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Analyst talent, information, and insider trading☆

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A R T I C L E I N F O

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A B S T R A C T

We examine 1984–2018 data and show that the talent or ability of sell-side financial analysts affects a covered firm's information environment—more so than the simple number of analysts covering a firm. We find that while analysts in general produce market and industry-level information, high-ability analysts contribute more firm-specific information. Firms covered by high-ability analysts experience significantly less insider trading prior to positive earnings news. Results only reside in opportunistic (not routine) trades. When an analyst initiates (terminates) coverage we find decreased (increased) subsequent insider trading. Both changes are primarily driven by analyst talent. Analyst ability also negatively relates to insider trading profitability.

1. Introduction

What makes some sell-side analysts better than others—in terms of forecast accuracy—and what are the implications if a firm is covered by a more talented (or high-ability) analyst? Previous studies suggest that *personal characteristics* of financial analysts, such as experience and reputation, may affect the information content of their forecasts of earnings.[1] However, other studies suggest that a large portion of the information content of earnings forecasts appears to reside in the analysts' unobservable natural *talents*, innate abilities, or aptitude, rather than other characteristics.[2] Our study focuses on analyst talent, controlling for such characteristics as experience, brokerage affiliation, and task complexity. We find that the talent of analysts following a particular company has a significant impact on the nature of information produced, as well as the amount and profitability of insider trading prior to positive earnings news.

We begin our study by developing a novel measure of sell-side financial analyst talent based on a fixed effects model of earnings

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[1] For example, Mikhail et al. (1997) find that sell-side analysts generate more accurate earnings forecasts and more profitable stock recommendations as their experience with a specific firm grows. Akyol et al. (2016) suggest that experienced analysts may help improve stock price efficiency through research and monitoring. Stickel (1995) finds that an analyst's reputation can affect stock returns through her buy and sell recommendations. Clement (1999) reports strong associations between earnings forecast accuracy and analyst characteristics, such as experience and job complexity.

[2] Sinha et al. (1997), Loh and Mian (2006), and Loh and Stulz (2011) show that compared to their peers, some star analysts can provide more accurate earnings forecasts on a consistent basis. Jacob, Lys, and Neal (1999) suggest that an analyst's talent is more important to forecast accuracy than firm-specific experience.

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forecast accuracy after controlling for analyst experience, job complexity, broker affiliation, timing, and luck. While we recognize that there may be no perfect measure of talent, we subject our measure to empirical analysis. We conjecture that a "high-ability" analyst—or one that we define as having greater talent—may be able to produce more information than a "low-ability" analyst (with observationally equivalent experience, job complexity, and so on). Subsequently, high ability analysts can further reduce the amount of inside information not yet incorporated into stock prices, thus reducing insider trading in terms of intensity and profitability.

In this paper, we specifically investigate these conjectures by examining how analyst talent affects insider trading when information asymmetry is high (e.g., before earnings announcements). Corporate insiders, such as managers and directors, possess private information that is unavailable to outside investors. As such, their trades often precede significant abnormal returns (Seyhun, 1986) and contain valuable information on future earnings and cash flows (Sivakumar and Waymire, 1994; Piotroski and Roulstone, 2005; Cline et al., 2017). Both the intensity and profitability of insider trading depend on a firm's information environment (see Aboody and Lev, 2000; Frankel and Li, 2004). By disclosing information to the public, analysts can reduce the information asymmetry between managers and outside investors, monitor managers, and improve a firm's information environment (Anantharaman and Zhang, 2011; Hong et al., 2014; Amiran et al., 2016).[3] Anecdotally, some analysts are able to detect illegal insider trading activities and provide better monitoring of corporate insiders. Monitoring is, to some extent, also related to a firm's information environment as well as it encourages information acquisition by outsiders (Fernandes and Ferreria, 2009; Edmans et al., 2017). Consistent with these views, previous empirical studies such as Frankel and Li (2004) and Ellul and Panayides (2018), show that insider trading intensity and profitability both decrease with analyst coverage. However, these studies rely on the implicit assumption that all analysts produce the same amount or same quality of information and ignore the significant variation in analyst talent.

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. While firms in general want more analyst coverage to lower information asymmetry (Aggarwal et al., 2002; Cliff and Denis, 2004; Kirk, 2011), quality of analyst coverage may be more important than quantity (Loh and Mian, 2006; Akyol et al., 2016). If high-ability analysts contribute more to a firm's information environment and thus reduce more information asymmetry,[4] we expect firms followed by high-ability analysts to have less insider trading prior to information events such as earnings announcements. We further expect these insiders to earn less trading profits.

Using a large sample of U.S. firms and all the analysts following these firms, we begin our analysis by attempting to identify the nature of information produced by high-ability analysts. Piotroski and Roulstone (2004) and Chan and Hameed (2006) show that the number of analysts following does not positively associate with the amount of firm-specific stock price variation, suggesting that analysts in general produce market and industry-level information, but not firm specific information. We postulate that this is because only a small number of high-ability analysts can produce firm-specific information. To test this hypothesis, we follow Piotroski and Roulstone (2004) and Chan and Hameed (2006) by estimating the "synchronicity" measure developed by Morck et al. (2000). We first corroborate the findings of Chan and Hameed (2006) that greater analyst coverage (i.e., the number of analysts following a particular stock) is associated with greater synchronicity (i.e., higher correlation with market returns). We then show that stock returns of firms covered by high-ability analysts incorporate greater firm-specific information (i.e., lower synchronicity), suggesting that while analysts generally produce market and industry-level information, high ability analysts produce relatively more firm-specific information. These results also reassure us that our measure does capture analyst talent.

Next, we document a strong association between our measure of analyst talent and insider trading activities. Specifically, we find significantly less buying by insiders prior to positive earnings news (measured by positive earnings surprise[5]) when firms are followed by high-ability analysts. Our results are largely consistent with the findings in Cheng and Lo (2006) that insiders time their buys based on private information, and Agrawal and Cooper (2015) that insiders sell more when they possess negative information. When we further divide insiders into opportunistic traders and routine traders, the results remain significant in opportunistic trades and disappear in routine trades. We also document lower insider trading profitability when firms are covered by high-ability analysts. These findings support the view that high-ability analysts help reduce information asymmetry between management and outside investors.

An alternative explanation for our results is that high-ability analysts choose to cover firms with less insider trading.[6] In our analysis, we first ensure that all analyst forecasts precede insider trades. To further address the endogeneity issue, we analyze analyst initial coverage and exogenous closures of brokerage houses. Previous literature shows that brokerage house closures exogenously reduce analyst coverage and thus increase information asymmetry (Kelly and Ljungqvist, 2012; Derrien and Kecskes, 2013; Chen et al.,

[3] In addition, analysts may indirectly improve a firm's earnings quality by pressuring the management (Dichev et al., 2016), which eventually lowers a firm's idiosyncratic return volatility (Rajgopal and Venkatachalam, 2011) and insider trading activities (Gider and Westheide, 2016).

[4] Low-ability analysts may even damage information environment of covered firms through, for example, their earnings forecasts (Easton and Monahan, 2005).

[5] Richardson et al. (2004) find that insiders have incentives to collude with analysts to "walk-down" expectations by issuing earnings guidance downward, especially after an SEC regulatory change in May 1991 that allowed managers to sell stocks from stock options six months after the options were issued rather than six months after the exercise date. In untabulated results, we show that our results hold before May 1991, and a before- May 1991 dummy variable is insignificant in our regressions.

[6] This alternative explanation is not supported by some empirical studies (e.g., Lustgarten and Mande, 1998; Sivakumar and Vijayakumar, 2001) which suggests that more accurate analyst forecasts, and thus analysts with higher ability, are associated with firms with more insider trading. This potential reverse causality works against the results we have.

2015; Billett et al., 2017). We show that after firms experience decreased analyst coverage due to brokerage house closures, insiders buy more before positive earnings news. The magnitude of the increase in insider net buy is positively associated with the talent of the analysts who stop their coverage due to these closures. In addition, we conduct an out-of-sample test using data from 2009 to 2018 to predict insider trading activities outside the estimation window of analyst talent. We show that our analyst talent measure estimated before 2008 can explain insider trading prior to positive earnings news even in the ten-year period from 2009 to 2018, suggesting that our results are unlikely driven by some analysts strategically choosing firms with less insider trading. In untabulated results, we also conduct an out-of-sample test of the association between talent and return synchronicity. In all of our robustness checks our talent measure remains significant.

We contribute to the literature on both financial analyst ability and insider trading. First, by introducing the AKM (Abowd et al., 1999) methodology to financial analyst research, which to the best of our knowledge is the first such application, and by decomposing analysts' forecasting performance, we are able to extract a unique measure of their talent. We then show that this measure of talent is the most important explanatory component with regards to analysts' forecasting performance—more important than experience, brokerage affiliation, and task complexity. Our work offers a potentially powerful measure of analyst talent which has predictive power out-of-sample. Such improvement on the measurement of analyst ability can help investors make better informed decisions in using analyst reports and can facilitate more efficient allocation of resources. Second, our results suggest that analyst talent is the key to better understanding analysts' forecasting performance and companies' information environment, and the relationship between the two. In contrast to previous studies that suggest that analysts on average produce market-wide or industry-level information (Piotroski and Roulstone, 2004; Chan and Hameed, 2006), we are the first to document that high-ability analysts can produce significantly more firm-specific information and thus may help improve a firm's overall information environment. Third, we are the first to investigate how the *quality* of financial analysts affects insider trading. While previous studies find that the number of analysts following has an impact on opportunistic trading by insiders (Frankel and Li, 2004; Ellul and Panayides, 2018), we show that the quality of financial analysts has a more significant impact. This finding suggests that it is important to examine the quality of financial analysts in the studies related to a firm's information environment; focusing on the number of analysts may not be sufficient.

