

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

by

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JEL Classification: G14, G24, G29, G32

Keywords: Coverage initiation, firm value, investor recognition, information asymmetry

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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 (e.g., Krigman et al., 2001; Cliff and Denis, 2004; Anantharaman and Zhang, 2011). 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 the 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 the cost of capital by decreasing information asymmetry. Some research suggests that analyst coverage can reduce information asymmetry among investors (Brennan and Subrahmanyam, 1995; Kelly and Ljungqvist, 2012; Wu, 2013), which in turn improves stock liquidity (Irvine, 2003; Roulstone, 2003) and reduces the 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 In fact, several recent studies show 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., Altinkılıç and Hansen, 2009; Altinkılıç et al., 2013; Kim and Song, 2014). Furthermore, even when analysts can produce new information, they may distribute their private information to a select group of investors (Irvine et al., 2007; Juergens and Lindsey, 2009), which could exacerbate information asymmetry of the stock (Chung et al., 1995).

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 serve as a good surrogate for market expectations, several recent studies challenge such a 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.

Another important, but less studied channel for analysts to reduce the cost of capital is by improving the investor recognition of stocks. Merton (1987) predicts that higher investor recognition leads to lower cost of capital and higher stock price. Under the assumption that investors can only hold stocks that they know, stocks with low investor recognition are held by a small number of investors who do know about them. Due to a lack of demand, these stocks 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 the 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 the investor recognition of the stocks.² 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 (Asquith, Mikhail, and Au, 2005), 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 stock³, leading to lower cost of capital and higher stock price.^{4,5}

² It is worth emphasizing that even though many investors may still be unaware of the stock, as long as *some* new investors become aware of the stock after coverage initiation, investor recognition increases.

³ 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 decrease or analysts drop coverage in anticipation of the loss of investor interest. Finally, Mola et al. focus on a

In this paper, we focus on a setting where a sell-side analyst initiates coverage of a stock to examine the impact of analyst coverage on firm value.⁶ 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 the change in fundamental performance, the change in the adverse selection component of the bid-ask spread (ΔASL) to proxy for the change in information asymmetry, and the change in institutional ownership breadth ($\Delta BREADTH$) to proxy for the change in investor recognition.⁷

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

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.

⁴ 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. Another related explanation is that some investors prefer to delegate their investment decisions to analysts, as they believe that analysts' stock picks "certify fair pricing." Consequently, they are more likely to buy stocks that receive analyst coverage. This hypothesis also implies that the demand for a stock increases after analyst coverage initiation. We thank the referee for pointing out this alternative explanation.

⁵ It is also worth emphasizing that investor recognition and information asymmetry are two related, but distinct effects. More investors knowing about a stock does not necessarily reduce the information asymmetry of the stock. For example, if the new investors who get to know the stock are informed traders, information asymmetry may actually increase after more informed traders enter the market.

⁶ Analyst coverage initiation represents a change in the number of analyst coverage; hence, it provides a natural setting to examine the effects of analyst coverage on firm value. However, we caution the readers that our findings may not be generalized to changes in other aspects of analyst coverage activities, such as upgrades or downgrades of recommendations.

⁷ Detailed variable definitions are provided in Appendix A.

to a sample of control firms, firms with initiations have a lower ΔASL and a higher $\Delta\text{BREADTH}$ in the year subsequent to initiations. Multivariate regression analysis shows that although both ΔASL and $\Delta\text{BREADTH}$ are significantly associated with CAR , the explanatory power of $\Delta\text{BREADTH}$ 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 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 $\Delta\text{BREADTH}$ 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 $\Delta\text{BREADTH}$ and CAR for the initiation sample continues to be significantly higher than that for the control sample.

