What is the value of sell-side analysts? Evidence from coverage initiation

by

Kevin K. Li* and Haifeng You+

Abstract: We investigate whether and how sell-side analysts create value for companies by examining what drives the market reaction to analyst coverage initiation. We identify three potential channels of analysts' value creation: improving fundamental performance, reducing information asymmetry and increasing investor recognition. Our analyses show that changes in investor recognition have the highest and most robust explanatory power over the initiation period returns. We find that the market reaction and changes in investor recognition tend to be larger when the initiating analyst is expected to devote more time and effort to promote the stocks, or when his prior initiations triggered a larger increase in investor recognition. Moreover, firms experiencing a drop in coverage for exogenous reasons have a significant decrease in investor recognition over the subsequent year. Collectively, the evidence indicates that analysts create value by improving investor recognition for firms under their coverage.

JEL Classification: G14, G24, G29, G32
Keywords: Coverage initiation, firm value, investor recognition, information asymmetry

* Rotman School of Management, University of Toronto, 105 St. George Street, Toronto, Canada, M5S 3E6; Email: kevin.li@rotman.utoronto.ca.
+ Corresponding author. School of Business and Management, Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong; Tel: (852) 2358-7576; Fax: (852) 2358-1693; Email: achy@ust.hk.

I. Introduction

Analysts are one of the most important information intermediaries in capital markets. There has been a large literature on the properties of analyst research outputs such as earnings forecasts and stock recommendations, and how these properties affect the usefulness of the outputs to investors (see the survey papers by Ramnath et al., 2008 and Bradshaw, 2011). In contrast, research on how analyst coverage affects companies has been limited. In this paper, we attempt to understand whether analysts create value, and more importantly, through what channels they create value for the firms under their coverage.

Extant research suggests that managers value analyst coverage and incur significant costs to acquire it. For example, Krigman et al. (2001) show that companies strategically acquire influential analyst coverage by hiring the employers of these analysts as underwriters in seasonal equity offerings (SEOs). Cliff and Denis (2004) suggest that the underpricing of initial public offerings (IPO) is intended, in part, to compensate for the expected post-IPO analyst coverage from the highly ranked analysts of the lead underwriter. If acquiring analyst coverage is a rational economic decision, these findings imply that analysts can add significant value to firms. Equity valuation theory prescribes that the value of a firm equals the present value of expected future cash flows. In order for an analyst to increase firm value, his coverage should lead to either an improvement in future cash flows (i.e., the fundamental effect), or a reduction in cost of capital (i.e., the discount rate effect), or both (e.g., Campbell and Shiller, 1988; Campbell, 1991).

Evidence on whether analyst coverage improves firms' fundamental performance is mixed. On the one hand, analysts may play a monitoring role so that their coverage can curb opportunistic managerial behaviors, reduce excessive executive compensation, and restrict asset mismanagement (e.g., Yu, 2008; Jung et al., 2012; Chen et al., 2014). If these effects are economically significant, analyst coverage can improve future operating performance. On the other hand, analyst following may put excessive pressure on managers and induce them to engage in myopic activities that boost short-term performance at the expense of long-term value (He and Tian, 2013). Furthermore, Francis and Philbrick (1993) show that analysts have incentives to please managers so that they can receive preferential disclosures of private information. Hence, a priori, it is unclear whether analysts can monitor managers effectively and improve firms' performance.

The second channel of analysts' value creation is to reduce cost of capital through decreasing information asymmetry. Some research suggests that analyst coverage can reduce information asymmetry among investors (Brennan and Subrahmanyam, 1995; Wu, 2013), which in turn improves stock liquidity (Irvine, 2003; Roulstone, 2003) and reduces cost of capital (Bowen et al., 2008). However, analysts often sacrifice their forecast or recommendation accuracy for other economic incentives, such as securing underwriting business and boosting trading volume (e.g., Lin and McNichols, 1998; Michaely and Womack, 1999; Irvine, 2004; Jackson, 2005; Cowen et al., 2006; Niehaus and Zhang, 2010). Given these economic incentives, it is unclear whether analysts are properly motivated to supply useful information to reduce information asymmetry.[1] Furthermore, even if analysts can produce new information, they may distribute their private information to a select group of investors (Irvine et al., 2007; Juergens

---

[1] Prior research provides mixed evidence on whether analyst forecasts and recommendations provide useful information to investors. Although some research (e.g., Givoly and Lakonishok, 1979; Fried and Givoly, 1982; Gleason and Lee, 2003) shows that analysts' earnings forecasts contain valuable information to investors and are a good surrogate for market expectations, several recent studies challenge such view. For example, Bradshaw et al. (2012) show that random walk time-series forecasts are more accurate than analyst forecasts over long horizons. In addition, analysts' recommendations and target price forecasts are shown to be optimistically biased (e.g., Bradshaw, 2004; Bradshaw et al., 2013) and contain little useful information. Finally, it has been documented that analysts tend to piggyback their recommendations and earnings forecasts on recent news and that they provide little information after controlling for confounding events and news (e.g. Altınkılıç and Hansen, 2009; Altınkılıç et al., 2013; Kim and Song, 2014).

and Lindsey, 2009), which could exacerbate information asymmetry of the stock (Chung et al., 1995).

Another important, but less studied channel for analysts to reduce cost of capital is through improving investor recognition for stocks. Merton (1987) predicts that higher investor recognition leads to lower cost of capital and higher stock prices. Under the assumption that investors can only hold stocks that they know, stocks with low investor recognition must be held by a small number of investors who do know about them. Due to the lack of demand, these stocks must trade at relatively lower prices in equilibrium in order for the market to clear. Building on Merton (1987), a large body of empirical studies confirms that investor recognition is negatively associated with cost of capital (e.g., Kadlec and McConnell, 1994; Foerster and Karolyi, 1999; Lehavy and Sloan, 2008; Bodnaruk and Ostberg, 2009; Richardson et al., 2012).

Given Merton's theory, an analyst should be able to increase the value of the firms under his coverage if such coverage activities increase investor recognition of the stocks. One of the primary functions of sell-side analysts is to promote securities to investors. Analysts' compensation and career success are closely tied to their ability to sell securities in brokerage and investment banking businesses (e.g., Hong and Kubik, 2003; Juergens and Lindsey, 2009; Niehaus and Zhang, 2010; Groysberg et al., 2011). To facilitate sales, analysts frequently distribute research reports to investors, engage in direct communication with clients, and arrange meetings between corporate executives and potential investors. By constantly directing investors' attention to the stock, these coverage activities may considerably improve investor recognition of the stock[2], leading to lower cost of capital and higher stock prices.[3]

[2] Consistent with this notion, a recent study by Mola et al. (2013) shows that after a complete loss of analyst coverage, the number of institutions holding the stock decreases. There are several important distinctions between Mola et al. and our paper. First, Mola et al. do not test whether a change in investor recognition is associated with firm value. Second, Mola et al. do not distinguish whether the loss of analyst coverage causes investor recognition to

In this paper, we focus on a setting where a sell-side analyst initiates coverage for a stock to examine the impact of analyst coverage on firm value. Prior research documents a positive market reaction around initiations (e.g., Branson et al., 1998; Irvine, 2003; Demiroglu and Ryngaert, 2010). However, the positive market reaction does not necessarily indicate that analysts create value for firms. For example, it may suggest that investors believe analysts are more likely to initiate coverage on stocks for which they have favorable private information (McNichols and O'Brien, 1997). We approach the research question from a unique angle by first investigating which of the three aforementioned value creation channels drives the favorable market reaction to initiations. We use the change in return on assets (ΔROA) to proxy for change in fundamental performance, the change in the adverse selection component of the bid-ask spread (ΔASL) to proxy for change in information asymmetry, and the change in institutional ownership breadth (ΔBR) to proxy for change in investor recognition.[4]

Consistent with the prior literature, we find that the market reacts positively to initiations. The initiation period return, measured as the cumulative abnormal return (CAR) over the five trading days surrounding the initiation date, averages approximately 82 basis points. Compared to a sample of control firms, firms with initiations have a lower ΔASL and higher ΔBR in the year subsequent to initiations. Multivariate regression analysis shows that although both ΔASL and ΔBR are significantly associated with CAR, the explanatory power of ΔBR is much higher. In contrast, we find no difference in ΔROA between the initiation and control firms. Neither do we find a significant association between ΔROA and CAR in the regression analysis. We further

---

decrease or analysts drop coverage in anticipation of the loss of investor interest. Finally, Mola et al. focus on a sample of very small firms. The median market capitalization for their sample is less than $28 million. Hence, it is unclear whether their findings are generalizable.

[3] Barber and Odean (2008) provide a related, but slightly different explanation on why investor recognition affects stock prices. They argue that individual investors tend to be net buyers of attention-grabbing stocks. The resulting buying pressure may temporarily increase stock prices. If analysts can attract investors' attention to the stocks under their coverage, the resulting buying pressure may increase stock prices.

[4] Detailed variable definitions are provided in Appendix A.

show that the more positive market reactions to initiations by star analysts and for firms with lower existing coverage documented by Branson et al. (1998) are also driven primarily by increases in investor recognition, and to a lesser extent, by decreases in information asymmetry.

We conduct a battery of tests to check the robustness of the results. First, to fully capture the effects of initiation, we expand the measurement window of ΔROA, ΔASL, and ΔBR to two and three years following coverage initiation. The results show that even the long-term changes in fundamental performance still have no explanatory power over the initiation period returns. Furthermore, the association between the long-term ΔASL and CAR becomes indistinguishable between the initiation and control samples. In contrast, the association between the long-term ΔBR and CAR for the initiation sample continues to be significantly higher than that for the control sample.

Second, *ex-post* ΔROA, ΔASL, and ΔBR are unobservable to investors at the time of initiation. Therefore, they are noisy proxies for market expectations on changes in fundamental performance, information asymmetry, and investor recognition generated by initiations. To address this issue, we investigate whether initiation period returns are associated with *ex-ante* proxies of market expectations measured by the average ΔROA, ΔASL, and ΔBR triggered by the initiating analyst's prior initiations. The results show that only the *ex-ante* proxy of the expected changes in investor recognition still explains the initiation period returns.

Third, the main results remain largely unchanged when we use other alternative proxies of the three value creation channels. Specifically, we use the change in the number of searches on the SEC's EDGAR website for a firm's filings to proxy for change in investor recognition, the change in the probability of informed trade and the change in the bid-ask spread to proxy for change in information asymmetry, and analyst forecast revisions and standardized unexpected earnings to proxy for change in fundamental performance. The results show that the initiation period return is always significantly associated with proxies of changes in investor recognition, is often significantly associated with proxies of changes in information asymmetry, and is uncorrelated with any proxies of changes in fundamental performance.