The rest of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 reports how analyst talent is associated with firm-specific information. Section 4 presents results for the effects of analysts' talent on insider trading intensity. Section 5 analyzes the effects of analysts' talent on insider trading profitability. Section 6 discusses endogeneity issues, and Section 7 concludes.

2. Data and methodology

2.1. Analyst ability

To develop a proxy for an analyst's talent, we employ a methodology similar to the one used by Abowd et al. (1999) and quantify how much variation in analyst forecasting performance can be explained by time-invariant analyst fixed effects in a three-way fixed effects model (analyst fixed effects, broker fixed effects, and year fixed effects). Specifically, we first identify analysts who switch brokers during the sample period and estimate the fixed effects for such analysts after controlling for other known factors explaining analyst forecasting performance. We then use the analyst fixed effects to estimate the fixed effects for the brokers who employed those analysts. Based on the estimated broker fixed effects, we can finally estimate analyst fixed effects for other analysts who work for the same brokers even if they do not move.

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), brokerage affiliation (broker size and broker fixed effects), task complexity (number of firms and industries covered, and number of estimates), time effect, and residual (luck).[7] The same method has been recently and successfully introduced to identify unobservable individual talent in the studies of managerial compensation (Graham et al., 2012), managerial incentives (Coles and Li, 2020), mutual fund managers (Huang and Wang, 2015), and corporate insiders (Hillier et al., 2015).[8] Our work is the first to apply the methodology in the financial analyst research. An analyst's forecast is affected by the analyst, the brokerage house and the firm, which makes it challenging to single out the analyst effects. This is important because brokerage houses can affect analyst forecasts in a substantial way (Jacob et al., 1999; Hong and Kubik, 2003; Cowen et al., 2006; Irvine et al., 2007), and analyst individual effects and brokerage effects can jointly affect forecast accuracy (Jacob et al., 1999; Sorescu and Subrahmanyam, 2006). Without the AKM method, analyst effects can be confused with brokerage house effects, and vice versa.

We gather all analyst earnings forecasts from the I/B/E/S Detail History database for the 1984–2018 period.[9] We stop our main

[7] Of course, while we try to include as many quantifiable factors as possible, we may have missed something and can never be sure that what is captured only reflects talent. For example, due to data limitations our measure could also incorporate all the experience 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 et al., 2010), conflict of interest (Ljungqvist et al., 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.

[8] For illustration and more detail of the method, see Graham et al. (2012).

[9] We begin our analysis period in 1984 because I/B/E/S data are censored in 1983; therefore, it is difficult to estimate our talent measure data before 1984. We have the data of brokerage closures until 2008.

analysis in 2008 in order to preserve data for out-of-sample testing, as described below. Following Clement (1999), 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 the codes are sometimes shared by a team of analysts. These analyst teams are removed from our sample using the I/B/E/S broker 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. Note that the AKM method's accuracy depends on the number of "movers" identified. Movers are analysts who changed brokerage house affiliation during our sample period. There are 24,537 analysts recorded in the I/B/E/S data during our sample period. Many of these analysts only cover one firm, or make a very small number of forecasts during the whole sample period; still, we are able to estimate analyst talent for 12,689 analysts. Of these analysts, 5079 are movers but they cover 71.1% firms in our sample. Since most of our sample firms are covered by mover analysts, the AKM method should give us accurate estimates.

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.[10] We do not use the absolute forecast error because of the selection bias problem (i.e., some analysts may strategically select firms that are easy to analyze).

To isolate analysts' time-invariant talent from time-variant, experience-based ability, we follow Clement (1999) and Clement et al. (2007) to 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 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 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 a few other factors that may affect forecast accuracy through channels other than talent. First, we consider job complexity. Forecast accuracy may decrease with job complexity; following Clement (1999), we measure analyst specialization or job complexity by the number of firms (NCOS) and number of industries (NSIC2) covered by an analyst. Second, we consider information advantage through large broker affiliation. Analysts employed by large brokers may have better access to research resources at work; following Stickel (1995), 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, as in Clement (1999). 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 it is bounded between 30 and 365.

After removing the effects of all the above determinants of earnings forecast accuracy, the analyst-fixed-effects portion of the forecast accuracy captures the analyst talent. Table 1 provides more details on the estimation. In Panel A, we report summary statistics for analyst's earnings, 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 portion of the forecast accuracy captures our measure of analyst talent.

In Panel B, we regress forecast accuracy on explanatory variables elaborated above, together with analyst fixed effects, year fixed effects, and broker fixed effects. Columns 1–3 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. The estimated analyst fixed effects increase the fit by 2% (0.18 in Column 1 vs. 0.20 in Column 3, and 0.19 in Column 2 vs. 0.21 in Column 4).

To provide a quantitative comparison of the relative economic significance of the variables, we follow Graham et al. (2012) in decomposing variation of the dependent variable (forecast accuracy) into percent variation explained by observable analyst characteristics, analyst/broker/year fixed effects, and the unexplained remainder. Specifically, the percent explanatory power of each variable is calculated as the ratio of covariance between forecast accuracy and the variable to the variance of forecast accuracy. As we apply the AKM (Abowd et al., 1999) methodology, we find that all observable analyst characteristics account for 16.78% of the total

[10] We also use ranked forecast errors following Jacob et al. (1999) as an alternative measure and obtain similar results.

Table 1
Measure of analyst talent.

Panel A: Summary Statistics for Analyst Earnings

	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	2907.00	2989.00			
Number of analysts	2644.36	2652.00	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

Panel B: Regression on Forecast Accuracy and Explanatory Power Decomposition

	1	2	3	4	R^2 Decomposition[a]
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)	
Number of forecasts per firm ($FREQ_{ijt}$)	0.001***	0.031***	0.032***	0.030***	3.85%
	(3.16)	(47.50)	(45.55)	(41.76)	
Top-ten largest broker dummy ($TOP10_{it}$)	0.039***	0.018***	0.020***	0.021***	0.50%
	(16.73)	(5.54)	(6.29)	(5.67)	
Number of companies ($NCOS_{it}$)	−0.000	−0.000	0.000	−0.000	0.09%
	(−0.98)	(−0.35)	(0.33)	(−0.20)	
Number of two-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	

This panel shows summary statistics for 642,656 analyst earnings estimates in I/B/E/S Detail during 1984–2008. AFE_{ijt} is the absolute forecast error of actual earnings per share (EPS) for analyst *i* on firm *j* in year *t.* The forecast on annual EPS is based on the most recent one if there are multiple forecasts (including revisions) by the same analyst. Forecast accuracy ($PMAFE_{ijt}$) is defined as $(\overline{AFE}_{jt} - AFE_{ijt})/\overline{AFE}_{jt}$, where $\overline{AFE}_{jt}$ is the mean AFE_{ijt} on firm *j* in year *t.*For other measures of forecast accuracy and some independent variables refer to Clement and Tse (2003, 2005). General experience ($GEXP_{it}$) is the number of years since the first estimate of analyst *i.* Firm experience ($FEXP_{ijt}$) is the number of years since the first estimate of analyst *i* on firm *j.* The number of forecasts per firm ($FREQ_{ijt}$) is the total number of earnings forecasts by analyst *i* on firm *j* in year *t.* Number of companies ($NCOS_{it}$) is the number of firms covered by analyst *i* in year *t.* Number of two-digit SIC ($NSIC2_{it}$) is the number of two-digit SIC industries covered by analyst *i* in year *t.* Top-ten largest broker dummy ($TOP10_{it}$) equals one if analyst *i* works for the brokers in the top size decile (measured by the number of analysts) in year *t*, and zero otherwise. Forecast age (AGE_{ijt}) is the number of days from the forecast announcement date to the fiscal year end date. This panel shows the results of OLS regressions for the testing period 1984–2008. The dependent variable is analyst forecast accuracy ($PMAFE_{ijt}$), which is defined as $(\overline{AFE}_{jt} - AFE_{ijt})/\overline{AFE}_{jt}$, Where AFE_{ijt} is the absolute forecast error of actual EPS for analyst *i* on firm *j* in year *t*, and $\overline{AFE}_{jt}$ is the mean AFE_{ijt} on firm *j* in year *t.* General experience ($GEXP_{it}$) is the number of years since the first estimate of analyst *i.* Firm experience ($FEXP_{ijt}$) is the number of year since the first estimate of analyst *i* on firm *j.* The number of forecasts per firm ($FREQ_{ijt}$) is the total number of earnings forecasts by analyst *i* on firm *j* in year *t.* Number of companies ($NCOS_{it}$) is the number of firms covered by analyst *i* in year *t.* Number of two-digit SIC ($NSIC2_{it}$) is the number of two-digit SIC industries covered by analyst *i* in year *t.* Top-ten largest broker dummy ($TOP10_{it}$) equals one if analyst *i* works for the brokers in the top size decile (measured by the number of analysts) in year *t*, and zero otherwise. Forecast age (AGE_{ijt}) is the number of days from the forecast announcement date to the fiscal year end date. All variables are demeaned in fiscal year *t.* Robust standard errors are clustered at the firm level and provided in parenthesis. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively. The explanation power of the independent variables, analyst fixed effects, broker fixed effect, and year fixed effects are presented in the last column.

[a] The 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.

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. The results show that a significant portion of analyst performance is not explained by observable analyst characteristics; the unobservable, time-invariant talent captured by analyst fixed effects plays an important role in explaining the variation in earnings forecasts. Specifically, the experience-based ability measures only account for about 1.42% of the total variation of forecast accuracy, while the brokerage affiliation accounts for just under 1%, much less than the 4.01% of variation explained by our analyst talent measure. We also show the distribution of estimated analyst talent to be a quasi-normal distribution in Fig. 1.

In untabulated results, we perform a placebo test in which there is no analyst talent by design; specifically, we randomly allocate analysts over firms and test how these “analyst dummies” explain forecast accuracy. The randomized analyst dummies decrease the adjusted R-squared from 0.19 to 0.17 (as compared to 0.21 in column 4), indicating that analyst talent indeed matters and that our results in Table 1 are not driven by the sheer number of analyst dummies.

