Determinants of Analyst Skill Specialization

by

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the requirements for the degree of Doctoral
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ABSTRACT

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Abstract

My dissertation examines individual analysts' specialization in earnings forecasting skill and stock picking skill. I analyze analyst utility maximization process and predict that non-specialization is optimal for analysts when there is considerable economy of scope between the two skills' development; that specialization is optimal when the costs of skill development are high; and that the marginal benefit of each skill is positively correlated with the chance that analysts choose to develop that particular skill. Consistent with my hypotheses, I find empirical evidence that an analyst's choice of non-specialization is positively correlated with his brokerage size, brokerage reputation, his all-star status, the industry skill spillover effect, all of which capture the inverse of the costs associated with skill development. I show that the economy of scope in skill development, measured with earnings relevance and earnings timeliness, can explain an analyst's choice of skill specialization versus non-specialization, albeit in a non-linear manner. Using earnings persistence, earnings predictability, and earnings fixation to measure investors' demand for analysts' earnings forecasting skill, and firms' shareholder base to measure the demand for analysts' stock picking skill, I show that these firm characteristics explain analysts' choices between the two skill specializations. I also find analysts who specialize in earnings forecasting utilize the skill more intensively than analysts who do not by issuing more frequent and more innovative

earnings forecast revisions. However, there is no significant relation between relative stock recommendation frequency and stock picking specialization probably due to the highly discrete nature of stock recommendations. My study not only empirically tests the theories of labor specialization but also improves our understanding of analyst utility maximization process and skill development.

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1. Introduction

Sell-side financial analysts (hereafter, analysts) are important information intermediaries in U.S. capital markets. The two key products they generate, earnings forecasts and stock recommendations are quantitative and verifiable measures. [1] These measures are used in various ways by investors as inputs to their investment strategies, by brokerage firms and their clients to evaluate analysts as performance measures, and by researchers to study the decision processes of sophisticated investors represented by analysts. It is well known and documented that analysts' career outcomes are affected by their performance in earnings forecasting and stock picking.[2] Hence, analysts have incentives to develop earnings forecasting skill and stock picking skill. In this paper, I study the relation between individual analysts' earnings forecasting skill and stock picking skill. Specifically, I examine the variation in the relative strength of individual analysts' earnings forecasting skill and stock picking skill, with skills measured relative to analysts' peers.

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[1] Target price is another quantitative measure available in analyst research reports, however, it is not subject to market scrutiny or used as performance measures in determining analysts' compensation as much as earnings forecasts and stock recommendations are (Bradshaw and Brown [2006]). It is suggested by Bradshaw [2002] that target prices are provided in research reports *ex post* to justify analysts' stock recommendations.

[2] For example, Mikhail, Walther and Willis [1999] find that analysts are more likely to turnover if their earnings forecast accuracy is lower than their peers; *The Wall Street Journal* ranks analysts based on their stock recommendation profitability.

Prior studies on earnings forecasts and stock recommendations mostly examine each of them *in isolation* (see Schipper [1991], Brown [1993] and Ramnath, Rock and Shane [2006]). Two pieces of evidence emerge from prior literature: i) analysts have differential earnings forecasting abilities; and ii) analysts have differential stock picking abilities. My paper extends the prior literature by studying the relation between analysts' differential earnings forecasting abilities and stock picking abilities. That is, for any given analyst, what is the relative strength between these two abilities? Compared to peers, does an analyst specialize in forecasting earnings or making profitable stock recommendations, or is an analyst equally good at both tasks? Is there any cross-sectional variation among analysts on the relative strengths? If yes, what are the determinants of such variation?

Note that I am interested in how analysts specialize in their *outputs*, i.e., their relative strength in earnings forecasting and stock picking skills. Such *skill specialization* is different from analysts' *industry specialization* which is well-known and documented in the extant literature. For example, *Nelson's Directory of Investment Research* lists analysts by industry groups; *Institutional Investor* and *Wall Street Journal* provide annual ranking of analysts by industry. Analysts' industry specialization is most likely driven by synergies in covering firms within that industry and analysts' time and inherent constraint on effort. O'Brien [1990] and Clement [1999] find that analysts' forecast accuracy increases with industry specialization. Analysts' industry specialization and skill specialization capture different area of specialization; and the extant literature speaks very little about the determinants of analysts' skill specialization. Using accounting academics as an analogy, specializing in specific areas, such as financial accounting, managerial accounting, and taxation, parallels industry specialization. However, accounting academics also serve dual roles of teaching and research. My paper is interested in what drives their relative strengths in teaching and research skills, i.e., their skill specialization. [3]

Theory and evidence on skill specialization are well-known and widely documented in the labor market research. For example, Smith [1776] begins *The Wealth of Nations* with a discussion of the division of labor; Babbage [1832] attributes the labor market specialization to workers' differential endowments and comparative advantages; Rosen [1978] discusses workers' heterogeneity and their selection of specialization; Rosenberg [1976] concludes that workers specialize because of greater returns to personal reputation and informational scale economy; Becker [1981] and Rosen [1983] attribute specialization to the increasing returns to utilization of human capital and the fixed cost element of skill development (Rosen [1974], Rosen [1983], and Rosen [2002] offer comprehensive reviews of this literature). A common theme in this literature is

[3] The inferences from my study are not affected by analysts' industry specialization because skill specialization is measured as the relative strength of earnings forecasting and stock picking skills at industry-year level, both of which are arguably affected by analysts' specialization in that industry by the same extent.

that skill specialization, also called division of labor, is driven by labor market competition, and is optimal both for individual workers and for the society as a whole.

Financial analysts, are subject to the same economic forces of labor market competition and individual utility maximization as any other. Therefore, we should observe predictable variations in analysts' skill specializations determined by factors such as the market demand for their services, their specific working environments, the returns and costs of their specific skill development process. Analysts provide a useful industry to test the labor market theories of skill specialization for several reasons. First, unlike many other work forces (such as nurses, scientists or engineers), analysts' skills in forecasting earnings and picking stocks are homogenous in that they are quantifiable and comparable cross-sectionally due to the relatively homogeneous nature of the tasks performed (i.e. issuing earnings forecasts and stock recommendations). Second, there is a large amount of data available to measure analysts' skills of forecasting earnings and picking stocks. Third, due to the economies of scope of developing earnings forecasting and stock picking skills and the interrelation between the two skills, it is likely that specialization is not the only optimal outcome for analysts. In contrast, for many other work forces, skill spillovers and economies of scope in skills are so low that specialization in a very narrow band of skill becomes the only outcome observed. Fourth, there are significant variations in analysts' working environments, in market's demand for their services, and in the characteristics of their covered firms, leading to potentially a higher level of variation in analysts' specialization choices.

Studying analysts' skill specialization is also interesting because analysts represent sophisticated investors in the financial market. As accounting researchers, we are interested in the nature of their expertise, their utility function and decision process. Moreover, analysts are important information intermediaries in U.S. capital markets. Investors can benefit from understanding and predicting individual analysts' expertise by putting higher weights on the outputs from specializing analysts in forming investment decisions. My study is motivated by the same broad questions as I examine how analysts choose their specializations to maximize utility and identify the determinants of their choice. I predict and find that the characteristics of the analysts, the analysts' brokerage house, and the analysts' covered firms affect analysts' specialization choice.

