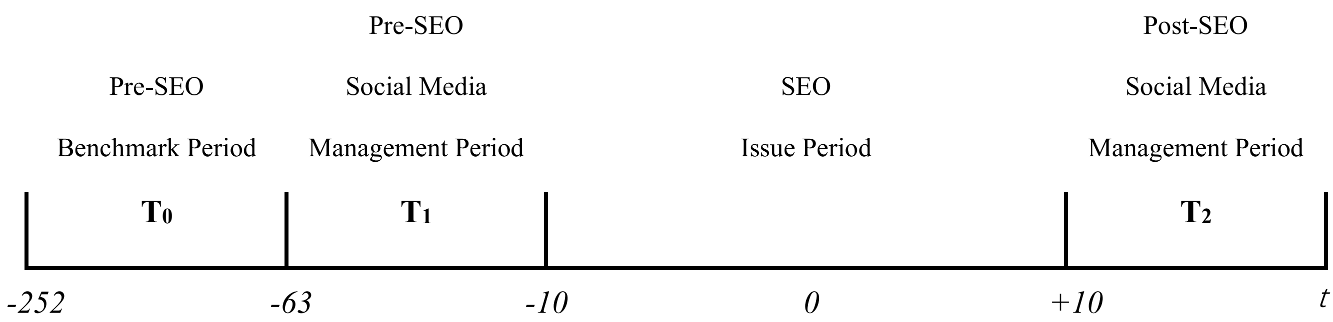
[1] We define the trading days and hours as 9am to 4pm Eastern Time (EST) from Monday to Friday excluding public holidays.

Additionally, we collect analyst forecasts on quarterly earnings from Institutional Brokers Estimate System (I/B/E/S) and institutional ownership data from Thomson-Reuters Institutional Holdings (13F) dataset via the portal of Wharton Research Data Services (WRDS).

To test our main hypothesis of active social media management, we propose the timeline of a typical SEO shown in Figure 1 that SEO firms have the incentive to actively increase their positive coverage on the social media platform during both pre-SEO social media management period (**T_1**) and post-SEO social media management period (**T_2**) in order to reduce SEO underpricing and increase post-lockup selling gains respectively. We use the actual expiration date of lockup agreement on SDC Platinum to determine the length of lockup agreement *t*. For the observations with missing records of lockup expiration dates, we manually check with SEC fillings via the Electronic Data Gathering, Analysis, and Retrieval System (EDGAR) and replace the missing records with the sample mode (*t*=90). Consistent with Karpoff et al. (2013), we use the shortest lockup period for the offerings with multiple lockup periods for different insiders.

Figure 1: Timeline of a Typical SEO

This figure illustrates the timeline of a typical SEO and the numbers represent trading days relative to the SEO issue date recorded in *SDC Platinum*.



We employ a DID design to empirically test our hypothesis, which is presented in equation (2). We add event-firm and event-date fixed effects to capture the unobservable time-invariant characteristics for event-firm observations and unobservable time-relevant characteristics. Standard errors are clustered at event-firm level. Therefore, the DID terms, $SEO_i *$

$\text{Pre SEO Media Management}_{i,t}$ and $SEO_i * \text{ Lockup Period}_{i,t}$, in model (2) are able to explain the abnormal patterns of social media activities of SEO firms during the hypothetical social media manipulation periods.

$$\begin{aligned} &Bullishness\ (i,t) \\ &= b_0 + b_1 * SEO_i * \text{ Pre SEO Media Management}_{i,t} + b_2 * SEO_i * \text{ Lockup Period}_{i,t} \\ &\qquad + Event - Firm\ Fixed\ Effects + Event - Date\ Fixed\ Effects \\ &\qquad + u_{i,t} \end{aligned} \quad (2)$$

Furthermore, we assess the impact of pre-SEO active social media management on SEO underpricing by model (3), where SEO underpricing is calculated the percentage return from the pre-SEO closing price to the offer price times negative one. We construct the $ACTIVE_{i,pre}$ dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the pre-SEO social media management period (**T_1**) and zero otherwise. Abnormal bullishness is the difference between mean bullishness during the pre-SEO social media management period (**T_1**) and mean bullishness during pre-SEO benchmark period (**T_0**). We include a list of SEO characteristics including offer size, relative offer size, natural logarithm of pre-SEO close price, pre-SEO cumulative abnormal returns, pre-SEO stock return volatility, IPO return in same month, number of managers, number of bookrunners, shelf dummy, tick size dummy and Nasdaq dummy consistent with previous SEO literature (e.g. Corwin, 2003; Mola & Loughran, 2004; Kim & Park, 2005; Chemmanur et al., 2009; Jeon & Ligon, 2011). We also include lagged firm-level controls as the proxies of information asymmetry including firm size, number of analysts following, analyst dispersion in earnings forecasts and institutional ownership, consistent with Karpoff et al. (2013). We further include the pre-SEO discretionary accruals as the control variable since Kim and Park (2005) suggest that the SEO firms with higher discretionary accruals tend to have lower level of SEO underpricing. We calculate the performance-matched quarterly discretionary accruals following Kothari, Leone and Wasley (2005) and Linck, Netter and Shu (2013). Moreover, we include industry fixed effects (by two-digit SIC codes) and year fixed effects to account for unobservable time-invariant industry factors and year trends respectively. If our hypothesis of active social media management holds, the slope of $ACTIVE_{i,pre}$ dummy is expected to be negatively significant.

To test , we regress the $ACTIVE_{i,post}$ and a set of same control variables on the post-issue stock performance metrics including the average effective spreads, quoted spreads, stock turnover, Amihud (2002) illiquidity ratio and buy-and-hold abnormal returns in model (4). Similar to model (3), $ACTIVE_{i,post}$ is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the lockup period (**T2**) and zero otherwise and Appendix A1 provides the detailed descriptions of the variables used in models (3) and (4).

$$\begin{aligned} &SEO\ Underpricing\ (i) \\ &= c_0 + c_1 * ACTIVE_{i,pre} + \mathbf{\Gamma} * \text{Firm} - \text{ Level Controls}_i + Industry\ Fixed\ Effects \\ &\qquad + Year\ Fixed\ Effects + u_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} &Post - Issue\ Performance\ (i) \\ &= d_0 + d_1 * ACTIVE_{i,post} + \mathbf{\Gamma} * \text{Firm} - \text{ Level Controls}_i + Industry\ Fixed\ Effects \\ &\qquad + Year\ Fixed\ Effects + u_{i,t} \end{aligned} \tag{4}$$

4 Main Results

4.1 Active Social Media Management

Table 3 reports the slope estimates of multivariate DID tests for three number-of-post measures and two bullishness measures as the dependent variables, and we further control for event-firm and event-date fixed effects and report the standard errors clustered at event-firm level. Consistent with **H1**, DID terms are positively significant for bullishness measures. Column (1) in Table 3 suggests that the SEO firms would tend to have 2.70 and 5.51 more posts per day on StockTwits during pre-SEO media management and post-SEO lockup period than pre-SEO benchmark period, compared to their non-SEO counterparts. Columns (2) and (3) report the results for number of posts with identifiable sentiments (both machine-learnings and self-reported sentiments) and number of posts with only self-reported sentiments respectively, which reveal the similar patterns of increasing StockTwits coverage in column (1) for SEO firms especially during the hypothesised post-SEO manipulation period ($\mathbf{T_2}$). These findings also support the validity of the use of machine-learning in classifying sentiments of StockTwits messages.