Second, *ex-post* ΔROA , ΔASL , and $\Delta\text{BREADTH}$ 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 for market expectations measured by the average ΔROA , ΔASL , and $\Delta\text{BREADTH}$ triggered by the initiating analyst's prior initiations. The results show that only the

ex-ante proxy for 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 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 to proxy for the change in investor recognition, the change in the probability of informed trade, the change in the number of days with zero or missing returns (see Kelly and Ljungqvist, 2012), the change in Amihud's (2002) illiquidity measure, and the change in the bid-ask spread to proxy for the change in information asymmetry, and analyst forecast revisions and standardized unexpected earnings to proxy for the change in fundamental performance. The results show that the initiation period return is always significantly associated with proxies for changes in investor recognition, is often significantly associated with proxies for changes in information asymmetry, and is uncorrelated with any proxies for 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. Although the change in information asymmetry also appears to contribute to the cross-sectional variations of initiation period returns, the effect is weaker and often becomes insignificant in additional analyses. The investor recognition 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.⁸ 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 return, nor the change in fundamental performance, information asymmetry, or 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 initiations by analysts who are expected to devote more time and effort to promote the newly covered stocks are associated with much larger Δ BREADTH and CAR. In contrast, we find no significant association between Δ ROA or Δ ASL and the proxies for the time and

⁸ 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).

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 the investor recognition and reducing the 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 the first time a broker issues a recommendation for a firm, and it is also the first time an 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 an initiation.⁹ In addition, we require that the recommendation be issued 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; after the first 12 months of the firm's appearance on CRSP to exclude the potentially mechanical initiations for IPO firms; and 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 without concurrent (same-day) initiations on the same firm by

⁹ It is uncommon for multiple analysts (other than a research team) from a broker to have concurrent coverage of 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.

other analysts to exclude clustered initiations that may be driven by news or events; and 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.¹⁰ 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.¹¹ We denote the initiation quarter as quarter t .

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 that: does not have an initiation in quarter t ; does not announce earnings in the initiation period; and 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

¹⁰ 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.

¹¹ 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 quantitatively. Furthermore, only 4% of the recommendation initiations have prior forecast initiations. When these observations are excluded, the results are essentially the same.

propensity score matching generates 18,086 initiation-control pairs.¹² 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, calculated as the size-adjusted return over the five trading days centering on the initiation date (CAR).¹³ We use the change in return on assets (Δ ROA) to measure the change in firms' fundamental performance. We use the change in the adverse selection component of the bid-ask spread (Δ ASL) constructed by Hendershott et al. (2011) to measure the change in information asymmetry.¹⁴ Finally, following Lehavy and Sloan (2008) and Richardson et al. (2012), we use

¹² 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.

¹³ 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.

¹⁴ In the recent literature, the most widely used proxies for information asymmetry include PIN, bid-ask spread, Amihud's illiquidity measure, and the adverse selection component of the bid-ask spread, etc. However, the literature has reached no consensus regarding the best measure of information asymmetry. For example, Duarte and Young (2009) show that PIN is only priced to the extent that it proxies for illiquidity rather than information asymmetry. Bid-ask spread and Amihud's illiquidity measure capture much more than information asymmetry (Clarke and Shastri, 2000). The adverse selection component of the bid-ask spread, albeit theoretically appealing,

the change in institutional ownership breadth (Δ BREADTH) to measure the change in investor recognition, where BREADTH is the number of 13F filers holding a firm's stock divided by the total number of 13F filers.¹⁵

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 to proxy for the change in investor recognition; the change in the probability of informed trade, the change in Amihud's (2002) illiquidity measure, the change in the number of days with zero or missing returns, and the change in the bid-ask spread to proxy for the change in information asymmetry; and analyst forecast revisions and standardized unexpected earnings to proxy for the change in fundamental performance. Detailed definitions and measurements of all variables are provided in Appendix A.

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 (Δ ROA), changes in information asymmetry (Δ ASL), and changes in investor recognition (Δ BREADTH) around the initiation of analyst coverage between the initiation sample and the control group. Panel A of Table 1 reports the mean CAR, Δ ROA, Δ ASL, and

appears to be uncorrelated with measures of information uncertainty (Van Ness et al., 2001). Given the inconclusive evidence, we use the ASL measure constructed by Hendershott et al. (2011) as the main proxy, and examine the robustness of the results using various alternative measures.

¹⁵ 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 .