The above results demonstrate that the (expected) change in investor recognition is the most important and robust determinant of the market reaction to initiation. The results are consistent with the "value creation hypothesis"—investors react favorably to initiations because they understand that analysts create value for firms by promoting the stocks to more investors. However, the results are also consistent with an alternative explanation that analysts tend to initiate coverage on stocks that they anticipate to have higher investor recognition (the "anticipation hypothesis"). We conduct several analyses to distinguish the two competing explanations. First, a necessary condition for the value creation hypothesis is that changes in analyst coverage must be able to *cause* investor recognition to change, rather than merely *reflect* future changes in investor recognition. We show that compared to the control sample, firms with exogenous terminations of coverage due to broker mergers or closures experience a larger decrease in investor recognition over the year following the terminations.[5] Because these terminations of coverage are due to exogenous reasons unrelated to analysts' anticipation, these results establish that changes in analyst coverage *cause* investor recognition to change rather than merely *reflect* the anticipated changes in investor recognition.

Second, if the anticipation hypothesis holds, we predict that the initiations by analysts with better ability to predict the future should be associated with a larger market reaction and increase in investor recognition. However, our analyses show that neither the initiation period

[5] Terminations of coverage caused by mergers or closures of brokerage firms have been used as exogenous shocks to analyst coverage in several recent studies (e.g., Kelly and Ljungqvist, 2012; Wu, 2013; Chen et al., 2014).

return, nor the change in investor recognition is significantly associated with the initiating analyst's ability to predict the future, proxied by the analyst's EPS forecast accuracy prior to initiation.

Third, if the value creation hypothesis holds, we expect that the initiations by analysts who are expected to devote more time and effort to promote the newly covered stocks will trigger greater increases in investor recognition and more favorable market reactions. Ceteris paribus, analysts with a smaller existing portfolio of covered stocks can devote more time to promote the initiated stocks, and the more diligent analysts who send their forecasts to investors more frequently exert more effort to market the newly covered stocks. Using these measures, we document that the initiations by analysts who are expected to devote more time and effort to promote the newly covered stocks are associated with much larger ΔBR and CAR. In contrast, we find no significant association between ΔROA or ΔASL and the proxies of the time and effort an analyst is expected to devote to promote the stocks. Hence, the overall evidence is generally consistent with the value creation hypothesis, that is, analysts create value for firms under their coverage by increasing investor recognition and reducing cost of capital of the stocks.

The rest of the paper is structured as follows. Section II describes the data and sample selection procedures; Section III presents the main empirical results; Section IV discusses and analyzes the alternative explanations of the results, and Section V concludes.

II. Sample selection and variable measurement

We collect the data of analyst coverage initiation from the I/B/E/S Recommendation Detail File. Based on prior research (e.g., Irvine, 2003; Irvine et al., 2007; Ertimur et al., 2011; Crawford et al., 2012), we define coverage initiation as: (1) the first time a given broker issues a recommendation for a firm; (2) it is also the first time a given analyst issues a recommendation for the firm. These two conditions ensure that neither a recommendation carried by an analyst from one broker to another, nor one transferred from one analyst to another within a broker is counted as initiation.[6] In addition, we require that the recommendation be issued (3) after the first two years of the I/B/E/S recommendation data (i.e., starting in 1996) to exclude recommendations added due to I/B/E/S data addition; (4) after the first 12 months of the firm's appearance on CRSP to exclude the potentially mechanical initiations for IPO firms; and (5) after the first six months of the broker's or analyst's appearance on I/B/E/S to exclude initiations due to new brokers or analysts expanding their coverage. Finally, to reduce the effects of confounding events, we require that the recommendation be issued (6) without concurrent (same-day) initiations on the same firm by other analysts to exclude clustered initiations that may be driven by news or events; and (7) without an earnings announcement or management forecast/guidance issued in the five trading days centering on the initiation date (i.e., initiation day-2 to initiation day+2, hereinafter "the initiation period"). We obtain earnings announcement dates from I/B/E/S and management forecast/guidance dates from the Company Issued Guidelines (CIG) of the First Call Historical Database.[7] Over the sample period (1996-2012), there are 55,428 initiations satisfying all of the seven conditions, consisting of recommendations from 7,805 unique analysts for 8,825 unique firms.[8] We denote the initiation quarter as quarter t.

[6] It is uncommon for multiple analysts (other than a research team) from a broker to have concurrent coverage for a firm. We find that at a monthly interval, 99.7% of the firms on I/B/E/S have only single coverage from a broker.

[7] The CIG data are available from January 1, 1996 to June 30, 2011. Hence, we are unable to identify and exclude initiations with concurrent management forecast/guidance after June 30, 2011. As a robustness check, we exclude all initiations after June 30, 2011 and obtain similar results.

[8] Consistent with prior literature (e.g., Irvine, 2003; Irvine et al., 2007; Ertimur et al., 2011; Crawford et al., 2012), we define analyst coverage initiation using recommendations. To test the robustness of our results, we also examine initiations defined using forecast data. The two types of initiations overlap significantly. From 1996 to 2012, there are 53,803 forecast initiations satisfying the same seven conditions, consisting of forecasts from 8,110 unique analysts for 8,982 unique firms. Approximately 95% of the firms and 90% of the analysts exist in both initiation samples. We replicate all of the tests using forecast initiations, and the results are similar, both qualitatively and

To isolate the effect of coverage initiation, we need to compare the initiation sample against a benchmark sample that has similar characteristics, but without initiation. Our main control sample is constructed using a propensity score matching procedure (Heckman et al., 1998; Rosenbaum and Rubin, 1983). For each initiation in quarter t, we select a control firm from the same quarter, which (1) does not have initiation in quarter t; (2) does not announce earnings in the initiation period; and (3) has a propensity score closest to the initiation firm. The matching is done without replacement. We impose the constraint that the control firm be within a distance (i.e., a ‘‘caliper’’) of 0.01 of the initiation firm’s propensity score to guarantee similarity of the observable variables between the initiation and control samples. Appendix B provides more details about the propensity score model and matching procedure. During the sample period, the propensity score matching generates 18,086 initiation-control pairs.[9] The diagnostic analyses in Tables A1 and A2 suggest that the matching effectively reduces differences in the observable determinants of initiation between the initiation and control samples. The differences in the mean values of the determinants between the initiation and control groups are statistically insignificant for all but one variable.

In our tests, we examine whether initiation firms have larger increases in fundamental performance and investor recognition, as well as a larger decrease in information asymmetry. Furthermore, we also investigate whether these changes drive the market reaction to analyst coverage initiation. We measure market reaction to initiation using initiation period returns,

---

quantitatively. Furthermore, only 4% of the recommendation initiations have prior forecast initiations. When these observations are excluded, the results are essentially the same.

[9] Our results are robust to the procedure of selecting the control sample. In addition to propensity score matching, we also adopt a simple matching method. Specifically, we pair each initiation with a control in quarter t, which is a firm from the same industry (defined by the two-digit SIGC codes in I/B/E/S), not announcing earnings in the initiation period, and with the number of analysts following (NUMREC) closest to the initiation firm. This simple matching generates 35,004 initiation-control pairs from 1996 to 2012. Using this alternative sample, we obtain similar results.

calculated as the size-adjusted return over the five trading days centering on the initiation date (CAR).[10] We use the change in return on assets (ΔROA) to measure change in firms' fundamental performance. We use the change in the adverse selection component of the bid-ask spread (ΔASL) as constructed in Hendershott et al. (2011) to measure change in information asymmetry. Finally, following Lehavy and Sloan (2008) and Richardson et al. (2012), we use the change in institutional ownership breadth (ΔBR) to measure change in investor recognition, where BR is the numbers of 13F filers holding a firm's stock divided by the total number of 13F filers.[11]

To examine the robustness of our results, we also adopt alternative proxies for the three value creation channels. Specifically, we use the change in the number of searches on the SEC's EDGAR website for a firm's filings (ΔEDGAR) to proxy for change in investor recognition; the change in the probability of informed trade (ΔPIN) and the change in the bid-ask spread to proxy for change in information asymmetry; and analyst forecast revisions and standardized unexpected earnings to proxy for change in fundamental performance. Detailed definitions and measurements of all variables are provided in Appendix A.

[10] To verify the accuracy of the announcement date of I/B/E/S recommendations, we randomly select 50 initiations each year between 1996 and 2012 (850 observations in total, representing 4.7% of our sample). We verify the initiation dates in I/B/E/S by cross-checking them against Investext. We find that I/B/E/S date errors are unlikely to affect our results significantly. Specifically, 633 observations have corresponding initiation reports on Investext. Among them, 421 initiation dates match precisely; 177 initiation dates in Investext are within the five trading days centering on the I/B/E/S initiation dates; and 35 initiation dates in Investext fall outside of the five-trading-day window. Hence, a five-day return window adequately captures the true initiation date for the majority (94.5%) of the observations. In addition, prior research on analyst initiations (e.g., Irvine, 2003; Irvine et al., 2007) also confirms that the errors in the I/B/E/S initiation dates are not likely to be a significant issue.

[11] Unless otherwise defined herein, Δ represents the difference between the value of the four quarters after quarter t and the value of the four quarters before quarter t.

III. Empirical results

3.1. Coverage initiation and changes in fundamental performance, information asymmetry, and investor recognition

We first test whether the initiation of analyst coverage is associated with changes in any of the three potential value drivers. Specifically, we compare the changes in fundamental performance (ΔROA), changes in information asymmetry (ΔASL), and changes in investor recognition (ΔBR) around the initiation of analyst coverage between the initiation sample and the control group. Panel A of Table 1 reports the mean CAR, ΔROA, ΔASL, and ΔBR for the two groups and the corresponding differences. The t-statistics are computed from two-way (by firm and quarter) cluster-robust standard errors (e.g., Petersen, 2008; Gow et al., 2010).

Consistent with prior studies (e.g., Branson et al., 1998; Irvine, 2003; Demiroglu and Ryngaert, 2010), the results confirm that stock markets react positively to analyst coverage initiations. On average, the firms in the initiation sample report 0.821% size-adjusted returns (t=9.88) during the five-trading-day initiation period. In contrast, the mean CAR over the same five days is -0.017% (t=-0.44) for the control firms. The difference in CAR between the two groups is highly significant (t=9.03). More importantly, compared to the control firms, the initiation firms are associated with a lower mean ΔASL (0.025 vs. 0.357) and a higher mean ΔBR (0.167 vs. 0.058) during the year subsequent to initiations. The differences in ΔASL and ΔBR between the two groups are both statistically significant (t=-2.36 and 5.44, respectively). In contrast, the difference in ΔROA is insignificant between the two groups (t=-0.48). The results suggest that the initiation of analyst coverage is associated with a decrease in information asymmetry and an increase in investor recognition, and is not associated with a change in fundamental performance.