Columns (4) and (5) present the outcomes for bullishness measures based on messages with identifiable sentiments and those with only self-reported sentiments, respectively. Both models record positively significant DID terms, which suggest that SEO firms exhibit positive coverage on the social media platform during manipulation periods, consistent with the active social-media manipulation hypothesis. This finding consequently rejects the alternative hypothesis of investor attention. Arguably, SEO firms exhibiting patterns of active social media management suggest that they may influence social media activity to generate more favourable posts during the hypothetical manipulation periods ($\mathbf{T_1}$ and $\mathbf{T_2}$) in order to reduce SEO underpricing and lift post-SEO selling gains.

[Insert Table 3]

4.2 SEO Underpricing

In this section we show evidence of reduced SEO underpricing for SEO firms with active social media management. We perform the regression of SEO underpricing on dummies equal to one for SEO firms ranked in the top quartile in mean abnormal bullishness during pre-SEO social media management period ($\mathbf{T_1}$). Abnormal bullishness is the difference between actual bullishness (or and mean bullishness during pre-SEO benchmark period ($\mathbf{T_0}$). We also control for SEO characteristics, pre-SEO firm-level controls, year fixed effects and industry fixed effects in models (2), (3), (5) and (6). Standard errors are clustered at the industry level. We show that findings are consistent with **H1.** SEO firms which rank in the top quartile in mean abnormal bullishness during the pre-SEO social media manipulation period experiences less underpricing by -1.12% ($p < 0.05$), compared to SEO firms with less active social media management proxied by the abnormal pre-SEO bullishness. Columns (4) to (6) present more evidence supporting the active social media management hypothesis. Even though SEO firms are more likely to receive more pre-SEO coverage due to the increasing investor attention, issuing firms with high general social media coverage do not benefit from the reduction of SEO underpricing in column (6) of Table 4 after controlling for firm-level control variables, year- and industry-fixed effects.

Moreover, we find the results consistent with previous findings in SEO underpricing (Corwin, 2003; Kim & Park, 2005; Chemmanur et al., 2009; Huang & Zhang, 2011). Issuers experience lower discount with more underwriting managers ($\beta_{Managers} = -0.735, p < 0.05$) and higher pre-SEO institutional ownership ($\beta_{IO} = -3.040, p < 0.01$). Additionally, we could provide evidence consistent with the issuer's greed hypothesis proposed by Kim and Park (2005) that SEO issuers are more aggressive in earnings recognitions before SEO with the attempt to manipulate their offer prices upward and lower SEO discount. We find one standard deviation increase in the quarterly performance-matched discretionary accruals before SEO would lead to 0.254% (=0.059*($\beta_{Discretionary\ Accurals} = -4.311$) decrease in SEO underpricing.

[Insert Table 4]

4.3 Post-SEO Short-Term Performance

Then, we regress the ACTIVE dummy on the post-SEO liquidity and stock performance metrics in Table 5. Active social media hypothesis yields the prediction that insiders in SEO firms have the incentive to push up the level of liquidity and stock returns during the post-SEO lockup period to manage the liquidity costs and increase their selling proceeds through increasing the bullish coverage of issuing firms on social media platform. We present the evidence supporting this hypothesis that SEO firms with active social media management in the lockup period have higher stock turnover by 5.252% ($p < 0.01$) than the less active issuers in model (6) of Panel B. We show that stocks of active issuers have higher post-issue liquidity in terms of quoted spreads, effective spreads and Amihud

(2002) illiquidity ratio in columns (2), (4) and (8) of Panel B, after controlling SEO characteristics, firm characteristics, year fixed effects and industry fixed effects.

The coefficient on ACTIVE dummy in column (10) of Panel B suggests that SEO firms which rank in the top quarter of mean abnormal bullishness on StockTwits during the lockup-period achieve higher buy-and-hold abnormal returns by 4.4% ($p < 0.01$) than other SEO firms. This finding is consistent with the active social media hypothesis that SEO firms push up the stock value before the expiration of lockup agreements. However, this would not lead to the rejection of the investor attention hypothesis since the value of SEO firms would increase due to heightened investor attention according to Merton (1987). We would assess those two competing hypotheses on long-run stock performance in the following section. Additionally, we present the regression output with the ACTIVE dummy based on pre-SEO activeness in social media management in Panel A, which shows consistent and robust results of outperformance of active SEO firms in post-issue liquidity and stock returns during the lockup periods.

[Insert Table 5]

4.4 Test of Price Reversal and Long-Run Underperformance

To validate our hypothesis of active social media management, we calculate the buy-and-hold abnormal returns (BHARs) adjusted by the returns on S&P 500 starting from the expiration date of lockup agreements over three-month, six-month, one-year, two-year and three-year periods for SEO firms. We measure the level of active social media management by the mean abnormal bullishness during both pre-SEO media management period ($\mathbf{T_1}$) and (or) post-SEO lockup period ($\mathbf{T_2}$) and the benchmark is the mean bullishness during the pre-SEO benchmark period ($\mathbf{T_0}$).

Table 6 reports the average market-adjusted BHARs sorted by abnormal bullishness during both periods, pre-SEO media management period and lockup period in Panel A to C respectively. SEO firms with active social media management exhibit significant underperformance from six-month to three-year period subsequent to post-SEO lockup period. Specifically, the SEO firms that rank in top quartile in abnormal bullishness during the manipulation periods (**T_1** and **T_2**) earn 6.07% ($p < 0.1$) less in BHARs over six months and 29.77% ($p < 0.01$) less over three years, compared to SEO firms ranking in the bottom quartile. Panels B and C present similar results of the long-term underperformance of active issuers if we determine the activeness in social media management according to abnormal bullishness on StockTwits only during each of the manipulation periods (**T_1** or **T_2**).

[Insert Table 6]

Table 7 shows the regression statistics of regressing the three-year buy-and-hold abnormal returns on ACTIVE dummy after controlling for firm characteristics, industry fixed effects and year-fixed effects. Column (2) present the consistent result of long-run underperformance of SEO firms with active social media management during **T_1** and **T_2** by 23.3% ($p < 0.1$) and active issuers during lockup period exhibit lower three-year buy-and-hold abnormal returns by 24.1%, which is indicated by column 6 of Table 7.

[Insert Table 7]

According to Merton (1987), increasing media coverage would boost the investor base of neglected firms, which consequently leads to the increasing market value, Therefore, it is rational to predict that the SEO firms with high social media coverage should not experience significant drop in price after the offerings since investors are less likely to neglect those firms after SEO if investor attention hypothesis holds. We present the evidence consistent with **H1** and reject the competing hypothesis **H2** that the inflated market valuation of SEO firm with active social media management would reverse to the normal level after post-SEO lockup period. Additionally, the long-term underperformance implies the relative weak fundamentals of active social media management SEO firms.