One might argue that being a good earnings forecaster implies a good stock picker for the following reasons. First, both abilities are likely to increase over time due to the experience gained via "learning by doing". [4] Therefore, one might expect to observe a high correlation between the two skills across analysts simply because each of

[4] Although we have evidence that forecast accuracy increases with experience (Mikhail, Walther and Willis [1997], Clement [1999]), current research finds no evidence that stock picking ability increases with experience (Mikhail et al. [1997], Chen and Cheng [2003], Mikhail, Walther, Wang and Willis [2006], Ertimur, Sunder and Sunder [2007]). Chen and Cheng [2003], Mikhail et al. [2006], and Ertimur et al. [2007] find some evidence that stock picking ability is negatively associated with experience.

them is positively correlated with experience. Second, both abilities are likely to be positively correlated with analysts' innate ability. Third, forecasted earnings represents an important input in the valuation models that analysts use. [5] Following the intuition that "better input leads to better output", it is likely that the ability to forecast more accurate earnings can automatically increase the ability to forecast more accurate target prices, thereby resulting in the greater ability to generate profitable stock recommendations.

However, an examination of the correlation between the relative strengths of the two skills suggests that such a conjecture is invalid. In particular, I find that the correlation between earnings forecasting skill and stock picking skill is a mere 0.02. [6] Furthermore, I plot analysts in a skill grid with each skill as one axis and find that there are a considerable number of analysts distributed off-diagonal. That is, analysts are not always good or bad at both skills. I argue that although forecasting earnings and picking stocks require related skill sets, there exist sufficient differences in the two skill

[5] There is evidence that analysts use simple heuristics instead of present value techniques to value stocks (Block [1999], Bradshaw [2002], Demirakos, Strong and Walker [2004], Bradshaw [2004], Asquith, Mikhail and Au [2005], and Gleason, Johnson and Li [2006]). Therefore, more accurate earnings forecasts might not translate into more profitable recommendations due to the poor valuation technique used.

[6] Depending on the different measures of returns (raw returns, market adjusted returns, and Fama-French three-factor adjusted returns) used to measure stock recommendation profitability, the correlation between analysts' earnings forecasting ability and stock picking ability ranges from 0.016 to 0.028. In a sensitivity test, after excluding affiliated analysts, the correlation between earnings forecasting skill and stock picking skill remains as low as 0.020, suggesting that the low correlation is unlikely due to analysts' biases arising from conflict of interests.

sets that can give rise to the possibility that one can excel as a good stock picker without being a good earnings forecaster, and vice versa.

Earnings forecasting skill requires a good understanding of a firm's accounting policies, managers' earnings guidance, short-term business strategies and performance, and historical time-series of earnings stream. On the other hand, stock picking skill is arguably more onerous. It depends on: i) the efficiency with which the analyst collects and analyzes value-relevant non-financial information; ii) the accuracy of the valuation model; iii) the precision of other inputs in the valuation model, and iv) the ability to assess the efficiency of current stock price. Other inputs needed to generate profitable recommendations include long-term growth forecast, risk assessment, and prediction of future time-series dynamics of earnings stream, all of which require a broader understanding of managerial abilities, strategic alliances, intangible assets, other growth opportunities, industry-wide conditions and macro-market environment. Hence, compared with the skill required to accurately forecast earnings, the skill required to generate profitable recommendations is likely more long-term oriented, involves more industry and market level analysis, and broader financial expertise (such as valuation expertise, risk assessment expertise and macro-level analysis). The above arguments suggest that both skills compete for an analyst's time and effort. For example, when an analyst spends more time on learning how to collect non-financial or long-term information about the firm, he might have less time to refine his earnings forecast model. The prior literature, however, provides limited evidence on how analysts allocate their resources, time and efforts in developing the two skills.

My paper complements and extends Loh and Mian [2006] and Ertimur et al. [2007] that document a systematic relation between forecast accuracy and recommendation profitability. These studies imply that analysts' skill distribution should concentrate on the diagonal when analysts are assigned into a 2x2 matrix based on the rankings of their skills, i.e. analysts with a higher (lower) earnings forecasting skill should have a correspondingly higher (lower) stock picking skill. My paper adds to this growing literature in three ways. First, I explore the characteristics that underlie analysts' specialization of one skill versus the other. Hence, my study offers explanations for analysts with unbalanced skills, i.e. analysts with a higher (lower) earnings forecasting skill but a lower (higher) stock picking skill.

Second, prior studies stop at examining the relation between the quality of inputs (earnings forecast accuracy) and the quality of outputs (recommendation profitability) – i.e., these studies test for a given analyst who has a more accurate earnings forecast, whether he on average would produce a more profitable recommendation. They implicitly assume that analysts are homogeneous, and hence, focus primarily on the average relation between earnings forecast accuracy and stock recommendation profitability. In contrast, I do not assume homogeneity among analysts. That is, I assume cross-sectional variations in the parameters of individual analysts' utility functions, which in turn enables me to examine whether an analyst's relative strengths in the two skills can be explained by economic factors such as the work environment, characteristics of the firms covered, etc. In essence, I argue that earnings forecast accuracy is only one of the contributors to the quality of stock recommendations. Consequently, analysts face tradeoffs in allocating their time and effort to specialize in earnings forecasting versus stock picking.

Third, Loh and Mian [2006] and Ertimur et al. [2007] only document a *contemporaneous* positive correlation between earnings forecast accuracy and stock recommendation profitability. Therefore, their results have little predictive implication for investors because by the time investors observe the accuracy of earnings forecast, the stock recommendation has turned stale. In contrast, my paper indentifies economic determinants of analysts' specializations. Hence investors can make better use of analysts' products, earnings forecasts and stock recommendations, by predicting analyst specialization and place appropriate weights to analysts' products when aggregating analysts' outputs cross-sectionally.

My paper also makes a methodological contribution to the literature in that my research design incorporates a unique way of controlling for analysts' innate ability when measuring analysts' specializations. Finding a good proxy to control for analysts' innate ability is a nontrivial task. The extant literature uses brokerage size, brokerage reputation, experience and performance as proxies for analysts' innate abilities. In my research design, the analysts who make the choice between specialization and non-specialization are of the same level of innate abilities (detailed discussions are deferred to the research design and variable measurement chapter). Therefore, in my study, brokerage size, brokerage prestigious level and analysts' experience are used to capture characteristics of analysts other than their innate ability and their working environment instead of serving merely as proxies for analysts' innate abilities.

My paper also extends extant literature by showing that an analyst's expertise depends on the type of firms/industries he covers. I show that the properties of earnings (earnings relevance, earnings timeliness, earnings persistence, and earnings fixation) influence both earnings forecasting skill and stock picking skill, and these in turn affect the nature of skill specialization. Currently, there is little research on how the characteristics of the firms being covered influence analysts' expertise development and learning process. I show that analysts' choice to specialize is influenced by the demands of their clients, i.e. the clientele effect. In particular, if a firm's investors are mostly individual investors, the demand for profitable stock recommendations is higher and analysts spend more time to develop stock picking ability. Therefore, by documenting that the economic environment surrounding the firms covered by an analyst influences the development of his specialization in earnings forecasting versus stock picking, I shed light on the forces that determine the cross-sectional variations in the relation between forecast accuracy and stock recommendation profitability.

The rest of my dissertation is organized as follows. Chapter 2 reviews relevant prior research. Chapter 3 develops research hypotheses. Chapter 4 discusses empirical design and variable measurements. Chapter 5 describes sample selection procedures and empirical results. Sensitivity test results are presented in Chapter 6. Chapter 7 concludes the paper.