Δ BREADTH 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 Δ ASL (0.025 vs. 0.357) and a higher mean Δ BREADTH (0.167 vs. 0.058) during the year subsequent to initiations. The differences in Δ ASL and Δ BREADTH between the two groups are both statistically significant ($t=-2.36$ and 5.44, respectively). In contrast, the difference in Δ ROA 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 Δ ROA, Δ ASL, and Δ BREADTH, respectively. Among the initiation firms, CAR is positively associated with Δ ROA ($t=2.12$) and Δ BREADTH ($t=11.51$), and is negatively associated with Δ ASL ($t=-5.18$). The adjusted R^2 of the regression on Δ BREADTH is 1.5%,

which is significantly higher than the adjusted R^2 of the regressions on ΔROA and ΔASL (0.1% and 0.4%, respectively). The results indicate that $\Delta BREADTH$ has much higher explanatory power on CAR than either ΔASL or ΔROA . The last column reports the multivariate regression of CAR on ΔROA , ΔASL , $\Delta BREADTH$, and RECOM, the level of the initiation recommendations coded by I/B/E/S. After controlling for recommendation levels, ΔASL and $\Delta BREADTH$ 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, the 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 $\Delta BREADTH$ 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 $\Delta BREADTH$. Because there is no initiation during the return window for the control sample, the associations between CAR and ΔROA , ΔASL , and $\Delta BREADTH$ 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, $\Delta BREADTH$ 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 the coefficients on ΔASL and $\Delta BREADTH$ 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.¹⁶ 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 all of the five-trading-day windows centering on the announcement dates of the analyst recommendations for the firm (from all analysts, hence including the initiation date), the firm's earnings announcement date, the announcement dates of the analyst EPS forecasts for the firm (from all analysts), or the management forecast/guidance issuance dates. We then randomly select five trading days from the remaining days in quarter t .

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 $\Delta BREADTH$. 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 $\Delta BREADTH$ is statistically significant. Furthermore, the last column confirms that both ΔASL and $\Delta BREADTH$ are still significantly associated with initiation period returns after controlling for their normal associations with CAR , estimated from the initiation sample itself.

¹⁶ Relative to the control sample approach, the advantage of the self-control approach is that it helps avoid the potential concern that the normal associations between stock returns and the value drivers may be different between the initiation and control firms. The disadvantage of the self-control approach is that the value drivers may be affected by the initiation and therefore, strictly speaking, are no longer "normal."

In summary, the results in Table 1 show that both changes in investor recognition and 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.¹⁷ 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 Δ ROA and Δ BREADTH are higher, and the mean Δ ASL is lower for coverage initiated by star analysts than non-star analysts. However, only the difference in Δ BREADTH between the two groups of analysts is statistically significant, with t-statistic of 4.27. The

¹⁷ We thank Xi Li for sharing the Institutional Investor ranking data with us. See Emery and Li (2009) for details about the ranking.

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 $\Delta BREADTH$ vary with firms' existing coverage before initiation (COV). In Table 2, Panel B, we report the mean CAR, ΔROA , ΔASL , and $\Delta BREADTH$ 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 $\Delta BREADTH$ decreases monotonically with COV. The differences in ΔASL and $\Delta BREADTH$ 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 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 $\Delta BREADTH$, which are *ex-post* and noisy proxies for 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 initiation, 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 $\Delta BREADTH$ to two and three years after initiation. In the first column of Table 3, Panel A, we report the regression of CAR on ΔROA , ΔASL , and $\Delta BREADTH$ over two years after initiation (denoted as ΔROA_2 , ΔASL_2 , and $\Delta BREADTH_2$, respectively) for the initiation sample. Similar to the results in Table 1, Panel C, CAR is positively associated with $\Delta BREADTH_2$ ($t=8.10$), negatively associated with ΔASL_2 ($t=-3.54$), and 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 $\Delta BREADTH_2$ ($t=4.31$), 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 $\Delta BREADTH_2$ 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 ($\Delta BREADTH_3$) 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 Δ BREADTH and CAR for the initiation sample continues to be significantly higher than that for the control sample.

3.3.2. The *ex-ante* market expectation proxies

In the previous analyses, we use realized Δ ROA, Δ ASL, and Δ BREADTH 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 for the market expectation, measured by the mean Δ ROA, Δ ASL, and Δ BREADTH triggered by an analyst's prior initiations (denoted as $P\Delta$ ROA, $P\Delta$ ASL, and $P\Delta$ BREADTH, 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 $P\Delta$ ROA and Δ ROA, 0.086 (0.082) between $P\Delta$ ASL and Δ ASL, and 0.133 (0.132) between $P\Delta$ BREADTH and Δ BREADTH. 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 $P\Delta$ ROA, $P\Delta$ ASL, and $P\Delta$ BREADTH for the initiation sample. The coefficient on $P\Delta$ BREADTH is significantly positive ($t=4.81$), while the coefficients on $P\Delta$ ROA and $P\Delta$ ASL 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 Δ ROA, Δ ASL, or Δ BREADTH triggered by an analyst's prior initiations. As expected, none of the coefficients on $P\Delta$ ROA, $P\Delta$ ASL, or $P\Delta$ BREADTH are statistically significant. Finally, the third column shows that only the

