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Analyst Talent, Information, and Investment Strategies

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Abstract

Analyst talent, rather than the number of analysts following a firm, matters most to investors. We find: 1) Analysts with greater "natural" forecasting talent—controlling for experience, brokerage affiliation, and task complexity—contribute relatively more firm-specific rather than industry or market information; 2) Earnings forecasts by low-talent analysts may lead to substantial mispricing; 3) When earnings surprises are large, post-earnings-announcement drift is more prominent among firms covered by low-talent analysts; 4) Firms with low-talent analysts have significantly more insider trading prior to positive earnings news; and 5) Investing following insider trading is more profitable in stocks followed by low-talent analysts.

Keywords: Financial analysts, Talent, Information asymmetry, Insider trading, Earnings announcements, Post-earnings-announcement drift

What makes some sell-side analysts better than others—in terms of forecast accuracy—and does it matter for investors if a firm is covered by a more talented analyst? We develop a novel measure of natural talent, distinct from characteristics such as experience and broker affiliation. Our results show that the profitability of investment strategies depends on the level of analyst talent covering a particular stock: earnings forecasts by low-talent analysts may lead to substantial mispricing. When earnings surprises are large, post-earnings-announcement drift is more prominent among firms covered by low-talent analysts. Firms with low-talent analysts have significantly more insider trading prior to positive earnings news, and investing following insider trading is more profitable in stocks followed by low-talent analysts. Furthermore, we show that analyst talent, rather than the number of analysts following a firm (as suggested by previous studies), matters most for investors.

Nature versus nurture is one of the oldest debates in many areas, and has been examined in the context of financial analysts. Some previous studies of financial analysts suggest that their personal characteristics, such as experience and reputation, may affect the information content of their forecasts of earnings. However, other studies find that a large portion of the information content of earnings forecasts appears to reside in the analyst's natural talent beyond such characteristics—just like Roy Hobbs' baseball talents as portrayed by Robert Redford in the film "The Natural." Our study focuses on estimating analyst natural talent (which we recognize can't be observed or measured directly) in a unique manner and investigating whether it matters to the covered firm's information environment. For example, if more talented analysts provide more accurate information about a firm's prospects, then stock prices may be more reflective of their true intrinsic value, leaving fewer opportunities for profitable insider trading, as well as profitable investment strategies for investors who follow insider trading, or taking advantage of post-earnings-announcement drift (the tendency for cumulative abnormal returns drifting in the direction of the earnings surprise). Conversely, investing in stocks followed by low-talent analysts may lead to abnormal profits.

We begin our study by developing a novel measure of a sell-side analyst's natural talent, controlling for experience, brokerage affiliation, and task complexity. Next, we identify the nature of information produced by high-talent analysts. We show that firms covered by high-talent analysts are associated with greater *firm-specific* information, suggesting that while analysts produce market and industry-level information as well, high-talent analysts produce relatively more firm-specific information. These findings are important because they are in contrast to previous studies that suggest that when *more* analysts cover a firm—regardless of the quality of the analysts—relatively *less* firm-specific information is created compared with market and industry-level information.

We then examine analyst talent in a specific information environment when information asymmetry between insiders and outsiders is high: before earnings announcements. By uncovering and disclosing information to the public, analysts can effectively reduce an insider's information advantage. Distinct from previous studies, we examine how analyst talent—rather than the simple presence or prevalence of analysts following—affects a firm's information environment, and in turn, insider trading activities. If high-talent analysts contribute more to a firm's information environment and thus reduce more information asymmetry, we expect firms followed by high-talent analysts to have less insider trading prior to information events such as earnings announcements, and to be fairly priced. We expect these insiders to earn less trading profits, as would investors who follow insiders. Furthermore, we expect less post-earnings-announcement drift. Our results are consistent with these conjectures.

Our findings have important practical implications. Our results suggest that investors should look beyond the number of analysts following a particular stock, or the reputation, experience, or star rating of such analysts, and instead focus on their talent—such as based on our measure of forecast accuracy after controlling for a number of effects. Firms followed by high-talented analysts are more likely to be fairly priced and less prone to profitable insider trading, and also less susceptible to post-earnings-announcement drift than those followed by a greater number of low-talent analysts. Investors can thus potentially earn abnormal trading profits by investing in firms with low-talent analysts in general, and in particular by following the disclosure of insider buying, as well as when earnings surprises are positive and large.

Data and Methodology for Estimating Analyst Talent

Our novel measure of a sell-side financial analyst's natural talent is based on a fixed effects model. Such fixed effects models essentially control for average differences *across* observable and unobservable variables, leaving only *within*-group differences and greatly reducing the biases of omitted variables in regressions. For example, if we only looked at the average demand for pizzas in various cities compared with each city's average prices, we might find a surprising relationship whereby demand is higher in cities when prices are higher.[1] But such limited analysis might not tell the whole story. There could be unobserved differences in tastes and preferences *across* cities, with some customers preferring higher quality and more expensive pizzas in some cities but not in others. So by looking *within* cities we may find the expected causal relationship whereby higher prices lead to lower demand, holding constant or "fixing" effects across cities that we can't observe.

[1] This example is based on Management Science course notes by J. Blumenstock http://www.jblumenstock.com/courses/econ174/FEModels.pdf (accessed February 8, 2019). See also M. Bogard's summary at http://econometricsense.blogspot.com/2014/04/intuition-for-fixed-effects.html (accessed February 8, 2019).

Similarly, our analyst fixed effects model of earnings forecast accuracy—described in more detail in Appendix A—captures what we claim is analyst natural talent, or what remains after removing the effects of analyst experience (firm-specific and general experience), job or task complexity (number of firms and industries covered, and number of estimates), broker affiliation (broker size and broker fixed effects), forecast timing, and luck (the residual of the regression). Of course, while we try to include as many quantifiable factors as we can, we may have missed something, and so we can never be sure that what is captured only reflects talent. For example, our measure, due to data limitations, could also incorporate all the experiences and education obtained by an analyst before the database was established. In addition, it may reflect some other analyst-specific characteristics, such as social connections (Cohen, Frazzini and Malloy, 2008), conflict of interest (Ljungqvist, Marston and Wilhelm 2009; Irvine 2004), diligence and confidence, that may help enhance analyst performance. Nonetheless, whatever it is called, our measure reflects analyst-specific characteristics that are associated with improved analyst forecasting performance. Our empirical results are consistent with our story, and regardless of our story, suggest the measure is important for investors.

We gather all analyst earnings forecasts from the I/B/E/S Detail History database.[2] We limit our analysis to the annual earnings forecasts issued during the first 11 months of a firm's fiscal year in order to exclude analysts who are not active forecasters. We also exclude single forecasts on a firm for any fiscal year in order to have enough data for our estimation. In the I/B/E/S database, each analyst has a unique identification code, although sometimes the codes are shared by a team of analysts. Those analyst teams are removed from our sample using the I/B/E/S broker

[2] We start our analysis period in 1984 because I/B/E/S data are censored in 1983; it is thus hard to estimate our talent measure data before 1984. We end our main analyses in 2008 because 1) we have the data of brokerage closures until 2008, which we use for robustness tests (reported in the online appendix); and 2) we preserve data for out-of-sample tests which run from 2009 to 2018.

translation file. We further remove non-U.S. firms, firms issuing non-common stock, and firms that cannot be fully identified in Compustat or CRSP. These screening steps lead to a sample of 642,186 annual earnings forecasts of 10,408 U.S. firms, issued by 12,689 unique analysts at 868 brokers.