Admittedly, our measure of analyst talent may also reflect noise or “luck”, which is an important component in successful earnings forecasting. By using information from all forecasts made by an analyst, our measure is conceptually and empirically a better measure than historical earnings forecast error for a firm. Under certain conditions, our analyst-specific talent measure should work even better; for example, when an analyst switches brokerage house, chooses a different firm to initiate coverage, or is compared to another analyst in a different time period.

2.2. Other variables

We follow Morck et al. (2000) and estimate a “return synchronicity” variable:

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

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

$$r_{ijt} = \widehat{\alpha}_i + \widehat{\beta}_i^M r_{Mt} + \widehat{\beta}_i^j r_{jt} + \varepsilon_{ijt} \tag{3}$$

where r_{ijt} is the daily return of stock i in industry j on day t, r_{Mt} is the value-weighted market return on day t, and r_{jt} 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).

For our insider trading results, we obtain insider trading data from Thomson Reuters Insider Filing Data Feed. The Securities Exchange Act of 1934, 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 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 that 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.[11] When we use shorter (2 weeks) or longer (1 year) windows for robustness, we find similar results. We keep observations with non-zero insider trading activities only; if a firm does not have insider trading in the window, the observation is dropped from our sample. Including observations with zero insider trading activities by setting the insider trading frequency to zero enlarges our sample but does not affect our results qualitatively.

Since insider trading prior to earnings announcement is largely based on private information about earnings, we consider earnings surprises. Specifically, we follow Livnat and Mendenhall (2006) and define earnings surprises as follows:

$$SUE = \frac{X_{it} - MFX_{it}}{P_{it}} \tag{4}$$

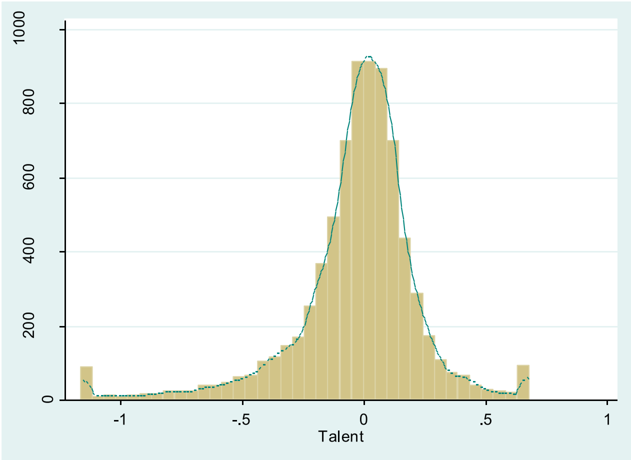
where X_{it} is the actual earnings per share (EPS) announced by firm i for fiscal year t, P_{it} is the stock price of firm i at the end of fiscal year t, and MFX_{it} is the median earnings forecast over the 90 days prior to earnings announcements for firm i in fiscal year t. As such, *SUE* uses the consensus forecast among analysts as expected earnings in year t. 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.

The data for control variables are collected from multiple sources. Stock returns are obtained from CRSP. We obtain analyst data, including the number of analysts following a firm (# Analysts), earnings forecast details, and Log(Timing) which measures the log of days from analyst forecast to earnings announcement, from I/B/E/S. We obtain other control variables, such as market capitalization (Log(MV)), book-to-market ratio (Book/Market), research and development (R&D) expenses, and property, plant, and equipment (PP&E) from COMPUSTAT. All the variables used in this study are summarized in Table 2.

It is interesting to note that in Table 2 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. As for the nature of the earnings forecasts, the mean earnings surprise is −0.5% for SUE.

We report the Pearson correlation matrix for the main variables in Table 3. We find that analyst talent (referred to as “*Talent*”) is negatively correlated with *netbuy_volume* and *netbuy_value* at the 5% and 1% significance levels respectively, which is consistent with our conjecture that high-ability analysts help restrict insider trading. Note that although the correlation between *Talent* and insider trading measures is low for the entire sample, when we examine these correlations in the periods of positive (and negative) earnings news, the correlations become significantly negative (and positive).

[11] Roulstone (2003) shows that executives may be subject to trading restrictions by firms. We use various tests to show that our results are not driven by these restrictions. First, when a high-ability analyst initiates or terminates coverage, insider trading decreases or increases afterwards which is not likely caused by trading restrictions. Second, our results hold when we remove transactions by officers and directors to whom the trading restrictions apply.



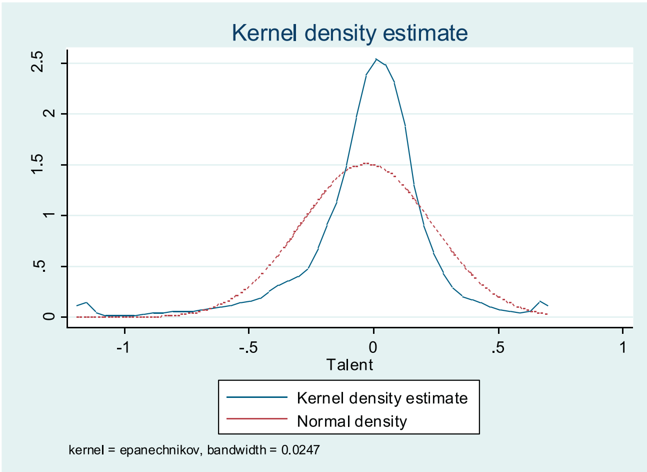


Fig. 1. The distribution of estimated analyst talent.
Fig. 1 depicts the distribution of estimated analyst talent, for 7540 analysts, with mean = −0.028, standard deviation = 0.264, minimum = −1.163, and maximum = 0.679. Fig. 1A presents the distribution of estimated analyst talent using histograms and the kernel density estimation (curved line). Fig. 1B is the comparison between the kernel density of analyst talent and the normal distribution. All data are winsorized at 1% level. Unwinsorizd data generate longer tails in the graphs (not reported).
Fig. 1A: Distribution of Estimated Analyst Talent.
Fig. 1B: Comparison between Kernel Density of Analyst Talent and Normal Distribution.

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 (Cohen et al., 2012). If an analyst's talent affects insider trading by changing the information environment, it should primarily affect opportunistic rather than routine insider trading. Following Cohen et al. (2012), we define a routine trader as an insider who trades in the same calendar month for at least three consecutive years and an opportunistic trader as anyone who does not fit the definition of a routine trader. We categorize all trades by routine traders as routine trades and all other trades as opportunistic trades. We then conduct our analysis separately for routine trades and opportunistic trades and present our empirical results in Section 4.2.

3. 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 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 specific industries, and the anticipated

Table 2
Sample summary statistics.

Variables	(1) # of obs.	(2) mean	(3) std	(4) min	(5) max
SUE(earnings surprise)	183,620	−0.005	0.118	−9.751	0.651
Talent	197,340	0.009	0.158	−0.638	0.417
Log(MV)	185,230	7.371	1.769	3.423	11.430
R&D	197,340	0.043	0.072	0	0.386
Book/Market	185,212	0.488	0.335	−0.149	1.906
# Analysts	185,196	2.763	0.741	0.693	3.951
PP&E	184,569	0.594	0.415	0.038	1.874
Netbuy_volume	197,340	−5.684	21.580	−146.600	60
Netbuy_value	197,340	−2.331	8.207	−61.730	9.356
Netbuy_adjusted volume	197,340	−1.049	5.343	−40.130	14.530
Log(Timing)	197,340	5.201	0.583	3.584	5.994

This table reports summary statistics of data at the forecast-firm-year level. The testing period is from 1985 to 2008. Insider trading data are in the 30-day window before annual earnings announcements by the firms. All data are winsorized at the 1% level. *SUE* is the 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 price); SIC is the 2-digit Standard Industrial Classification code; *Talent* is analysts' innate ability or natural talent measured by the analyst fixed effect from the regressions on analysts' forecast accuracy; *Log(MV)* is the logarithm of market capitalization; *R&D* is the research and development expenses divided by total assets; *PP&E* is the property, plant and equipment divided by total assets; *Book/Market* is the ratio of book value of the firm to its market value; *# analysts* is the logarithm of the number of analysts following the firm in a fiscal year; *Netbuy_volume* is buys volume minus sells volume and divided by 10,000; *Netbuy_value* is buys value (buys volume times monthly stock price) minus sells value (buy volumes times monthly stock price) and divided by 1,000,000; *Netbuy_adjusted_volume* is adjusted sell volumes (sells volume divided by the number of shares outstanding) minus buys volume (buys volume divided by the number of shares outstanding); *Log(Timing)* is the logarithm of the number of days between the earnings forecast date (before insider trading window) by the analyst and the earnings announcement date by the firm.