2. Prior Research

My paper is related to two literatures. It closely relates to both the research on individuals' skill specialization in the labor market and the research on analysts' expertise with respect to the interrelation between earnings forecasting and stock recommendation.

My paper is closely related to a strand of the economics literature on the division of labor that deals with individuals' specialization decision. Research on division of labor dates back to discussions in Plato's [380BC] *The Republic*, and Smith's [1776] *The Wealth of Nations*. Both classical thinkers attribute society's development to labor specialization. Smith points out that individual rationality and self-interest add up to the social good. Despite the importance of the idea, research on division of labor, both theoretically and empirically, was scarce until the last few decades. In 1976, Stigler [1976] called for researchers' attention,

> "…there is no standard, operable theory to describe what Smith argued to be the mainspring of economic progress. Smith gave the division of labor an immensely convincing presentation – it seems to me as persuasive a case for the power of specialization today as it appeared to Smith. Yet there is no evidence, so far as I know, of any serious advance in theory of the subject since his time, and specialization is not an integral part of the modern theory of production, which may well be an explanation for the fact that the modern theory of economics of scale is little more than a set of alternative possibilities."

Since the mid-1970s, theoretical research by Becker and Rosen helped advance the research on individuals' specialization decision. Rosen [1978] formally shows that it is optimal to assign workers to tasks with skills in which they have comparative advantages. In a similar vein, Becker [1981] formally develops a model to show that division of labor within a household is efficient because household members can exploit comparative advantages and avoid duplicate learning and training costs. Further, Rosen [1983] shows that given the independence of skill development cost and the subsequent utilization of skills, a higher skill development cost leads to specialization. Other representative papers that model individual's specialization decisions include Baumgardner [1988a], Kim [1989], Locay [1990], and Becker and Murphy [1992].

Compared to the thriving theoretical research in this area, empirical research on individuals' specialization decision remains scarce, due to the difficulty in quantifying skills for workers in many professions as well as the lack of data availability even if the skills are quantifiable. I am aware of two exceptions. One is Baumgardner [1988b] who examines specialization by general physicians. Using the range of procedures performed by general physicians as proxy for level of specialization, Baumgarder [1988b] finds that general physicians who are working fewer hours, practicing in more populated markets, or practicing in counties with more elderly, specialize more. A recent paper by Kendall [2002] examines the specialization of academic economists. Using the number of JEL classification codes assigned to each publication to measure the level of specialization, he finds that economics professors who graduated from higher-ranked Ph.D. programs write less specialized papers than professors who work for the same university but graduated from lower-ranked Ph.D. programs. He argues that rankings of the Ph.D. programs can capture economists' general abilities and the results are consistent with the differences in general abilities can lead to differential choices of specializations.

The extant literature on financial analysts is yet another area where specialization, i.e., individual analysts' expertise in this context, has been exclusively examined. First, there is some empirical evidence that analysts exhibit differential earnings forecasting abilities. Early research (O'Brien [1990], Butler and Lang [1991] and Jacob, Lys, and Neale [1997) fails to reject that analysts are homogeneous in their forecasting abilities. Recent work by Sinha, Brown, and Das [1997] show that earnings forecasting abilities among analysts are persistent. Clement [1999] and Mikhail et al. [1997] test the idea of "learning by doing" by studying the cross-sectional relation between earnings forecast accuracy and experience. Both papers document that analysts develop earnings forecasting ability over time by showing a positive association between analysts' earnings forecast accuracy and firm-specific experience. However, Mikhail et al. [1997] do not find significant association between firm-specific experience and stock picking ability. Moreover, Chen and Cheng [2003], Mikhail et al. [2006], and Ertimur et al. [2007] find evidence that stock picking ability is negatively associated with experience. However, none of these studies explore this seemingly unintuitive result.

Our current understanding about how analysts develop stock picking ability remains rudimentary. A recent paper by Mikhail, Walther and Willis [2004] finds that individual analysts' stock picking ability is persistent. Specifically, they place analysts into quintiles based on stock recommendation profitability in the prior one, three and five years, and compute the characteristic-adjusted excess returns for the portfolios of stock recommendations formed for each quintile. They find that the portfolio returns are significantly higher from the most profitable prior stock recommendations quintile. Using a similar approach, Li [2005] also finds that past stock recommendation profitability persists into a one-year holding period at analyst level and that a trading strategy based on past stock picking ability can be economically profitable.

The overall message from these papers (Chen and Cheng [2003], Mikhail et al. [2004], Li [2005], Mikhail et al. [2006], and Ertimur et al. [2007]) is that stock picking ability represents a persistent skill that does not improve with experience. Mikhail et al. [2006] extend Mikhail et al. [2004] and find that analysts' recommendation profitability is negatively correlated with the number of industries covered by analysts and positively correlated with the size of their brokerage houses.

My research is partially motivated by the same broad question on the nature of analysts' expertise. I attempt to explain whether analysts develop different abilities by examining the relation between individual analysts' relative strengths in earnings forecasting and stock picking skills. My paper contributes to our understanding of the nature of analysts' expertise by documenting that analysts' relative strength in the two types of expertise, i.e. their specialization choices, is individual specific and is the outcome of analysts' utility maximization.

Loh and Mian [2006] and Ertimur et al. [2007] are two recent papers that are most closely related to my paper. These studies examine the contemporaneous correlation between earnings forecast accuracy and stock recommendation profitability. Loh and Mian [2006] use a portfolio approach where, for every firm-year, they sort analysts into quintiles of the accuracy of their outstanding earnings forecasts on June 30th. They then form hedge portfolios by taking long (short) position on firms with favorable (unfavorable) stock recommendations. Monthly market adjusted returns and abnormal returns based on the intercepts from CAPM, Fama-French, and Four-Factor models for the same year are calculated for each quintile-portfolio. They find that the monthly hedge returns from the most accurate forecast quintile portfolio are significantly greater than the hedge returns from the least accurate forecast quintile portfolio. They interpret the results as indicating "better inputs lead to better outputs" and as indirect support for the valuation models in the finance and accounting literatures.

However, Loh and Mian [2006] stop at documenting the positive abnormal returns generated from the long/short strategy without testing what exactly is contributing to the abnormal returns. It could be because earnings forecasts are an important input to analysts' valuation models, and because better inputs lead to better outputs, as the authors argue. Alternatively, it is plausible that the analysts in the most accurate forecast portfolio have higher innate ability and hence, they tend to be better stock pickers as well, i.e, both earnings forecast accuracy and stock recommendation profitability are positively correlated with analyst innate ability.

Ertimur et al. [2007] extend Loh and Mian [2006] and study the relation between earnings forecast accuracy and stock recommendation profitability at analyst-firm level using a regression approach. They find that stock recommendation profitability is positively correlated with earnings forecast accuracy for the firm after controlling for the analyst's expertise proxied by his firm experience, size of his brokerage house, number of firms he follows, his recommendation frequency, leader-follower-ratio and the number of analysts following the firm. They find conflicting results on the proxies for analysts' "expertise" (i.e. which I refer to as innate ability). While they find that stock recommendation profitability is positively correlated with the analyst's brokerage size and the leader-follower-ratio, it is negatively correlated with his firm experience, the number of firms followed by the analyst, recommendation frequency, all of which can potentially represent analysts' "expertise".