coefficient of $P\Delta BREADTH$ 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 for the 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 the 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 ($\Delta EDGAR$).¹⁸ 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, $\Delta EDGAR$ serves as a reasonable alternative proxy for the change in investor recognition.

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.

¹⁸ We thank Jake Thornock for kindly sharing the EDGAR search data with us. See Drake et al. (2014) for details about the data.

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

3.3.4. Alternative proxies for the change in fundamental performance and the 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 (Δ PIN) as the proxy for the 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 Δ ASL (Table 1, Panel C). The difference in the coefficients of Δ PIN between the initiation and the control (random self-control) samples is significant at the 1% (5%) level, with t-statistic of -3.22 (-2.60).

In addition, we also use the change in the number of days with zero or missing returns, the change in Amihud's (2002) illiquidity measure, and the change in the bid-ask spread as an alternative proxy for the change in information asymmetry, and standardized unexpected earnings (see Bernard and Thomas, 1989) or the change in analyst consensus forecasts of the future two-year earnings as alternative proxies for the 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, the 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 Δ BREADTH 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 Δ ROA or Δ ASL between the two groups. The results suggest that investors may lose knowledge of a firm over time after coverage on the firm is terminated. In Panel B, we extend the analysis to two years after the exogenous termination of coverage. The difference in Δ BREADTH₂ 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 Δ BREADTH₃ 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

BREADTH 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.

While we document an insignificant change in information asymmetry following exogenous termination of analyst coverage, Kelly and Ljungqvist (2012) show that information asymmetry increases over the six months following the termination of coverage. The difference between their finding and our result is mainly due to the difference in the proxies for information asymmetry. We repeat the tests replacing ΔASL with three information asymmetry proxies adopted by Kelly and Ljungqvist: the bid-ask spread ($\Delta SPREAD$), Amihud's (2002) illiquidity measure ($\Delta ILLIQ$), and days with zero or missing returns ($\Delta DMISS$). The results are presented in Panel D of Table 5. Over the first year following the termination of coverage, both $\Delta SPREAD$ and $\Delta ILLIQ$ of the termination sample are significantly higher than those of the control sample, which is consistent with the finding in Kelly and Ljungqvist (2012). In addition, the difference in $\Delta DMISS$ between the termination and control samples is statistically insignificant, consistent with the weak results of $\Delta DMISS$ in Kelly and Ljungqvist (2012). Finally, we find that the differences in $\Delta SPREAD$ and $\Delta ILLIQ$ between the termination and control samples disappear when we extend the tests to two years following the termination.

In sum, the evidence in Table 5 shows that changes in analyst coverage *cause* a significant change in investor recognition, and to a lesser extent, a change in information asymmetry. Thus, the evidence 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.¹⁹ 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 Δ ROA, Δ ASL, or Δ BREADTH 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.

¹⁹ Analysts may have different abilities to forecast the future because they have different levels of experience (e.g., Mikhail et al., 2003). Lee et al. (2012) use the accuracy of management forecast to proxy for a CEO's ability to anticipate future events. Accordingly, we use an analyst's EPS forecast accuracy to proxy for his ability to anticipate future events.

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 Δ BREADTH 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 Δ ROA or Δ ASL 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, Δ BREADTH 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 about 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. 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, $\Delta\text{BREADTH}$ 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 for 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 the 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, the change in the bid-ask spread, the change in Amihud's (2002) illiquidity measure, or the change in the number of days with zero or missing returns as the proxy for the 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 the 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.