To provide more direct evidence on whether any of the three value creation channels drives the market reaction, we turn to regression analysis to examine whether the magnitude of the market reaction in the initiation sample can be explained by the corresponding changes in any of the three value drivers. In Table 1, Panel B, we first report the univariate regressions of CAR on ΔROA, ΔASL, and ΔBR, respectively. Among the initiation firms, CAR is positively associated with ΔROA (t=2.12) and ΔBR (t=11.51), and is negatively associated with ΔASL (t=-5.18). The adjusted R^2 of the regression on ΔBR is 1.5%, significantly higher than the adjusted R^2 of the regressions on ΔROA and ΔASL (0.1% and 0.4%, respectively). The results indicate that ΔBR has much higher explanatory power on CAR than either ΔASL or ΔROA. The last column reports the multivariate regression of CAR on ΔROA, ΔASL, ΔBR, and RECOM, the level of initiation recommendations coded by I/B/E/S. After controlling for recommendation levels, ΔASL and ΔBR still have the predicted cross-sectional associations with CAR (t=-3.66 and 8.54, respectively). However, the coefficient on ΔROA is no longer statistically significant (t=0.41).

Changes in fundamental performance, information asymmetry, and investor recognition are value-relevant information. Such information may be anticipated by investors and reflected in stock prices gradually over time. Consequently, stock returns of any random days may be associated with the changes in these value drivers. The results in Panel B may simply reflect this normal association instead of the market reacting to the effects of coverage initiation. To isolate the effects of initiations, we examine the associations between CAR and ΔROA, ΔASL, and ΔBR after controlling for the "normal" associations between short-window returns and the three value drivers.

We first estimate the "normal" associations using the control sample by regressing the control firms' stock returns over the same five days on their ΔROA, ΔASL, and ΔBR. Because there is no initiation during the return window for the control sample, the associations between CAR and ΔROA, ΔASL, and ΔBR estimated in this group should approximate the "normal" relation between short-window returns and the value drivers. The second column in Table 1, Panel C shows that among control firms, ΔBR is positively associated with CAR (t=6.67). Although the coefficients of ΔROA and ΔASL both have the predicted signs, they are not statistically significant (t=1.08 and -1.30, respectively). The third column reports the differences in the coefficients between the initiation sample and the control sample. The differences in coefficients on ΔASL and ΔBR between the initiation and control samples are both statistically significant with t-statistics of -2.79 and 3.08, respectively.

In addition to the control sample, we also use the initiation sample itself to estimate the normal associations between stock returns and the value drivers.[12] Specifically, we use stock returns over the five randomly selected non-event trading days within the initiation quarter for each initiation firm as a self-control benchmark. To select the random trading days, we first exclude the five trading days centering on (1) the announcement dates of analyst recommendations for the firm (from all analysts, hence including the initiation date); (2) the firm's earnings announcement date; (3) the announcement dates of analyst EPS forecasts for the firm (from all analysts); or (4) the management forecast/guidance issuance dates. We then randomly select five trading days from the remaining days in quarter t.

[12] Relative to the control sample approach, the advantage of the self-control approach is that it helps avoid the potential problem that the normal associations between stock returns and the value drivers may be different between initiation and control firms. The disadvantage of the self-control approach is that the value drivers may be affected by initiation and therefore, strictly speaking, are no longer "normal".

The fourth column of Panel C reports the regression results of the size-adjusted returns of the initiation firms over the five randomly selected trading days (CAR_RS) on ΔROA, ΔASL, and ΔBR. The results show that the normal associations between stock returns and the value drivers estimated from non-event days of the initiation firms are remarkably similar to those estimated from the control sample. Although all of the coefficients bear the predicted sign, only the coefficient on ΔBR is statistically significant. Furthermore, the last column confirms that both ΔASL and ΔBR are still significantly associated with initiation period returns after controlling for their normal associations with CAR, estimated from the initiation sample itself.

In summary, the results in Table 1 show that both changes in investor recognition and changes in information asymmetry contribute to the cross-sectional variation in initiation period returns. The results are robust to the specifications controlling for the normal associations between short-window returns and the value drivers. Among the two, changes in investor recognition have much higher explanatory power on initiation period returns. In contrast, the association between initiation period returns and changes in fundamental performance is statistically insignificant, suggesting that the positive market response to initiation is unlikely due to the (expected) change in fundamental performance.

3.2. What drives the cross-sectional variation in initiation period returns associated with star analyst ranking and firms' existing coverage?

Prior literature (e.g., Branson et al., 1998) finds that initiations by star analysts generate bigger market reactions. In this section, we examine which of the three value creation channels drives the more positive market reaction by comparing changes in fundamental performance, information asymmetry, and investor recognition triggered by coverage initiations by star vs.

non-star analysts. We define an analyst as a "star" if she/he is ranked as an All-American analyst by Institutional Investor.[13] Consistent with Branson et al. (1998), Table 2, Panel A shows that the mean CAR is higher for initiations by star analysts than by non-star analysts (1.208% vs. 0.811%), with the difference significant at the 5% level (t=2.47). Among the three value drivers, the mean ΔROA and ΔBR are higher, and the mean ΔASL is lower for coverage initiated by star analysts than non-star analysts. However, only the difference in ΔBR between the two groups of analysts is statistically significant with a t-statistics of 4.27. The evidence suggests that the market expects star analysts to trigger a larger increase in investor recognition through initiations, given their prominent status, and hence reacts to their initiations more favorably.

Branson et al. (1998) also find that market reactions to initiations tend to be greater for stocks with lower existing coverage, indicating a diminishing marginal effect of initiations. We test which of the three value creation channels contributes to the difference in market reactions by investigating how ΔROA, ΔASL, and ΔBR vary with firms' existing coverage before initiation (COV). In Table 2, Panel B, we report the mean CAR, ΔROA, ΔASL, and ΔBR in quintile portfolios, partitioned by COV. Consistent with Branson et al. (1998), the initiation period return decreases monotonically with firms' existing coverage. The mean CAR of the bottom COV quintile is 1.882%, which is significantly higher than that of the top COV quintile (-0.005%). Furthermore, the results show that ΔASL increases, while ΔBR decreases monotonically with COV. The differences in ΔASL and ΔBR between the two extreme quintiles are both statistically significant (t=2.60 and -4.99, respectively). In contrast, there is no clear pattern in ΔROA across these portfolios. The evidence suggests that both changes in information

[13] We thank Xi Li for sharing the Institutional Investor ranking data with us. See Emery and Li (2009) for details about the ranking.

asymmetry and investor recognition may contribute to greater market reactions to coverage initiated on firms with lower existing coverage.

3.3. Alternative model specifications

The above results are based on ΔROA, ΔASL, and ΔBR, which are *ex-post* and noisy proxies of the market expectation of future changes in fundamental performance, information asymmetry, and investor recognition. In this section, we examine the robustness of the results to alternative proxies.

3.3.1. Longer measurement windows

In the above tests, we focus on the changes in fundamental performance, information asymmetry, and investor recognition over the first year subsequent to initiations, which may not fully capture the benefits of additional coverage if the benefits take a longer time to materialize. To examine this possibility, we expand the measurement window of ΔROA, ΔASL, and ΔBR to two and three years after initiations. In the first column of Table 3, Panel A, we report the regression of CAR on ΔROA, ΔASL, and ΔBR over two years after initiation (denoted as ΔROA_2, ΔASL_2, and ΔBR_2, respectively) for the initiation sample. Similar to the results in Table 1, Panel C, CAR is positively associated with ΔBR_2 (t=8.10), is negatively associated with ΔASL_2 (t=-3.54), and is not associated with ΔROA_2 (t=-0.15). In the second column, we observe that the CAR of the control firms is positively associated with ΔBR_2 (t=4.31), and is not associated with ΔROA_2 or ΔASL_2. The results for the random self-control sample (the fourth column) are similar to those for the control sample. After removing the normal associations between firms' returns and the three long-term proxies, only ΔBR_2 is significantly associated with the abnormal return over the initiation period, as shown in both the third and fifth columns.

In Table 3, Panel B, we extend our analysis to three years after initiation, and still find that only the change in investor recognition (ΔBR_3) is significantly associated with the initiation period returns after controlling for the normal associations between firms' returns and the three value drivers.

Overall, the evidence in Table 3 suggests that even the long-term ΔROA still has no explanatory power over CAR. Furthermore, the association between the long-term ΔASL and CAR becomes indistinguishable between the initiation and control samples. In contrast, the association between the long-term ΔBR and CAR for the initiation sample continues to be significantly higher than that for the control sample.

3.3.2. The en-ante market expectation proxies

In the previous analyses, we use realized ΔROA, ΔASL, and ΔBR as proxies for the market expectation of the changes in future fundamental performance, information asymmetry, and investor recognition generated by initiations. However, the realized values are not observable to the market at the time of initiation. What the market observes at initiation is the outcome of the analyst's prior initiations. In this section, we investigate whether initiation period returns are associated with the *ex-ante* proxies of the market expectation, measured by the mean ΔROA, ΔASL, and ΔBR triggered by an analyst's prior initiations (denoted as PΔROA, PΔASL, and PΔBR, respectively). Untabulated results show that all of the *ex-ante* measures are positively correlated with the *ex-post* measures. The Pearson (Spearman) correlation is 0.034 (0.051) between PΔROA and ΔROA, 0.086 (0.082) between PΔASL and ΔASL, and 0.133 (0.132) between PΔBR and ΔBR. All of the correlations are statistically significant at the 0.1% level.

The first column in Table 4, Panel A reports the regression results of CAR on PΔROA, PΔASL, and PΔBR for the initiation sample. The coefficient on PΔBR is significantly positive (t=4.81), while the coefficients on PΔROA and PΔASL are both insignificant (t=0.06 and 1.10, respectively). The second column reports the results for the random self-control sample. Because the dependent variable (CAR_RS) is the return over a non-event period, we do not expect it to be correlated with ΔROA, ΔASL, or ΔBR triggered by an analyst's prior initiations. As expected, none of the coefficients on PΔROA, PΔASL, or PΔBR are statistically significant. Finally, the third column shows that only the coefficient of PΔBR is significantly different (t=3.69) between the two regressions. The results show that investors react more favorably to coverage initiated by analysts whose prior initiations triggered a larger increase in investor recognition, thereby confirming early evidence that investors view a potential increase in investor recognition as one of the most important benefits of additional coverage.

3.3.3. Alternative proxy of change in investor recognition

Measuring investor recognition about a firm has been a challenge for academic research because the number of investors who "know about" a particular security is not directly observable. Following prior research (e.g., Lehavy and Sloan, 2008; Richardson et al., 2012), we use the change in institutional ownership breadth as the primary proxy for change in investor recognition. To verify the robustness of our results, we adopt an alternative proxy—the change in the number of searches on the SEC's EDGAR website for a firm's filings (ΔEDGAR).[14] Ceteris paribus, we expect the number of investors who search for information about a firm to be positively correlated with the number of investors who know about the security. Hence, ΔEDGAR serves as a reasonable alternative proxy for change in investor recognition.

---

[14] We thank Jake Thornock for kindly sharing the EDGAR search data with us. See Drake et al. (2014) for details about the data.