Table 3
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10
1 = Netbuy_volume	1									
2 = Netbuy_value	0.884	1								
	(0.00)									
3 = Netbuy_adj. vol.	0.764	0.610	1							
	(0.00)	(0.00)								
4 = Talent	−0.005	−0.007	−0.001	1						
	(0.03)	(0.00)	(0.55)							
5 = Log(MV)	−0.084	−0.139	0.117	0.056	1					
	(0.00)	(0.00)	(0.00)	(0.00)						
6 = Book/Market	0.036	0.065	−0.027	0.007	−0.323	1				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
7 = # Analysts	−0.040	−0.078	0.106	0.058	0.765	−0.158	1			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
8 = PP&E	0.069	0.058	0.038	0.045	0.099	0.164	0.181	1		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
9 = R&D	0.034	0.025	0.034	−0.022	−0.077	−0.261	−0.056	−0.376	1	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
10 = Log(Timing)	0.009	0.008	0.014	0.008	0.007	−0.016	−0.006	−0.022	0.024	1
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	

This table reports the Pearson correlation matrix for the variables in the whole sample at the forecast-firm-year level. The testing period is from 1985 to 2008. The number of observations is the same as that in Table 3. Insider trading data are in the 30-day window before annual earnings announcements by the firms. All data are winsorized at 1% level. *Netbuy_volume* is the volume of buys minus the volume of sells then divided by 10,000. *Netbuy_value* is the value of buys (volume times monthly stock price) minus the value of sells then divided by 1,000,000. *Netbuy_adjusted_volume* is the adjusted net buy volume (volume of buys minus volume of sells) and then divided by the number of shares outstanding. *Log(MV)* is the logarithm of market capitalization of the firm. *Book/Market* is the ratio of book value of the firm to its market value. *# analysts* is the logarithm of the number of analysts following the firm in a fiscal year. *PP&E* is the property, plant and equipment divided by total assets. *R&D* is the research and development expenses divided by total assets. *Log(timing)* is the logarithm of the number of days between the earnings forecast date (before insider trading window) by the analyst and the earnings announcement date by the firm. Corresponding *p*-values are in the parentheses.

outlook for a company's new product launch and subsequent profitability may impact 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 (one-third) of monthly (daily) 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 (1988) work by examining the information content of stock markets in emerging versus developed markets. They also contribute to the literature econometrically by applying a simple transformation of R-squared to create a dependent variable that is an unbounded measure of synchronicity.

Previous studies have examined the role of analysts in the generation of firm-specific information that is impounded into stock prices, using the Morck et al. (2000) R-squared or synchronicity proxy. Higher synchronicity implies that more of the stock's 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, it is conjectured that greater analyst involvement with a stock should be *negatively* associated with synchronicity to the extent that analysts are conveying firm-specific versus industry or market-wide information. However, previous research such as Piotroski and Roulstone (2004) and Chan and Hameed (2006) suggests that 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 revisions and 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 able to uncover firm-specific information that is impactful for stock prices—such as the anticipated success or failure of a new product launch. Thus, we predict that even after controlling for the number of analysts, 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, after controlling for other standard variables.

We regress return synchronicity, as defined in Section 2.2 using eq. (2), on median analyst talent for each firm-year observation. Since a firm can be linked to multiple analysts, we employ the median of analyst ability at the firm-year level, *Talent,* measured at the beginning of the year (results are robust using the mean instead of median). We include control variables such as log(MV), book/market ratio, number of analysts following, research and development costs (R&D) and fixed assets (PP&E). We also include firm, industry and year fixed effects, and cluster standard errors at the firm level.

We report the regression results in Table 4. First, in columns (1) and (2), 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 column (1) *Synch* is estimated in regressions with only the market model. In column (2) *Synch* is estimated in regressions with both market and industry variables. Our *# Analysts* coefficient is larger and more significant in column (2), suggesting that more coverage adds both industry and market-level information.

In comparison, in columns (3) and (4) we include our *Talent* measure. In column (3) *Synch* is estimated in regressions with only the market model. In column (4) *Synch* is estimated in regressions with both market and industry variables. As we conjectured, we find a negative association between analyst talent and the market component of return variation, or *Synch* as captured by our *Talent* measure, 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-ability analysts produce more firm-specific information that is incorporated into stock prices. As for the economic significance, a one standard deviation increase in analyst talent corresponds to a 2% decrease in return synchronicity relative to the mean value. These results are robust to equal-weighting and different industry definitions (SIC 2-digit, Fama-French 48 industries and Fama-French 17 industries).

It is worth noting that these results do not necessarily predict a negative association between return synchronicity and idiosyncratic return volatility (IVOL) because firms have different levels of total return volatility. In untabulated results, we regress firm IVOL estimated using daily returns on analyst talent and find that analyst talent is in fact negatively associated with idiosyncratic volatility.

Overall, our results extend previous findings on the nature of information analysts produce (Piotroski and Roulstone, 2004; Chan and Hameed, 2006). High ability analysts are able to produce more firm-specific information and thus reduce insiders' firm-specific information advantage in trading.

4. Insider trading intensity

Next, we investigate our research questions in a setting of insider trading, which has been shown to be largely determined by information asymmetry between firm management and outside investors, and hence should be sensitive to the talent of analysts following.[12] For robustness, we define net insider buys in several ways:

$$\text{Netbuy\_volume} = \text{total volume of insider buys minus total volume of insider sells}$$

$$\text{Netbuy\_value} = \text{total trading value of insider buys minus the value of total insider sells}$$

[12] 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 do not exhibit significant within-firm variation over time for powerful statistical tests, while insider trading exhibits more within-firm variation (although analyst talent is time-invariant, the median analyst talent can vary over time for each firm in our firm level regressions); and 3) insider trading measures primarily reflect more firm-specific information than market- or industry-level information.

Table 4
Analyst talent and firm-specific information.

Dep. Var.	(1)	(2)	(3)	(4)
	Synch_Mkt	Synch_Mkt + Ind	Synch_Mkt	Synch_Mkt + Ind
Median Talent			−0.278**	−0.207**
			(−2.433)	(−2.419)
Log(MV)	0.567***	0.557***	0.567***	0.557***
	(50.372)	(66.217)	(50.339)	(66.184)
Book/Market	−0.017**	−0.011*	−0.017**	−0.011*
	(−2.247)	(−1.885)	(−2.226)	(−1.864)
# Analysts	−0.066***	−0.045***	−0.065***	−0.044***
	(−4.095)	(−3.733)	(−4.033)	(−3.671)
PP&E	−0.204***	−0.045	−0.205***	−0.046
	(−3.434)	(−1.022)	(−3.457)	(−1.045)
R&D	−0.151	−0.115	−0.149	−0.113
	(−1.148)	(−1.172)	(−1.132)	(−1.157)
Constant	−4.462***	−4.915***	−4.453***	−4.917***
	(−20.042)	(−21.538)	(−19.998)	(−21.549)
Observations	37,920	37,887	37,920	37,887
R-squared	0.307	0.381	0.307	0.381
Firm & Year FE	Yes	Yes	Yes	Yes

This table reports how analyst talent affects the incorporation of market, industry, and firm-specific information. The dependent variables are the value-weighted return synchronicity measure *Synch*, i.e., $\log(R^2/(1-R^2))$ estimated by Eq. 3 using daily stock returns; regressions (1) and (3) exclude an industry variable in Eq. 3. *Talent* is the median analyst talent at the firm-year level. The control variables are: *Log(MV)*, the logarithm of market capitalization of the firm; *Book/Market*, the ratio of book value of the firm to its market value; *# Analysts*, the logarithm of the number of analysts following the firm in a fiscal year; *PP&E,* the property, plant and equipment divided by total assets*; R&D*, the research and development expenses divided by total assets. Robust standard errors are clustered at firm level. T-statistics are reported in parentheses and ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

$$\text{Netbuy\_adjusted\_volume} = \text{total volume of insider buys minus total volume of insider sells, then divided by the number of outstanding shares}$$

The direction of insider trading is dependent on the earnings information. One would expect insiders to buy more before positive earnings news and sell more before negative earnings news. To analyze insider trading prior to the earnings announcements, we limit our insider net buys (sells) analysis to observations with positive (negative) earnings surprises (SUE) as defined in eq. (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. Consistent with this view, previous empirical studies show that both insider trading intensity and profitability 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 rely 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.

4.1. Baseline results

First, we examine the effects of analyst talent (or natural talent) on open market insider trading preceding annual earnings announcements at the earnings forecast level. Each earnings forecast represents specific information at the time of the forecast. To account for a better information environment right before earnings announcements (either due to voluntary disclosures or other earnings forecasts), we control for the number of days between when an earnings forecast is made and when official earnings are announced. We use the following specification to explore the effects of analyst talent on corporate insider trading:

$$Insider\,Trading_{it} = \alpha + \beta_1 Talent_k + \beta_2 Log(MV)_{it} + \beta_3 \left(\frac{Book}{Market}\right)_{it} + \beta_4 number\,of\,analyst_{it} + \beta_5 PP\&E_{it} + \beta_6 R\&D_{it} + \beta_7 Log(Timing)_{itkm} + \varepsilon_{it} \tag{5}$$

where *Insider Trading*$_{it}$ is the net buying or net selling (as defined in Section 2) of shares by corporate insiders in the 30-day window prior to earnings announcement by firm i for fiscal year t; our main variable of interest, *Talent*$_k$, is analyst k's talent (measured by the estimated analyst fixed effects) if analyst k covers firm i in fiscal year t. The remaining variables are control variables. *Log*(*MV*)$_{it}$ is the logarithm of market capitalization of firm i in fiscal year t; $\left(\frac{Book}{Market}\right)_{it}$ is the ratio of book value of firm i to its market value in fiscal year t; *number of analyst*$_{it}$ is the logarithm of the number of analysts following firm i in fiscal year t; *PP & E*$_{it}$ is property, plant and equipment divided by total assets of firm i in fiscal year t; *R & D*$_{it}$ is research and development expenses divided by total assets of firm i in fiscal year t; *Log*(*Timing*)$_{itkm}$ is the logarithm of the number of days between the date of EPS forecast m (before insider trading window) by analyst k and the date of earnings announcement by the firm i for fiscal year t. We also include firm, year and industry fixed effects in regressions. Note that unlike the previous section, we perform the analysis at the *analyst* level so we can control for the exact timing of

Table 5
Analyst talent and insider net buys.