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Appendix A. Sample selection and variable definition

Sample		Definition
Initiation	IN	The initiation sample is from 1996 to 2012. We define initiations as the first time a broker issues a recommendation for a firm, and it is also the first time an analyst issues a recommendation for the firm. In addition, we require that the recommendation be issued after the first two years of the I/B/E/S recommendation data (i.e., starting in 1996) and before 2013; after the first 12 months of the firm's appearance on CRSP; after the first six months of the broker's or analyst's appearance on I/B/E/S; without concurrent (same-day) initiation on the same firm by other analysts; 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 that: does not have an initiation in quarter t ; does not announce earnings in the initiation period; and has a propensity score 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 all of the five-trading-day windows centering on the announcement dates of the analyst recommendations for the firm (from all analysts, hence including the initiation date), the firm's earnings announcement date, the announcement dates of the analyst EPS forecasts for the firm (from all analysts), 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 \times 100).
Change in breadth	Δ BREADTH, Δ BREADTH ₂ , Δ BREADTH ₃ , P Δ BREADTH	Δ BREADTH (Δ BREADTH ₂ , Δ BREADTH ₃) is the mean institutional ownership breadth (BREADTH) of quarters $t+1$ to $t+4$ ($t+5$ to $t+8$, $t+9$ to $t+12$), subtracting the mean BREADTH of quarters $t-4$ to $t-1$. P Δ BREADTH is the average Δ BREADTH on all of the initiating analyst's prior initiations. BREADTH is measured as in Leavy and Sloan (2008), i.e., the number 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	Δ ROA, Δ ROA ₂ , Δ ROA ₃ , P Δ ROA	Δ ROA (Δ ROA ₂ , Δ ROA 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 Δ ROA is the average Δ ROA 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 , $P\Delta ASL$	ΔASL (ΔASL_2 , ΔASL_3) 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. $P\Delta ASL$ 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.
Initiation recommendation	RECOM	The level of the 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.
Analyst coverage	COV	The number of existing recommendations (NUMREC) before an initiation. The initiation sample is sorted into quintiles each quarter based on $\log(1 + \text{NUMREC})$.
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.
Change in the probability of informed trade	ΔPIN	The mean probability of informed trade (PIN) of quarters t+1 to t+4 minus 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 bid-ask spread	ΔSPREAD	The mean bid-ask spread (SPREAD) of quarters t+1 to t+4 minus the mean SPREAD of quarters t-4 to t-1. SPREAD is the daily closing ask price minus the bid price divided by the midpoint of the bid and ask prices, multiplied by 100 and then averaged over the quarter.
Change in illiquidity	ΔILLIQ	The mean illiquidity measure (ILLIQ) of quarters t+1 to t+4 minus 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.
Change in days with zero or missing returns	ΔDMISS	The average days with zero or missing returns (DMISS) of quarters t+1 to t+4 minus the average DMISS of quarters t-4 to t-1. Following Kelly and Ljungqvist (2012), we identify DMISS using zero return or the missing return codes: ., .C, .B, or .A.

Appendix A. Continued

Variable		Definition
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'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.
Change in trading volume	Δ VOL	The mean turnover of quarters t+1 to t+4 minus the mean turnover of quarters t-4 to t-1. Turnover is the quarterly average of the daily ratio of the trading volume divided by the total shares outstanding. To account for the different market microstructures, we standardize Δ VOL in the same way as Δ ILLIQ.

Appendix A. Continued

<i>Determinants of initiation in propensity score matching</i>		
Variable		Definition
Change in size	ΔSIZE_{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	ΔSALE_{t-1}	The sum of sales (SALEQ) from quarters t-1 to t-4 minus the sum of SALEQ from quarters t-5 to t-8, divided by the sum of SALEQ from quarters t-5 to t-8. The ratio is multiplied by 100.
Change in equity issuance	$\Delta\text{EQUITY}_{t-1}$	The sum of equity issuance from quarters t-1 to t-4 minus the sum of equity issuance from quarters t-5 to t-8, divided 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 minus PSINT in quarter t-5. PSINT is total shares held by 13F filers, divided by the total shares outstanding.
Change in trading volume	ΔVOL_{t-1}	The mean turnover of quarters t-1 to t-4 minus 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 the 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 minus 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 minus NUMREC in quarter t-5, divided 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, minus 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	$\Delta\text{BREADTH}_{t-1}$	The mean BREADTH of quarters t-1 to t-4 minus the mean BREADTH 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 minus 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 that: does not have an initiation in quarter t ; does not announce earnings in the initiation period; and 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):²⁰

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

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 $\Delta EQUITY$ 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.