The *contemporaneous* relation documented in Ertimur et al. [2007] between earnings forecast accuracy and stock recommendation profitability does not imply that investors will benefit by choosing stock recommendations from analysts who make accurate forecasts. This is because by the time investors observe forecast accuracy, when actual earnings are released, it is already too late to form investment strategy by following the stock recommendations from the analysts who issue the more accurate earnings forecasts. Moreover, they do not consider *individual* analyst's utility maximization process; that is, earnings forecast accuracy is considered as exogenous. In contrast, I look at individual analyst utility maximization process with analysts' relative strengths in earnings forecasting and stock picking skills as choice variables. In my setting, both skill levels are endogenous and are chosen by analysts, and the determinants of these choices, i.e., characteristics of the analysts, the brokerage house they work for and the firms they follow, are estimated based on historical information.

3. Hypothesis Development [1]

As discussed in Chapter 1, developing skills in forecasting earnings and picking stocks likely has economies of scope. That is, investing in one skill decreases the marginal cost of investing in the other. It is reasonable to assume that analysts enjoy certain economies of scope for forecasting earnings and picking stocks and the economies of scope depends on the characteristics of the firms covered by the analyst. If the analyst covers firms where the skills for predicting earnings and price movement facilitate each other, [2] then developing one skill reduces the cost of developing the other. Therefore, it is more efficient for the analyst to develop both skills than other analysts who cover firms where the two types of skills do not facilitate each other, suggesting that the analyst would be more likely to choose non-specialization than other analysts. Presumably, the two types of skills facilitate each other more in firms where earnings and stock price movements are highly synchronized, i.e., earnings news triggers larger stock price changes (earnings relevance) and stock price changes covary to a higher

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[1] I also provide a formalized development of the hypotheses in this chapter in Appendix I and II, where I follow Rosen [1983] and develop a simple analytical model to show the circumstances where an analyst will choose to specialize in one of the two skills in order to maximize the return to his human capital.
[2] Predicting earnings facilitates generating profitable stock recommendations since short-term earnings forecast is an input variable to analysts' valuation models. Predicting price movement facilitates predicting earnings both because current period real transactions are determined by firms' long-term growth opportunities or business strategies, and because many accounting estimates and assumptions managers make are also driven by long-term business strategies reflected in stock movements.

degree with earnings changes (earnings timeliness). Therefore, we have the following hypotheses:

H1a: An analyst would be less likely to specialize in one skill if the covered firms have higher earnings relevance.

H1b: An analyst would be less likely to specialize in one skill if the covered firms have higher earnings timeliness.

Note that for non-specialization to be optimal, the economies of scope in developing skills must be large enough to overcome the effect of increasing marginal cost of developing skills. Stated differently, only if the marginal cost and the changing rate of the marginal cost of developing earnings forecasting skill or stock picking skill are sufficiently low for an analyst, would he develop both skills. Presumably, the marginal costs of developing skills are related to many characteristics of the analyst's working environment. If an analyst works for a larger brokerage house, he is likely to enjoy more resources and support that can lower his marginal costs of developing the skills in forecasting earnings or picking stocks than analysts who work for smaller brokerage houses. It is also possible that brokerage houses would allocate more support and resources to a star analyst because of his established reputation than they do to a non-star analyst. Moreover, analysts' marginal cost of developing skills would be lower when they can learn more from their peers. For example, if an analyst covers an industry with a large number of analysts following, it is easier for him to develop skills since he can observe other analysts' forecasting behaviors, learn from the questions they ask during conference calls, and read their research report. The larger the number of analysts covering the industry, the greater the skill spillover effect, which lowers the marginal costs of developing earnings forecasting and stock picking skills. The above discussion leads to the following hypotheses (in alternative form):

H2a: An analyst will be more likely to specialize in one of the two skills with limited resources and support from his/her brokerage house.

H2b: An analyst who is an Institutional Investor All-American Research Team analyst will be less likely to specialize in one of the two skills.

H2c: An analyst will be more likely to specialize in one of the two skills, if there are a large number of other analysts following the same industry he covers.

If specialization is optimal for an analyst, the decision to specialize in a particular skill depends on which skill specialization provides a higher benefit, which is in turn determined by the market demand for the skills. The market demand for superior earnings forecasting skill is higher when firms' earnings are difficult to predict but useful for investment decisions, therefore, providing analysts with incentives to specialize in earnings forecasting skill. I use earnings persistence to capture earnings' usefulness for investment decision since transitory earnings are less value relevant.

Note that earnings persistence and earnings predictability capture two different properties of firms' earnings stream. That is, one firm can have highly persistent but unpredictable earnings and vice versa. Another measure for market's demand for superior earnings forecasting is based on the investors' fixation on earnings widely documented both empirically by researchers (Burgstahler and Dichev [1997], Matsunaga and Park [2001], Matsumoto [2002], Kasznik and McNichols [2002], Bartov, Givoly and Hayn [2002], Graham, Harvey and Rajgopal [2005], and Burgstahler and Eames [2006]) and anecdotally (e.g. the remarks by former SEC Chairman Arthur Levitt, Fox [1997]). Also documented empirically and anecdotally is that investors penalize companies' shares if earnings miss analysts' forecasts by just one cent. Therefore, such fixation on earnings pressures analysts to develop superior earnings forecasting skill since a small deviation from the forecasted earnings can trigger a large market reaction.

The market demand for stock recommendation is higher when the investors of the firms are individual investors who do not have the financial expertise to process earnings forecasts and construct investment strategies based on the them, but can follow analysts' stock recommendations directly. Therefore, we have the following hypotheses:

H3a: An analyst will be more likely to specialize in forecasting earnings when the covered firms have persistent earnings.

H3b: An analyst will be more likely to specialize in forecasting earnings when the covered firms have unpredictable earnings.

H3c: An analyst will be more likely to specialize in forecasting earnings when the investors of the covered firms fixate on earnings.

H3d: An analyst will be more likely to specialize in picking stocks when the covered firms attract more individual investors.

Note that skill development and skill utilization are two different processes. [3] Assuming that once a certain level of skill is acquired, utilizing the skill does not incur any costs. Therefore, the return to a skill is increasing in utilization and is maximized by utilizing the specialized skill as intensively as possible. The intensity of such skill utilization can be proxied by the total number of revisions and the percentage of "high-innovation" revisions analysts issue for earnings forecasts and the number of stock recommendations respectively. [4] Therefore, we have the following hypotheses:

H4a: Earnings forecast frequency is higher when an analyst specializes in forecasting earnings.

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[3] Analysts can develop skills by self-studying, learning from their peers, obtain training from the brokerage house, and etc.

[4] Note that, analysts do not always issue earnings forecasts and stock recommendations together. There are 2,762,440 unique analyst-firm earnings forecasts and 924,861 unique analyst-firm stock recommendations in Zacks. 86% of all the earnings forecasts in Zacks are issued without accompanying stock recommendations; 59% of all the stock recommendations in Zacks are issued without accompanying earnings forecasts. It is unlikely that the above statistics are due to Zacks recording earnings forecasts and stock recommendations on different days because treating earnings forecasts and stock recommendations issued within one/two day(s) from each other as being issued together yields almost the same result. Therefore, the statistics from Zacks suggest that analysts do not always issue these two products together.

H4b: The percentage of "high-innovation" earnings forecast revisions is higher when an analyst specializes in forecasting earnings.