Dep. Var.	Type of Inside Information: Positive			Type of Inside Information: Negative		
	(1)	(2)	(3)	(4)	(5)	(6)
	Netbuy_Volume	Netbuy_Value	Netbuy_adjusted Volume	Netsell_Volume	Netsell_Value	Netsell_adjusted Volume
Talent	−1.147***	−0.545***	−0.237***	0.536**	0.195**	0.010
	(−4.71)	(−5.62)	(−4.04)	(2.27)	(2.40)	(0.18)
Log(MV)	0.871***	0.579***	0.704***	0.707***	0.365***	−0.370***
	(6.26)	(10.45)	(20.99)	(3.88)	(5.84)	(−8.56)
Book/Market	−0.421	0.069	0.505***	0.822**	−0.904***	−0.531***
	(−1.41)	(0.58)	(7.03)	(2.48)	(−7.95)	(−6.76)
# Analysts	−1.575***	−1.433***	−0.251***	1.417***	−0.230***	0.950***
	(−7.11)	(−16.22)	(−4.70)	(6.03)	(−2.85)	(17.05)
PP&E	7.964***	3.731***	2.156***	−2.872***	−0.765***	−0.811***
	(15.48)	(18.20)	(17.39)	(−5.70)	(−4.41)	(−6.78)
R&D	8.992***	1.160	−5.251***	−25.498***	0.407	−5.425***
	(4.41)	(1.43)	(−10.68)	(−8.74)	(0.41)	(−7.84)
Log(Timing)	−0.036	−0.006	−0.007	−0.047	−0.029	−0.021
	(−0.55)	(−0.25)	(−0.44)	(−0.79)	(−1.40)	(−1.50)
Constant	−2.333	2.441**	−8.384***	−7.958	−1.179	0.300
	(−0.89)	(2.34)	(−13.28)	(−1.27)	(−0.55)	(0.20)
Observations	111,483	111,483	111,483	56,323	56,323	56,323
R-squared	0.104	0.115	0.090	0.140	0.180	0.055
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table provides results of pooled ordinary least squares (OLS) regressions on the effects of analyst talent on open market insider trading based on the 30-day window before annual earnings announcements for forecast-firm-year level observations from 1985 to 2008. All variables are winsorized at 1% level. Columns (1)–(3) are 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 columns (4)–(6) are based on the sample of negative insider information corresponding to negative earnings surprise. *Netbuy_volume* is the volume of buys minus the volume of sells then divided by 1,000,000. *Netbuy_value* is the value of buys (volume times monthly stock price) minus the value of sells then divided by 1,000,000. *Netbuy_adjusted_volume* is the adjusted net buy volume (volume of buys minus volume of sells) and then divided by the number of shares outstanding. All measures of insiders' net sells are the opposite numbers of the corresponding net buy measures. The key independent variable is analyst innate ability or natural talent, referred to as "*Talent*" in the regressions. The control variables are: *Log(MV)*, the logarithm of market capitalization of the firm; *Book/Market*, the ratio of book value of the firm to its market value; *# Analysts*, the logarithm of the number of analysts following the firm in a fiscal year; *PP&E,* the property, plant and equipment divided by total assets*; R&D*, the research and development expenses divided by total assets. *Log(Timing)* is the logarithm of the number of days between the earnings forecast date (before insider trading window) by the analyst and the earnings announcement date by the firm. All regressions include firm, year and industry (2-digit SIC) fixed effect. Robust standard errors are clustered at firm level. T-statistics are reported in parentheses and ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

each analyst forecast. This is because our dependent variable of insider net buying is sensitive to earnings surprises and the timing of each earnings forecast. A low-ability analyst who issues his/her most recent forecast right before the earnings announcement may affect subsequent insider trading more than a high-ability analyst who issues earlier forecasts. Our findings hold if we perform analysis at the firm level without controlling for analyst forecast timing.

If insiders have positive (negative) inside information about EPS, we expect $\beta_1 < 0$ for net buys (sells) by corporate insiders because analysts with high talent can 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. In addition, the results of Finnerty (1976), Seyhun (1986), Lakonishok and Lee (2001), and Frankel and Li (2004) all indicate that smaller firms are associated with higher insider trading profits. 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. 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. Finally, β_7 corresponds to the timing effect of the earnings forecasts by analysts. However, the result is driven by two conflicting effects. First, the earlier the forecast is announced, the lower the level of information asymmetry of earnings becomes. Second, it is quite possible that insiders obtain private information very early in the event windows and aim to trade early to avoid the blackout windows required by firms.

Table 5 reports the main empirical results based on the 30-day window[13] before earnings announcements. We regress insider net buy measures on the continuous measure of analyst talent, together with the control variables previously described. We report results for positive earnings surprises ($SUE > 0$) in columns 1–3, and results for negative earnings surprises ($SUE < 0$) in columns 4–6. As expected, we find that higher analyst ability is associated with lower volumes of net buys, and lower adjusted volumes of net buys when insiders have "positive" inside information about earnings. The economic significance is substantial; a one standard deviation increase of analyst talent is associated with a 3.2% decrease in *netbuy_volume*, a 3.7% decrease in *netbuy_value*, and a 3.6% decrease in *netbuy_adjustedvolume* relative to their means. We also have results suggesting that analyst talent affects insider selling prior to negative earnings news, although the results are weaker in magnitude. This is consistent with previous studies that find that insiders are more cautious in exploiting negative information in order to lower litigation risk (Cheng and Lo, 2006), and that insider sales are less likely to contain information (Lakonishok and Lee, 2001; Gider and Westheide, 2016). Furthermore, the weaker results on insider selling may reflect the fact that insiders cannot freely sell all shares and are not allowed to short sell their own company's shares.

It is worth noting that the forecast timing has positive effects on insiders' net buys, which implies that corporate insiders may obtain positive earnings information and aim to trade early to avoid the blackout windows required by their firms. Also, analyst talent may affect the likelihood and magnitude of earnings surprises, although in this paper we focus on how it reduces insider trading around earnings surprises.

To address the concern that our results on the association between analyst talent and insider trading may be spurious, in untabulated results we perform placebo tests that randomly scramble the actual analyst-firm match found in the data. This severs the analyst-firm connection. Our procedure resembles that in Jarosiewicz and Ross (2020). We find that this procedure removes the significance of the analyst talent variable in explaining insider trading, which supports the notion that the results described in the paper reflect a genuine significant relation rather than being a spurious statistical artifact. Our results are not affected if we only use "mover" analysts who changed brokerage house affiliation during our sample period, for which the talent should be more accurately estimated, although it substantially reduces our sample size. In addition, our results are not significantly affected when we include a post-Reg FD dummy (Regulation Fair Disclosure, October 2000) or a post-SOX dummy in our analysis, to account for regulatory changes. Our analyst talent effect appears significant regardless of regulatory environment.

4.2. *Opportunistic trading and routine trading*

We postulate that insiders' net buys are driven by positive inside information. However, it is possible that some trades do not reflect private information. If high-ability 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. Separating the insider trading sample into opportunistic and routine subsamples also serves our research purpose better and allows us to perform sharper tests as opportunistic insider trades are much more likely to be based on material private information. As described in Section 2, we follow Cohen et al. (2012) and 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 and report the coefficient estimates in Table 6. Columns 1–3 report results when only opportunistic trades are analyzed, and columns 4–6 reports results when only routine trades are analyzed. In columns 1–3, the coefficients of volume and adjusted volume of net buys for opportunistic traders are statistically significant at the 1% level. However, as expected, these coefficients are not statistically significant in columns 4–6 for routine trades. In equality tests, we find that the coefficient difference between opportunistic vs. routine trades is statistically significant at the 5% level for insider net buys adjusted for trading volume.

Overall, these results suggest that the results in Table 5 mainly stem from opportunistic trades rather than routine trades. This is consistent with our hypothesis, suggesting that high-ability analysts impound information that primarily resides in opportunistic insider trades.

4.3. *Initial coverage: The incremental effect on increased insider trading*

We recognize that there are potential endogeneity issues related to analyst ability (further discussed in section 6). For example, if shrewd analysts choose more transparent firms to follow, what we document could merely reflect a known association between insider trading and a firm's information environment. To examine whether the effects come from analyst ability or firm characteristics, we

[13] Although insiders can trade any time during a fiscal quarter, trades within 30 days prior to earnings announcements are more likely based on solid information (see Garfinkel, 1997; Fu et al., 2020). Insider trading in the one-month window prior to earnings announcements can be affected by factors such as firm-level insider trading restrictions and corporate governance (see Lee et al., 2014; Dai et al., 2016; Ali and Hirshleifer, 2017). We show that our results hold when firm fixed effects are included. As a further robustness check we consider insider trading over a one-year period prior to earnings announcement; that is, we use basically the universe of insider trading. We show that our results are qualitatively the same, although the net buy volume results become weaker.

Table 6
Opportunistic trading and routine trading.

Dep. Var.	Routine Traders' Trading			Opportunistic Traders' Trading		
	(1)	(2)	(3)	(4)	(5)	(6)
	Netbuy_Volum	Netbuy_Value	Netbuy_adjusted Volume	Netbuy_Volum	Netbuy_Value	Netbuy_adjusted Volume
Talent	−0.735*	−0.319	−0.028	−0.939***	−0.387***	−0.254***
	(−1.89)	(−1.63)	(−0.81)	(−2.82)	(−3.03)	(−2.64)
Log(MV)	0.079	−0.477	0.220	0.888	0.460	0.542
	(0.05)	(−0.72)	(1.42)	(0.57)	(0.80)	(1.12)
Book/Market	0.991	−0.692	0.751	−2.954	−0.748	−0.244
	(0.19)	(−0.33)	(1.61)	(−0.94)	(−0.69)	(−0.26)
# Analysts	−6.152***	−2.719***	−0.521	−0.136	−0.889	0.132
	(−2.86)	(−3.01)	(−1.54)	(−0.05)	(−0.93)	(0.14)
PP&E	−6.336	−3.189	−0.580	16.056*	5.314*	3.737
	(−0.83)	(−0.99)	(−1.09)	(1.82)	(1.84)	(1.47)
R&D	31.521	11.006	2.873*	−3.901	−2.035	−11.999
	(1.46)	(1.16)	(1.88)	(−0.14)	(−0.25)	(−1.25)
Log(Timing)	0.072	0.033	0.016*	−0.053	0.001	−0.009
	(0.93)	(0.86)	(1.92)	(−0.53)	(0.04)	(−0.28)
Constant	20.342*	15.143***	−0.831	−23.063	−3.766	−10.269**
	(1.88)	(3.04)	(−0.62)	(−1.59)	(−0.67)	(−2.25)
Observations	45,088	45,088	45,088	83,042	83,042	83,042
R-squared	0.155	0.145	0.097	0.154	0.163	0.130
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
T-statistics for equality tests: Routine vs. Opportunistic				1.83*	1.79*	2.37**