²⁰ 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*** (-24.90)	-0.048 (-0.49)
ΔSIZE_{t-1}	0.409*** (9.07)	0.010 (0.56)
ΔSALE_{t-1}	0.237*** (9.02)	0.129 (2.56)
$\Delta\text{EQUITY}_{t-1}$	-0.001 (-1.54)	0.002 (1.25)
ΔIO_{t-1}	0.357*** (2.90)	-0.044 (-0.29)
ΔVOL_{t-1}	0.229*** (2.72)	0.018 (0.24)
ΔAFE_{t-1}	-0.239 (-1.38)	0.298 (1.19)
ΔCOV_{t-1}	0.105*** (5.53)	0.031 (1.08)
ΔROA_{t-1}	-0.003*** (-3.44)	0.001 (0.99)
$\Delta\text{BREADTH}_{t-1}$	0.287*** (12.73)	-0.018 (-2.09)
ΔASL_{t-1}	-0.011*** (-4.74)	0.003 (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
ΔSIZE_{t-1}	0.111	0.108	0.003
ΔSALE_{t-1}	0.162	0.148	0.014***
$\Delta\text{EQUITY}_{t-1}$	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
$\Delta\text{BREADTH}_{t-1}$	0.164	0.165	-0.001
ΔASL_{t-1}	0.193	0.061	0.132

*** Indicates two-tailed significance at $p \leq 0.01$.

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

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

	Dependent variable: CAR			
Intercept	0.826*** (9.86)	0.822*** (9.81)	0.713*** (9.14)	3.454*** (18.81)
ΔROA	0.010** (2.12)			0.002 (0.41)
ΔASL		-0.055*** (-5.18)		-0.036*** (-3.66)
ΔBREADTH			0.647*** (11.51)	0.486*** (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*** (9.29)	-0.036 (-0.86)	0.758*** (8.82)	0.077 (1.54)	0.645*** (6.98)
ΔROA	0.002 (0.51)	0.003 (1.08)	-0.001 (-0.10)	0.005 (0.90)	-0.003 (-0.43)
ΔASL	-0.040*** (-3.87)	-0.007 (-1.30)	-0.033*** (-2.79)	-0.008 (-0.99)	-0.032** (-2.55)
ΔBREADTH	0.603*** (10.57)	0.387*** (6.67)	0.216*** (3.08)	0.265*** (5.60)	0.338*** (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 the initiation period returns (CAR) and the proxies for the three value creation channels (ΔROA, ΔASL, and ΔBREADTH) for the initiation and control samples. Panel B reports the OLS regressions of CAR on ΔROA, ΔASL, ΔBREADTH and initiation recommendations for the initiation sample. Panel C reports the OLS regressions of initiation period returns on ΔROA, ΔASL, and ΔBREADTH 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	ΔBREADTH
STAR	1.208 ^{***} (3.97)	-0.477 (-1.26)	-0.276 (-0.45)	0.401 ^{***} (6.15)
NONSTAR	0.811 ^{***} (8.53)	-0.514 [*] (-1.73)	0.274 (0.55)	0.164 ^{***} (3.41)
STAR-NONSTAR	0.397^{**} (2.47)	0.037 (0.11)	-0.550 (-1.33)	0.237^{***} (4.27)