The SEC maintains a log file of all activities performed by users on EDGAR. Following Drake et al. (2014), we exclude searches by automated computer programs, identified by a high frequency of search requests (more than 5 requests per minute or more than 1,000 requests per day from a unique IP address). The interception of the EDGAR search data and our main sample consists of 2,708 initiation-control pairs in 2009 and 2010.

Table 4, Panel B reports the regressions of CAR on ΔROA, ΔASL, and ΔEDGAR for the initiation, control, and random self-control samples, and compares the coefficients between the samples. The coefficient of ΔEDGAR is positive for the initiation sample (t=3.51), but is insignificant for the control sample (t=0.04) and the random self-control sample (t=0.21). The difference in the coefficients of ΔEDGAR between the initiation and control (random self-control) samples is significant at the 5% level, with t-statistics of 2.57 (2.54). These results are consistent with those using ΔBR as a proxy for change in investor recognition. The association between ΔASL and CAR is much less significant than that reported in Table 1, Panel C. Specifically, the coefficient of ΔASL is only marginally significant at the 10% level for the initiation sample (t=-2.01). The difference in the coefficients of ΔASL between the initiation and control (random self-control) samples is no longer significant, with t-statistics of -1.47 (-1.29). Finally, ΔROA still remains insignificant in explaining the cross-sectional variation of CAR.

3.3.4. Alternative proxies for change in fundamental performance and change in information asymmetry

We also investigate whether our results are sensitive to alternative ways of measuring changes in information asymmetry and fundamental performance. In Table 4, Panel C, we report the results using changes in the probability of informed trade (ΔPIN) as the proxy for change in information asymmetry. Following Brown and Hillegeist (2007), PIN is computed using the

Venter and De Jongh (2006) model. The results are generally consistent with those using ΔASL (Table 1, Panel C). The difference in the coefficients of ΔPIN between the initiation and the control (random self-control) samples is significant at the 1% (5%) level, with t-statistics of -3.22 (-2.60).

In addition, we also use the change in the bid-ask spread as an alternative proxy for change in information asymmetry, and standardized unexpected earnings (see Bernard and Thomas, 1989) or change in analyst consensus forecasts of the future two-year earnings as alternative proxies for change in fundamental performance. Because these results are similar to our main tests, we do not tabulate them.

To summarize, our analyses suggest that among the three value creation channels of initiation, change in investor recognition has the highest and most robust explanatory power over the cross-sectional variation in initiation period returns. The more favorable market reactions to coverage initiated by star analysts and for firms with lower existing coverage are both driven primarily by larger increases in investor recognition, and to a lesser extent, by larger decreases in information asymmetry triggered by these initiations. The effects of changes in investor recognition on initiation period returns are robust to various alternative proxies for the three value drivers. In the following section, we discuss and discriminate among several competing explanations.

IV. Alternative explanations

4.1. Value creation hypothesis vs. anticipation hypothesis

The results so far suggest that the change in investor recognition is the most significant and robust determinant of the cross-sectional variation in initiation period returns. The evidence is consistent with the value creation hypothesis—investors react favorably to initiations because they understand that analysts create value for firms by promoting the stocks to more investors. However, the evidence is also consistent with an alternative hypothesis that analysts tend to initiate coverage on stocks they anticipate to have higher investor recognition in the future (the anticipation hypothesis), and the initiation is merely a positive information event revealing the analysts' expectation. To distinguish between the value creation hypothesis and the anticipation hypothesis, we first examine a necessary condition for the value creation hypothesis, then develop three tests focusing on an analyst's ability to forecast the future, and the expected effort and time he devotes to promote the stock.

4.1.1. The causal relation between analyst coverage and change in investor recognition

A necessary condition for the value creation hypothesis is that changes in analyst coverage must be able to *cause* investor recognition to change, rather than merely *reflect* future changes in investor recognition. However, an analyst's decision to initiate coverage is endogenous by nature. In addition, McNichols and O'Brien (1997) document that analysts tend to initiate coverage on stocks for which they have favorable private information. Therefore, it is very difficult to establish causality using the initiation sample, as one can always argue that the increase in investor recognition following an initiation is due to analysts' proclivity to initiate coverage on stocks with an expected increase in investor recognition.

To test whether changes in coverage cause investor recognition to change, we take advantage of a natural experiment where analyst coverage is terminated for exogenous reasons, such as mergers and closures of brokerage firms. If the change in coverage can cause investor recognition to change, we expect investor recognition to decrease, following the exogenous termination of coverage. Because these terminations are not due to analysts' voluntary choice, and hence, are not a decision based on their expectation of future changes in investor recognition, any documented changes in investor recognition should not be attributed to the analysts' anticipation.

Following the same procedures as Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012), we collect a sample of 48 brokerage firms that were merged or closed from 2000 to 2008. We follow Kelly and Ljungqvist (2012) and Derrien and Kecskes (2013) to identify firms for which analyst coverage was terminated due to the merger or closure of the brokerage firms. We pair each termination firm with a control firm, which is a firm from the same industry (defined by the two-digit SIGC codes in I/B/E/S) and with the number of analysts following (NUMREC) closest to that of the termination firm. The sample consists of 1,937 termination-control pairs.

As Table 5, Panel A shows, the termination firms experience a much larger decrease in investor recognition than the control firms over the first year following the termination. The mean ΔBR is -0.279 (t=-2.66) for the termination sample and -0.099 (t=-1.47) for the control sample, with the difference significant at the 1% level (t=-3.20). We do not observe a significant difference in ΔROA or ΔASL between the two groups.[15] The results suggest that investors may lose knowledge of a firm over time after coverage on the firm is terminated. In Panel B, we

[15] Kelly and Ljungqvist (2012) find that information asymmetry increases over the six months following termination of coverage. The difference between their finding and our result is mainly due to the difference in the proxies of information asymmetry. We repeat the tests replacing ΔASL with two information asymmetry proxies adopted in Kelly and Ljungqvist, the bid-ask spread and Amihud's (2002) illiquidity measure. We find that compared to those of the control sample, both the bid-ask spread and the illiquidity of the termination sample increase more over the year following termination of coverage, which is consistent with the finding in Kelly and Ljungqvist (2012). We also find that the differences in the bid-ask spread and the illiquidity measure between the termination and control samples disappear when we extend the tests to two years following termination.

extend the analysis to two years after the exogenous termination of coverage. The difference in ΔBR_2 between the two groups is still significant at the 10% level (t=-1.99). Finally, in Panel C we extend the analysis to three years after the termination of coverage and find that the difference in ΔBR_3 between the two groups is no longer significant (t=-1.17). This is perhaps not surprising. Following the exogenous termination of coverage, other brokers may start to cover the firm to fill the vacancy, which may slow down the decrease in investor recognition. Consistent with this conjecture, we find that the cumulative reduction in BR over the two years after termination (-0.163 in Panel B) is smaller than the reduction in the first year (-0.279 in Panel A), suggesting an increase in investor recognition in the second year after termination. In sum, the evidence in Table 5 shows that changes in analyst coverage *cause* a significant change in investor recognition, which is more consistent with the value creation hypothesis.

4.1.2. Analysts' ability to forecast the future

If the anticipation hypothesis is correct, we expect the initiation period returns to be more positive and the increases in investor recognition to be larger for coverage initiated by analysts who have a better ability to predict the future. We use the EPS forecast accuracy (ACCY) over the 90 days prior to an initiation as the proxy for the initiating analyst's ability to predict the future. We sort the sample into quintiles every quarter, based on ACCY.

The first column in Table 6, Panel A shows that CAR is unrelated to ACCY. Specifically, the mean CAR is 1.089% (t=6.40) for firms in the bottom quintile of ACCY, and 0.841% (t=5.58) for firms in the top quintile of ACCY. The difference between the two extreme quintiles is insignificant (t=-1.22). In addition, there is no clear pattern in ΔROA, ΔASL, or ΔBR across the ACCY quintiles. The results show that the initiations by analysts who have a better ability to predict the future do not generate higher initiation period returns or larger increases in investor recognition. Thus, the evidence fails to support the anticipation hypothesis.

4.1.3. Analysts' effort to promote the newly covered stock

If the value creation hypothesis is correct, we expect both the initiation period returns and changes in investor recognition to be higher for coverage initiated by analysts who are expected to exert more effort to promote the newly covered stocks. We use the average number of EPS forecasts that the initiating analyst issues for each firm under his coverage over the 90 days prior to an initiation as the proxy for the expected effort (EFFT) he uses to promote the stocks. We sort the sample into quintiles every quarter, based on EFFT.

As Table 6, Panel B shows, CAR increases monotonically with EFFT, ranging from 0.540% (t=3.80) for firms in the bottom quintile of EFFT to 1.040% (t=8.87) for firms in the top quintile of EFFT. The difference between the two extreme quintiles is significant at the 1% level (t=2.94). In addition, we observe that ΔBR also increases monotonically with EFFT, ranging from 0.120 (t=2.67) for the bottom quintile of EFFT to 0.209 (t=4.85) for the top quintile of EFFT. The difference (0.089) is statistically significant at the 1% level (t=2.67). In contrast, there is no clear pattern in ΔROA or ΔASL across the EFFT quintiles. The results suggest that initiations by analysts who are expected to exert more effort to promote the newly covered stocks tend to generate larger increases in investor recognition. Consequently, investors react more favorably to coverage initiated by these more diligent analysts.

4.1.4. Time devoted to the newly covered stock

If the value creation hypothesis is correct, the market reaction and change in investor recognition should also be higher for coverage initiated by analysts who are expected to devote more time to promote the stocks. Ceteris paribus, analysts who already cover a large number of stocks may have little time to promote the newly covered stock. We use the inverse of the number of firms for which the initiating analyst issues recommendations over the 90 days prior to an initiation as the proxy for the expected time (TIME) that he uses to promote the newly covered stocks. We sort the sample into quintiles every quarter, based on TIME.

As Table 6, Panel C shows, CAR increases with TIME, ranging from 0.336% (t=2.30) for firms in the bottom quintile of TIME to 1.035% (t=8.36) for firms in the top quintile of TIME. The difference between the two extreme quintiles is significant at the 1% level (t=4.48). In addition, ΔBR also increases with TIME, ranging from 0.119 (t=3.08) for the bottom quintile of TIME to 0.209 (t=3.89) for the top quintile of TIME. In contrast, there is no clear pattern in ΔROA or ΔASL across TIME quintiles. The results suggest that initiations by analysts who are expected to devote more time to promote the newly covered stocks tend to generate larger increases in investor recognition, which in turn trigger more favorable market reactions.

In sum, the above results show that changes in investor recognition and market reactions to initiations are uncorrelated with analysts' ability to forecast the future, but are significantly correlated with the expected time and effort analysts devote to promote the stocks. The overall evidence supports the hypothesis that investors perceive additional coverage as value enhancing because the new coverage increases investor recognition.