We measure an analyst's forecasting performance by comparing the analyst's absolute forecast accuracy to the average absolute forecast accuracy of other analysts following the same stock during the same time period. Specifically, we first define each analyst's forecast error on every firm for every fiscal year as the difference between her 30-day minimum horizon forecast and the actual earnings per share (EPS). We then define the proportional mean absolute forecast error ($PMAFE_{ijt}$) as:

$$PMAFE_{ijt} = \frac{\overline{AFE}_{jt} - AFE_{ijt}}{\overline{AFE}_{jt}} \tag{1}$$

where $\overline{AFE}_{jt}$ is the average absolute forecast error on firm j in year t, and AFE_{ijt} is the absolute forecast error for analyst i on firm j in year t. A positive value of $PMAFE$ represents better-than-average forecasts, while a negative value suggests worse-than-average forecasts. This measure controls for the firm-year effects that result from events that make a firm's earnings easier or more difficult to predict in some years than others.[3]

To isolate analysts' time-invariant talent from time-variant, experience-based ability, we define three proxies for analyst experience: general forecasting experience (GEXP), firm experience (FEXP), and the intensity of an analyst's firm-specific experience (FREQ). The general experience is the number of years for which an analyst has appeared in our dataset (by issuing at least one annual earnings forecast on any firm during the first 11 months of a fiscal year). The

[3] We also use ranked forecast errors following Jacob, Lys and Neale (1999) as an alternative measure and obtain similar results.

firm-specific experience is an analyst's number of years following a particular firm (by issuing at least one annual earnings forecast on the firm during the first 11 months of a fiscal year). The intensity of firm experience is the number of annual earnings forecasts issued on a particular firm in a given fiscal year. In addition to analyst experience, we consider other factors which may affect forecast accuracy through channels other than talent. First, we consider job complexity. Forecast accuracy might decrease with job complexity; we measure analyst specialization or task complexity by the number of firms (NCOS) and the number of industries (NSIC2) covered by an analyst. Second, we consider information advantage through large broker affiliation. Analysts employed by large brokers might have better access to research resources at work; we use a dummy variable (TOP10) equal to one when an analyst is employed by a broker in the top size decile during a fiscal year, and zero otherwise. Broker size is defined as the number of analysts employed by the broker in a fiscal year. Finally, we consider forecast noise arising from the amount of time between forecast dates and earnings announcement dates. Forecasting accuracy is naturally lower due to uncertainty and noise when earnings forecasts are issued earlier in the fiscal year. As such, we consider the forecast age (AGE), which is defined as the number of days between the earnings forecast date and the earnings release date. We also apply screening criteria to AGE so that it is bounded between 30 and 365.

In Table 1, we report summary statistics for analyst earnings forecasts, forecast accuracy, and observable time-variant characteristics (including experience, job complexity, broker affiliation, and forecast age). On average, analysts in our sample have 8 years of work experience, have worked for a firm for 3 years, cover 13 stocks, and half work for Top 10 brokerages. After removing the effects of all the above determinants of earnings forecast accuracy, the analyst-fixed-effects portion of the forecast accuracy captures our measure of analyst talent.

[Insert Table 1 here.]

In Table 2, we regress forecast accuracy on the explanatory variables described above, together with analyst fixed effects, broker fixed effects, and year fixed effects. Columns 1 to 3 report coefficient estimates including year fixed effects only, both broker and year fixed effects, and both analyst and year fixed effects, respectively. Column 4 reports our main results, including all three fixed effects: analyst, broker, and year. When we don't control for analyst fixed effects (columns 1 and 2), general and firm experience matter for forecasting accuracy. However when we control for analyst fixed effects (columns 3 and 4) experience has a negative effect. In all cases, working for a Top 10 brokerage is associated with better forecasting accuracy.

To provide a quantitative comparison of the relative economic significance of the variables, we decompose variation of the dependent variable (forecast accuracy) into percent variation explained by observable analyst characteristics, analyst/broker/year fixed effects, and the unexplained remainder. As we apply the Abowd, Kramarz, and Margolis (1999) or AKM fixed-effects methodology, we find that all observable analyst characteristics we include account for 16.78% of the total variation of forecast accuracy, most of which is contributed by forecast age. Analyst fixed effects, broker fixed effects, year fixed effects, and the unexplained part (which can be considered luck), account for 4.01%, 0.97%, 0.61%, and 77.65% of the total variation of forecast accuracy, respectively. These results show that a significant portion of analyst performance is not explained by observable analyst characteristics; the unobservable, time-invariant talent measure captured by analyst fixed effects plays an important role in explaining the variation in earnings forecasts. Specifically, the experience-based ability measures (general and firm) only account for about 1.42% of the total variation of forecast accuracy, while the brokerage affiliation accounts for 0.97%, much less than the 4.01% of variation explained by our analyst talent measure. In other words, we show that natural talent matters much more than experience, task complexity, or broker affiliation.

[Insert Table 2 here.]

Firm-Specific Information

In this section we examine the nature of information produced by analysts, particularly those with greater talent—is it firm-specific, industry-wide, or market-wide? In efficient markets stock prices are equal to intrinsic values, and hence, they represent the present value of expected future cash flows to investors, discounted at an appropriate rate that reflects the riskiness of those cash flows. Stock prices impound new information that is related to both expected cash flows and the discount rate. Such information can be categorized as firm-specific, industry-level, or market-level. For example, economic news related to GDP outlook or interest rates may impact most firms' expected cash flows and discount rates, anticipated regulatory changes may impact on specific industries, and the anticipated outlook for a company's new product launch and subsequent profitability may impact on that stock only. We expect high-talent analysts to contribute relatively more firm-specific information.

Roll (1988) attempts to measure the extent to which market and industry factors can explain the variability of stock returns, as measured by R-squared from market model regressions, and finds that market and industry factors explain only about one-fifth of monthly stock return variability. These results suggest the relative importance of firm-specific information on impacting stock returns, since the majority of return variability cannot be explained by market and industry factors. Morck et al. (2000) build on Roll's work by examining the information content of stock markets in emerging versus developed markets. They apply a simple transformation of R-squared to create a "synchronicity" variable:

$$Synch_{i,t} = \log\left(\frac{R^2}{1-R^2}\right), \tag{2}$$

where R^2 is the coefficient of determination for firm i in year t from the estimation of the following equation:

$$r_{i,j,t} = \hat{\alpha}_i + \hat{\beta}_i^M \, r_{M,t} + \hat{\beta}_i^j \, r_{j,t} + \varepsilon_{i,j,t} \tag{3}$$

where $r_{i,j,t}$ is the daily return of stock i in industry j on day t, $r_{M,t}$ is the value-weighted market return on day t, and $r_{j,t}$ is the value-weighted return of industry j on day t using the 2-digit SIC industry classes (in some of our regressions we omit the industry variable).