This table provides results of pooled ordinary least squares (OLS) regressions on the effects of analyst talent on opportunistic and routine insider trading based on the 30-day window before annual earnings announcements for forecast-firm-year level observations from 1985 to 2008. Opportunistic traders and routine traders are identified as in Cohen et al. (2012). All variables are winsorized at 1% level. Results are 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). Three dependent variables are employed: *Netbuy_volume* is the volume of buys minus the volume of sells then divided by 10,000. *Netbuy_value* is the value of buys (volume times monthly stock price) minus the value of sells then divided by 1,000,000. *Netbuy_adjusted_volume* is the adjusted net buy volume (volume of buys minus volume of sells) and then divided by the number of shares outstanding. The key independent variable is analyst talent. The control variables are: *Log(MV)*, the logarithm of market capitalization of the firm; *Book/Market*, the ratio of book value of the firm to its market value; *# Analysts*, the logarithm of the number of analysts following the firm in a fiscal year; *PP&E,* the property, plant and equipment divided by total assets*; R&D*, the research and development expenses divided by total assets. *Log(Timing)* is the logarithm of the number of days between the earnings forecast date (before insider trading window) by the analyst and the earnings announcement date by the firm. Robust standard errors are clustered at firm level. T-statistics are reported in parentheses and ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

investigate an initial coverage setting following Irvine (2003), Irvine et al. (2007), and Crawford et al. (2012). To isolate talent from firm-specific experience, our sample is limited to analysts covering a firm for the first time.

We use the difference in insider trading intensity, which is measured by net buys (sells) minus lagged or previous year net buys (sells) prior to announcements of positive earnings surprises, as the dependent variable. We use the talent of the new analyst as our variable of interest and estimate the following regression:

$$\Delta Insider\ Trading_{it} = \alpha + \beta_1 Talent_k + \beta_2 Log(MV)_{it} + \beta_3 \left(\frac{Book}{Market}\right)_{it} + \beta_4 number\ of\ analyst_{it}$$

$$+ \beta_5 PP\&E_{it} + \beta_6\ R\&D_{it} + \beta_7 Log(Ann.Timing)_{itkm} + \varepsilon_{it} \tag{6}$$

where $\Delta Insider\ Trading_{it}$ is the change of insiders' net buys from fiscal year *t-1* to year *t*; $Talent_k$ is analyst *k*'s talent if analyst *k* covers firm *i* for the first time on the I/B/E/S tape (in fiscal year *t*); all other independent variables are defined in the same way as previously described.

Table 7 reports the results of the regression. In general, we have very similar empirical findings as analyst talent exhibits a strong relation to the change in insider trading prior to positive earnings news. For a robustness check, we also use the 14-day window and obtain similar results.

5. Insider trading profitability

The profitability of insider trading is well documented in the literature, although the SEC requires that no trading by corporate insiders be based on non-public and material information. For example, studies like Finnerty (1976), Seyhun (1986), Rozeff and Zaman (1988), and Lakonishok and Lee (2001) find that corporate insiders earn abnormal returns. For our research purpose, we care about how analyst talent can affect insider trading profitability. Piotroski and Roulstone (2004) and Chan and Hameed (2006) find that the

Table 7
Initial coverage: incremental impact of analyst talent.

	(1)	(2)	(3)
	Netbuy_volum	Netbuy_Value	Netbuy_adjusted Volume
Talent	−4.474**	−2.779**	−1.279**
	(−2.10)	(−2.02)	(−1.99)
Log(MV)	−0.196	−0.306	0.419*
	(−0.23)	(−0.42)	(1.77)
Book/Market	−6.220**	−4.292*	−1.075
	(−2.11)	(−1.75)	(−1.26)
# Analysts	−1.823	−1.476	−0.096
	(−1.18)	(−1.15)	(−0.20)
PP&E	0.912	−0.772	0.966
	(0.29)	(−0.32)	(1.14)
R&D	12.155	12.329	3.741
	(0.82)	(1.09)	(0.83)
Log(Timing)	0.491	0.312	0.125
	(0.50)	(0.48)	(0.41)
Constant	14.943	13.605*	−1.159
	(1.53)	(1.89)	(−0.40)
Observations	4036	4036	4036
R-squared	0.071	0.114	0.081
Firm & Year FE	Yes	Yes	Yes

This table provides results of pooled ordinary least squares (OLS) regressions on the incremental effects of analyst talent on open market insider trading based on the 30-day windows before annual earnings announcements for analyst-firm-year level observations from 1985 to 2008. Initial coverage is defined as the case that an analyst covers a stock for the first time in his/her career. All variables are winsorized at 1% level. Results are 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). Three dependent variables are employed according to the annual changes of the following measures: *Netbuy_volume* is the volume of buys minus the volume of sells then divided by 10,000. *Netbuy_value* is the value of buys (volume times monthly stock price) minus the value of sells then divided by 1,000,000. *Netbuy_adjusted_volume* is the adjusted net buy volume (volume of buys minus volume of sells) and then divided by the number of shares outstanding. The key independent variable is analyst talent. The control variables are: *Log(MV)*, the logarithm of market capitalization of the firm; *Book/Market*, the ratio of book value of the firm to its market value; *# Analysts*, the logarithm of the number of analysts following the firm in a fiscal year; *PP&E,* the property, plant and equipment divided by total assets*; R&D*, the research and development expenses divided by total assets. *Log (Timing)* is the logarithm of the number of days between the initial earnings forecast date (before insider trading window) by the analyst and the earnings announcement date by the firm. Robust standard errors are clustered at firm level. T-statistics are reported in parentheses and ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

number of analysts following positively affects the relative amount of market-level and industry-level information in stock prices, while Liu (2011) and Crawford et al. (2012) argue the opposite. We argue that analysts with higher ability are more capable of collecting firm-specific information, and can thus 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). 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 that occur no more than a week prior to earnings announcements to eliminate possible information leakage through channels other than insider trading. The insider transactions used in our analysis are thus from a [−30, −7] window relative to annual earnings announcement dates. Our analysis is robust to the selection of windows.

We begin our analysis by analyzing different quantiles of analyst talent in post-trading periods. We divide the ability data into 9 quantiles[14] (quantile 1 refers to low ability, quantile 5 refers to median ability, and quantile 9 refers to high ability). 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 Fig. 2A, we find higher ability is related to less positive CARs when insiders have "positive" information about earnings. In Fig. 2B, higher ability is related to smaller absolute values of CARs when the information type is "negative". These two results are consistent with our hypothesis that analyst ability mitigates information asymmetry and therefore, reduces the profitability of insiders trading on their private information.

We calculate t-statistics for the difference in CAR between the high ability group and the low ability group. We test the difference in CAR using six different windows: three days (CAR[0,3]), ten days (CAR[0,10]), one month (CAR[0,30]), two months (CAR[0,60]), three months (CAR[0,90]), and six months (CAR[0,120]). Table 8 presents the differences and t-statistics. We find that all of the differences are statistically significant at the 1% level, and the signs are consistent with Fig. 2. Higher ability is related to a lower level of insider trading profitability for insider buys (sells) if insiders have "positive" ("negative") information about earnings. These results

[14] It is convenient to identify the median quantile in odd quantiles. We also conduct a sensitivity analysis for 5, 7, and 11 quantiles. The results are quite similar for the time-series of mean CARs.