5 Robustness Tests

5.1 Test for Traditional Media

Previous studies reveal that firms may manipulate their market valuation through the dissemination of press release (Ahern & Sosyura, 2014). In this section, we conduct the robustness tests by testing the evidence of traditional media management using the same DID design used in Table 3. Firstly, we separate the news data on Ravenpack into RPNA news and press releases since Ahern and Sosyura (2014) argue that the firm-originated press-releases are easier to manipulate. Then, we follow the articles (Jung et al. 2018; Cookson & Niessner. 2020) using Ravenpack database to classify the bullish and bearish news based on the event sentiment score (ESS), which ranges from 0 to 100. Specifically, bearish news has the ESS below 50 and the bullish news has the ESS above 50. Lastly, we compute the firm-day level news or press-release bullishness measures using Equation (1).

Table 8 reports the DID tests on number and bullishness of traditional media through Column (1) to (4) and we do not find the evidence of traditional media management for the SEO firms during the pre-SEO media management period or post-SEO lockup period, which further implies that the social media platform such as StockTwits may serve as the better venue for SEO firms to engage in media manipulation than traditional media platforms.

[Insert Table 8]

5.2 Test for Heterogenous Treatment Effects

In this subsection, we investigate characteristics of firms with higher level of active social media management. We propose two main categories for firm-level characteristics. Firstly, we hypothesise that SEO firms with high level of information asymmetry are more likely to actively manage their social media coverage and we use following proxies including total assets, institutional ownership, idiosyncratic volatility and analyst dispersion to account for the informational asymmetry. Secondly, we hypothesise that firm with lower market valuation has more incentive to manipulate its valuation upward through active social media management and therefore, we propose the firms with low market-to-book ratio are more likely to manage social media.

We then perform the DID tests for 10 groups of sub-samples determined by the median of each characteristics of SEO firms and value in bold is the p-value for corresponding test whether the slope estimates are statistically different between two sub-groups. Consistent with our hypothesis, Table 9 reports the sub-sample regression results that SEO firms with smaller size, lower institutional ownership, lower market-to-book ratios, higher idiosyncratic volatility and higher analyst dispersion exhibit the statistically significance evidence of social media management in both periods ($\mathbf{T_1}$ and $\mathbf{T_2}$). Moreover, small firms, compared to large firms, have more bullish social media coverage (0.043, $p < 0.1$) in the pre-SEO period $\mathbf{T_1}$. Issuers with low institutional ownership and high idiosyncratic volatility tend to have more positively significant StockTwits messages during the lockup period with 0.070 ($p < 0.05$) and 0.085 ($p < 0.01$) higher in bullishness measures, compared to their counterparts with low informational asymmetry. Additionally, we provide the sub-sample analyses for heterogenous treatment effects on SEO underpricing, post-issue liquidity and returns and long-term stock performance in Table A2 to A4 in the Appendix, most of which present consistent results.

[Insert Table 9]

6 Conclusion

This paper studies the active use of social media by corporate managers to affect firm valuations and SEO outcomes using a DID framework. We show that SEO firms receive more favourable messages around this event compared to non-SEO counterparts and abnormal social media activities directly lead to higher liquidity and post-SEO firm valuation.

We propose two competing hypotheses, namely *Active Social Media Management Hypothesis* and *Investor Attention Hypothesis*, to explain the abnormal patterns of social media coverage around SEOs. Our results are consistent with the first hypothesis in three ways. Firstly, SEO firms tend to experience more favourable social media coverage around hypothetical manipulation periods, while the sentiment of StockTwits messages should not be biased upward if the investor attention hypothesis holds. Secondly, we document that the active social media management firms, which receive more bullish messages during pre-SEO media management period, experience less underpricing. Meanwhile, the ACTIVE dummy determined by abnormal number of total posts has insignificant power in predicting SEO underpricing. Lastly, if the investor attention hypothesis holds, firms which exhibit higher StockTwits coverage should not experience persistent reversals after SEO since they are no longer neglected. However, our results reject this hypothesis and document significant reversals and long-term underperformance that the BHAR difference between SEO firms ranking in top quartile in abnormal bullishness during the manipulation periods ($\mathbf{T_1}$ and $\mathbf{T_2}$) and the bottom quartile firms is -6.07% in six months and -29.77% in three years.

Furthermore, we present evidence that SEO firms with high information asymmetry and low market-to-book tend to employ the active social media management strategy. This finding would help market regulators to monitor the types of firms that would seek to use social media platforms to manipulate their stock market performances. Additionally, we show that SEO firms do not exhibit patterns of active media management using traditional media including news or press releases, which suggests that the specialised financial microblog platform, StockTwits, may serve as the better venue for SEO firms to engage in social media manipulation.

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Table 1 Descriptive Statistics

This table reports descriptive statistics for the variables used in the analysis. Panel A reports descriptive statistics for SEO sample after applying filtering criteria and propensity score matching. Panel B reports descriptive statistics for the variables used in the within-SEO-firm analysis. Detailed descriptions of variables are included in Appendix A1. All continuous variables are winsorized at 1 percent and 99 percent levels.

Panel A: SEO Firms

Year	Obs	Offer Price	Under pricing	Offer Size	Relative Offer Size	Nasdaq Listed	NYSE Listed	Book runners	Managers	Rule-415
2010	31	23.441	5.214	5.022	0.140	22	9	0.957	1.320	28
2011	77	22.954	3.552	4.958	0.314	45	32	0.972	1.422	60
2012	106	22.180	2.758	4.390	0.148	71	35	0.967	1.374	88
2013	152	29.166	3.851	4.642	0.166	95	57	1.046	1.546	127
2014	133	31.786	5.384	4.682	0.131	87	46	1.062	1.480	113
2015	167	31.589	5.520	4.782	0.147	110	57	1.106	1.493	137
Total	666	28.200	4.431	4.699	0.167	430	236	1.039	1.467	553

Panel B: Variables in Within-SEO Firm Analysis

VARIABLES	N	mean	sd	p1	p5	p50	p95	p99
SEO Underpricing	408	3.804	3.843	-3.558	0.000	2.803	11.890	18.300
IPO Return	408	16.460	9.656	-6.000	2.400	15.700	30.300	38.000
Offer Size	408	4.872	1.121	2.695	2.996	4.787	6.745	7.613
Relative Offer Size	408	0.124	0.071	0.014	0.037	0.109	0.272	0.377
Bookrunners	408	1.077	0.389	0.693	0.693	1.099	1.792	2.079
Managers	408	1.577	0.644	0.693	0.693	1.609	2.639	3.091
Rule-415	408	0.880	0.325	0.000	0.000	1.000	1.000	1.000
Log(Close Price)	408	3.109	0.872	1.379	1.593	3.137	4.522	5.198
Pos_ CAR[-5,-1]	408	0.030	0.079	0.000	0.000	0.000	0.137	0.600
Neg_ CAR[-5,-1]	408	-0.037	0.051	-0.209	-0.149	-0.009	0.000	0.000
Tick	408	0.936	0.245	0.000	0.000	1.000	1.000	1.000
Volatility	408	0.031	0.020	0.008	0.012	0.026	0.066	0.136
Nasdaq	408	0.632	0.483	0.000	0.000	1.000	1.000	1.000
AT	408	6.509	1.885	3.113	3.709	6.248	9.658	10.920
IO	408	0.723	0.249	0.067	0.259	0.764	1.052	1.192
MB	408	5.348	14.540	-68.660	-9.285	3.666	26.320	66.250
Analysts Following	408	2.180	0.568	1.099	1.386	2.079	3.178	3.497
Analyst Dispersion	408	0.299	0.596	0.000	0.017	0.119	1.000	4.000
Discretionary Accruals	408	0.011	0.059	-0.127	-0.076	0.002	0.137	0.232
BHAR(Market)	408	-0.018	0.172	-0.559	-0.308	-0.006	0.262	0.507
Q_Spread	408	11.050	11.410	1.401	2.113	7.374	31.650	65.850
E_Spread	408	12.880	11.680	2.345	3.643	9.403	31.190	71.300
Turnover	408	1.319	1.270	0.198	0.313	0.925	3.606	8.314
Amihud_ILL	408	0.551	1.100	0.004	0.006	0.134	2.855	6.172