Higher synchronicity implies more of the stock's return variability can be explained by the market's return variability. In other words, with higher synchronicity, a firm's stock return is more closely related to the market's return, and returns (i.e., price movements) for that stock are less driven by firm-specific information. Since analysts play a key role in information creation, one should expect that greater analyst involvement with a stock should be *negatively* associated with synchronicity to the extent that analysts are expected to convey firm-specific information. However, previous research by Piotroski and Roustone (2004) and Chan and Hameed (2006) suggests analyst involvement, as measured by earnings forecast revisions or the number of analysts covering a stock, in general, does not create firm-specific information—rather such involvement is *positively* related to synchronicity.

We conjecture that measures such as the number of analysts do not tell the entire information story—rather, it is the quality or talent of analysts that matters. In other words, analysts only "matter" in creating firm-specific information to the extent that those analysts are talented and are able to uncover and disclose firm-specific information, which is impactful for stock prices, such as the anticipated success or failure of a new product launch. Thus, we predict that, after controlling for the number of analysts and other factors, greater talent following a stock—which we proxy as the median of our analyst talent measure for a firm in a particular year—should be *negatively* associated with synchronicity.

The *Synch* measures (i.e., with and without industry effects) are our dependent variables in a number of regressions at the firm-year level. For some of our regressions our main independent variable is *Median Talent,* the median talent value of all analysts following the firm in a given year measured at the firm-year level. Consistent with previous studies, we include the same control variables such as the logarithm of market capitalization of the firm, (log(MV)), the ratio of book value of the firm to its market value, (Book/Market), the number of analysts following (# Analyst), research and development costs (R&D) and fixed assets (PP&E). We also include industry and year fixed effects.

We corroborate findings by Chan and Hameed (2006) who show that analyst coverage (i.e., number of analysts) is positively related to market synchronicity, in regressions with both market and industry variables. Our *#Analysts* coefficient is large and significant, suggesting more coverage adds both industry and market-level information. In comparison, when we include our *Median Talent* measure, as we conjectured, we find (in untabulated results) a significant negative association between analyst talent and the market component of return variation, or *Synch*, even while analyst coverage, in general, continues to have a positive association. These results suggest that while analysts in general help to impound industry and market-level data into stock prices, high-talent analysts produce more firm-specific information that is incorporated into stock prices, thus reducing insiders' firm-specific information advantage in trading, and mitigating post-earnings-announcement drift effects.

Analyst Talent and Insider Trading

Having established that high-talented analysts generate firm-specific information, we examine the impact of such information as it pertains to insider trading before earnings announcements (later we revisit the insider trading environment from an investor's perspective and also examine earnings-announcements more broadly).[4] The presence of high-talent analysts should reduce information asymmetry and further discourage informed trading by corporate insiders who possess private information unavailable to outside investors. Anecdotally, some analysts are able to detect illegal insider trading activities and provide better monitoring of corporate insiders. Consistent with these views, previous empirical studies show that insider trading intensity and profitability both decrease with analyst coverage. Frankel and Li (2004) find that firms with more analysts following experience less frequent and less profitable insider trades; Ellul and Panayides (2018) show that the loss of analyst coverage leads to more informed trading (as captured by the probability of informed trading or PIN measure of Easley et al. (1996)) and an increase in the profitability of insider buys and sells. However, these studies rest on the assumption that all analysts produce the same quality of information, ignoring the significant variation in analyst talent. Our focus is on the *quality* of analysts.

We obtain insider trading data from the Thomson Reuters Insider Filing Data Feed.[5] We analyze insider trading activities at the firm level during the 30-day window, by calculating net

[4] We chose the setting of insider trading because 1) insider trading directly reflects the degree of information asymmetry between management and outside investors, while many information measures, such as the probability of informed trading (PIN), are indirect; 2) many information measures, such as board independence, corporate diversification, and R&D, are largely time-invariant and dependent on many other factors like firm size and industry, while insider trading exhibits more within-firm variation; and 3) insider trading measures primarily reflect more firm-specific information than market- or industry-level information.

[5] The Securities Exchange Act of 1934, under Section 16(a), defines a list of corporate insiders who may have access to non-public and material information. These corporate insiders include board directors, corporate executives, and

insider buys before each earnings announcement. We define net insider buys, *Net Buy*, as the total volume of insider buys minus the total volume of insider sells, then divided by the number of outstanding shares.

The direction of insider trading depends on the earnings information: insiders buy more before positive earnings news and sell more before negative earnings news. To analyze insider trading prior to the earnings announcements, we first define positive and negative earnings news using earnings surprises. Following Livnat and Mendenhall (2006), we define earnings surprises or Standardized Unexpected Earnings (SUE) as follows:

$$SUE1 = \frac{X_{ij} - X_{ij-1}}{P_{ij}} \tag{4}$$

$$SUE2 = \frac{X_{ij} - MFX_{ij}}{P_{ij}} \tag{5}$$

where X_{ij} is the actual earnings per share (EPS) announced by firm *i* for fiscal year *j*, X_{ij-1} is the actual EPS announced by firm *i* for fiscal year *j-1*, P_{ij} is the stock price of firm *i* at the end of fiscal year *j*, and MFX_{ij} is the median earnings forecast over the 90 days prior to earnings announcements for firm *i* in fiscal year *j*. As such, *SUE1* uses actual earnings in year *j-1* as expected earnings in year *j*, while *SUE2* uses the consensus forecast among analysts as expected earnings in year *j*. We define an earnings announcement as positive earnings or "good" news if *SUE* is positive, and an earnings announcement as negative earnings or "bad" news if *SUE* is negative. We use *SUE2* as our main measure (henceforth referred to simply as SUE) since results using earnings news based on *SUE1* are qualitatively similar.

beneficial owners with more than 10% ownership of shares outstanding. They are required to file their trades with the SEC within two business days, and information regarding their trades is available in the database. We keep open-market trades only and delete trades which are related to options, grants, and gifts. Same day trades by the same insider are cumulated and counted as one trade. Furthermore, for our main results, we limit insider trades to those in a 30-day window prior to the earnings announcements.

The data for our control variables are from multiple sources. Stock returns are from CRSP. We obtain analyst data, including the number of analysts following a firm and earnings forecast details, from I/B/E/S. We obtain other control variables, such as (log) market capitalization (MV), book-to-market ratio (Book/Market), R&D expenses (R&D), and property, plant, and equipment (PP&E), from COMPUSTAT. The number of analysts (# Analysts) is from I/B/E/S.[6] The mean earnings surprise is -0.5% (for both SUE measures).

We examine correlations among the variables and find that *Talent* is significantly negatively correlated with our *Net Buy* measure, which is consistent with our conjecture that high-talent analysts help to restrict insider trading. Although the correlation between *Talent* and insider trading measures are low for the entire sample, during the periods of positive earnings news (i.e., positive *SUE*), these correlations become economically and statistically more significant, roughly twice the size. *Talent* is also negatively correlated with earnings surprise, which suggests that talented analysts may be able to provide more firm-specific information and therefore reduce earnings surprise.