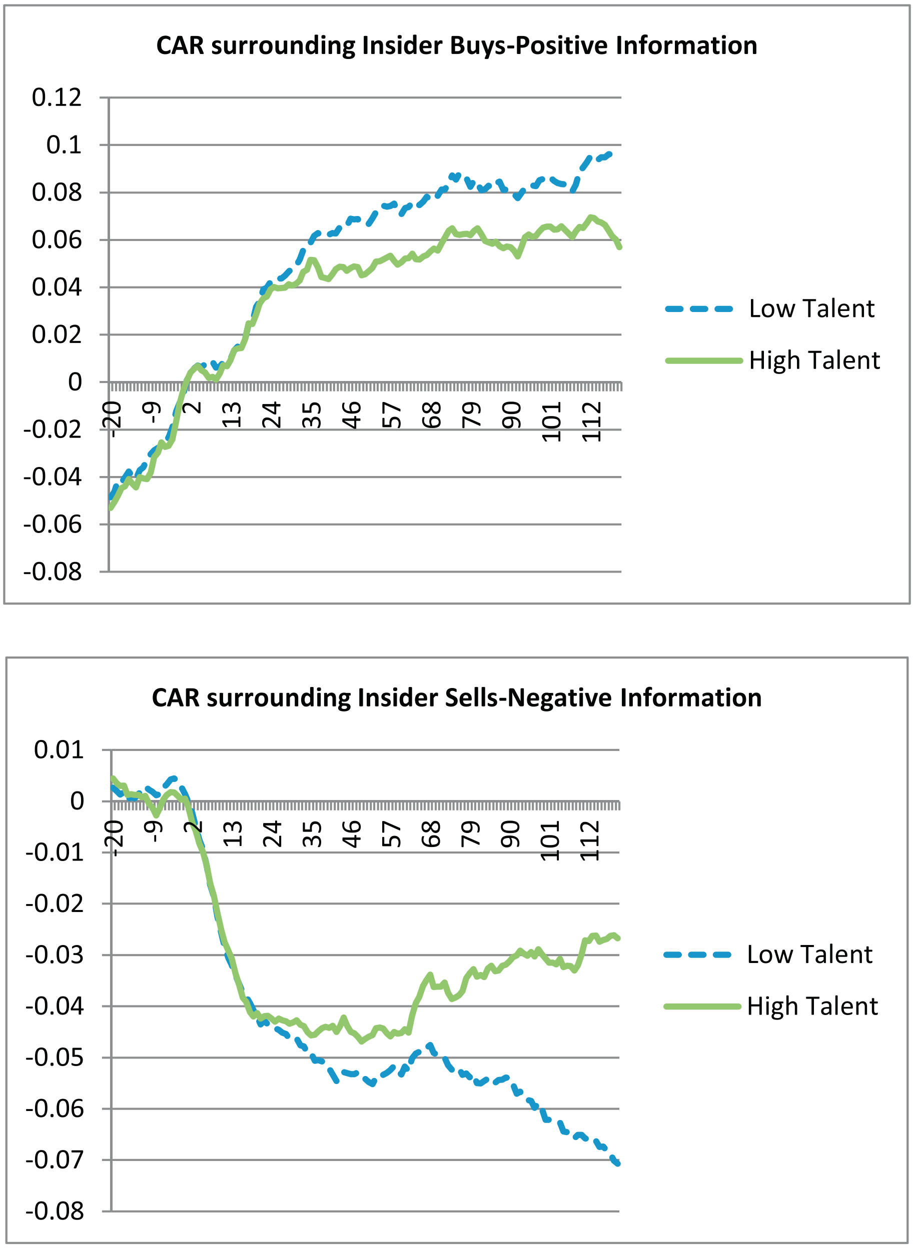


Fig. 2. Ability quantiles and market reactions to insider trading.
Fig. 2 shows stock market reactions (Cumulative Abnormal Returns or CARs) surrounding insider trading among different ability quantiles for 367,973 observations at the forecast-analyst-firm-trading day level. The talent data are divided into 9 quantiles, where quantile 1 = low and quantile 9 = high. 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.
Fig. 2A. Market Reactions around Insider Buys.
Fig. 2B. Market Reactions around Insider Sells.

support the view that high-ability analysts can contribute firm-specific information and lower insider trading profitability.

Overall, we find evidence proving that analyst talent matters for insider trading profitability. When insiders have “positive” inside information about earnings, an analyst’s talent is negatively related to the cumulative abnormal return following insider trades. These results suggest that analyst talent may help reduce the information advantage of insiders. Analyst talent may mitigate information asymmetry between insiders and outsiders or play a monitoring role of detecting illegal insider trading activities. While it is difficult to disentangle the two mechanisms, our paper focuses on the first role of analyst talent. The results on market return synchronicity

Table 8
Talent difference and market reactions to insider trading.

	High Talent minus Low Talent	
	sells+negative	buys+positive
CAR[0,3]	0.00433	−0.00488**
	(1.04)	(−5.37)
CAR[0,10]	0.01278**	−0.00919**
	(4.48)	(7.19)
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)

This table provides the differences of means and the t-statistics 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 (SUE2). Data include insider trading in the [−30, −7] days of window before annual earnings announcements by the firms. ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

(Table 4), insider trading profitability (Table 8), market reactions to insider trading (Fig. 2) all support the information story (but they do not rule out the monitoring story). Our findings also shed light on the nature of information produced by high-ability analysts. Since insider trading profits are primarily based on firm-specific information (Piotroski and Roulstone, 2004), our results suggest that high-ability analysts may produce firm-specific information that is in the possession of corporate insiders, while other analysts with lower talent produce primarily market-level and industry-level information (Piotroski and Roulstone, 2004; Chan and Hameed, 2006).

6. Further analysis

In this section, we discuss various additional issues such as endogeneity issues and the explanatory power of analyst talent relative to other measures of analyst quality.

6.1. Endogeneity and reverse causality

It is possible that certain types of analysts follow certain types of firms. For example, talented analysts might follow firms with more insider trading, which could potentially impact our results in Sections 4 and 5. Talented analysts might also follow firms with low *Synch*, which could possibly affect the results in Section 3. However, we note that not all analysts have a say regarding which stocks they cover. Liang et al. (2008) report that brokerage houses may retain some or all of the decisions about which firms' analysts will follow. Anecdotally, we spoke to a former analyst who indicated that some analysts may have some ability to choose the stocks they follow, but only on the margin. Analysts are typically hired to follow stocks in particular industries, and in small sectors an analyst might need to cover all stocks in that sector or may be required to follow the stocks of the clients of the brokerage house. That said, there may be endogenous matching between brokerage houses and firms covered, analysts hired, and allocation of analysts, in any study using measures of analyst talent. We argue that this endogenous matching problem is more serious when using *observable* analyst characteristics. Our measure conceptually captures unobservable talent that brokers cannot use (easily) for their hiring decisions. This may be another advantage of our measure in comparison to other measures.

We next consider whether corporate fraud drives our results. Agrawal and Cooper (2015) find that top managers sold abnormally more shares before earnings restatement announcement. Dyck et al. (2010) note that analysts detect around 16% of known major U.S. frauds, a higher rate than regulators. Chen et al. (2016) show that analyst coverage (i.e., the number of analysts following) contributes to fraud deterrence in emerging markets with weaker investor protection. Although open-market insider transactions used in our study are legal and not necessarily related to fraud, to see if alleged cases of fraud documented by Dyck et al. impact our results, we use their data to create a dummy variable of alleged fraud uncovered by analysts. We add the variable to Tables 4 and 5 in untabulated results and find that our results are not driven by the channel of corporate fraud.

To further mitigate the endogenous selection issue, in untabulated results we not only control for the past level of insider trading and lagged *Synch* but also limit our sample to the analysts who have already followed certain firms for at least two years. This robustness check should reduce endogeneity issues by excluding the effect of an analyst's initial selection. We obtain qualitatively similar results.

Another endogeneity problem arises when insider trading and analyst ability are simultaneously affected by a firm's information environment. Analyst forecasting accuracy has proven to be higher in firms with higher transparency (e.g., Brown et al., 1987, and

Lang and Lundholm, 1996). If an analyst always picks high-transparency firms to follow, she may have more accurate forecasts and may be considered a high-ability analyst.[15] It is also plausible that corporate insiders trade less when a firm has more transparent information. This leads to a spurious negative relationship between analyst talent and insider trading. To address this issue, following Kelly and Ljungqvist (2012), we examine our results in the context of an exogenous shock—the closure of brokerage houses.[16] The exogenous analyst coverage termination, as a result of brokerage closures, imposes a significantly negative effect on a firm's information environment (Kelly and Ljungqvist, 2012; Irani and Oesch, 2013). We expect more insider net buying prior to positive earnings information and also expect this effect to be more pronounced when analysts of higher talent are involved in closure-related coverage terminations.[17] Using the brokerage closure dates from Appendix A in Kelly and Ljungqvist (2012), we repeat our analysis (similar to Table 5) and report the results in Table 9. Specifically, we construct our three measures of changes in insider net buying activities prior to positive earnings information (SUE>0), by calculating the increase in net buying from year t-1 (the year before closure-related terminations) to year t + 1 (the year after closure-related terminations). We also calculate changes in stock return synchronicity from year t-1 to year t + 1. We then regress these measures on *Talent*, our analyst talent measure. Control variables, discussed in Section 3.1, include market value, book-to-market ratio, number of analysts, PP&E, and R&D. We find that analyst talent has significantly positive coefficients in regressions with all dependent variables. When analysts of higher talent terminate coverage due to exogenous brokerage closures, firms see significantly more insider buying prior to positive earnings news and greater return synchronicity, which is consistent with our hypothesis and previous results.

We also try to mitigate the possibility of reverse causality related to insider trading; that insider trading and other factors related to insider trading "cause" analyst forecasts. We use insider trading data in the 30-day window prior to annual earnings announcements by the firms, and all analyst forecasts in our sample are restricted to at least one month prior to earnings announcements; thus, all forecasts precede insider trading. To further address the reverse causality issue, we run an out-of-sample test. Specifically, we regress insider net buying prior to earnings announcements in 2009–2018 on analyst talent (*Talent*) estimated in 1985–2008. This out-of-sample approach helps with identification in that there is strictly no overlap between the estimation sample of talent and the hold-out sample for our empirical tests. The distinct time windows alleviate reverse causality concerns and provide a clean test.[18]

In Table 10, we report results for our out-of-sample test. Specifically, we regress our insider net buying measures prior to positive earnings information (SUE>0) on analyst talent together with control variables discussed before, including log market value, book-to-market, number of analysts, PP&E and R&D. Timing of analyst forecasts is no longer applicable and not included. The coefficient estimates of *Talent* are negative, which is consistent with our hypothesis. In columns 2 and 3, when trading value and adjusted trading volume are used as dependent variables, the coefficient estimates of *Talent* are significant at the 5% level. The analysts' talent estimated in 1985–2008 can still predict the insider trading activities in the firms they follow in 2009–2018. The ability an analyst demonstrates in the estimation period still plays a role in their future work. The results are weaker compared to those in Table 5 for two possible reasons. Although we assume analyst talent generally does not vary over time or varies slowly, dramatic changes could happen in this 30-year sample period in a specific analyst's life.[19] In addition, the out-of-sample test excludes many new analysts who joined after 2008 and disregards a large amount of information if analysts retired after 2009; being unable to account for these analysts' abilities introduces a bias against our results.

We try to avoid measurement errors in both dependent variables and independent variables by using a variety of different measures. For measures of insider trading intensity, we use trading volume, trading value (volume x price), and adjusted trading volume (volume/number of shares outstanding). We also consider insider trading frequency (the number of trades) as an additional dependent variable and obtain similar yet weaker results. For analysts' unobservable talent or natural talent, our measure, the isolated analyst fixed effect, is novel and its "quasi" normal distribution is consistent with what we might expect for any talent measure. We could not find any closely related measures in the existing literature that could serve as alternative proxies.