Table 2 Statistics for Propensity Score Matching

This table reports statistics for propensity-score matching. Panel A reports the descriptive statistics for SEO firms and non-SEO control firms before and after PSM. Panel B reports the pre- and post-match statistics of the fixed-effect logit regressions on whether the firm performs an SEO in year t. We match the SEO firms with their nearest non-SEO counterparts without replacement by each year and industry and the maximum difference between matched propensity scores is 1%. Detailed descriptions of variables are included in Appendix A1. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Pairwise Comparisons

	Pre-Match			Post-Match		
VARIABLES	SEO=0	SEO=1	Difference	SEO=0	SEO=1	Difference
AT	7.056	6.908	0.148*	7.07	6.96	0.110
	(2.138)	(2.038)		(2.287)	(2.021)	
Debt Ratio	0.575	0.564	0.012	0.58	0.58	0.006
	(0.310)	(0.347)		(0.342)	(0.346)	
ROA	-0.018	-0.110	0.092***	-0.11	-0.10	-0.014
	(0.271)	(0.339)		(0.449)	(0.338)	
Sales	6.384	5.529	0.855***	5.86	5.72	0.141
	(2.293)	(2.554)		(2.741)	(2.332)	
Observations	15485	701		666	666	

Panel B: Logit Regression Statistics

	Pre-Match	Post-Match
	(1)	(2)
VARIABLES	Prob(SEO)	Prob(SEO)
AT	0.376***	0.003
	(0.041)	(0.071)
Debt Ratio	-0.093	0.181
	(0.150)	(0.229)
ROA	-0.149	0.341
	(0.146)	(0.222)
Sales	-0.352***	-0.066
	(0.036)	(0.065)
Constant	-3.537***	0.283
	(0.777)	(1.068)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Observations	15,437	1,332
Pseudo R2	0.108	0.002

Table 3 Difference-in-Differences Analysis on Social Media Activities around SEOs

This table reports the result of the multivariate DID test. Dependent variables are number of total posts, number of posts whose sentiments are identified by either machine learning techniques or self-disclosed by the users, number of posts with self-disclosed sentiments, bullishness measure estimated by posts whose sentiments are identified by either machine learning techniques or self-disclosed by the users, and bullishness measure estimated by posts with self-disclosed sentiment from columns (1) to (5). Both pre-SEO media management and lockup period are defined in Figure 1. *Pre SEO Media Management* is the dummy variable equal to one for observations in the pre-SEO media management period and zero otherwise. *Lockup Period* is the dummy variable equal to one for observations in the lockup period and zero otherwise. Event-firm and event-day fixed effects are included in the regressions. Standard errors clustered at event-firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Total Posts	(2) Number of Posts (Full)	(3) Number of Post(Self)	(4) Bullishness (Full)	(5) Bullishness (Self)
SEO*Pre SEO Media Management	**2.696**	**0.682**	**1.198**	**0.024****	**0.025****
	(1.714)	**(0.446)**	**(0.780)**	**(0.012)**	**(0.011)**
SEO*Lockup Period	**5.508****	**1.484***	**2.719****	**0.042*****	**0.044*****
	(2.526)	**(0.838)**	**(1.324)**	**(0.016)**	**(0.015)**
Constant	Yes	Yes	Yes	Yes	Yes
Event-Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Event-Date Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	382,112	382,112	382,112	382,112	382,112
Adjusted R-squared	0.282	0.277	0.289	0.402	0.280

Table 4 The Effect of Active Social Media Management on SEO Underpricing

This table reports the slope estimates of regressions on SEO underpricing. *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness (or number of posts) during the pre-SEO social media management period (T1) and zero otherwise. Abnormal bullishness (or number of posts) is the difference between average bullishness (or number of posts) during the pre-SEO social media management period (T1) and mean bullishness (or number of posts) during pre-SEO benchmark period (T0). Other control variables are defined in Appendix A1. Both year- and industry (by two-digit SIC codes)-fixed effects are included. Standard error clustered at industry-level are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	Bullishness			**Total Post**		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	SEO Underpricing			SEO Underpricing		
ACTIVE	**-0.859***	**-0.933***	**-1.117****	**-0.519**	**-0.113**	**-0.436**
	(0.430)	**(0.492)**	**(0.540)**	**(0.416)**	**(0.470)**	**(0.443)**
Offer Size		-0.176	-0.086		-0.218	-0.114
		(0.358)	(0.387)		(0.367)	(0.379)
Relative Offer Size		0.765	1.601		1.146	1.699
		(2.355)	(2.442)		(2.348)	(2.462)
BookRunners		-0.350	0.375		-0.488	0.187
		(0.666)	(0.568)		(0.617)	(0.530)
Managers		-0.295	-0.735**		-0.210	-0.619**
		(0.362)	(0.271)		(0.349)	(0.281)
Rule415		0.668	0.834		0.669	0.821
		(0.601)	(0.564)		(0.583)	(0.544)
Log(Close Price)		-0.778***	-1.049***		-0.740**	-1.013***
		(0.286)	(0.276)		(0.289)	(0.282)
Pos_ CAR[-5,-1]		3.771**	2.742**		4.333***	3.126**
		(1.559)	(1.288)		(1.603)	(1.241)
Neg_ CAR[-5,-1]		9.687*	7.504		9.744*	8.112
		(5.491)	(5.255)		(5.270)	(5.069)
Tick		-0.001	-0.154		-0.150	-0.341
		(0.569)	(0.694)		(0.549)	(0.676)
Volatility		8.992	4.413		6.215	3.166
		(15.951)	(14.314)		(14.367)	(13.874)
IPO Return		0.004	0.011		0.004	0.011
		(0.014)	(0.011)		(0.013)	(0.011)
Nasdaq		0.171	0.169		0.214	0.184
		(0.373)	(0.551)		(0.386)	(0.528)
Analysts Following		0.683*	0.377		0.649*	0.311
		(0.354)	(0.390)		(0.351)	(0.387)
Analysts Dispersion		0.066	0.009		0.051	-0.023
		(0.219)	(0.222)		(0.221)	(0.226)
MB		-0.006	0.001		-0.005	0.004
		(0.009)	(0.011)		(0.009)	(0.010)
IO		-3.101***	-3.040***		-2.944***	-2.851***
		(0.934)	(1.024)		(0.898)	(0.966)
AT		-0.252	-0.017		-0.223	-0.006
		(0.174)	(0.190)		(0.172)	(0.192)
Discretionary Accruals		-3.599**	-4.311**		-3.230*	-3.613*
		(1.667)	(1.878)		(1.785)	(2.068)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	No	Yes	Yes	No	Yes
Observations	398	408	398	398	408	398
Adjusted R-squared	0.087	0.188	0.204	0.082	0.178	0.192