Generally, insider trades provide a wealth of information. However, some insiders routinely trade (primarily sell) shares at certain times of a year, and these routine trades usually contain less information than other "opportunistic" trades. If an analyst's talent affects insider trading by changing the information environment, it should primarily affect opportunistic rather than routine insider trading. We define a routine trader as an insider who trades in the same

[6] Interestingly, all measures related to net buys are negative on average. This is because insiders can obtain shares through grants and option exercises; such transactions do not count as open-market purchases and thus are not included in our analysis. However, we do not exclude sales of shares even if these shares are resulted from the execution of options or stock grants, because the decisions of selling sooner rather than later may still be based on inside information.

calendar month for at least three consecutive years and an opportunistic trader as anyone who does not fit the definition of a routine trader.

Insider Trading Buys and Sells

First, we examine the effects of analyst talent on open market insider trading preceding annual earnings announcements at the firm-year level. We use the following specification to explore the effects of analyst talent on corporate insider trading:

$$Insider\ Trading_{ij} = \alpha + \beta_1 Median\ Talent_{ij} + \beta_2 Log(MV)_{ij} + \beta_3 (\frac{Book}{Market})_{ij} + \beta_4 \#\ Analysts_{ij} + \beta_5 PP\&E_{ij} + \beta_6\ R\&D_{ij} + \varepsilon_{ij} \quad (6)$$

where $Insider\ Trading_{ij}$ is the net buying or net selling of shares by corporate insiders in the 30-day window prior to earnings announcement by firm i for fiscal year *j*. Our main variable of interest, $Median\ Talent_{ij}$, is the median talent value (measured by the estimated analyst fixed effects) of all analysts covering firm i in fiscal year *j*. The remaining variables are the control variables described earlier. We also include year fixed effects and industry (2-digit SIC) fixed effects in regressions.

If insiders have positive (negative) inside information about EPS, we expect $\beta_1 < 0$ for net buys (sells) by corporate insiders because analysts with more talent can better mitigate information asymmetry. As for the control variables, most are related to information asymmetry. β_2 captures the effect of firm size. Elliott et al. (1984) hypothesize that corporate insiders have more inside information because smaller firms are followed by fewer analysts. Thus, we expect β_2 to be negative. β_3 captures the effects of the informativeness of financial statements in the sense that firms with higher book-to-market ratios tend to have lower levels of information asymmetry; thus, we expect β_3 to be negative. β_4 measures the effects of the intensity of analyst activities. Bhushan (1989) uses analyst following as a measure of private information collection, and Frankel and Li

(2004) find that increased analyst following is related to reduced insider trading profits and reduced insider buys. Therefore, we expect β_4 to be negative. β_5 reveals the effects of the proportion of vital assets that cannot be readily liquidated and consequently, a larger proportion of tangible assets implies a lower level of information asymmetry, so we expect β_5 to be negative. Finally, β_6 indicates the effects of information asymmetry induced by R&D investment. Aboody and Lev (2000) provide evidence that insider trading profits are higher for firms with R&D investment. Thus, we expect β_6 to be positive.

Table 3 reports the empirical results. We report results for positive earnings surprises (*SUE*>0) in column 1, and results for negative earnings surprises (*SUE*<0) in column 2. As expected, we find that greater analyst talent is associated with lower volumes of net buys when insiders have "positive" inside information about earnings. The economic significance is substantial and is interpreted as follows: a one standard deviation increase in *Median Talent* is associated with a 26.5% decrease in the *Net Buy* variable, relative to its absolute mean value.[7] However, we do not find any significant changes in insider net sells prior to negative earnings news, as indicated by the insignificant *Median Talent* coefficient in column 2. This is consistent with previous studies which find that insiders are more cautious in exploiting negative information in order to lower litigation risks, and that insider sales are less likely to contain information. Furthermore, the asymmetry in results may also reflect the fact that insiders cannot freely sell all shares and are not allowed to short sell their own company's shares.

We run an out-of-sample test, reported in column 3, in order to ensure that our measure can be robustly applied to future investment decisions. Specifically, we regress insider net buying

[7] To calculate the percentage changes relative to the mean value, we first multiply the coefficient of -5.461 (reported in Table 3) by the unreported standard deviation of *Median Talent* of 0.093, and then divide the product by the unreported mean value of the insider trading measure of -1.915.

prior to earnings announcements in 2009-2018 on analyst talent (*Median Talent*) estimated in 1985-2008. The coefficient estimate of *Median Talent* is negative and significant, which is consistent with our hypothesis. The analysts' talent estimated in 1985-2008 can still predict the insider trading activities in the firms they follow in 2009-2018. The talent an analyst demonstrated in the estimation period still plays a role in their future works.[8]

[Insert Table 3 here.]

Opportunistic Trading and Routine Trading

We postulate that insiders' net buys are driven by positive insider information. However, it is possible that some trades do not reflect private information. Focusing on the opportunistic trades allows us to perform sharper tests: if high-talent analysts truly impound more information, when they cover a firm, the firm should have less opportunistic insider trading, but not necessarily less routine insider trading. We classify all trades into routine trades and opportunistic trades. Before positive earnings news, about 65% of total trades are opportunistic trades.

We regress insider net buys prior to positive earnings news on *Talent* and control variables. The absolute values of the net buys coefficients for opportunistic traders are larger than those in Table 3 with similar significance levels. However, as expected, these coefficients are not statistically significant for routine trades. Overall, these results suggest that the results in Table 3 mainly stem from opportunistic trades rather than routine trades. This is consistent with our hypothesis, suggesting that high-talent analysts impound information which primarily resides in opportunistic insider trades.

[8] When we further winsorize the data, for example at 2.5% or 5%, to reduce the effect of the outliers, we find even more significant results. In addition, the out-of-sample test excludes many new analysts who joined after 2008; not being able to account for these analysts' (relative) talent introduces a bias against our results.

Insider Trading Profitability

Although Securities Exchange Commission regulations stipulate that no trading by corporate insiders should be based on non-public and material information, the profitability of insider trading is well documented. For our study, we care about how analyst talent can affect insider trading profitability, as well as investor trading following the disclosure of insider trading. We argue that analysts with more talent are more capable of collecting and disclosing firm-specific information, and thus can reduce the magnitude of insider trading profitability around earnings announcements through more accurate earnings forecasts.

We measure insider trading profitability by post-trade cumulative abnormal returns (CARs).[9] The insider transactions used in our analysis are from a -30 to -7 day window relative to annual earnings announcement dates. We start our analysis by analyzing the different quantiles of analyst talent in post-trading periods. We divide the talent data into 9 quantiles (quantile 1 refers to low talent, quantile 5 refers to median talent, and quantile 9 refers to high talent). We then calculate the average CAR by cumulating daily abnormal returns following insider trading dates. When we distinguish insiders by the information type, we see some differences. In Figure 1A, we find higher talent is related to less positive CARs when insiders have "positive" information about earnings. In Figure 1B, higher talent is related to smaller absolute values of CARs when the information type is "negative." These two results are consistent with our hypothesis that analyst talent mitigates information asymmetry, and therefore, reduces the profitability of insiders trading on their private information.

[9] To generate CARs, we employ the market model and sum up daily abnormal returns. Consistent with the window used in the main regressions, we restrict the insider trading sample at the forecast-analyst-firm-year level within one month prior to annual earnings announcements by firms. In addition, we exclude insider trades which occur no more than a week prior to earnings announcements to eliminate possible information leakage through channels other than insider trading.

[Insert Figure 1 here.]