4.2. Changes in liquidity and trading volume as alternative explanations

Irvine (2003) argues that analyst coverage initiation enhances competition between informed traders and reduces the asymmetric information component of the bid-ask spread, which in turn improves liquidity. Similar arguments are also made by Roulstone (2003). Irvine shows that the liquidity gain has significant explanatory power over the market reaction to initiations. Because a larger investor base is associated with higher liquidity, a potential concern of our results is that the positive association between changes in institutional ownership breadth and initiation period returns simply reflects the effects of the improved liquidity brought by coverage initiation. Relatedly, recent studies in the trading literature (e.g., Jackson, 2005; Juergens and Lindsey, 2009) show that analysts use recommendations to boost brokerage trading income. Thus, an additional concern may be that the investor recognition effect simply reflects the change in trading volume after initiations.

It is worth noting that in our early regression analyses, we already include the change in information asymmetry, one of the key drivers of the change in liquidity, as an independent variable, which should alleviate these concerns. Nevertheless, to further address these concerns, we include the change in illiquidity (ΔILLIQ) and the change in trading volume (ΔVOL) as additional control variables. Following Amihud (2002), we measure ILLIQ as the quarterly average of the daily ratio of the absolute stock return to its dollar trading volume. We standardize ΔILLIQ and ΔVOL separately for stocks traded on the NYSE/AMEX versus those traded on NASDAQ to account for the different market microstructures (Atkins and Dyl, 1997). Consistent with Irvine (2003), Table 7 shows that ΔILLIQ is negatively associated with abnormal initiation period returns, as shown in the third and fifth columns. In contrast, ΔVOL is only marginally associated with the CAR of initiation firms (t=1.88), while the difference in the coefficients of ΔVOL between the initiation and control (random self-control) samples is insignificant. More importantly, ΔBR and ΔASL are still significantly associated with CAR in the predicted direction after controlling for ΔILLIQ and ΔVOL, suggesting that changes in liquidity and trading volume cannot explain our findings.

V. Conclusion

This paper attempts to shed light on the important question of whether and how financial analysts create value for the firms under their coverage. We tackle this question by examining the driving forces of the market reaction to the initiation of analyst coverage. We identify three potential channels of analysts' value creation: improving fundamental performance, reducing information asymmetry, and increasing investor recognition of the stocks. Our analysis shows that both changes in investor recognition and changes in information asymmetry have significant explanatory power over the cross-sectional variation in initiation period returns; however, changes in investor recognition have much stronger effects. We further show that the more favorable market reaction to coverage initiated by star analysts and for stocks with lower existing coverage are both driven primarily by larger increases in investor recognition.

Further analyses show that the results remain unchanged if we i) extend our analysis to three years after initiation to fully capture the benefits of coverage initiation; ii) replace the *ex-post* changes in fundamental performance, information asymmetry, and investor recognition with *ex-ante* proxies of the market expectation of the changes; iii) replace the change in institutional ownership breadth with the change in the number of searches on the SEC's EDGAR website as the proxy for change in investor recognition; iv) replace the change in the adverse selection component of the bid-ask spread with the change in the probability of informed trade or the change in the bid-ask spread as the proxy for change in information asymmetry; and vi) replace the change in return on assets with analyst forecast revisions or standardized unexpected earnings as the proxy for change in fundamental performance.

We provide direct evidence that changes in analyst coverage cause (rather than merely reflect) significant changes in investor recognition by investigating the dynamics of investor recognition following exogenous terminations of analyst coverage. Furthermore, we document that both the increase in investor recognition following coverage initiation and the market reaction are uncorrelated with initiating analysts' ability to forecast the future, but they tend to be larger when initiating analysts are expected to devote more time and effort to promote the stocks. Collectively, the results of the paper provide compelling evidence that, at least from the perspective of the market, analyst coverage is considered as value enhancing because it improves investor recognition and reduces cost of capital of the stocks.

References:

Altınkılıç, O. and R.S. Hansen. 2009. On the information role of stock recommendation revisions. Journal of Accounting and Economics 48, 17-36.

Altınkılıç, O., V. Balashov, and R.S. Hansen. 2013. Are analysts' forecasts informative to the general public? Management Science 59 (11), 2550-2565.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31-56.

Atkins, A. and E. Dyl. 1997. Transactions costs and holding periods for common stocks. Journal of Finance 52(1), 309-325.

Anantharaman, D. and Y. Zhang. 2011. Cover me: Managers' responses to changes in analyst coverage in the post-Regulation FD period. The Accounting Review 86 (6), 1851-1885.

Barber, B. and T. Odean. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21(2), 785-818.

Bernard, V. and J. Thomas. 1989. Post-earnings announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27, 1–36.

Bodnaruk, A. and P. Ostberg. 2009. Does investor recognition predict returns? Journal of Financial and Economics 91, 208-226.

Bowen, R. M., X. Chen, and Q. Cheng. 2008. Analyst coverage and the cost of raising equity capital: Evidence from underpricing of seasoned equity offerings. Contemporary Accounting Research 25(3), 657-699.

Bradshaw, M. 2004. How do analysts use their earnings forecasts in generating stock recommendations? The Accounting Review 79, 25−50.

Bradshaw, M. 2011. Analysts' forecasts: What do we know after decades of work? Working paper, Boston College. Available via http://ssrn.com/abstract=1880339.

Bradshaw, M., L. D. Brown, and K. Huang. 2013. Do sell-side analysts exhibit differential target price forecasting ability? Review of Accounting Studies 18 (4), 930-955.

Bradshaw, M., M. Drake, J. Myers, and L. Myers. 2012. A re-examination of analysts' superiority over time-series forecasts of annual earnings. Review of Accounting Studies 17, 944-968.

Branson, B. C., D. M. Guffey, and D. P. Pagach. 1998. Information conveyed in announcements of analyst coverage. Contemporary Accounting Research 15(2), 119-143.

Brennan, M. and A. Subrahmanyam. 1995. Investment analysis and price formation in securities markets. Journal of Financial Economics 38, 361-381.

Brown, S. and S. Hillegeist. 2007. How disclosure quality affects the level of information asymmetry. Review of Accounting Studies 12, 443-477.

Campbell, J. 1991. A variance decomposition for stock returns. Economic Journal 101, 157-179.

Campbell, J. and R. Shiller. 1988. The dividend-price ratio and expectations of future dividends and discount factors. Review of Financial Studies 1, 195-228.

Crawford, S., D. Roulstone, and E. So. 2012. Analyst initiations of coverage and stock return synchronicity. The Accounting Review 87(5), 1527-1553.

Chen, T., J. Harford, and C. Lin. 2014. Do analysts matter for governance? Evidence from natural experiments. Journal of Financial Economics, forthcoming.

Chung, K. H., T. H. McInish, R. A. Wood, and D. J. Wyhowski. 1995. Production of information, information asymmetry, and the bid-ask spread: Empirical evidence from analysts' forecasts. Journal of Banking and Finance 19, 1025-1046.

Cliff, M. T. and D. J. Denis. 2004. Do initial public offering firms purchase analyst coverage with underpricing? Journal of Finance 59(6), 2871-2901.

Cowen, A., B. Groysberg, and P. Healy. 2006. Which types of analyst firms are more optimistic? Journal of Accounting and Economics 41, 119-146.

Derrien, F. and A. Kecskes. 2013. The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. Journal of Finance 68, 1407-1440.

Demiroglu, C. and M. Ryngaert. 2010. The first analyst coverage of neglected stocks. Financial Management, 555-584.

Drake, M., D. Roulstone, and J. Thornock, 2014. The determinants and consequences of information acquisition via EDGAR. Contemporary Accounting Research, forthcoming.

Emery D. and X. Li. 2009. An anatomy of all-star analyst rankings. Journal of Financial and Quantitative Analysis 44, 411-437.

Ertimur, Y., V. Muslu, and F. Zhang. 2011. Why are recommendations optimistic? Evidence from analysts' coverage initiation. Review of Accounting Studies 16, 679-718.

Foerster, S. R. and A. G. Karolyi. 1999. The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States. Journal of Finance 54(3), 981-1013.

Francis, J. and D. Philbrick. 1993. Analysts' decisions as products of a multi-task environment. Journal of Accounting Research 31(2), 216–230.

Fried, D. and D. Givoly. 1982. Financial analysts' forecasts of earnings: A better surrogate for market expectations. Journal of Accounting and Economics 4(2), 85-107.

Givoly, D. and J. Lakonishok. 1979. The information content of financial analysts' forecast of earnings: Some evidence on semi-strong inefficiency. Journal of Accounting and Economics 1(3), 165-185.

Gleason, C. and C. Lee. 2003. Analyst forecast revisions and market price discovery. The Accounting Review 78 (1), 193-225.

Gow, I., G. Ormazabal, and D. Taylor. 2010. Correcting for cross-sectional and time-series dependence in accounting research. The Accounting Review 85, 483-512.

Groysberg, B., P. M. Healy, and D. A. Maber. 2011. What drives sell-side analyst compensation at high-status investment banks? Journal of Accounting Research 49 (4), 969-1000.

He, J. and X. Tian. 2013. The dark side of analyst coverage: The case of innovation. Journal of Financial Economics 109(3), 856-878.

Heckman, J., H. Ichimura, and P. Todd. 1998. Matching as an econometric evaluation estimator. Review of Economic Studies 65, 261-294.

Hendershott, T., C. Jones, and A. Menkveld. 2011. Does algorithmic trading improve liquidity? Journal of Finance 66(1), 1-33.

Hong, H. and J. Kubik. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. Journal of Finance 58, 313−351.

Hong, H. and M. Kacperczyk. 2010. Competition and bias. Quarterly Journal of Economics 125, 1683-1725.

Irvine, P. J. 2003. The incremental impact of analyst initiation of coverage. Journal of Corporate Finance 9, 431-451.

Irvine, P. J. 2004. Analysts' forecasts and brokerage-firm trading. The Accounting Review 79 (1), 125-149.

Irvine, P. J., M. Lipson, and A. Puckett. 2007. Tipping. Review of Financial Studies 20 (3), 741-768.

Juergens, J. and L. Lindsey. 2009. Getting out early: An analysis of market making activity at the recommending analyst's firm. Journal of Finance 64 (5), 2327-2359.

Jackson, A. 2005. Trade generation, reputation and sell-side analysts. Journal of Finance 60, 673−717.

Jung, B., K. Sun, and S. Yang. 2012. Do financial analysts add value by facilitating more effective monitoring of firms' activities? Journal of Accounting, Auditing and Finance 27(1), 61-99.

Kadlec, G. and J. McConnell. 1994. The effect of market segmentation and illiquidity on asset prices: Evidence from exchange listings. Journal of Finance 49 (2), 611-636.

Kelly, B. and A. Ljungqvist. 2012. Testing asymmetric-information asset pricing models. Review of Financial Studies 25, 1366-1413.

Kim, Y. and M. Song. 2014. Management earnings forecasts and value of analyst forecast revisions. Management Science, forthcoming.

Krigman, L., W. H. Shaw, and K. Womack. 2001. Why do firms switch underwriters? Journal of Financial Economics 60, 245-284.