Table 5 Market Impacts of Active Social Media Management

This table reports the slope estimates of regressions on market impacts of active social media management. In Panel A, *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the pre-SEO social media management period (T1) and zero otherwise. In Panel B, *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the lockup period (T2) and zero otherwise. Abnormal bullishness is the difference between average bullishness during the pre-SEO social media management period (T1) or the lockup period (T2) and mean bullishness during pre-SEO benchmark period (T0). Other variables are defined in Appendix A1. *Q_Spread, E_Spread* and *Turnover* are the mean value over the lockup period. *Amihud_ILL* and *BHAR(Market)* are estimated over the lockup period. Both year- and industry (by two-digit SIC codes)-fixed effects are included. Standard error clustered at industry-level are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: By Activeness During Pre-SEO Media Management Period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Q_Spread		E_Spread		Turnover		Amihud_ILL		BHAR(Market)	
ACTIVE	**-2.182****	**-2.556*****	**-1.991****	**-2.653*****	**5.355*****	**4.449*****	**-0.314*****	**-0.304*****	**0.042****	**0.029***
	(0.864)	**(0.574)**	**(0.856)**	**(0.618)**	**(1.882)**	**(1.531)**	**(0.112)**	**(0.095)**	**(0.016)**	**(0.017)**
Offer Size		-3.213***		-3.786***		2.567**		-0.412***		0.027
		(0.818)		(0.905)		(1.077)		(0.111)		(0.018)
Relative Offer Size		18.934**		20.608***		-15.231		3.131***		-0.054
		(7.731)		(7.273)		(9.314)		(1.030)		(0.193)
BookRunners		1.333		1.873		0.209		0.248		0.017
		(1.486)		(1.797)		(2.124)		(0.156)		(0.018)
Managers		-1.293*		-1.175		-0.278		-0.273***		-0.023
		(0.702)		(0.932)		(1.120)		(0.092)		(0.016)
Rule415		-0.303		-0.968		-1.173		0.048		-0.020
		(1.092)		(1.348)		(2.576)		(0.104)		(0.027)
Log(Close Price)		-3.206***		-3.387***		-1.215		-0.142		-0.014
		(0.716)		(0.717)		(1.072)		(0.136)		(0.017)
Pos_ CAR[-5,-1]		0.960		-0.542		20.070**		-0.049		-0.241***
		(3.141)		(3.680)		(8.520)		(0.465)		(0.061)
Neg_ CAR[-5,-1]		-2.594		-4.374		-2.002		0.017		-0.024
		(7.748)		(8.744)		(14.766)		(1.051)		(0.196)
Tick		-2.066		-1.756		1.588		-0.326		0.005
		(1.509)		(1.644)		(2.231)		(0.207)		(0.035)
Volatility		-4.482		7.582		224.081**		-5.458**		0.759

		(18.037)		(20.403)		(96.043)		(2.688)		(0.484)
IPO Return		0.121***		0.128***		-0.064		0.018***		-0.002***
		(0.040)		(0.045)		(0.071)		(0.005)		(0.001)
Nasdaq		1.702**		-1.870*		1.466		-0.006		0.001
		(0.802)		(1.067)		(1.374)		(0.117)		(0.015)
Analysts Following		-0.336		0.142		4.983*		-0.042		-0.032
		(1.010)		(1.023)		(2.670)		(0.086)		(0.019)
Analysts Dispersion		-0.058		-0.349		2.828		0.046		-0.025**
		(0.713)		(0.893)		(1.855)		(0.113)		(0.010)
MB		0.027		0.021		0.013		0.002		-0.000
		(0.040)		(0.038)		(0.022)		(0.003)		(0.000)
IO		-9.852***		-11.106***		1.874		-0.809**		0.015
		(2.974)		(2.829)		(2.306)		(0.306)		(0.034)
AT		-0.391		-0.136		-1.490		0.031		0.011
		(0.394)		(0.408)		(1.001)		(0.044)		(0.008)
Discretionary Accruals		-4.867		-3.189		23.364**		-0.706		-0.019
		(8.740)		(10.000)		(11.422)		(1.034)		(0.085)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	398	398	398	398	398	398	398	398	398	398
Adjusted R-squared	0.087	0.550	0.076	0.511	0.180	0.386	0.064	0.428	0.015	0.026

Panel B: By Activeness During Lockup Period										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Q_Spread		E_Spread		Turnover		Amihud_ILL		BHAR(Market)	
ACTIVE	**-1.056**	**-1.899***	**-0.459**	**-1.655***	**7.322*****	**5.252*****	**-0.335****	**-0.317****	**0.051*****	**0.044*****
	(1.362)	**(0.986)**	**(1.299)**	**(0.935)**	**(1.923)**	**(1.453)**	**(0.147)**	**(0.124)**	**(0.011)**	**(0.013)**
Offer Size		-3.341***		-3.935***		2.688**		-0.423***		0.027
		(0.833)		(0.941)		(1.033)		(0.113)		(0.018)
Relative Offer Size		18.875**		20.693**		-14.227		3.082***		-0.044
		(8.268)		(7.745)		(9.949)		(1.094)		(0.203)
BookRunners		1.129		1.622		0.323		0.235		0.017
		(1.595)		(1.937)		(2.097)		(0.163)		(0.019)
Managers		-1.029		-0.896		-0.714		-0.243**		-0.026
		(0.711)		(0.965)		(1.147)		(0.099)		(0.018)
Rule415		-0.220		-0.894		-1.391		0.062		-0.022
		(1.088)		(1.377)		(2.592)		(0.098)		(0.028)
Log(Close Price)		-3.193***		-3.353***		-1.114		-0.146		-0.013
		(0.754)		(0.753)		(1.069)		(0.142)		(0.017)
Pos_ CAR[-5,-1]		1.560		0.271		20.197**		-0.032		-0.235***
		(3.099)		(3.501)		(8.790)		(0.521)		(0.062)
Neg_ CAR[-5,-1]		-1.461		-3.270		-4.413		0.172		-0.042
		(7.850)		(8.747)		(14.974)		(1.059)		(0.188)
Tick		-2.358		-2.098		1.861		-0.350*		0.006
		(1.504)		(1.623)		(2.055)		(0.205)		(0.036)
Volatility		-1.258		9.030		206.767**		-4.528		0.591
		(21.762)		(24.349)		(98.198)		(3.232)		(0.565)
IPO Return		0.124***		0.132***		-0.068		0.018***		-0.002***
		(0.041)		(0.046)		(0.067)		(0.004)		(0.001)
Nasdaq		1.721*		-1.849		1.437		-0.004		0.001
		(0.901)		(1.226)		(1.635)		(0.123)		(0.015)
Analysts Following		-0.380		0.089		5.018*		-0.045		-0.032
		(0.988)		(1.000)		(2.835)		(0.087)		(0.019)