In Table 4 we test the difference in CARs between the high talent group and the low talent group using four different windows: one month (CAR[0,30]), two months (CAR[0,60]), three months (CAR[0,90]), and four months (CAR[0,120]). We find the difference between the means of the high-talent group and the low-talent group becomes larger as the event window we use widens. These results support the view that high-talent analysts are able to uncover and disclose more firm-specific information and reduce insider trading profitability. We find that, except for sells in the 30-day period, all of the differences are statistically significant at the 1% level, and the signs are consistent with Figure 1. Higher talent is related to a lower level of insider trading profitability for insider buys (sells) if insiders have "positive" ("negative") information about earnings.

[Insert Table 4 here.]

Horse Race Among Analyst Talent, Past Forecast Accuracy, Experience, and Star Analysts

The advantage of previously used measures of analyst ability such as analyst forecasting accuracy, length of work experience, is that they are estimated directly. The disadvantage is that these measures, though widely used, can be very noisy, reflecting brokerage information advantage, firm information environment, time effects, and pure luck. To illustrate that our measure of analyst talent performs better than simple forecast accuracy or other ability measures such as experience, we conducted a horse race by including all such measures in our main tests. Specifically, when we regress opportunistic insider buying on *Median Talent* and median forecast accuracy (PMAFE) and/or median analyst experience, only the coefficient of *Median Talent* is statistically significant.

These results suggest that while forecast accuracy and analyst experience are easier to measure, they do not explain insider trading as strongly as *Median Talent* does.

We also examine whether the effect of analyst talent on opportunistic insider buying can be subsumed by analyst star rating. Specifically, we use Institutional Investor data and identify All-Star analysts as those who have received top 3 rankings for each industry between 2001 and 2017 in the All-American annual polls in the Institutional Investor magazine based on a survey of fund managers. Our analysis reveals that star analysts indeed have more accurate forecasts and greater talent on average; however, when we regress opportunistic insider buying on *Median Talent* and analyst star rating, the coefficient of analyst star rating is either insignificant or significant but with a sign opposite to prediction.

Thus, although our refined measure of analyst talent is less straightforward to construct, it provides more benefits to investors in terms of fostering better investment decisions, as we show in the next section.

Analyst Talent and Investment Strategies

Since we have established that analyst talent impacts a firm’s information environment, we now examine the extent to which investors can potentially benefit from making investments based on the talent of analysts following particular firms and in certain situations. First, we show how earnings forecasts by low-talent analysts may lead to substantial mispricing. Second, we show that when earnings surprises are large, post-earnings-announcement drifts (PEAD) are more prominent among firms with low-talent analysts. Third, we show that investment strategies that invest following insider trading are more successful for firms followed by low-talent analysts.

Earnings Forecasts and Valuation

Sell-side analysts generally issue research reports with buy/hold/sell recommendations based on target prices for stocks they follow. A common approach to the estimation of a stock's intrinsic value is the price-earnings (P/E) method whereby the analyst forecasts a firm's expected earnings and then multiplies that amount by an appropriate forward-looking P/E ratio. That P/E multiple typically incorporates the analyst's assessment of the firm's growth prospects and riskiness. Assuming there is no difference, on average, in forward-looking P/E multiples assigned to each stock, then intrinsic valuation assessments will depend on differences in earnings forecasts. If high-talent analysts are more accurate with their earnings estimates than low-talent analysts, then their target prices should be closer to actual intrinsic values and hence the stocks they cover should be more fairly priced. On the other hand, stocks followed by low-talent analysts should be more susceptible to mispricing.

We first examine median absolute forecast errors (AFE) in earnings estimates for high-talent (i.e., above-median) analysts versus low-talent analysts. As expected, the median AFE for high-talent analysts is \$0.183 versus \$0.236 for low-talent analysts, with a statistically significant difference of \$0.053.[10] To put this amount in perspective, the median stock price in our sample is around \$15, and the median P/E is generally between 15 and 20 times over our sample period. Using a P/E multiple of 17.5 times—which is close to the long-run P/E for U.S. stocks as estimated by Robert Shiller[11]—the valuation difference between high-talent and low-talent analysts is around \$0.93. Based on an average stock price of around \$15, this results in a valuation difference of about 6.2%. While this is clearly a high-level perspective, we conclude that stocks followed by low-

[10] Results are virtually the same when we winsorize the data at the 1% and 99% levels: the median difference is \$0.052, while the mean difference is \$0.073.
[11] See http://www.econ.yale.edu/~shiller/data.htm (accessed January 21, 2019). The 1871-2019 average was 16.9 times.

talent analysts may be substantially mispriced and therefore may represent an investment opportunity. The next sub-sections identify some specific strategies.

Post-Earnings-Announcement-Drift

In Table 5 we present results on how analyst talent affects PEAD. We define earnings surprises as the difference between realized earnings per share and the median forecasts of all I/B/E/S analyst forecasts in the 90 days prior to earnings announcements, and then scaled by stock prices. We then sort earnings surprises into five quintiles from 1 to 5. We focus on *SUE5*, the quintile with the largest earnings surprises, because PEAD is most significant when the earnings surprise is large.[12] We measure PEAD using the 60-day cumulative abnormal returns starting from two days following annual earnings announcements, and include our control variables used in other tables and firm/year fixed effects.

In columns 1 and 2 of Table 5, we analyze firms covered by high-talent and low-talent analysts, respectively. We find that PEAD is only statistically significant with high earnings surprises for firms covered by low-talent analysts but not for firms covered by high-talent analysts. Specifically, when earnings surprises are in the highest quintile (SUE5), abnormal returns of stocks followed by high-talent analysts are not significantly different (0.03%) from any other surprises. However, abnormal returns of stocks followed by low-talent analysts experience 60-day abnormal returns that are 1.91% greater than with other earnings surprises, or approximately 12.2% annualized.

In column 3, we find similar results with a slightly different methodology by examining all the data and using *Low Talent* and SUE5 dummy variables along with a SUE5 x *Low Talent*

[12] Abnormal returns are calculated as daily returns minus daily returns on the portfolio of firms with similar size and book-to-market ratio. Portfolio returns and breakpoints are obtained from Kenneth French's website. We drop firms with stock prices less than $1 or that are covered by less than 5 analysts, or firms for which we have more than 10 missing observations in the daily abnormal return estimation.

interactive term, with the latter significant coefficient of 1.86% suggesting that analyst (low) talent matters more to PEAD when earnings surprise is higher. For investors, a profitable investment strategy is to invest in firms followed by low-talent analysts upon earnings announcement with a large earnings surprise. In column 4, we run another horse race by also including SUE5 interactive terms for median forecast accuracy (PMAFE) and median experience (Exp) of all analysts following the firm in the year before the earnings announcement, as well as a dummy variable indicating whether the firm is covered by at least one All-Star analyst (Star), as additional controls to illustrate the superior explanatory power of our measure of analyst talent. The low talent interactive term remains significant, with a coefficient of 1.86%, similar to the previous regressions, while all of the forecast accuracy, experience and star analyst coefficients are not significant. In untabulated results, we also show that these results are robust in an out-of-sample test using forecasts from 2009-2018.

[Insert Table 5 here.]