H4c: Stock recommendation frequency is higher when an analyst specializes in picking stocks.

4. Research Design and Variable Measurement

To test H1 and H2, I use the following logit regression:

$$\text{Special}_{\text{idt}} = \text{fn}\begin{pmatrix} \text{Earnings Relevance}_{\text{idt}}, \text{Earnings Timeliness}_{\text{idt}}, \\ \text{Brokerage Size}_{\text{it}}, \text{Brokerage Reputation}_{\text{it}}, \\ \text{Star Status}_{\text{it}}, \text{Industry Skill Spillover}_{\text{idt}}, \text{Controls}_{\text{idt}} \end{pmatrix}$$

where, $\text{Special}_{\text{idt}}$ is an indicator variable that equals one if analyst i has specialization in industry d, year t, zero otherwise.

For the subsample of analysts with specialization, I use the following logit regression to test H3:

$$\text{S\_Special}_{\text{idt}} = \text{fn}\begin{pmatrix} \text{Earnigns Persistence}_{\text{idt}}, \text{Earnings Predictability}_{\text{idt}}, \\ \text{Earnings Fixation}_{\text{idt}} \\ \text{Shareholder Base}_{\text{idt}}, \text{Controls}_{\text{idt}} \end{pmatrix}$$

where, $\text{S\_Special}_{\text{idt}}$ is an indicator variable that equals one if analyst i specializes in stock picking skills in industry d, year t; zero if he specializes in earnings forecasting skills.

For the subsample of analysts with specialization, I test H4 with the following OLS regressions:

$$\text{Earnings Forecast Frequency}_{\text{idt}} = \text{fn}(\text{S\_Special}_{\text{idt}}, \text{Controls}_{\text{idt}}),$$

$$\text{Earnings Forecast Innovation}_{\text{idt}} = \text{fn}(\text{S\_Special}_{\text{idt}}, \text{Controls}_{\text{idt}}),$$

$$\text{Stock Recommendation Frequency}_{\text{idt}} = \text{fn}(\text{S\_Special}_{\text{idt}}, \text{Controls}_{\text{idt}}).$$

where, $\text{S\_Special}_{\text{idt}}$ is an indicator variable that equals one if analyst i specializes in stock picking skills in industry d, year t; zero if he specializes in earnings forecasting skills.

Detailed measurement of the above variables is discussed in the following sections.

4.1 Dependent Variables: Skill Specialization

I measure skill based on the analyst's relative performance to his peers; and skill specialization is a measure of the analyst's relative strength in the earnings forecasting and the stock picking skills. Note that, I use ex post measure of performance to proxy for analysts' ex ante choices of skill levels, since the latter are unobservable. I argue that the ex post measure of performance is a valid proxy for analysts' choice of skill levels since arguably one's performance is positively correlated with the effort he exerts on that skill, which in turn captures the ex ante concept of skill choices. Even though the ex post measure might be a noisy proxy and cannot capture the ex ante concept perfectly, it does not introduce systematic bias to the empirical tests. I discuss the measurement of skill and skill specialization in turn.

I adopt an industry-year perspective to evaluate an analyst's skill (industry defined by 2-digit SIC codes). [1] That is, I determine analysts' earnings forecast accuracy and stock recommendation profitability for each industry. The reasons are the

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[1] My results remain the same if Fama-French [1997] industry grouping is adopted.

following. First, measuring analyst skill at the firm-year level will likely induce noise in the skill proxy. This is because an analyst's earnings forecasting and stock picking skills are likely to be highly transferable across firms in the same industry that he covers, and hence, likely to be significantly correlated. Thus, analyzing skill at the industry level as opposed to the firm level reduces cross-sectional correlation as well as noise. Second, it does not make sense to measure skills at analyst-year level, because analysts tend to develop their skills and reputations at the industry level as evidenced by the fact that both *Institutional Investors* annual all-star rankings and *The Wall Street Journal*'s "Best on the Street" annual analyst rankings rank analysts at industry level. The significant difference in industry-specific knowledge prevents analysts from transferring skills across industries, thus measuring skills at analyst-year level will likely reduce the power of my proxy and bias towards finding insignificant results.

4.1.1 Earnings Forecasting Skill

Following Hong and Kubik [2003] I measure analysts' skill in forecasting earnings based on their relative earnings forecast accuracy. Specifically, I define the relative forecasting performance of analyst i for firm j in year t based on the ranking of AFE (absolute forecast error) of his last annual earnings forecast for firm j during the fiscal year t. AFE is calculated as the absolute difference between the forecasted annual earnings per share (Forecast) and the realized annual earnings per share (Actual):

$$\mathrm{AFE}_{\mathrm{ijt}} = \left|\mathrm{Forecast}_{\mathrm{ijt}} - \mathrm{Actual}_{\mathrm{ijt}}\right|.$$

A greater AFE implies a less accurate forecast. The analyst with the largest AFE for firm j in year t receives a rank of zero; the analyst with the next largest AFE receives a rank of one. I continue to assign ranks and the most accurate analyst receives the highest rank. Analysts with the same AFE are assigned the same rank. In order to normalize AFE rankings, I divide all raw rankings with the number of analysts following firm j in year t minus one so that all rankings are between 0 and 1:

$$\text{Normalized Ranking}_{ijt} = \text{Raw Ranking}_{ijt}/\left(\text{Number of Analysts}_{jt} - 1\right).$$

Since I adopt an industry-year perspective to evaluate analysts' skills, I average the normalized rankings analyst i receives for all the firms he covers within industry d in year t to measure his earnings forecasting skill for this specific industry-year (E_Skill):

$$\text{E\_Skill}_{idt} = \sum\nolimits_{j \in d} \text{Normalize Ranking}_{ijt}/\text{Number of Firms Followed}_{idt}.$$

I further rank all the analysts covering this industry-year by their earnings forecasting skill (E_Skill_{idt}), and assign them into quintiles (E_Skill_Q_{idt}) in such way that a higher E_Skill_Q_{idt} indicates an analyst with a better earnings forecasting skill among analysts who cover industry d in year t.

4.1.2 Stock Picking Skill

Similar to the earnings forecasting skill measurement, I measure an analyst's stock picking skill based on the profitability of stock recommendations relative to industry peers. Note that Zacks database uses a five-point scheme and codes analyst stock recommendation of Strong Buy as 1, Buy as 2, Hold as 3, Sell as 4, and Strong Sell as 5. Due to the well known bias in analyst recommendations during my sample period (1991-2003), I treat all strong buy and buy recommendations (1 and 2 in the Zacks database) as buy recommendations (hereafter BUY), and all hold, sell and strong sell recommendations (3, 4 and 5 in Zacks database) as sell recommendations (hereafter SELL).[2] For analyst i, I calculate his recommendation profitability for firm j in year t using the average daily buy-and-hold returns based on the investment strategy implied by the recommendations.[3] I use average daily buy-and-hold returns instead of cumulative buy-and-hold returns because different analysts' stock recommendations generate different windows for long/short positions. The investment strategy is executed as follows. From the first recommendation analyst i issues for firm j in calendar year t, buy stock j when the most recent recommendation is BUY, and short stock j when the most recent recommendation is SELL until the last recommendation issued in calendar year t. I omit the days stock recommendations are made available to the market in my test to avoid capturing market's reactions to the recommendations rather than analysts' stock picking skills.[4] If analyst i's last recommendation for firm j in year t is a BUY (SELL), I continue to long (short) stock j until twelve months after the last