Analysts Dispersion		-0.164		-0.456		3.037		0.033		-0.023**
		(0.688)		(0.875)		(1.914)		(0.106)		(0.011)
MB		0.030		0.025		0.011		0.002		-0.000
		(0.039)		(0.036)		(0.023)		(0.003)		(0.000)
IO		-9.867***		-11.026***		2.483		-0.837***		0.022
		(2.929)		(2.762)		(2.243)		(0.278)		(0.032)
AT		-0.303		-0.049		-1.667		0.043		0.009
		(0.405)		(0.431)		(1.051)		(0.048)		(0.009)
Discretionary Accruals		-3.626		-1.882		21.313**		-0.563		-0.032
		(8.277)		(9.640)		(9.985)		(0.931)		(0.088)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	398	398	398	398	398	398	398	398	398	398
Adjusted R-squared	0.082	0.546	0.071	0.506	0.205	0.392	0.066	0.428	0.020	0.031

Table 6 Post-Lockup Long-Run BHARs Sorted by ACTIVE Quartiles

This table reports the mean buy-and-hold abnormal returns by quartiles of abnormal bullishness. Abnormal bullishness is the difference between average bullishness during media management periods (T1 and T2) and mean bullishness during pre-SEO benchmark period (T0) in Panel A, and it is the difference between average bullishness during pre-SEO media management period (T1) and mean bullishness during pre-SEO benchmark period (T0) in Panel B, and it is the difference between average bullishness during the lockup period (T2) and mean bullishness during pre-SEO benchmark period (T0) in Panel C. Buy-and-hold abnormal returns are adjusted to the returns on S&P 500. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: By Activeness During Both Periods					
ACTIVE	BHAR(90)	BHAR(180)	BHAR(360)	BHAR(720)	BHAR(1080)
Low	-2.91%	-2.92%	-2.85%	3.87%	5.47%
2	-1.66%	0.05%	3.22%	12.59%	14.65%
3	-1.92%	-2.92%	-3.33%	-1.67%	-3.38%
High	-2.56%	-8.99%	-11.75%	-12.89%	-24.30%
Low-High	**-0.35%**	**6.07%**	**8.90%**	**16.76%**	**29.77%**
T-Stats	**(-0.13)**	**(1.75)***	**(1.74)***	**(1.65)***	**(2.79)*****
Panel B:By Activeness During Pre-SEO Media Management Period					
ACTIVE	BHAR(90)	BHAR(180)	BHAR(360)	BHAR(720)	BHAR(1080)
Low	-3.16%	-1.97%	-1.79%	9.25%	6.04%
2	-1.56%	-2.13%	-0.47%	-0.10%	0.80%
3	-1.24%	-3.28%	-2.81%	3.53%	3.73%
High	-3.09%	-7.41%	-9.64%	-10.85%	-17.83%
Low-High	**-0.07%**	**5.43%**	**7.85%**	**20.09%**	**23.86%**
T-Stats	**(-0.02)**	**(1.53)**	**(1.49)**	**(1.81)***	**(2.03)****
Panel C:By Activeness During Lockup Period					
ACTIVE	BHAR(90)	BHAR(180)	BHAR(360)	BHAR(720)	BHAR(1080)
Low	-3.98%	-6.21%	-9.53%	-10.10%	-11.56%
2	-2.03%	0.05%	6.96%	20.00%	28.07%
3	-0.18%	-0.13%	-0.77%	6.05%	2.23%
High	-2.85%	-8.50%	-11.34%	-14.01%	-26.18%
Low-High	**-1.13%**	**2.29%**	**1.81%**	**3.91%**	**14.63%**
T-Stats	**(-0.43)**	**(0.68)**	**(0.37)**	**(0.43)**	**(1.63)**

Table 7 Regression Results on Long-Run Return Reversal of Active Social Media Management Firms

This table reports the regression statistics for the tests on price reversal of active social media management firms. In Panel A, *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the media management periods (T1 and T2) and zero otherwise. In Panel B, *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the pre-SEO media management period (T1) and zero otherwise. In Panel C, *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the lockup period (T2) and zero otherwise. Abnormal bullishness is calculated against the mean bullishness during pre-SEO benchmark period (T0). Buy-and-hold abnormal returns are adjusted to the returns on S&P 500. T-stats are reported in the parentheses. Other control variables are defined in Appendix A1. Both year- and industry (by two-digit SIC codes)-fixed effects are included. Standard error clustered at industry-level are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	[A] By Activeness During Both Periods		**[B] By Activeness During Pre-SEO Social Media Management Period**		**[C] By Activeness During SEO Lockup Period**	
VARIABLES	BHAR(1080)		BHAR(1080)		BHAR(1080)	
ACTIVE	**-0.224****	**-0.233***	**-0.116**	**-0.012**	**-0.258***	**-0.241***
	(0.104)	**(0.125)**	**(0.087)**	**(0.101)**	**(0.144)**	**(0.134)**
AT		0.017		0.013		0.016
		(0.027)		(0.026)		(0.028)
MB		-0.006		-0.006		-0.006
		(0.006)		(0.006)		(0.005)
IO		-0.085		-0.031		-0.099
		(0.228)		(0.245)		(0.217)
Analysts Dispersion		-0.197***		-0.196***		-0.199***
		(0.071)		(0.070)		(0.073)
Analysts Following		-0.004		-0.017		-0.005
		(0.062)		(0.056)		(0.059)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	633	496	633	496	633	496
Adjusted R-squared	0.017	0.020	0.011	0.012	0.019	0.021

Table 8 Difference-in-Differences Analysis on Traditional Media Coverage around SEOs

This table reports the result of the multivariate DID test on traditional media coverage. Dependent variables are number of non-press-release Ravenpack news, number of press-releases, bullishness of non-press-release Ravenpack news and bullishness of press releases from columns (1) to (4). Bullishness measures of Ravenpack news and press-releases are determined using the same formula described in Equation (1). Both pre-SEO media management and lockup period are defined in Figure 1. *Pre SEO Media Management* is the dummy variable equal to one for observations in the pre SEO media management period and zero otherwise. *Lockup Period* is the dummy variable equal to one for observations in the lockup period and zero otherwise. Event-firm and event-day fixed effects are included in the regressions. Standard errors clustered at event-firm level are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)
VARIABLES	Number of RPNA News	Number of Press Releases	Bullishness (News)	Bullishness (Press Release)
SEO*Pre SEO Media Management	**0.037**	**0.007**	**0.002**	**0.002**
	(0.053)	**(0.008)**	**(0.007)**	**(0.002)**
SEO*Lockup Period	**0.018**	**-0.018**	**-0.008**	**-0.004**
	(0.067)	**(0.017)**	**(0.007)**	**(0.002)**
Constant	Yes	Yes	Yes	Yes
Event-Firm Fixed Effects	Yes	Yes	Yes	Yes
Event-Date Fixed Effects	Yes	Yes	Yes	Yes
Observations	382,112	382,112	382,112	382,112
Adjusted R-squared	0.176	0.062	0.047	0.032

Table 9 Heterogenous DID Tests on Active Social Media Management

This table reports the result of the multivariate DID test for 10 sub-samples. Dependent variable is the bullishness measure estimated by posts whose sentiments are identified by either machine learning techniques or self-disclosed by the users. Sub-samples are determined by the medians of nearest observations of natural logarithm of total assets, institutional ownership, market-to-book ratio, idiosyncratic volatility, and analyst dispersion before the pre-SEO benchmark period. Idiosyncratic volatility is estimated with the daily stock returns as the standard error of the residuals estimated from Fama-French (1993) 3-Factor model over 180-day period. Both pre-SEO media management and lockup period are defined in Figure 1. *Pre SEO Media Management* is the dummy variable equal to one for observations in the pre-SEO media management period and zero otherwise. *Lockup Period* is the dummy variable equal to one for observations in the lockup period and zero otherwise. Event-firm and event-day fixed effects are included in the regressions. Standard errors clustered at event-firm level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Values in bold are p-values associated with the tests whether two slope estimates are different.