Investing After Insider Trading

In Table 6, we also analyze how analyst talent affects abnormal returns following insider trading.[13] We show that abnormal returns following insider buys (sells) are significantly more positive (negative) in firms covered by low-talent analysts. In column 1 we measure the impact of talent on insider buys. The economic significance is substantial and is interpreted as follows: a one standard deviation increase in *Median Talent* is associated with a 0.57% decrease in 60-day CAR,

[13] Abnormal returns are again defined as daily returns minus daily returns on the portfolio of firms with similar size and book-to-market ratio. Portfolio returns and breakpoints are obtained from Kenneth French's website. To ensure that investors can easily implement the strategy, we calculate 60-day and 120-day cumulative abnormal returns starting from two days after insider transactions, because insiders are required to file their trades within two days (results are similar so we only present the 60-day results). We drop firms with stock prices less than $1 or covered by less than 5 analysts, or firms with more than 10 missing observations in the daily abnormal return estimation. We exclude insider trades smaller than $100,000 (the average trading size is around $750,000) because smaller trades are often made by non-executive insiders and contain more noise. We include the same control variables and firm/year fixed effects.

or about 3.5% annualized.[14] In other words, the lower the median talent, the more profitable the strategy. In column 2 we see there is no relationship associated with insider sells.

In columns 3 and 4, we provide another horse race by also including median forecast accuracy (PMAFE) and median experience (Exp) of all analysts following the firm in the prior year, as well as a dummy variable indicating whether the firm is covered by at least one All-Star analyst, as additional controls. We show in column 3 that *Median Talent* better explains abnormal returns following insider transactions, in the expected direction, and similar size as in the previous regression reported in column 1. The coefficients of forecast accuracy, experience and star analyst are either insignificant or significant in the wrong direction. As in column 2, in column 4 we see there is no relationship between *Median Tale*nt and insider sells although there is a significant relationship between forecasting accuracy and insider sells, but not in the expected direction. Our results suggest that the analyst talent measure can better explain profits generated by a trading strategy following insider buys compared to other measures such as past forecast accuracy, experience or analyst star rating.[15]

[Insert Table 6 here.]

Conclusions

Our study presents an innovative measure of analyst forecasting talent that captures analyst-specific characteristics that are associated with enhanced earnings forecasting performance. We show that our measure of talent does matter to investors, more than other

[14] To calculate the percentage change we multiply the coefficient of -9.195 by the unreported standard deviation of 0.062.

[15] Analyst talent may have many other implications. For example, an increase in analyst talent should improve liquidity because the enhanced quality of information reduces the asymmetric information component of the bid-ask spread. The hypothesis is that by generating better information, a more capable analyst can further improve liquidity. In untabulated results, we do find analyst talent is negatively related to changes in bid-ask spread.

measures of analyst ability and the number of analysts following a firm. Investors who use our measure of talent may be rewarded with superior trading profits by investing in firms followed by low-talent analysts, particularly around earnings announcements.

Financial analysts play an important role in the efficient allocation of capital by providing information such as forecasts of earnings that can help investors better assess the true intrinsic value of a firm. Our findings shed light on the nature of the information produced by analysts. Though previous studies suggest analysts in general produce market-level and industry-level information, our study shows that high-talent analysts contribute more firm-specific information to a firm's information environment. We also show that high-talent analysts make more accurate earnings forecasts. Firms followed by low-talent analysts may be trading at prices that do not reflect their true intrinsic value. Our results suggest low-talent analysts may be mispricing stocks by over 6% compared to high-talent analysts.

Analysts can also potentially affect insider trading through the information channel. We postulate that analysts with more talent can significantly reduce information asymmetry between corporate insiders and outside investors, thereby mitigating insider trading intensity and profitability. Indeed, our results show that firms followed by high-talent analysts are associated with less insider buying intensity and profitability prior to positive earnings news. This effect is significant in opportunistic trades but not in routine trades. Out-of-sample tests further support our conclusions. We also show that, unlike previous studies, the key to a better information environment is not analyst coverage, per se, but analyst quality.

Our results have important practical implications. First, investors need to look beyond simple proxies for talent, such as work experience or the brokerage house for which an analyst works, or the number of analysts following a company, in order to potentially earn abnormal profits. Second, from a valuation perspective, our results show that when a stock is followed by high-talent analysts, its stock prices should be more reflective of its true intrinsic value and hence less likely to be mispriced. Conversely, when a stock is followed by low-talent analysts, mispricing can be substantial. Third, trading profits may be possible by focusing on stocks covered by low-talent analysts. We provide two such examples: following insider trading and following large earnings surprises. Future research may point to other opportunities. In addition, further research may provide more refined measures of talent.

Appendix A: Fixed Effects Methodology

To develop a proxy for an analyst's talent, we employ a fixed-effects methodology similar to the one used by Abowd, Kramarz, and Margolis (1999), or AKM for short. We estimate a three-way fixed effects model (analyst fixed effects, broker fixed effects, and year fixed effects) in a bootstrap procedure. Specifically, we first identify analysts who switch brokers during the sample period, so we can disentangle the analyst fixed effects and broker fixed effects. We then estimate the fixed effects for such analysts after controlling for other known factors explaining analyst forecasting performance such as analyst experience, job complexity, broker size, and the timing of forecast. Next, based on the analyst fixed effects we then estimate the fixed effects for the brokers who employed those analysts. Finally, we estimate analyst fixed effects for other analysts who work for the same brokers all the time.

We use this method to extract the information of analyst-specific talent from earnings forecast accuracy by purging all the effects of analysts' experience (firm-specific and general experience), task complexity (number of firms and industries covered, and number of estimates), brokerage affiliation (broker size and broker fixed effects), time effect, and residual (luck).[16] We then use this estimated analysts talent to study the insider trading activities and post-earnings-announcement drift of their covered firms.

Thanks to Cornelissen (2008)'s algorithm and many Stata programmers' recent efforts, researchers with Stata software can use the Stata command "felsdvreg" to implement this method. In Stata, first load our data provided through University of Michigan's online data repository, ICPSR (https://www.openicpsr.org/openicpsr/project/108302/version/V1/view/), and then run the following command:

[16] The estimated analyst talent is simply the coefficient of each analyst's dummy variable in the 3-way fixed effects model with earnings forecast accuracy as the dependent variable.

felsdvreg pmafe age gexp fexp ncos nsic2 top10, i(analyst_id) j(broker_id) f(broker) p(talent) m(mover) g(group) xb(xb) r(res) mnum(mnum) pobs(pobs)

where the dependent variable pmafe is the measure of analyst forecasting accuracy defined in the section "Data and Methodology for Estimating Analyst Talent"; "age gexp fexp ncos nsic2 top10" represent analyst age, general experience, firm-specific experience, number of companies followed, number of industries followed, whether in a large brokerage (top size decile), respectively, all of which are defined in detail in the section "Data and Methodology for Estimating Analyst Talent"; the i() option is used to input the variable name of the analyst ID; the j() option does the same for the broker ID. The f() and p() options define the names of new variables to be created to store the broker and analyst fixed effects after estimation. The variable in p(), talent, is the measure of analyst talent. The xb() and res() options store the linear combinations Xb and the residual e in the equation y = Xb + e. The remaining options define the names of the new variables that store a dummy variable indicating analyst who has moved between brokerage houses, m(); a group variable indicating the groups of brokers connected through these movers, g(); a variable containing the number of movers per broker, mnum(); and a variable indicating the number of observations per analyst, pobs().