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[2] Treating all HOLD recommendations as not taking a position in the stock instead of shorting the stock does not change the results of my paper.
[3] Note that I measure analyst earnings forecasting skill at the firm fiscal year level, but stock recommendation skill at calendar year level. I'm aware of this problem and it will be addressed by future sensitivity tests.
[4] Including the recommendation announcement date in calculating recommendation profitability does not change my results.

recommendation in year t or when analyst i changes his recommendation to SELL (BUY), whichever comes first. [5] [6] Basically, the average daily buy-and-hold returns of this investment strategy capture the raw daily returns from following all analyst i's recommendations for firm j in calendar year t (Raw_Ret_{ijt}). [7] Market adjusted returns (Mkt_Ret_{ijt}) are computed as subtracting the average daily value-weighted returns of all NYSE, AMEX, and NASDAQ stocks for the same period (i.e., the value-weighted CRSP index) from the raw returns (Raw_Ret_{ijt}). Fama-French three-factor adjusted returns (FF_Ret_{ijt}) are computed by subtracting the expected daily returns from the following Fama-French three-factor model estimated over each long/short period for each firm: [8]

$$Raw\_Ret_{jq} - R_{fq} = \alpha_j + \beta_j \cdot (R_{mq} - R_{fq}) + s_j \cdot SMB_q + h_j \cdot HML_q + \varepsilon_{jq},$$

where,	R_{fq}	=	the day q returns on treasury bills having one month until maturity;
	R_{mq}	=	the value-weighted returns of all NYSE, AMEX, and NASDAQ stocks in day q;
	SMB_q	=	the difference between the day q returns of a value-weighted portfolio of small stocks and one of large stocks;

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[5] I use twelve months because analyst stock recommendations are usually stated in research reports to predict stock price movement in the next twelve months. Changing the assumption to nine months does not change my results.

[6] Note that this investment strategy uses analysts' stock recommendations in year t+1. I choose to incorporate such future information because, even if an investor follows all stock recommendations of an analyst in year t, it is unlikely that the investor will continue to have a long (short) position on a stock when analyst i changes his recommendation to SELL (BUY) in the future. Sensitivity test results show that ignoring recommendations in year t+1 will not yield different results.

[7] My measure of stock recommendation profitability mitigates the measurement error due to analysts' herding behavior. If an analyst is a better stock picker, and other analysts copy his recommendation, the market price will move in the direction of the better stock picker's recommendation after he issues his recommendation but before the mimickers issue theirs. Therefore, the better stock picker scores a higher recommendation profitability using my measure than the mimickers.

[8] Sensitivity tests using the four-factor model (including momentum factor) yields the same results.

HML_q = the difference between the day q returns of a value-weighted portfolio of high book-to-market stocks and one of low book-to-market stocks. [9]

For each measure of returns (Raw_Ret_{ijt}, Mkt_Ret_{ijt} and FF_Ret_{ijt}), I calculate the mean value across all the firms analyst i covers in industry d year t and use it to rank all the analysts covering this industry-year into quintiles. This quintile ranking (denoted $S\_Skill\_Q_{idt}$) of analyst i measures his stock picking skill relative to his peers in industry d year t. I compute quintile ranking, for raw returns, market adjusted returns and Fama-French three-factor adjusted returns separately.

4.1.3 Skill Specialization and Non-Specialization

As discussed at the beginning of this chapter, skill specialization captures an analyst's strength in earnings forecasting skill or stock picking skill relative to his peers.

In order to capture skill specialization, I first assign analysts in each industry-year into a 5×5 matrix (illustrated by Figure 1) based on the quintile rankings of their relative earnings forecasting and stock picking skills for industry d in year t, i.e., ($E\_Skill\_Q_{idt}$, $S\_Skill\_Q_{idt}$). [10] The number in each cell in Figure 1 is the absolute difference between these analysts' E_Skill quintile and S_Skill quintile, and it proxies for his relative strength in the two skills (denoted as Strength). If the absolute difference

[9] Daily Fama-French factors and momentum factor are obtained from WRDS database.

[10] The results are not sensitive to the choice of $S\_Skill\_Raw\_Q_{idt}$, $S\_Skill\_Mkt\_Q_{idt}$, or $S\_Skill\_FF\_Q_{idt}$.

between the two skills (hereafter, Strength) is greater than two, i.e. there is substantial difference between the levels of his two skills, then the analyst is deemed to have a specialization. Therefore, the cells with horizontal lines (in the upper right corner) contain analysts who specialize in forecasting earnings; the cells with vertical lines (in the bottom left corner) contain analysts who specialize in picking stocks. I define $S\_Special_{idt}$ as an indicator variable that equals one (zero) if analyst i specializes in forecasting earnings (picking stocks) in industry d year t.

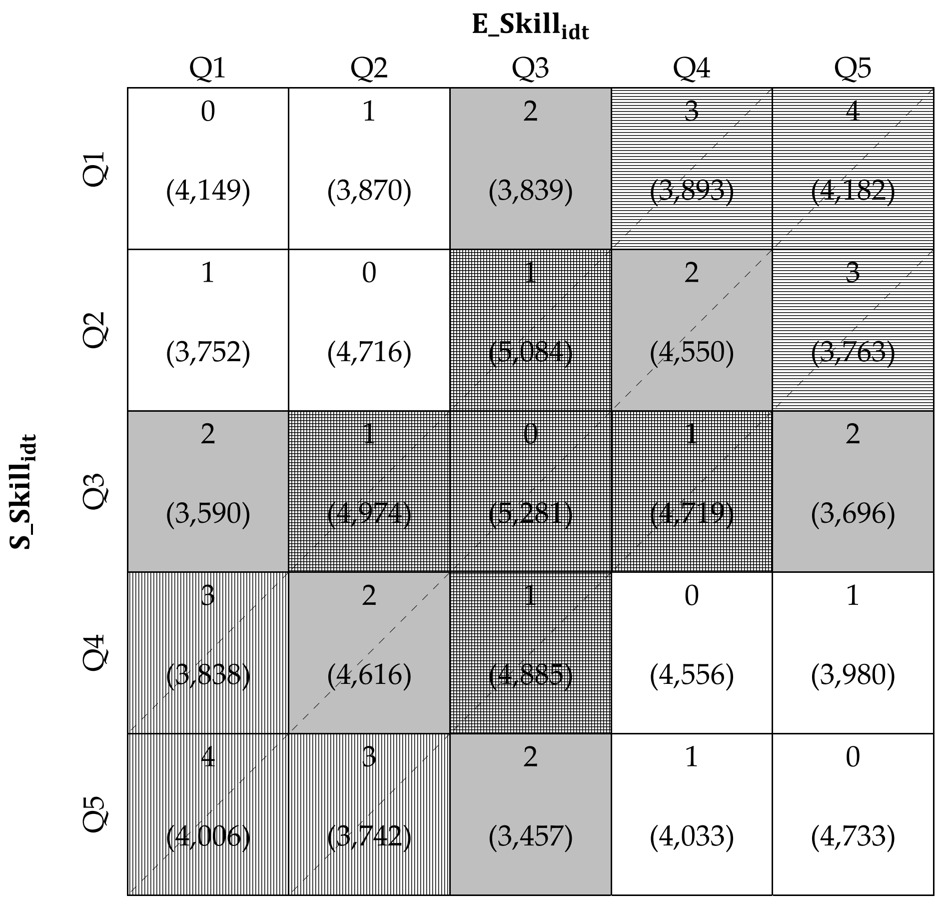

Figure 1: Measures of Skill Specialization and Non-Specialization

Numbers in the cells are the absolute difference between analysts' two skill quintiles rankings, i.e., $|S\_Skill\_Q_{idt} - E\_Skill\_Q_{idt}|$. Numbers in the parentheses are the numbers of observations. Cells with horizontal lines contain analysts with earnings forecast specialization. Cells with vertical lines contain analyst with stock picking specialization. Cells with grids contain analysts with skill non-specialization. Grey cells contain analysts with ambiguous specialization. White cells contain analysts with extremely abilities in both skills. Dash lines represent choices of specialization versus non-specialization available for analysts.