Lehavy, R. and R. Sloan. 2008. Investor recognition and stock returns. Review of Accounting Studies 13, 327-361.

Lin, H. and M. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics 25(1), 101–127.

McNichols, M. and P. O'Brien. 1997. Self-selection and analyst coverage. Journal of Accounting Research 35, 167-199.

Merton, R. C. 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483-510.

Michaely, R. and K. Womack. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. Review of Financial Studies 12, 653−686.

Mola, S., P.R. Rau, and A. Khorana. 2013. Is there life after the complete loss of analyst coverage? The Accounting Review 88 (2), 667-705.

Niehaus, G. and D. Zhang. 2010. The impact of sell-side analyst research coverage on an affiliated broker's market share of trading volume. Journal of Banking and Finance 34, 776-787.

Petersen, M. 2008. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435-480.

Ramnath, S., S. Rock, and P. Shane. 2008. The financial analyst forecasting literature: A taxonomy with suggestions for future research. Internal Journal of Forecasting 24, 34-75.

Richardson, S., R. Sloan, and H. You. 2012. What makes stock prices move? Fundamentals vs. investor recognition. Financial Analyst Journal 68 (2), 30-50.

Rosenbaum, P. and D. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41-55.

Roulstone, D.T. 2003. Analyst following and market liquidity. Contemporary Accounting Research 20 (3), 551-578.

Venter, J. H. and D. De Jongh. 2006. Extending the EKOP model to estimate the probability of informed trading. Studies in Economics and Econometrics 30, 25-39.

Yu, F. 2008. Analyst coverage and earnings management. Journal of Financial Economics 88, 245-271.

Wu, W. 2013. Information asymmetry and insider trading: Evidence from exogenous changes in analyst coverage. Working paper, University of Chicago. Available via http://ssrn.com/abstract=2323537

Appendix A. Sample selection and variable definition

Sample		Definition
Initiation	IN	The initiation sample is from 1996 to 2012. We define initiations as: (1) The first time a given broker issues a recommendation for a firm; and (2) It is also the first time a given analyst issues a recommendation for the firm. In addition, we require that the recommendation be issued (3) after the first two years of the I/B/E/S recommendation data (i.e., starting in 1996) and before 2013; (4) after the first 12 months of the firm's appearance on CRSP; (5) after the first six months of the broker's or analyst's appearance on I/B/E/S; (6) without concurrent (same-day) initiation on the same firm by other analysts; (7) without an earnings announcement or management forecast/guidance issued in the five trading days centering on the initiation date (i.e., initiation day-2 to initiation day+2, or "the initiation period") The quarter of the initiation is denoted as quarter t. Over the sample period from 1996 to 2012, there are 55,428 recommendations satisfying all of the conditions above.
Control	CL	We pair each initiation with a control firm in quarter t, which (1) does not have initiation in quarter t; (2) does not announce earnings in the initiation period; and (3) has a propensity score of receiving initiation closest to the initiation firm. See Appendix B for the propensity score matching procedure. During the sample period, the propensity score matching generates 18,086 initiation-control pairs.
Random self-control	RS	The five randomly selected trading days in quarter t. We first exclude the five trading days centering on (1) the announcement dates of analyst recommendations for the firm (from all analysts, hence including the initiation date); (2) the firm's earnings announcement date; (3) the announcement dates of analyst EPS forecasts for the firm (from all analysts); (4) or the management forecast/guidance issuance dates. We then randomly select five trading days from the remaining days in quarter t.
Termination and control		The termination sample includes firms that lost analyst coverage because of broker mergers or closures from 2000 to 2008. We pair each termination firm with a control firm, which is a firm from the same industry (defined by the two-digit SIGC codes in I/B/E/S) and with the number of analysts following (NUMREC) closest to that of the termination firm. The sample consists of 1,937 termination-control pairs.
Variable		**Definition**
Abnormal return	CAR_IN, CAR_CL, CAR_RS	CAR_IN (CAR_CL) is the size-adjusted return (adjusted by the return of the CRSP size-matched decile portfolio) over the initiation period (i.e., initiation day-2 to initiation day+2) for the initiation (control) firms. CAR_RS is the size-adjusted return of the initiation firms over the random self-control period (i.e., the five randomly selected trading days in quarter t). We measure CAR in percentages (i.e., return×100).
Change in breadth	ΔBR, ΔBR_2, ΔBR_3, $P\Delta BR$	ΔBR (ΔBR_2 / ΔBR_3) is the mean institutional ownership breadth (BR) of quarters t+1 to t+4 (t+5 to t+8 / t+9 to t+12) subtracting the mean BR of quarters t-4 to t-1. $P\Delta BR$ is the average ΔBR on all of the initiating analyst's prior initiations. BR is measured as in Lehavy and Sloan (2008), i.e., the numbers of 13F filers holding a firm's stock, divided by the total number of 13F filers. The resulting values are multiplied by 100.
Change in return on assets	ΔROA, ΔROA_2, ΔROA_3, $P\Delta ROA$	ΔROA (ΔROA_2 / ΔROA_3) is the sum of the quarterly income before extraordinary items (IBQ) from quarters t+1 to t+4 (t+5 to t+8 / t+9 to t+12), scaled by the total assets (ATQ) of quarters t (t+4 / t+8), subtracting the sum of IBQ from quarters t-4 to t-1, scaled by the ATQ of quarter t-5. $P\Delta ROA$ is the average ΔROA on all of the initiating analyst's prior initiations. The resulting values are multiplied by 100.

Appendix A. Continued

Variable		Definition
Change in the adverse selection component of the bid-ask spread	ΔASL, ΔASL_2, ΔASL_3, PΔASL	ΔASL (ΔASL2 / ΔASL3) is the mean adverse selection component of the bid-ask spread (ASL) of quarters t+1 to t+4 (t+5 to t+8 / t+9 to t+12) subtracting the mean ASL of quarters t-4 to t-1. PΔASL is the average ΔASL on all of the initiating analyst's prior initiations. Following Hendershott et al. (2011), we measure ASL using the 5-minute price impact of a trade: $q_t(m_{t+5min} - m_t)/m_t$, where q_t is the buy-sell indicator (+1 for buys, -1 for sells), m_t is the midpoint prevailing at the time of the t^{th} trade, and m_{t+5min} is the quote midpoint 5 minutes after the t^{th} trade. The daily ASL is the average of ASLs of all trades of a stock in a given day, and the quarterly ASL is the average of the daily ASLs of that stock. The resulting values are multiplied by 10,000. The intraday trade and quote data are from the Trade and Quote (TAQ) database.
Change in illiquidity	ΔILLIQ	The mean illiquidity measure (ILLIQ) of quarters t+1 to t+4 subtracts the mean ILLIQ of quarters t-4 to t-1. Following Amihud (2002), we measure ILLIQ as the quarterly average of the daily ratio of the absolute stock return to its dollar trading volume. We standardize ΔILLIQ separately for stocks traded on the NYSE/AMEX versus those traded on NASDAQ to account for the different market microstructures (Atkins and Dyl, 1997). We sort on ΔILLIQ within each quarter (separately for NYSE/AMEX and NASDAQ stocks) and assign percentile ranks to each observation, ranging from 0 (low ΔILLIQ) to 99 (high ΔILLIQ). We then standardize the percentiles by dividing them by 99. The standardized value ranges between 0 and 1.
Change in the probability of informed trade	ΔPIN	The mean probability of informed trade (PIN) of quarters t+1 to t+4 subtracts the mean PIN of quarters t-4 to t-1. Following Brown and Hillegeist (2007), PIN is computed using the Venter and De Jongh (2006) model. The data are downloaded from Stephen Brown's website (http://www.rhsmith.umd.edu/faculty/sbrown/). The resulting values are multiplied by 100. The interception of the PIN data and our main sample consists of 13,169 initiation-control pairs from 1996 to 2009.
Change in trading volume	ΔVOL	The mean turnover of quarters t+1 to t+4 subtracts the mean turnover of quarters t-4 to t-1. Turnover is the quarterly average of the daily ratio of trading volume divided by total shares outstanding. To account for the different market microstructures, we standardize ΔVOL in the same way as ΔILLIQ.
Change in the number of searches on the EDGAR website	ΔEDGAR	The logarithm of the ratio of the number of unique searches on the SEC's EDGAR website for a firm's filings (EDGAR) from quarters t+1 to t+4, divided by EDGAR from quarters t-4 to t-1. Following Drake et al. (2014), we exclude searches by automated computer programs, identified by a high frequency of search requests (more than 5 requests per minute or more than 1,000 requests per day from a unique IP address). The interception of the EDGAR search data and our main sample consists of 2,708 initiation-control pairs in 2009 and 2010.
Analyst forecast accuracy	ACCY	ACCY is computed in the following steps: (1) for each firm in the analyst's existing portfolio, compute the forecast error (FE), which is the absolute value of the difference between analysts' one-quarter ahead forecast (FPI=6) and the actual EPS divided by the absolute value of the actual EPS, on the last review date (REVDATS) prior to a new initiation, provided that REVDATS is within the 90 days prior to the initiation date, and that the announcement date of the actual EPS is earlier than the initiation date; (2) compute the average FE (AFE) of all firms in the analyst's existing portfolio prior to an initiation; (3) ACCY is the inverse of AFE. Firms are sorted into quintiles every quarter based on ACCY.
Analyst coverage	COV	The number of existing recommendations (NUMREC) before an initiation. The initiation sample is sorted into quintiles each quarter based on log (1+NUMREC).

Appendix A. Continued

Variable		Definition
Analyst's effort to market the stock	EFFT	The average number of EPS forecasts that the initiating analyst issues for each firm under his coverage over the 90 days prior to a new coverage initiation. Firms are sorted into quintiles every quarter based on EFFT.
Analyst's time to market the stock	TIME	The inverse of the size of the initiating analyst's existing portfolio (PORF). PORF is the number of firms for which the analyst issues recommendations over the 90 days prior to new coverage initiation. Firms are sorted into quintiles every quarter based on TIME.
Initiation recommendation	RECOM	The level of initiation recommendation coded by I/B/E/S: 1 for Strong Buy, 2 for Buy, 3 for Hold, 4 for Underperform, and 5 for Sell.
Star analyst	STAR	The All-American analysts ranked by Institutional Investor, available annually from 1996 to 2009. We remove the star status of an analyst if she/he is dropped from the Institutional Investor list.