	(i) Asset			**(ii) IO**		
	High	Low	High-Low	High	Low	High-Low
VARIABLES	Bullishness(Full)			Bullishness(Full)		
SEO*Pre SEO Media Management	0.008	0.051***	-0.043	0.020	0.040**	-0.020
	(0.013)	(0.020)	**0.066**	(0.013)	(0.019)	**0.391**
SEO*Lockup Period	0.025*	0.053*	-0.028	0.004	0.074***	-0.070
	(0.015)	(0.027)	**0.367**	(0.018)	(0.025)	**0.024**
Constant	Yes	Yes		Yes	Yes	
Event-Firm Fixed Effects	Yes	Yes		Yes	Yes	
Event-Date Fixed Effects	Yes	Yes		Yes	Yes	
Observations	149,628	151,708		150,070	151,266	
Adjusted R-squared	0.195	0.294		0.238	0.274	

	(iii) MB			**(iv) Idiosyncratic Volatility**			**(v) Analyst Dispersion**		
	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
VARIABLES	Bullishness(Full)			Bullishness(Full)			Bullishness(Full)		
SEO*Pre SEO Media Management	0.027	0.031**	-0.004	0.042**	0.006	0.036	0.038**	0.001	0.037
	(0.018)	(0.015)	**0.867**	(0.020)	(0.011)	**0.111**	(0.016)	(0.019)	**0.129**
SEO*Lockup Period	0.038	0.043**	-0.005	0.085***	-0.000	0.085	0.050**	0.007	0.043
	(0.027)	(0.017)	**0.874**	(0.027)	(0.013)	**0.005**	(0.025)	(0.022)	**0.187**
Constant	Yes	Yes		Yes	Yes		Yes	Yes	
Event-Firm Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
Event-Date Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	150,270	149,994		191,066	188,580		128,986	128,800	
Adjusted R-squared	0.269	0.231		0.314	0.199		0.274	0.208	

Appendix

Appendix A1: List of Variables

Name	Description	Source
AT	Ln (Total Assets)	Compustat
M/B	Market-to-book ratio measured at the fiscal year end	Compustat
ROA	Income Before Extraordinary Items / Total Assets	Compustat
Debt Ratio	Total Liabilities / Total Assets	Compustat
Sales	Ln (Net Sales)	Compustat
Discretionary Accruals	Firm's performance-matched quarterly discretionary accruals and the steps to calculate are described in the Appendix B	Compustat
IO	The percentage of outstanding shares owned by institutional investors	Thomson Reuters 13/F
Analysts Following	Ln (1 + number of analysts following)	IBES
Analyst Dispersion	Standard deviation of earnings forecasts scaled by the Absolute value of the mean earnings forecast	IBES
Offer Size	Natural logarithm of SEO proceeds.	Refinitiv SDC Platinum
Relative Offer Size	Ratio of SEO proceed to the pre-SEO market capitalisation.	Refinitiv SDC Platinum
Nasdaq	Dummy variable equal to one if the SEO firm is listed in Nasdaq and zero other wise	Refinitiv SDC Platinum
Bookrunners	Ln (1 + number of bookrunners on the issue)	Refinitiv SDC Platinum
Managers	Ln (1 + number of lead and co-managers on the issue)	Refinitiv SDC Platinum
Rule-415	Dummy variable equal to one if the issue using Rule-415 shelf registration and zero otherwise	Refinitiv SDC Platinum
Log(Close Price)	Natural logarithm of the close price prior to the SEO	CRSP
Pos_ CAR[-5,-1]	Equals to cumulative market-adjusted return (CAR) over five days prior to the SEO if the CAR is positive and zero otherwise	CRSP
Neg_ CAR[-5,-1]	Equals to cumulative market-adjusted return (CAR) over five days prior to the SEO if the CAR is negative and zero otherwise	CRSP
Volatility	Standard deviation of the SEO firm's stock return over 30 trading days ending 10 days prior to the SEO	CRSP
Tick	Dummy variable equals to one if the decimal portion of the pre-SEO closing price doesn't fall on the $0.25 increment and zero otherwise	CRSP
Q_Spread	Daily quoted spread in the basis point, calculated as (Ask Price - Bid Price)/Mid-quote	CRSP
E_Spread	Daily effective spread in the basis point, calculated as ((Close Price – Mid-quote)*2)/Mid-quote.	CRSP
Turnover	Daily number of shares traded as the percentage of the number of shares outstanding.	CRSP
Amihud_ILL	Amihud (2002) illiquidity measure estimated as follows $\frac{10^8}{Number\ of\ Trading\ Days}\sum\frac{\lvert Daily\ Return\rvert}{Daily\ Dollar\ Volume\ Traded}$	CRSP
BHAR	Buy-and-hold abnormal returns for the firm against the returns on S&P 500.	CRSP
IPO Return	Average IPO initial return during the same month as the SEO	Jay Ritter's Website (https://site.warrington .ufl.edu/ritter /files/2020/01/ IPOALL_2019.xlsx)
SEO Underpricing	The percentage return from the pre-SEO closing price to the offer price times negative one	Refinitiv SDC Platinum, CRSP
Bullishness	$\frac{n_{bull,i,t}-n_{bear,i,t}}{n_{bull,i,t}+n_{bear,i,t}} * Ln\left(1+n_{bull,i,t}+n_{bear,i,t}\right)$	StockTwits,Ravenpack

Table A2 Subsample Analyses of Social Media Management on SEO Underpricing

This table reports the regression result of the effect of active social media management on SEO underpricing for 10 sub-samples. Sub-samples are determined by the medians of nearest observations of natural logarithm of total assets, institutional ownership, market-to-book ratio, idiosyncratic volatility, and analyst dispersion before the pre-SEO benchmark period. Idiosyncratic volatility is estimated with the daily stock returns as the standard error of the residuals estimated from Fama-French (1993) 3-Factor model over 180-day period. *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the pre-SEO social media management period (T1) and zero otherwise in each sub-sample. Abnormal bullishness is the difference between average bullishness during the pre-SEO social media management period (T1) and mean bullishness during pre-SEO benchmark period (T0). Other control variables are defined in Appendix A1. Both year- and industry (by two-digit SIC codes)-fixed effects are included. Standard error clustered at industry-level are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. Values in bold are p-values associated with the tests whether two slope estimates are different.