I define an analyst as having non-specialization when his Strength is 0 or 1, i.e. the levels of his earnings forecasting skill and stock picking skill are indistinguishable. To reduce measurement errors, I do not define analysts with Strength 2 (denoted by the grey cells in Figure 1) as having specialization or non-specialization. Note that, only the analysts in the cells along the three dash lines in Figure 1 have the choices between specialization and non-specialization. The analysts in the top-left white cells do not have a choice because their innate ability is too low or they have not developed enough skills in either task. Therefore, their choice of specialization or non-specialization is unobservable in my research design. Similarly, the analysts in the bottom-right white cells have high innate abilities so that even if they specialize in one skill, the weaker skill is still better than most peers, which makes their choice between specialization and non-specialization unobservable in this research design. Therefore, only the analysts who have a choice between specialization and non-specialization and whose two skills are not distinguishable are considered as having non-specialization (denoted by cells in the middle with grids in Figure 1).[11] Note that analysts in the cells with horizontal and vertical lines (the bottom left and upper right corners) are also along the dash lines, which means that specialization defined in this way captures analysts' choice. $Special_{idt}$ is an indicator variable that equals one if analyst i has either specialization (i.e., an

[11] In a sensitivity test, I treat analysts in the white cells in Figure 1 as non-specializing analysts in testing H1 and H2. The results are unchanged.

analyst falls in the cells with horizontal or vertical lines), zero if he has non-specialization (i.e. an analyst falls in the cells with grids).

4.2 Independent Variables

Earnings Relevance ($E\_Relevance_{idt}$)

As discussed in the hypothesis development chapter, I use earnings relevance and earnings timeliness to capture the economy of scope between earnings forecasting skill and stock picking skill, because these two variables measure the information overlap between earnings and stock prices.

I follow the convention in prior literature (e.g. Easton and Harris [1991], Francis and Schipper [1999], Francis, LaFond, Olsson and Schipper [2004]) and measure earnings relevance as the ability of earnings to explain variation in returns. I run the following firm specific regression for a rolling ten year window and use the adjusted R^2 to proxy for the earnings relevance for this firm year. To measure the earnings relevance at analyst-industry-year level ($E\_Relevance_{idt}$), I take the average of the earnings relevance across all the firms covered by analyst i in industry d year t. In this way, $E\_Relevance_{idt}$ is one of the analyst characteristics since it is determined by individual analysts' coverage of firms in an industry.

$$RET_{j\tau} = \alpha_{0j} + \beta_{1j} \cdot \Delta EARN_{j\tau} + \beta_{2j} \cdot EARN_{j\tau} + \varepsilon_{j\tau}$$

where, $RET_{j\tau}$ = firm j's five-month return ending two months after the end of fiscal quarter τ;

$EARN_{j\tau}$ = firm j's income before extraordinary items in quarter τ,

		scaled by the market value of equity at the end of quarter $\tau - 1$ = data69/(data61×data14);
$\Delta EARN_{j\tau}$	=	firm j's change in NIBE in quarter τ, scaled by the market value of equity at the end of quarter $\tau - 1$ = Δdata69/(data61×data14).

Earnings Timeliness ($E\_Timeliness_{idt}$)

Earnings Timeliness is used to capture the ability of returns to explain changes in earnings. Following convention in prior literature (e.g. Ball, Kothari and Robin [2000], Francis, LaFond, Olsson and Schipper [2004]), I measure earnings timeliness as the adjusted R^2 from the following reverse regression of earnings on returns for a rolling ten year window. The earnings timeliness of all the firms covered by analyst i in industry d year t, $E\_Timeliness_{idt}$ is simply the mean value of the adjusted R^2's across all the firms covered by analyst i in industry d year t.

$$EARN_{j\tau} = \alpha_{0j} + \beta_{1j} \cdot NEG_{j\tau} + \beta_{2j} \cdot RET_{j\tau} + \beta_{3j} \cdot RET_{j\tau} \cdot NEG_{j\tau} + \varepsilon_{j\tau}$$

where,	$EARN_{j\tau}$	=	firm j's income before extraordinary items in quarter τ, scaled by market value at the end of quarter $\tau - 1$ = data69/(data61×data14);
	$RET_{j\tau}$	=	firm j's five-month return ending two months after the end of fiscal quarter τ;
	$NEG_{j\tau}$	=	1 if $RET_{j\tau} < 0$, and 0 otherwise.

Brokerage Size ($Broker\_Size_{it}$) and Brokerage Reputation ($Broker\_Reputation_{it}$)

I use brokerage size and brokerage reputation to measure the resources and support available to analysts. $Broker\_Size_{it}$ is measured as the number of analysts in analyst i's brokerage house in year t. I measure a brokerage house's reputation using the strength of its underwriting business based on its Carter-Manaster ranking. Carter-Manaster rankings are based on the relative placement of underwriter names in IPO tombstones (Carter and Manaster [1990]) and range from zero to nine with scores above eight considered highly prestigious (e.g. Corwin and Schultz [2005]).

All-Star Analysts (All_Star_{it})

Presumably, an all-star analyst receives more resources and support from his employer than a non-star analyst. I define All_Star_{it} as an indicator variable that equals one if analyst i is named on the *Institutional Investor All-American Research Team* list in the previous year, and zero otherwise. [12]

Skill Spillover Effect ($Skill\_Spillover_{dt}$)

Stark and Wang [2002] define skill spillover effect as the phenomenon that working with a large group of skilled workers raises one's productivity. Therefore, I use the number of analysts covering industry d in year t to proxy for the skill spillover effect in an industry-year, and expect it to decrease an analyst's marginal cost of skill development.

Earnings Properties ($E\_Persistence_{idt}$, $E\_Predictability_{idt}$, and $E\_Fixation_{idt}$)

In order to capture investor's demand for accurate forecasts of earnings from analysts, I use three properties of earnings that have been used in prior literature

[12] My results remain the same if All_Star_{it} is measured as an indicator variables that equals one if analyst i has been named on the II all-star analyst list in the prior three years.

(earnings persistence, earnings predictability and earnings management). I argue that investors prefer persistent earnings since they are useful for investment decision; investors demand for analysts' earnings forecast skill when actual earnings are unpredictable; when investors fixate on earnings and thus demand for analysts' earnings forecast skill, managers would have high incentive to deliver earnings number by earnings management.