Determinants of initiation in propensity score matching

Change in size	$\Delta SIZE_{t-1}$	The logarithm of the ratio of the market value of equity (PRCCQ*CSHOQ) in quarter t-1 divided by the market value of equity in quarter t-5.
Change in sales	$\Delta SALE_{t-1}$	The sum of sales (SALEQ) from quarters t-1 to t-4 subtracts the sum of SALEQ from quarters t-5 to t-8, dividing by the sum of SALEQ from quarters t-5 to t-8. The ratio is multiplied by 100.
Change in equity issuance	$\Delta EQUITY_{t-1}$	The sum of equity issuance from quarters t-1 to t-4 subtracts the sum of equity issuance from quarters t-5 to t-8, dividing by the market value of equity in quarter t-4. The ratio is multiplied by 100. Quarterly equity issuance is calculated from SSTKY.
Change in institutional ownership	ΔIO_{t-1}	The percent of institutional ownership (PSINT) in quarter t-1 subtracts PSINT in quarter t-5. PSINT is total shares held by 13F filers divided by total shares outstanding.
Change in trading volume	ΔVOL_{t-1}	The mean turnover of quarters t-1 to t-4 subtracts the mean turnover of quarters t-5 to t-8. Turnover is the quarterly average of the daily ratio of the trading volume divided by total shares outstanding. To account for the different market microstructures, we standardize ΔVOL in the same way as ΔILLIQ.
Change in absolute forecast error	ΔAFE_{t-1}	Absolute forecast error (AFE) in quarter t-1 subtracts AFE in quarter t-5. AFE is the absolute difference between a firm's actual EPS and the latest consensus forecast, divided by the price at the time of the consensus.
Change in coverage	ΔCOV_{t-1}	NUMREC in quarter t-1 subtracts NUMREC in quarter t-5, dividing by NUMREC in quarter t-5.
Change in return on assets	ΔROA_{t-1}	The sum of IBQ from quarters t-1 to t-4, scaled by the ATQ of quarter t-4, subtracting the sum of IBQ from quarters t-5 to t-8, scaled by the ATQ of quarter t-8. The resulting values are multiplied by 100.
Change in breadth	ΔBR_{t-1}	The mean BR of quarters t-1 to t-4 subtracts the mean BR of quarters t-5 to t-8. The resulting values are multiplied by 100.
Change in the adverse selection component of the bid-ask spread	ΔASL_{t-1}	The mean ASL of quarters t-1 to t-4 subtracts the mean ASL of quarters t-5 to t-8. The resulting values are multiplied by 10,000.

Appendix B. Control sample selected using propensity score matching

We use a propensity score matching procedure (Heckman et al., 1998; Rosenbaum and Rubin, 1983) to select the control sample. For each initiation in quarter t, we select a matching firm from the same quarter, which (1) does not have initiation in quarter t; (2) does not announce earnings in the initiation period; and (3) has a propensity score closest to the initiation firm. The matching is done without replacement. We impose the constraint that the control firm be within a distance (i.e., a ‘‘caliper’’) of 0.01 of the initiation firm’s propensity score to guarantee similarity of the observable variables between the initiation and control samples.

Initiation represents an addition in analyst coverage. We develop the following model of initiation based on the determinants of changes in analyst coverage in Anantharaman and Zhang (2011) (See Appendix A for variable definitions):[16]

$$\begin{aligned} INITIATION_t = {} & \alpha + \beta_1 \Delta SIZE_{t-1} + \beta_2 \Delta SALE_{t-1} + \beta_3 \Delta EQUITY_{t-1} + \beta_4 \Delta IO_{t-1} + \beta_5 \Delta VOL_{t-1} \\ & + \beta_6 \Delta AFE_{t-1} + \beta_7 \Delta COV_{t-1} + \beta_8 \Delta ROA_{t-1} + \beta_9 \Delta BR_{t-1} + \beta_{10} \Delta ASL_{t-1} + Industry \\ & fixed\ effects + Year\ fixed\ effects + \varepsilon_t \end{aligned}$$

We estimate the pooled logit model on all firms in the I/B/E/S universe with available data from 1996 to 2012. The industry fixed effects are based on the two-digit SIGC codes in I/B/E/S. The propensity score-matching procedure generates a final sample of 18,086 initiation-control pairs over the sample period from 1996 to 2012.

Table A1 reports the pooled logistic regressions before and after matching, with z-statistics adjusted for two-way (by firm and quarter) cluster-robust standard errors (e.g., Petersen, 2008; Gow et al., 2010). All of the determinants significantly predict the probability of initiation, except for ΔEQUITY and ΔAFE. After matching, none of the determinants are significant, suggesting that the matching effectively reduces the differences in these observable determinants of initiation between the initiation and control samples. The mean values of the determinants and propensity scores for the initiation and control samples are given in Table A2.

[16] Our results are not sensitive to the determinants included in the model. As a robustness check, we include all of the control variables in Anantharaman and Zhang’s model. The results are quantitatively similar.

Table A1. Logistic regression of initiation on the determinants

	Before matching	After matching
Intercept	-2.655***	-0.048
	(-24.90)	(-0.49)
$\Delta SIZE_{t-1}$	0.409***	0.010
	(9.07)	(0.56)
$\Delta SALE_{t-1}$	0.237***	0.129
	(9.02)	(2.56)
$\Delta EQUITY_{t-1}$	-0.001	0.002
	(-1.54)	(1.25)
ΔIO_{t-1}	0.357***	-0.044
	(2.90)	(-0.29)
ΔVOL_{t-1}	0.229***	0.018
	(2.72)	(0.24)
ΔAFE_{t-1}	-0.239	0.298
	(-1.38)	(1.19)
ΔCOV_{t-1}	0.105***	0.031
	(5.53)	(1.08)
ΔROA_{t-1}	-0.003***	0.001
	(-3.44)	(0.99)
ΔBR_{t-1}	0.287***	-0.018
	(12.73)	(-2.09)
ΔASL_{t-1}	-0.011***	0.003
	(-4.74)	(1.35)
Industry fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No of obs.	310,562	36,172
Pseudo R^2	12.9%	0.2%

Table A2. Mean values of the determinants of initiation and propensity score for initiation and control samples

	Initiation	Control	Difference
Propensity Score	0.105	0.105	0.000
$\Delta SIZE_{t-1}$	0.111	0.108	0.003
$\Delta SALE_{t-1}$	0.162	0.148	0.014***
$\Delta EQUITY_{t-1}$	0.324	0.136	0.188
ΔIO_{t-1}	0.027	0.027	0.000
ΔVOL_{t-1}	0.522	0.519	0.003
ΔAFE_{t-1}	0.001	0.000	0.001
ΔCOV_{t-1}	0.167	0.158	0.009
ΔROA_{t-1}	0.090	-0.147	0.237
ΔBR_{t-1}	0.164	0.165	-0.001
ΔASL_{t-1}	0.193	0.061	0.132

*** Indicates two-tailed significance at p<=0.01.

Table 1. Initiation return and changes in fundamental performance, information asymmetry, and investor recognition

Panel A: Summary statistics for the initiation and control samples

	N	CAR	ΔROA	ΔASL	ΔBR
Initiation	18,086	0.821***	-0.539**	0.025	0.167***
		(9.88)	(-2.10)	(0.06)	(4.29)
Control	18,086	-0.017	-0.431	0.357	0.058**
		(-0.44)	(-1.24)	(0.80)	(2.16)
Initiation-Control	**18,086**	**0.838*** **	**-0.108**	**-0.332** **	**0.109*** **
		(9.03)	**(-0.48)**	**(-2.36)**	**(5.44)**

Panel B: Regression of initiation period return on the three value creation proxies

	Dependent variable: CAR			
Intercept	0.826***	0.822***	0.713***	3.454***
	(9.86)	(9.81)	(9.14)	(18.81)
ΔROA	0.010**			0.002
	(2.12)			(0.41)
ΔASL		-0.055***		-0.036***
		(-5.18)		(-3.66)
ΔBR			0.647***	0.486***
			(11.51)	(8.54)
RECOM				-1.262***
				(-18.61)
Adj. R-square	0.1%	0.4%	1.5%	4.7%

Panel C: Comparison of the explanatory power of the three value creation proxies on initiation return between the initiation, control and random self-control samples

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	0.722***	-0.036	0.758***	0.077	0.645***
	(9.29)	(-0.86)	(8.82)	(1.54)	(6.98)
ΔROA	0.002	0.003	-0.001	0.005	-0.003
	(0.51)	(1.08)	(-0.10)	(0.90)	(-0.43)
ΔASL	-0.040***	-0.007	-0.033***	-0.008	-0.032**
	(-3.87)	(-1.30)	(-2.79)	(-0.99)	(-2.55)
ΔBR	0.603***	0.387***	0.216***	0.265***	0.338***
	(10.57)	(6.67)	(3.08)	(5.60)	(5.82)
Adj. R-square	1.7%	0.4%	-	0.4%	-

See Appendix A for variable definitions and sample selection, and Appendix B for the propensity score-matching procedure. Panel A reports the sample size and the pooled mean of initiation period return (CAR) and the proxies for the three value creation channels (ΔROA, ΔASL, and ΔBR) for the initiation and control samples. Panel B reports the OLS regressions of CAR on ΔROA, ΔASL, ΔBR and initiation recommendations for the initiation sample. Panel C reports the OLS regressions of initiation period returns on ΔROA, ΔASL, and ΔBR for the initiation (CAR_IN), control (CAR_CL), and random self-control (CAR_RS) samples, and compares the regression coefficients. The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 2. The effects of star analysts and firms' existing coverage prior to initiation

Panel A: Star analyst

Portfolio formed on star ranking	CAR	ΔROA	ΔASL	ΔBR
STAR	1.208***	-0.477	-0.276	0.401***
	(3.97)	(-1.26)	(-0.45)	(6.15)
NONSTAR	0.811***	-0.514*	0.274	0.164***
	(8.53)	(-1.73)	(0.55)	(3.41)
STAR-NONSTAR	**0.397****	**0.037**	**-0.550**	**0.237*****
	(2.47)	**(0.11)**	**(-1.33)**	**(4.27)**

Panel B: Firms' existing coverage prior to initiation

Portfolio ranking on COV	CAR	ΔROA	ΔASL	ΔBR
Bottom	1.882***	-0.113	-0.527	0.302***
	(11.40)	(-0.26)	(-1.02)	(8.91)
2	1.054***	-0.662*	-0.301	0.268***
	(8.09)	(-1.80)	(-0.57)	(7.00)
3	0.632***	-0.518	0.185	0.256***
	(5.93)	(-1.46)	(0.37)	(5.37)
4	0.534***	-0.684**	0.284	0.075
	(5.64)	(-2.48)	(0.75)	(1.51)
Top	-0.005	-0.720**	0.487	-0.067
	(-0.04)	(-2.33)	(1.56)	(-0.89)
Top-Bottom	**-1.887*****	**-0.607**	**1.014****	**-0.369*****
	(-10.43)	**(-1.41)**	**(2.60)**	**(-4.99)**

See Appendix A for variable definitions and sample selection. Panel A reports the pooled mean of initiation period returns (CAR) and the proxies for the three value creation channels (ΔROA, ΔASL, and ΔBR) for the groups partitioned by the initiating analysts' star ranking. Panel B reports the pooled mean of CAR, ΔROA, ΔASL, and ΔBR for the quintile portfolios formed on the firm's existing coverage prior to initiations. The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3. Initiation return and changes in fundamental performance, information asymmetry, and investor recognition over longer horizons