	(i) Asset			**(ii) IO**		
	High	Low	High-Low	High	Low	High-Low
	(1)	(2)		(3)	(4)	
VARIABLES	SEO Underpricing			SEO Underpricing		
ACTIVE	-0.598	-1.201	0.603	-0.737	-1.206	0.469
	(0.357)	(0.962)	**0.534**	(0.517)	(0.976)	**0.465**
Controls	Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes	
Year Fixed Effects	Yes	Yes		Yes	Yes	
Industry Fixed Effects	Yes	Yes		Yes	Yes	
Observations	177	175		175	175	
Adjusted R-squared	0.237	0.135		0.193	0.172	

	(iii) MB			**(iv) Idiosyncratic Volatility**			**(v) Analyst Dispersion**		
	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	(5)	(6)		(7)	(8)		(11)	(12)	
VARIABLES	SEO Underpricing			SEO Underpricing			SEO Underpricing		
ACTIVE	-1.348	-1.371**	0.023	-1.151	-0.774*	-0.377	-0.904	-0.693	-0.211
	(1.156)	(0.564)	**0.981**	(1.368)	(0.410)	**0.758**	(0.911)	(0.543)	**0.764**
Controls	Yes	Yes		Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes		Yes	Yes	
Year Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
Industry Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes	
Observations	170	177		195	191		159	159	
Adjusted R-squared	0.156	0.197		0.101	0.121		0.076	0.154	

Table A3 Subsample Analyses of Social Media Management on Short-Term Market Impacts

This table reports the regression result of the short-term market impacts of active social media management for 10 sub-samples. Sub-samples are determined by the medians of nearest observations of natural logarithm of total assets, institutional ownership, market-to-book ratio, idiosyncratic volatility, and analyst dispersion before the pre-SEO benchmark period. Idiosyncratic volatility is estimated with the daily stock returns as the standard error of the residuals estimated from Fama-French (1993) 3-Factor model over 180-day period. *ACTIVE* is the dummy equals to one for the SEO firms which rank in the top quartile in mean abnormal bullishness during the lockup period (T2) and zero otherwise in each sub-sample. Abnormal bullishness is the difference between average bullishness during the lockup period (T2) and mean bullishness during pre-SEO benchmark period (T0). Other control variables are defined in Appendix A1. *Q_Spread*, *E_Spread* and *Turnover* are the mean value over the lockup period. *Amihud_ILL* and *BHAR(Market)* are estimated over the lockup period. Both year- and industry (by two-digit SIC codes)-fixed effects are included. Standard error clustered at industry-level are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. Values in bold are p-values associated with the tests whether two slope estimates are different.

	(i) Asset			**(ii) IO**			**(iii) MB**			**(iv) Idiosyncratic Volatility**			**(v) Analyst Dispersion**		
	H	L	H-L	H	L	H-L	H	L	H-L	H	L	H-L	H	L	H-L
	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)		(9)	(10)	
VARIABLES							**Turnover**								
ACTIVE	1.206	5.506***	-4.300	0.623	6.787***	-6.164	4.763*	2.800	1.963	8.007***	0.283	7.724	5.815**	2.928	2.887
	(2.553)	(1.148)	**0.108**	(2.170)	(2.301)	**0.080**	(2.250)	(2.101)	**0.508**	(2.714)	(0.848)	**0.001**	(2.108)	(1.710)	**0.282**
Controls	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Industry Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	177	175		175	175		170	177		195	191		159	159	
Adjusted R-squared	0.473	0.439		0.237	0.546		0.331	0.588		0.495	0.460		0.381	0.337	
	(11)	(12)		(13)	(14)		(15)	(16)		(17)	(18)		(19)	(20)	
VARIABLES							**Amihud_ILL**								
ACTIVE	-0.008	-0.540**	0.532	-0.022	-0.404**	0.382	-0.387***	0.087	-0.474	-0.409**	-0.079	-0.330	-0.093	-0.050	-0.043
	(0.029)	(0.213)	**0.007**	(0.229)	(0.157)	**0.061**	(0.116)	(0.178)	**0.016**	(0.186)	(0.082)	**0.110**	(0.223)	(0.052)	**0.819**
Controls	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Industry Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	177	175		175	175		170	177		195	191		159	159	
Adjusted R-squared	0.463	0.480		0.330	0.409		0.387	0.359		0.433	0.447		0.351	0.486	
	(21)	(22)		(23)	(24)		(25)	(26)		(27)	(28)		(29)	(30)	
VARIABLES							**BHAR(Market)**								
ACTIVE	0.039**	0.051*	-0.012	-0.002	0.093**	-0.095	0.070***	0.038	0.032	-0.009	0.033*	-0.042	0.063*	-0.001	0.064
	(0.019)	(0.025)	**0.706**	(0.018)	(0.035)	**0.014**	(0.020)	(0.027)	**0.115**	(0.034)	(0.017)	**0.301**	(0.035)	(0.029)	**0.108**
Controls	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Constant	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Industry Fixed Effects	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Observations	177	175		175	175		170	177		195	191		159	159	
Adjusted R-squared	0.191	-0.108		0.032	-0.027		-0.015	0.102		-0.063	0.116		-0.050	-0.096	

Table A4 Subsample Analyses of Post-Lockup Long-Run BHARs Sorted by ACTIVE Quartiles

This table reports the mean buy-and-hold abnormal returns by quartiles of abnormal bullishness for 10 sub-samples. Sub-samples are determined by the medians of nearest observations of natural logarithm of total assets, institutional ownership, market-to-book ratio, idiosyncratic volatility, and analyst dispersion before the pre-SEO benchmark period. Idiosyncratic volatility is estimated with the daily stock returns as the standard error of the residuals estimated from Fama-French (1993) 3-Factor model over 180-day period. Abnormal bullishness is the difference between average bullishness during media management periods (T1 and T2) and mean bullishness during pre-SEO benchmark period (T0). Buy-and-hold abnormal returns are adjusted to the returns on S&P 500. *** p<0.01, ** p<0.05, * p<0.1.

	(i) Asset		**(ii) IO**		**(iii) MB**	
	Low	High	Low	High	Low	High
Least ACTIVE	8.98%	-0.35%	20.86%	-5.93%	5.38%	2.58%
2	32.23%	26.59%	22.56%	20.66%	30.10%	30.78%
3	-8.24%	19.25%	2.28%	5.59%	-2.28%	11.94%
Most ACTIVE	0.22%	-9.16%	-6.94%	11.53%	6.06%	-12.41%
Most-Least	**-8.76%**	**-8.81%**	**-27.80%**	**17.45%**	**0.68%**	**-14.99%**

	(iv) Idiosyncratic Volatility		**(v) Analyst Dispersion**	
	Low	High	Low	High
Least ACTIVE	-12.97%	8.64%	-0.55%	7.61%
2	25.12%	9.22%	21.76%	36.48%
3	6.69%	-3.19%	12.07%	-0.04%
Most ACTIVE	-9.48%	-38.90%	31.44%	-26.64%
Most-Least	**3.49%**	**-47.55%*** **	**31.99%**	**-34.25%** **