Panel B: Firms' existing coverage prior to initiation

Portfolio ranking on COV	CAR	ΔROA	ΔASL	ΔBREADTH
Bottom	1.882 ^{***} (11.40)	-0.113 (-0.26)	-0.527 (-1.02)	0.302 ^{***} (8.91)
2	1.054 ^{***} (8.09)	-0.662 [*] (-1.80)	-0.301 (-0.57)	0.268 ^{***} (7.00)
3	0.632 ^{***} (5.93)	-0.518 (-1.46)	0.185 (0.37)	0.256 ^{***} (5.37)
4	0.534 ^{***} (5.64)	-0.684 ^{**} (-2.48)	0.284 (0.75)	0.075 (1.51)
Top	-0.005 (-0.04)	-0.720 ^{**} (-2.33)	0.487 (1.56)	-0.067 (-0.89)
Top-Bottom	-1.887^{***} (-10.43)	-0.607 (-1.41)	1.014^{**} (2.60)	-0.369^{***} (-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 (Δ ROA, Δ ASL, and Δ BREADTH) for the groups partitioned by the initiating analysts' star ranking. Panel B reports the pooled mean of CAR, Δ ROA, Δ ASL, and Δ BREADTH 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 ^{***} (9.75)	0.007 (0.13)	0.787 ^{***} (8.27)	0.102 [*] (1.88)	0.692 ^{***} (6.86)
ΔROA_2	-0.001 (-0.15)	0.000 (0.01)	-0.001 (-0.13)	0.002 (0.42)	-0.003 (-0.33)
ΔASL_2	-0.029 ^{***} (-3.54)	-0.005 (-0.96)	-0.024 (-1.29)	-0.006 (-1.04)	-0.023 (-1.20)
$\Delta BREADTH_2$	0.334 ^{***} (8.10)	0.176 ^{***} (4.31)	0.158 ^{***} (2.85)	0.134 ^{***} (4.15)	0.200 ^{***} (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 ^{***} (8.14)	0.041 (0.66)	0.747 ^{***} (6.66)	0.113 [*] (1.89)	0.675 ^{***} (5.58)
ΔROA_3	-0.009 (-1.33)	0.002 (0.26)	-0.011 (-1.27)	-0.005 (-1.05)	-0.004 (-0.48)
ΔASL_3	-0.017 ^{**} (-2.47)	-0.003 (-0.44)	-0.014 (-0.90)	-0.010 ^{**} (-2.12)	-0.007 (-0.69)
$\Delta BREADTH_3$	0.243 ^{***} (6.63)	0.113 ^{***} (3.36)	0.130 ^{**} (2.47)	0.105 ^{***} (3.77)	0.138 ^{***} (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 $\Delta BREADTH$) 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 for 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 ^{***} (9.27)	0.097 [*] (1.76)	0.626 ^{***} (6.49)
PΔROA	0.000 (0.06)	-0.005 (-1.23)	0.005 (0.74)
PΔASL	0.013 (1.10)	0.012 (1.29)	0.001 (0.04)
PΔBREADTH	0.392 ^{***} (4.81)	0.044 (0.80)	0.348 ^{***} (3.69)
Adj. R-square	0.2%	0.0%	-

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

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

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

	CAR_IN	CAR_CL	IN-CL	CAR_RS	IN-RS
Intercept	0.647 ^{***} (6.45)	-0.086 [*] (-1.84)	0.733 ^{***} (6.79)	0.058 (0.88)	0.589 ^{***} (5.06)
ΔROA	-0.003 (-0.43)	0.005 (1.36)	-0.008 (-1.12)	0.002 (0.35)	-0.005 (-0.67)
ΔPIN	-0.078 ^{***} (-4.30)	-0.011 (-0.91)	-0.067 ^{***} (-3.22)	-0.025 [*] (-1.99)	-0.053 ^{**} (-2.60)
ΔBREADTH	0.586 ^{***} (10.14)	0.381 ^{***} (6.72)	0.205 ^{***} (3.03)	0.264 ^{***} (4.68)	0.322 ^{***} (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	$\Delta BREADTH$
Termination	1,937	-0.151 (-0.11)	-0.448 (-0.19)	-0.279** (-2.66)
Control	1,937	1.615 (0.95)	-0.530 (-0.26)	-0.099 (-1.47)
Difference	1,937	-1.766 (-1.38)	0.082 (0.26)	-0.180 *** (-3.20)

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

	N	ΔROA_2	ΔASL_2	$\Delta BREADTH_2$
Termination	1,937	0.438 (0.29)	-0.786 (-0.34)	-0.163 (-1.74)
Control	1,937	1.652 (1.08)	-0.845 (-0.41)	-0.019 (-0.28)
Difference	1,937	-1.214 (-1.13)	0.059 (0.18)	-0.144 * (-1.99)

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

	N	ΔROA_3	ΔASL_3	$\Delta BREADTH_3$
Termination	1,937	1.687 (0.96)	-1.118 (-0.66)	-0.139 (-0.63)
Control	1,937	2.624* (1.77)	-0.661 (-0.49)	-0.023 (-0.16)
Difference	1,937	-0.937 (-0.73)	-0.457 (-0.92)	-0.116 (-1.17)