Panel A: Two years after initiation

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	0.794***	0.007	0.787***	0.102*	0.692***
	(9.75)	(0.13)	(8.27)	(1.88)	(6.86)
ΔROA_2	-0.001	0.000	-0.001	0.002	-0.003
	(-0.15)	(0.01)	(-0.13)	(0.42)	(-0.33)
ΔASL_2	-0.029***	-0.005	-0.024	-0.006	-0.023
	(-3.54)	(-0.96)	(-1.29)	(-1.04)	(-1.20)
ΔBR_2	0.334***	0.176***	0.158***	0.134***	0.200***
	(8.10)	(4.31)	(2.85)	(4.15)	(4.17)
Adj. R-square	1.1%	0.2%	-	0.2%	-

Panel B: Three years after initiation

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	0.788***	0.041	0.747***	0.113*	0.675***
	(8.14)	(0.66)	(6.66)	(1.89)	(5.58)
ΔROA_3	-0.009	0.002	-0.011	-0.005	-0.004
	(-1.33)	(0.26)	(-1.27)	(-1.05)	(-0.48)
ΔASL_3	-0.017**	-0.003	-0.014	-0.010**	-0.007
	(-2.47)	(-0.44)	(-0.90)	(-2.12)	(-0.69)
ΔBR_3	0.243***	0.113***	0.130**	0.105***	0.138***
	(6.63)	(3.36)	(2.47)	(3.77)	(3.32)
Adj. R-square	0.8%	0.1%	-	0.2%	-

See Appendix A for variable definitions and sample selection. This table reports the OLS regressions of initiation period returns on the three value creation proxies (ΔROA, ΔASL, and ΔBR) over two and three years after initiation for the initiation (CAR_IN), control (CAR_CL) and random self-control (CAR_RS) samples, and compares the regression coefficients. The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4. Alternative proxies of the market expectation of changes in fundamental performance, information asymmetry, and investor recognition

Panel A: Ex-ante market expectation proxies

	CAR_IN	CAR_RS	IN-RS
Intercept	0.723***	0.097*	0.626***
	(9.27)	(1.76)	(6.49)
PΔROA	0.000	-0.005	0.005
	(0.06)	(-1.23)	(0.74)
PΔASL	0.013	0.012	0.001
	(1.10)	(1.29)	(0.04)
PΔBR	0.392***	0.044	0.348***
	(4.81)	(0.80)	(3.69)
Adj. R-square	0.2%	0.0%	-

Panel B: Use the change in EDGAR searches as the proxy for change in investor recognition

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	0.641***	-0.031	0.672***	-0.117	0.758**
	(4.27)	(-0.35)	(3.41)	(-0.98)	(2.89)
ΔROA	0.007	0.001	0.006	0.015	-0.008
	(0.28)	(0.18)	(0.21)	(1.45)	(-0.28)
ΔASL	-0.070*	0.017	-0.087	0.001	-0.071
	(-2.01)	(1.38)	(-1.47)	(0.04)	(-1.29)
ΔEDGAR	1.751***	0.023	1.728**	0.048	1.703**
	(3.51)	(0.04)	(2.57)	(0.21)	(2.54)
Adj. R-square	1.1%	0.0%	-	0.0%	-

Panel C: Use the change in PIN as the proxy for change in information asymmetry

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	0.647***	-0.086*	0.733***	0.058	0.589***
	(6.45)	(-1.84)	(6.79)	(0.88)	(5.06)
ΔROA	-0.003	0.005	-0.008	0.002	-0.005
	(-0.43)	(1.36)	(-1.12)	(0.35)	(-0.67)
ΔPIN	-0.078***	-0.011	-0.067***	-0.025*	-0.053**
	(-4.30)	(-0.91)	(-3.22)	(-1.99)	(-2.60)
ΔBR	0.586***	0.381***	0.205***	0.264***	0.322***
	(10.14)	(6.72)	(3.03)	(4.68)	(5.56)
Adj. R-square	1.9%	0.5%	-	0.5%	-

See Appendix A for variable definitions and sample selection. Panel A reports the OLS regressions of initiation period returns on the three ex-ante proxies for the initiation (CAR_IN) and random self-control (CAR_RS) samples, and compares the regression coefficients. The sample in Panel B consists of 2,708 initiation-control pairs with available ΔEDGAR data in 2009 and 2010. The sample in Panel C consists of 13,169 initiation-control pairs with available ΔPIN data from 1996 to 2009. The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5. Exogenous termination in analyst coverage and changes in fundamental performance, information asymmetry, and investor recognition

Panel A: One year after the exogenous termination of analyst coverage

	N	ΔROA	ΔASL	ΔBR
Termination	1,937	-0.151	-0.448	-0.279**
		(-0.11)	(-0.19)	(-2.66)
Control	1,937	1.615	-0.530	-0.099
		(0.95)	(-0.26)	(-1.47)
Difference	**1,937**	**-1.766**	**0.082**	**-0.180*****
		(-1.38)	**(0.26)**	**(-3.20)**

Panel B: Two years after the exogenous termination of analyst coverage

	N	ΔROA_2	ΔASL_2	ΔBR_2
Termination	1,937	0.438	-0.786	-0.163
		(0.29)	(-0.34)	(-1.74)
Control	1,937	1.652	-0.845	-0.019
		(1.08)	(-0.41)	(-0.28)
Difference	**1,937**	**-1.214**	**0.059**	**-0.144***
		(-1.13)	**(0.18)**	**(-1.99)**

Panel C: Three years after the exogenous termination of analyst coverage

	N	ΔROA_3	ΔASL_3	ΔBR_3
Termination	1,937	1.687	-1.118	-0.139
		(0.96)	(-0.66)	(-0.63)
Control	1,937	2.624*	-0.661	-0.023
		(1.77)	(-0.49)	(-0.16)
Difference	**1,937**	**-0.937**	**-0.457**	**-0.116**
		(-0.73)	**(-0.92)**	**(-1.17)**

See Appendix A for variable definitions and sample selection. This table reports the sample size and the pooled mean of the proxies for the three value creation channels (ΔROA, ΔASL, and ΔBR) for the termination and control samples over one, two and three years following the exogenous terminations of coverage due to broker mergers or closures. The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6. The effects of forecast accuracy and expected effort and time by the analyst to promote the stock

Panel A: Forecast accuracy

Portfolio ranking on ACCY	CAR	ΔROA	ΔASL	ΔBR
Bottom	1.089***	-0.585	-0.062	0.194***
	(6.40)	(-1.51)	(-0.13)	(4.26)
2	0.979***	-0.414	-0.154	0.168***
	(5.64)	(-0.90)	(-0.32)	(4.11)
3	1.185***	-0.712**	0.037	0.225***
	(8.59)	(-2.07)	(0.09)	(5.59)
4	0.823***	-0.912**	0.194	0.179***
	(6.83)	(-2.57)	(0.44)	(4.23)
Top	0.841***	-0.616**	0.252	0.224***
	(5.58)	(-2.43)	(0.57)	(4.43)
Top-Bottom	**-0.248**	**-0.031**	**0.314**	**0.030**
	(-1.22)	**(-0.09)**	**(1.46)**	**(0.68)**

Panel B: Expected effort by the analyst to promote the stock

Portfolio ranking on EFFT	CAR	ΔROA	ΔASL	ΔBR
Bottom	0.540***	-0.280	0.127	0.120***
	(3.80)	(-0.86)	(0.35)	(2.67)
2	0.731***	-0.071	0.041	0.129**
	(5.27)	(-0.23)	(0.10)	(2.26)
3	0.749***	-0.740*	0.144	0.186***
	(5.64)	(-1.98)	(0.33)	(4.78)
4	1.037***	-0.514	-0.014	0.189***
	(8.28)	(-1.56)	(-0.03)	(4.49)
Top	1.040***	-1.102***	-0.170	0.209***
	(8.87)	(-3.01)	(-0.37)	(4.85)
Top-Bottom	**0.500***	**-0.822**	**-0.297**	**0.089***
	(2.94)	**(-2.14)**	**(-1.01)**	**(2.67)**

Panel C: Expected time by the analyst to promote the stock

Portfolio ranking on TIME	CAR	ΔROA	ΔASL	ΔBR
Bottom	0.336**	-0.232	0.204	0.119***
	(2.30)	(-0.60)	(0.51)	(3.08)
2	0.521***	-0.569	0.066	0.129**
	(3.92)	(-1.59)	(0.16)	(2.29)
3	0.962***	-0.220	0.126	0.203***
	(7.68)	(-0.63)	(0.27)	(4.67)
4	1.240***	-0.786**	-0.257	0.225***
	(9.10)	(-2.11)	(-0.57)	(4.51)
Top	1.035***	-0.862***	-0.012	0.209***
	(8.36)	(-2.81)	(-0.03)	(3.89)
Top-Bottom	**0.699***	**-0.630**	**-0.216**	**0.090***
	(4.48)	**(-1.64)**	**(-0.87)**	**(3.33)**

See Appendix A for variable definitions and sample selection. This table reports the pooled mean of initiation period returns (CAR) and the three value creation proxies (ΔROA, ΔASL, and ΔBR) for the quintiles formed on the analyst's forecast accuracy (Panel A), the expected effort he uses to promote the stocks (Panel B), and the expected time he devotes to the stocks (Panel C). The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 7. Control for change in liquidity and trading volume

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	1.352***	0.515**	0.837***	0.368*	0.984***
	(6.15)	(2.26)	(2.84)	(1.85)	(3.78)
ΔROA	0.002	0.003	-0.001	0.005	-0.003
	(0.51)	(1.02)	(-0.06)	(0.90)	(-0.42)
ΔASL	-0.036***	-0.004	-0.032***	-0.006	-0.030**
	(-3.69)	(-0.76)	(-2.84)	(-0.82)	(-2.38)
ΔBR	0.506***	0.337***	0.169**	0.229***	0.277***
	(8.59)	(6.58)	(2.49)	(4.72)	(4.42)
ΔILLIQ	-1.660***	-0.975***	-0.685*	-0.674***	-0.986***
	(-5.49)	(-3.34)	(-1.76)	(-2.70)	(-2.74)
ΔVOL	0.379*	-0.117	0.496	0.086	0.293
	(1.88)	(-0.58)	(1.62)	(0.40)	(1.11)
Adj. R-square	2.0%	0.6%	-	0.5%	-

See Appendix A for variable definitions and sample selection. This table reports the OLS regressions of initiation period returns on the three value creation proxies (ΔROA, ΔASL, ΔBR) and the change in illiquidity (ΔILLIQ) and trading volume (ΔVOL) for the initiation (CAR_IN), control (CAR_CL), and random self-control (CAR_RS) samples, and compares the regression coefficients. The numbers in parentheses are t-statistics adjusted for two-way cluster-robust standard errors (clustered by firm and quarter). ***, **, and * denote two-tailed significance at the 0.01, 0.05, and 0.10 levels, respectively.