In summary, we are aware of and where possible, try to address issues related to reverse causality, measurement error, and omitted variables in order to mitigate the endogeneity problem.

6.2. *Analyst talent versus other measures of analyst ability*

Our findings suggest that analyst talent explains stock return synchronicity and insider trading. Note that our analyst talent

[15] When we measure an analyst's ability, we indeed control for a firm's information environment by calculating the analyst's relative forecast accuracy, relative to all other analysts' forecasts for the same firm. We also explicitly control for R&D, market-to-book, analyst coverage, and firm size as proxies for information environment.

[16] The same experiment has been used in recent studies, including Billett et al. (2017), Bradley et al. (2016), Chen et al. (2015), Derrien and Kesckes (2013), and Merkley et al. (2017).

[17] The presence of high-ability analysts has positive externalities (Merkley et al., 2017); thus, the termination of high-ability analysts may affect the forecast accuracy of other analysts.

[18] We use firm fixed effects in our out-of-sample test, so the time-invariant omitted variables that persist in both the estimation period and evaluation period are controlled for. Time-variant omitted variables in the evaluation period should not affect analyst talent measure. However, time-variant omitted variables in the estimation period could determine both analyst talent and firm outcomes if they have very long-term effects on firms in the evaluation period and short-term effects on talent in the estimation period. Note that other analyst measures (e.g., forecast error) may suffer from this endogeneity issue more severely because they capture more firm and brokerage information that correlates with dependent variables of firm outcomes while our measure is analyst specific.

[19] When we further winsorize the data, for example at 2.5% or 5%, to reduce the effect of the outliers, we do find more significant results.

Table 9
Brokerage house closure, insider trading and return synchronicity.

Variables	(1)	(2)	(3)	(4)	(5)
	Netbuy_Volume	Netbuy_Value	Netbuy_Adj. Volume	Synch_Ind + Mkt	Synch_Mkt
Talent	27.051**	10.665*	1.070	0.280**	0.406**
	(2.17)	(1.75)	(0.65)	(2.03)	(2.21)
Log(MV)	7.406*	2.632	0.459	0.008	0.055
	(1.99)	(1.52)	(1.15)	(0.32)	(1.54)
Book/Market	6.135	−1.937	2.649*	0.028	−0.063
	(0.27)	(−0.23)	(1.96)	(0.34)	(−0.61)
# Analysts	−12.816	−5.044	−3.077	−0.126*	−0.006
	(−1.45)	(−1.21)	(−1.58)	(−1.82)	(−0.07)
PP&E	13.472	5.919	−1.903	0.079	0.332**
	(1.16)	(1.30)	(−0.90)	(0.75)	(2.22)
R&D	−84.217*	−36.194*	−11.362	−0.436	−0.568
	(−1.91)	(−1.96)	(−1.65)	(−0.90)	(−0.81)
Constant	−24.156	11.997	9.353	−0.529**	−0.654**
	(−0.78)	(0.88)	(1.24)	(−2.36)	(−2.15)
Observations	1917	1917	1917	1044	1044
R-squared	0.806	0.816	0.525	0.259	0.390
Firm & Year FE	Yes	Yes	Yes	Yes	Yes

This table reports how analyst ability affects insider trading and return synchronicity for firms which experience changes in analyst coverage due to brokerage house closures. Columns (1)–(3) are 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). We do not report the insignificant results for negative insider information for brevity. The dependent variables are the changes from year t-1 to year t + 1 (year t is the year in which the firm loses analyst coverage due to brokerage house closures) in *Netbuy_volume*, *Netbuy_value*, and *Netbuy_adjusted_volume*, measured over the 30-day window prior to earnings announcements. In columns (4) and (5), the dependent variables are return synchronicity estimated using Eq. (3). The key independent variable is analyst talent. The control variables are: *Log (MV)*, the logarithm of market capitalization of the firm; *Book/Market*, the ratio of book value of the firm to its market value; *# Analysts*, the logarithm of the number of analysts following the firm in a fiscal year; *PP&E,* the property, plant and equipment divided by total assets*; R&D*, the research and development expenses divided by total assets. Continuous variables are winsorized at the 1% level. All regressions include year fixed effects and industry (2-digit SIC) fixed effects. Robust standard errors are clustered at firm level. T-statistics are reported in parentheses and ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

Table 10
Out of sample test (2009–2018).

Dep. Var.	(1)	(2)	(3)
	Netbuy_volum	Netbuy_Value	Netbuy_adjusted Volume
Talent	−0.005	−0.374*	−0.024**
	(−0.59)	(−1.70)	(−2.24)
Log(MV)	−0.007	0.588*	0.019***
	(−0.32)	(1.69)	(3.96)
Book/Market	0.069	−0.009	0.113***
	(0.87)	(−0.02)	(6.54)
# Analysts	0.034	−0.193	0.004
	(0.59)	(−0.29)	(0.34)
PP&E	−0.089*	−2.685*	0.086***
	(−1.74)	(−1.72)	(3.90)
R&D	0.037	0.939	−0.052
	(0.23)	(0.73)	(−0.63)
Constant	−0.083	−3.356*	−0.288***
	(−1.02)	(−1.72)	(−5.45)
Observations	50,712	50,712	50,712
R-squared	0.011	0.015	0.048
Firm & Year FE	Yes	Yes	Yes

This table reports the out-of-sample test results using data from 2009 to 2018. Analyst talent is estimated between 1985 and 2008. Columns (1)–(3) are 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). The dependent variables are three measures of insider net purchase in the 30-day window prior to earnings announcements: *Netbuy_volume*, *Netbuy_value*, and *Netbuy_adjusted_volume*. The key independent variable is analyst talent. The control variables are: *Log(MV)*, the logarithm of market capitalization of the firm; *Book/Market*, the ratio of book value of the firm to its market value; *# Analysts*, the logarithm of the number of analysts following the firm in a fiscal year; *PP&E,* the property, plant and equipment divided by total assets*; R&D*, the research and development expenses divided by total assets. Continuous variables are winsorized at the 1% level. Robust standard errors are clustered at firm level. T-statistics are reported in parentheses and ***, ** and * stand for statistical significance at 0.01, 0.05 and 0.1 levels, respectively.

measure is obtained from regressions that control for a wide range of analyst ability measures such as analyst experience, brokerage house affiliation, and other personal characteristics. Our method allows us to separate analyst, broker, firm, time, and luck (i.e., residuals) effects and extract the information about the analyst specific talent by purging all the other effects and noises.

In this subsection, we further examine the explanatory power of analyst talent relative to other measures of analyst ability suggested in the literature. Specifically, we consider the following measures. Analyst experience (*Experience*) is defined as the total number of estimates issued for a firm by an analyst (this measure is similar to the "intensity of firm experience" used by Clement (1999) and Clement et al. (2007). Cumulative forecast error (*FC Error*) is the historical forecast error for a firm by an analyst. Both experience and forecast error are shown to affect firm information environment by Wu (2019), and we follow Wu (2009) to define these two variables. In addition, we consider analyst general experience (General Experience), defined as the number of years of an analyst's general experience, following Clement (1999) and Clement et al. (2007). We also define All-Star analysts (Star Analyst) as a dummy that equals one if an analyst is listed as an *Institutional Investor* "All-Star" analyst during our sample period.

To assess the relative explanatory power, we run "horse race" regressions by including all measures of analyst talent in Tables 4 and 5, together with other control variables and fixed effects for firms, years and industries. We report the results in Online Appendix Tables A and B. In general, our analyst talent measure remains statistically significant in all regressions, while the other commonly used ability measures cannot effectively explain stock return synchronicity or insider net buy. Their coefficient estimates are either statistically insignificant, or statistically significant but with sign opposite to our prediction. To conclude, we show that our variable, while granted not as easy to measure, provides stronger results in support of theories and hypotheses.

7. Conclusions

Financial analysts affect insider trading through the information channel. Our study employs a novel measure of sell-side financial analyst talent and explores its effects on reported corporate insider trading. We postulate that analysts with high talent can reduce information asymmetry between corporate insiders and outside investors through more accurate earnings forecasts, thereby negatively affecting insider trading intensity and profitability.

The empirical results show that analysts with higher talent are associated with less insider trading intensity and profitability. This effect is significant in opportunistic trades but not in routine trades. Furthermore, the results are stronger when high-ability analysts initiate coverage and terminate coverage due to brokerage closures. As a robustness check, we conduct an out-of-sample test to predict insider trading outside the estimation window of analyst talent and find that our results hold.

These findings suggest that high-ability analysts can contribute more than low-ability peers to a firm's information environment. Expanding on previous studies that focus on the quantity of analyst following and its negative association with insider trading activities, we show that the negative association is largely driven by analysts with higher talent. This suggests that the key to a better information environment is not analyst coverage per se but analyst quality. To the best of our knowledge, this paper is the first to connect analyst talent with insider trading while advocating quality over quantity.

Furthermore, our findings shed light on the nature of information contained in analyst forecasts. The nature of information produced by an analyst depends on her talent; while analysts in general produce market-level and industry-level information, high ability analysts contribute more firm-specific information to a firm's information environment. Thus, our findings extend previous studies (e.g., Piotroski and Roulstone, 2004; Chan and Hameed, 2006) which suggest that analysts on average produce more market and industry-level information than firm-specific information.

These results have practical implications. First, our results suggest that both the intensity and profitability of insider trading can be significantly reduced when firms are followed by high ability analysts. For example, by producing firm-specific information through more accurate forecasts, talented analysts can effectively reduce the critical information asymmetry between managers and outside investors. Second, from a risk management perspective, our results show that when a firm is followed by high-ability analysts, its stock prices should be more reflective of its true intrinsic value and hence less likely to be mispriced. Third, in the arduous campaign against illegal insider trading which is based on material private firm-specific information, high-ability analysts can play an important role. Analyst ability, rather than the number of analysts following, can help alleviate such insider trading and lead to more efficient capital markets.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2020.101803.

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