After running the "felsdvreg" command on our sample data, the measure of analyst talent, a new variable called "talent" is automatically generated and added to the existing data. Using the command and our sample data in the online repository, or similar data gathered from other sources, any researcher or practitioner can then decompose analyst forecasting performance to identify analyst-specific talent. Researchers can then use this measure to test any theories which include analyst talent as an economic force in the model.

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Table 1: Summary Statistics for Analyst Earnings Forecasts

	Mean	Median		Mean	Median
Sample size at the year level			**Analysts' observable time-variant characteristics and control variables**		
Number of forecasts	25,706.24	26,338.00			
Number of covered firms	2,907.00	2,989.00			
Number of analysts	2,644.36	2,652.00	General experience ($GEXP_{it}$)	8.12	6.72
Number of brokers	225.28	237.00	Firm experience ($FEXP_{ijt}$)	2.82	1.61
Number of analysts per broker	12.06	11.64	Number of companies ($NCOS_{it}$)	13.06	9.00
Forecast accuracy			Number of two-digit SIC ($NSIC2_{it}$)	3.98	3.00
Absolute forecast error (AFE_{ijt})	0.29	0.06	Top-ten largest broker dummy ($TOP10_{it}$)	0.49	0.00
Forecast accuracy ($PMAFE_{ijt}$)	0.00	0.16	Forecast age (AGE_{ijt})	88.46	45.00

Table 2: Regression on Forecast Accuracy and Decomposition of Explanatory Power

	1	2	3	4	R^2 Decomposition
General experience ($GEXP_{it}$)	0.001**	0.000*	-0.002**	-0.006**	1.01%
	(6.32)	(2.05)	(-4.90)	(-12.35)	
Firm experience ($FEXP_{ijt}$)	0.001**	-0.000	-0.002**	-0.002**	0.41%
	(3.16)	(-0.45)	(-3.91)	(-3.80)	
# forecasts per firm ($FREQ_{ijt}$)	0.001**	0.031**	0.032**	0.030**	3.85%
	(3.16)	(47.50)	(45.55)	(41.76)	
Top 10 broker dummy ($TOP10_{it}$)	0.039**	0.018**	0.020**	0.021**	0.50%
	(16.73)	(5.54)	(6.29)	(5.67)	
# companies ($NCOS_{it}$)	-0.000	-0.000	0.000	-0.000	0.09%
	(-0.98)	(-0.35)	(0.33)	(-0.20)	
# 2-digit SIC ($NSIC2_{it}$)	-0.003**	0.000	0.002**	0.003**	0.64%
	(-5.83)	(0.58)	(3.08)	(3.34)	
Forecast age (AGE_{ijt})	-0.005**	-0.005**	-0.005**	-0.005**	10.28%
	(-233.30)	(-306.90)	(-298.61)	(-290.37)	
Analyst fixed effects	No	No	Yes	Yes	4.01%
Broker fixed effects	No	Yes	No	Yes	0.97%
Year fixed effects	Yes	Yes	Yes	Yes	0.61%
Number of observations	642,186	642,186	642,186	642,186	
Adjusted R^2	0.18	0.19	0.20	0.21	

Notes: This table shows the results of OLS regressions for the determinants of the dependent variable, analyst forecast accuracy ($PMAFE_{ijt}$), and their explanatory power. The decomposition or relative explanatory power of an explanatory variable is calculated as the ratio of the covariance between the dependent variable and the explanatory variable to the variance of the dependent variable. T-statistics reported in parenthesis are clustered at the firm level. ** and * indicate statistical significance at the 1%, and 5% level, respectively. The explanatory power of the independent variables, analyst fixed effects, broker fixed effect, and year fixed effects are presented in the last column.

Table 3: Analyst Talent and Insider Net Buys and Sells

	(1)	(2)	(1)
Earnings Surprise:	Positive	Negative	Positive
Buys or Sells:	Buys	Sells	Buys
Sample:	In-Sample	In-Sample	Out-of-Sample
Median Talent	-5.461*	14.981	-3.135*
	(-2.02)	(1.43)	(-2.00)
Log(MV)	0.484**	0.156	0.060
	(2.97)	(0.33)	(0.63)
Book/Market	-0.160	-0.538	1.347**
	(-0.26)	(-0.30)	(2.76)
# Analysts	0.272	-1.381	0.741**
	(0.69)	(-1.04)	(3.13)
PP&E	0.729	-1.227	1.182**
	(1.39)	(-0.91)	(3.57)
R&D	2.305	-37.772*	2.435
	(1.02)	(-2.00)	(1.94)
Constant	-3.161	3.800	-4.455**
	(-1.83)	(0.71)	(-4.47)
Observations	2,291	1,203	2,413
R-squared	0.108	0.050	0.074
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes

Notes: This table provides results of pooled ordinary least squares (OLS) regressions on the effects of median analyst talent on open market insider trading based on the 30-day window before annual earnings announcements for firm-year level observations from 1985 to 2008 (columns 1 and 2) and out-of-sample test results using data from 2009 to 2018 (column 3). The dependent variable is the total volume of insider buys minus the total volume of insider sells, then divided by the number of outstanding shares. All variables are winsorized at the 1% level. Column (1) is based on the sample of positive insider information which is measured by positive earnings surprise (SUE>0), i.e., positive difference between actual EPS and the median of forecasts reported to I/B/E/S in the 90 days prior to the earnings announcement (rescaled by share prices), and column (2) is based on the sample of negative insider information corresponding to negative earnings surprise. Column (3) is the out-of-sample test for positive earnings surprises. T-statistics reported in parentheses are clustered at the firm level. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 4: Talent Differences and Market Reactions to Insider Trading

	High Talent minus Low Talent	
	sells+ negative	buys+ positive
CAR[0,30]	0.00049	-0.00238**
	(2.00)	(-5.75)
CAR[0,60]	0.00387**	-0.00980**
	(7.79)	(-9.00)
CAR[0,90]	0.00792**	-0.01404**
	(10.52)	(-14.44)
CAR[0,120]	0.01436**	-0.01652**
	(12.01)	(-19.20)

Notes: This table provides the differences of means for the comparisons of paired samples in the time-series means of stock market reactions (CARs) between high talent group and low talent group surrounding insider trading (day 0 is the day of insider trading). The abnormal returns are calculated by the market model. The talent data is divided into 9 quantiles, where quantile 1=low and quantile 9=high. Positive (negative) information is measured by positive (negative) earnings surprise (SUE). Data include insider trading in the [-30, -7] days of window before annual earnings announcements by the firms. T-statistics reported in parentheses are clustered at the firm level. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 5: Analyst Talent and Post Earnings Announcement Drift (PEAD)