Panel D: Alternative proxies for information asymmetry

	N	<i>One year after termination</i>			<i>Two years after termination</i>		
		$\Delta SPREAD$	$\Delta ILLIQ$	$\Delta MISS$	$\Delta SPREAD$	$\Delta ILLIQ$	$\Delta MISS$
Termination	1,937	0.681 (1.15)	0.474*** (23.51)	-3.082 (-1.58)	-0.922*** (-3.95)	0.530*** (16.08)	-4.752** (-2.17)
Control	1,937	0.511 (0.96)	0.459*** (22.50)	-2.904* (-2.01)	-0.905*** (-3.98)	0.527*** (14.44)	-4.091** (-2.48)
Difference	1,937	0.170 * (1.99)	0.015 ** (2.89)	-0.178 (-0.31)	-0.017 (-0.26)	0.003 (0.48)	-0.661 (-1.07)

See Appendix A for variable definitions and sample selection. Panels A, B and C report the sample size and the pooled mean of the proxies for the three value creation channels (ΔROA , ΔASL , and $\Delta BREADTH$) for the termination and control samples over one, two and three years following the exogenous terminations of coverage due to broker mergers or closures. Panel D reports the pooled mean of the alternative proxies for information asymmetry in the two groups. 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	Δ ROA	Δ ASL	Δ BREADTH
Bottom	1.089 ^{***} (6.40)	-0.585 (-1.51)	-0.062 (-0.13)	0.194 ^{***} (4.26)
2	0.979 ^{***} (5.64)	-0.414 (-0.90)	-0.154 (-0.32)	0.168 ^{***} (4.11)
3	1.185 ^{***} (8.59)	-0.712 ^{**} (-2.07)	0.037 (0.09)	0.225 ^{***} (5.59)
4	0.823 ^{***} (6.83)	-0.912 ^{**} (-2.57)	0.194 (0.44)	0.179 ^{***} (4.23)
Top	0.841 ^{***} (5.58)	-0.616 ^{**} (-2.43)	0.252 (0.57)	0.224 ^{***} (4.43)
Top-Bottom	-0.248 (-1.22)	-0.031 (-0.09)	0.314 (1.46)	0.030 (0.68)

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

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

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

Portfolio ranking on TIME	CAR	Δ ROA	Δ ASL	Δ BREADTH
Bottom	0.336 ^{**} (2.30)	-0.232 (-0.60)	0.204 (0.51)	0.119 ^{***} (3.08)
2	0.521 ^{***} (3.92)	-0.569 (-1.59)	0.066 (0.16)	0.129 ^{**} (2.29)
3	0.962 ^{***} (7.68)	-0.220 (-0.63)	0.126 (0.27)	0.203 ^{***} (4.67)
4	1.240 ^{***} (9.10)	-0.786 ^{**} (-2.11)	-0.257 (-0.57)	0.225 ^{***} (4.51)
Top	1.035 ^{***} (8.36)	-0.862 ^{***} (-2.81)	-0.012 (-0.03)	0.209 ^{***} (3.89)
Top-Bottom	0.699 (4.48)	-0.630 (-1.64)	-0.216 (-0.87)	0.090 (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 (Δ ROA, Δ ASL, and Δ BREADTH) 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 ^{***} (6.15)	0.515 ^{**} (2.26)	0.837 ^{***} (2.84)	0.368 [*] (1.85)	0.984 ^{***} (3.78)
Δ ROA	0.002 (0.51)	0.003 (1.02)	-0.001 (-0.06)	0.005 (0.90)	-0.003 (-0.42)
Δ ASL	-0.036 ^{***} (-3.69)	-0.004 (-0.76)	-0.032 ^{***} (-2.84)	-0.006 (-0.82)	-0.030 ^{**} (-2.38)
Δ BREADTH	0.506 ^{***} (8.59)	0.337 ^{***} (6.58)	0.169 ^{**} (2.49)	0.229 ^{***} (4.72)	0.277 ^{***} (4.42)
Δ ILLIQ	-1.660 ^{***} (-5.49)	-0.975 ^{***} (-3.34)	-0.685 [*] (-1.76)	-0.674 ^{***} (-2.70)	-0.986 ^{***} (-2.74)
Δ VOL	0.379 [*] (1.88)	-0.117 (-0.58)	0.496 (1.62)	0.086 (0.40)	0.293 (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 (Δ ROA, Δ ASL, Δ BREADTH) and the change in illiquidity (Δ ILLIQ) and trading volume (Δ VOL) 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.