	(1)	(2)	(3)	(4)
Sample	High Talent	Low Talent	All	All
Low Talent			-0.883*	-0.883*
			(-2.30)	(-2.30)
SUE5	0.033	1.911**	0.006	0.155
	(0.06)	(2.62)	(0.01)	(0.23)
SUE5 * Low Talent			1.858*	1.859*
			(2.06)	(2.06)
Low PMAFE				0.104
				(0.14)
SUE5 * Low PMAFE				0.070
				(0.33)
Low Exp				0.348
				(0.45)
SUE5 * Low Exp				-0.138
				(-0.60)
Star				4.458
				(1.81)
SUE5*Star				-1.208
				(-1.62)
Log(MV)	-0.247	-0.463	-0.321*	-0.340*
	(-1.33)	(-1.77)	(-2.12)	(-2.23)
Book/Market	-1.270	0.014	-0.595	-0.628
	(-1.63)	(0.02)	(-1.01)	(-1.06)
# Analysts	1.152**	0.947	1.084**	1.077**
	(2.84)	(1.61)	(3.24)	(3.21)
PP&E	4.143**	3.340**	3.680**	3.706**
	(4.67)	(3.03)	(5.36)	(5.40)
R&D	-3.911	-11.360**	-7.872**	-8.094**
	(-1.28)	(-3.34)	(-3.51)	(-3.60)
Constant	-12.145	6.354	-1.859	-1.793
	(-1.09)	(0.63)	(-0.26)	(-0.25)
Observations	7,906	5,816	13,722	13,722
R-squared	0.029	0.029	0.021	0.022
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: This table reports how analyst talent affects post earnings announcement drift. The dependent variable is PEAD. Subsamples of firms covered by high talent analysts and low talent analysts are analyzed in columns 1 and 2, and the whole sample is analyzed in columns 3 and 4. T-statistics are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Table 6: Analyst Talent and Abnormal Returns Following Insider Trading

	(1)	(2)	(3)	(4)
	Buy	Sell	Buy	Sell
Dependent Variable	CAR_60	CAR_60	CAR_60	CAR_60
Median Talent	-9.195**	0.968	-9.531**	0.967
	(-4.01)	(1.38)	(-4.15)	(1.38)
PMAFE			-0.825	-2.489**
			(-0.22)	(-2.78)
Exp			22.507*	-0.636
			(2.54)	(-0.27)
Star			9.478*	-0.121
			(2.37)	(-0.13)
Log(MV)	-0.978**	-0.408**	-0.978**	-0.405**
	(-7.58)	(-12.46)	(-7.54)	(-12.32)
Book/Market	-2.504**	-1.007**	-2.549**	-1.002**
	(-5.00)	(-6.03)	(-5.07)	(-6.00)
# Analysts	2.558**	1.425**	2.533**	1.423**
	(8.41)	(16.74)	(8.30)	(16.70)
PP&E	-3.558**	1.684**	-3.611**	1.681**
	(-7.18)	(11.45)	(-7.28)	(11.40)
R&D	0.296	5.995**	0.140	5.994**
	(0.16)	(8.96)	(0.07)	(8.96)
Constant	-4.511	3.623	-4.363	3.602
	(-1.44)	(1.85)	(-1.40)	(1.84)
Observations	41,307	347,123	41,307	347,123
R-squared	0.065	0.015	0.065	0.015
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: This table reports how analyst talent affects abnormal returns following insider trading. The dependent variables are the 60-day cumulative abnormal returns starting from two days following insider purchases (columns 1 and 3) or sales (columns 2 and 4). The variables of interest are *Median Talent,* the median talent value of all analysts following the firm in a given year, *PMAFE*, median analyst forecast accuracy, and *Exp*, median general experience which is the number of years since the first estimate of analyst *i*. T-statistics reported in parentheses are clustered at the firm level. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

Figure 1: Talent Quantiles and Market Reactions to Insider Trading

Figure 1A. Market Reactions around Insider Buys

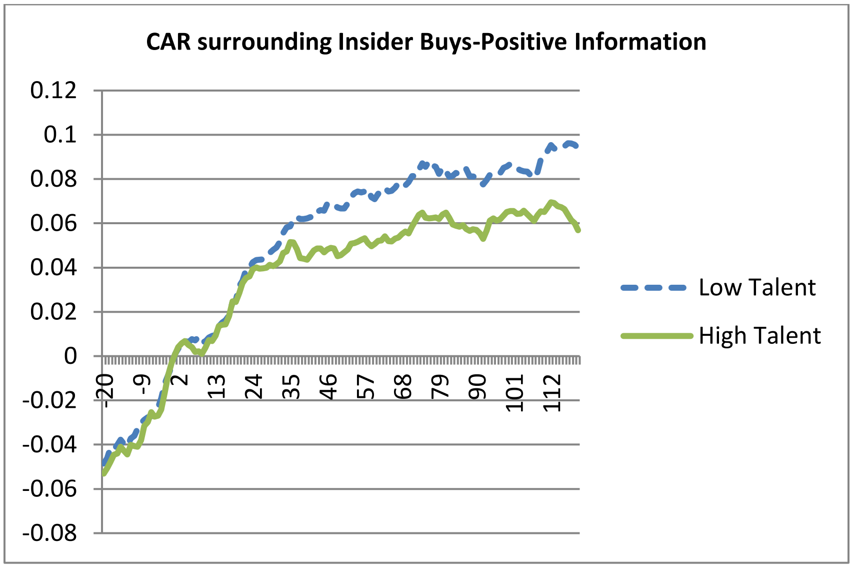
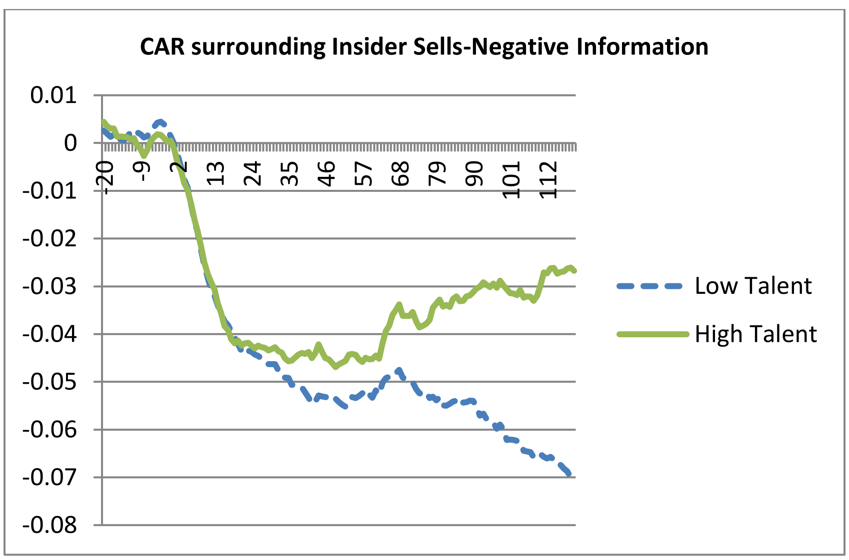


Figure 1B. Market Reactions around Insider Sells



Notes: The figure shows stock market reactions (Cumulative Abnormal Returns or CARs) surrounding insider trading among different talent quantiles for 367,973 observations at the forecast-analyst-firm-trading day level. The talent data are divided into 9 quantiles, where quantile 1=low and quantile 9=high. The horizontal axis is the event days, where day 0 is the day of insider trading. The CARs are calculated by the market model. Pooled results are based on the entire sample, and positive (negative) information is measured by positive (negative) earnings surprise. Data include all insider trading in the [-30, -7] days of the window prior to annual earnings announcements by the firms.