Earnings persistence captures earnings sustainability or recurrence. Obviously, a more persistent earnings number is more desirable for equity valuation purpose since a larger extent of current earnings will become a permanent component in future earnings series. Following literature convention (e.g. Ball and Watts [1972], Lev [1983], and Lipe [1990]), I measure earnings persistence as firm-specific autocorrelation in earnings, i.e., the slope coefficient estimate from an autoregressive model of order one (AR1) for annual earnings per share over a rolling ten year window:

$$\mathrm{EPS}_{j\tau} = \alpha_j + \beta_j \cdot \mathrm{EPS}_{j\tau-1} + \varepsilon_{j\tau}$$

where, $\mathrm{EPS}_{j\tau}$ = firm j's net income before extraordinary items in year τ divided by the average number of outstanding shares at the beginning and the end of year τ.

Mean value of the autocorrelation coefficients across all the firms covered by analyst i in industry d year t is called $\mathrm{E\_Persistence}_{idt}$. It captures investors' demand for accurate earnings forecasts for the firms covered by analyst i for industry d year t, and is expected to be positively correlated with analyst i's incentive to develop earnings forecasting skill in industry d year t.

Earnings predictability measures the relative noise in firms' historical earnings streams and captures the easiness to predict earnings based on historical time series of earnings. Therefore, when a firm's earnings is difficult to predict based on historical data, investors would demand for analysts' forecasts. Following Lipe [1990], I compute the negative square root of the error variance ($-\sqrt{\sigma^2(\hat{\varepsilon}_{j\tau})}$) from the above regression to measure firm-year specific earnings predictability. The mean value across all the firms covered by analyst i in industry d year t is used as a proxy for the predictability of earnings for firms covered by him in industry d year t ($\mathrm{E\_Predictability}_{idt}$). I expect it to be positively correlated with the marginal benefit of developing earnings forecasting skill, task 1 (w_1).

Unlike earnings persistence and earnings predictability, earnings management is not intended to capture the time-series properties of earnings but to capture investors' fixation on earnings. Extant literature finds that managers are pressured to manage earnings to meet and beat earnings targets since investors fixate on earnings. Therefore, I use an earnings management proxy to capture investors' fixation on earnings. Following the literature convention, I measure earnings management with the abnormal amount of total accruals. I use a modified version of Jones [1991] model developed by

Dechow, Richardson and Tuna's [2003] to estimate the normal level of total accruals (i.e., nondiscretionary accruals): [13]

$$\frac{TAC_{jt}}{A_{jt-1}} = \frac{\alpha_{0d}}{A_{jt-1}} + \beta_{1d} \cdot \frac{(1 + k_{dt}) \cdot \Delta S_{jt} - \Delta REC_{jt}}{A_{jt-1}} + \beta_{2d} \cdot \frac{PPE_{jt}}{A_{jt-1}} + \beta_{3d} \cdot \frac{TAC_{jt-1}}{A_{jt-1}}$$

$$+\beta_{4d} \cdot \frac{\Delta S_{jt+1}}{S_{jt}} + \varepsilon_{jt}$$

where, TAC_{jt} = total accruals of firm j in year t = Data 123 – Data 308;
ΔS_{jt} = $Sales_t - Sales_{t-1}$ =ΔData 12;
ΔREC_{jt} = change in account receivable = ΔData 2;
k_{dt} = estimated slope coefficient from a regression of ΔREC_{jt} on ΔS_{jt} for each 2-digit SIC industry-year grouping, i.e., $\Delta REC_{jt} = a_{dt} + k_{dt} \cdot \Delta S_{jt} + \varepsilon_{jt}$;
PPE_{jt} = property, plant and equipment = Data 8.

The above regression is estimated cross-sectionally for all 2-digit SIC industry-years with at least 15 observations. [14] Dechow et al. [2003] (hereafter DRT) improve the cross-sectional modified Jones model developed by Dechow et al. [1995] in several ways. First, DRT's model does not assume that all credit sales are discretionary. Instead, it estimates k_{dt} as the slope coefficient of ΔREC_{jt} on ΔS_{jt} for each industry-year; k_{dt} captures the expected change in credit sales for a given change in sales. Second, lag total accruals (TAC_{jt-1}/A_{jt-1}) is included to better capture the predictable portion of total

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[13] The results of my paper are similar if I use modified Jones model developed by Dechow, Sloan and Sweeney [1995]. My results are also similar if I measure accruals using balance sheet approach rather than cash flow statement approach.
[14] Using industry grouping from Fama-French [1997] does not change my results.

accruals. Third, the model is forward-looking since it includes next-year's sales growth ($\Delta S_{jt+1}/S_{jt}$) to incorporate the increase in inventory that is due to growth prospects.

I use the absolute value of the residual from the above regression ($|\hat{\varepsilon}_{jt}|$) to measure earnings management by firm j in year t. [15] Higher $|\hat{\varepsilon}_{jt}|$ means higher earnings management resulting from higher earnings fixation from investors. I take the average of all $|\hat{\varepsilon}_{jt}|$ across all the firms covered by analyst i in industry d year t and obtain the third earnings property measure of the covered firms, denoted as $E\_Fixation_{idt}$. I expect this measure to be positively correlated with the demand from investors for accurate earnings forecast. Note that, the implicit assumption here is that analysts' objective is to minimize forecast error, that is, to forecast earnings reported by firms/managers (i.e., earnings after potential manipulation). To the extent that some analysts' objective is to forecast earnings before earnings management, and investors are sophisticated enough to understand these analysts' objective, there would be no demand for earnings forecasting skill defined in my paper, since my measure of earnings forecasting skill is based on the ranking of forecast errors and it would not capture analysts' skill of forecasting earnings before manipulation. Nevertheless, there is no evidence in the extant literature that analysts have the incentives or ability to forecast earnings before manipulation (as discussed by Dechow and Schrand [2004]). Therefore, I expect this

[15] I use unsigned abnormal accruals since I intend to capture managers' distortion of actual earnings and do not distinguish between the sign of the distortion.

measure to be positively correlated with the incentive for analysts to develop superior earnings forecasting skill, which is measured according to the relative ranking of their forecast errors.

Shareholder Base ($Brand\_Name_{idt}$, *and* $Size_{idt}$)

Grullon, Kanatas, and Weston [2004] show that firms with greater visibility and brand name recognition attract a larger number of both individual investors and institutional investors with a disproportionately larger group of individual investors. Their results are consistent with documented evidence of "home bias" or "buy what you know" by individual investors who tend to invest based on familiarity (e.g. Merton [1987], French and Poterba [1991], Kadlec and McConnell [1994]). As discussed in the hypothesis development chapter, unlike institutional investors, individual investors either lack the financial expertise to process and construct investment strategies based on analysts' earnings forecasts or do not have sufficient time and resources to process earnings forecasts for each firm they invest in, and tend to follow analysts' stock recommendation directly. Therefore, the number of individual investors is expected to be positively correlated with investors' demand for analysts' stock picking skill. Following Grullon et al. [2004], I use unscaled advertising expenditure and firm size (measured as log of market value of equity) to proxy for firms' shareholder base. [16] The average value of the advertising expenditure and firm size across all the firms covered

[16] An alternative measure of firm size, log of total assets, yields the same results.

by analyst i in industry d year t, denoted as Brand_Name_{idt}, and Size_{idt} respectively, are used in the main tests.

Relative Earnings Forecast Revision Frequency (E_Freq_{idt}) and Relative Stock Recommendation Revision Frequency (S_Freq_{idt})

As discussed in the previous chapter, after a skill is acquired, an individual's utility is maximized by utilized the specialized skill as intensively as possible. I use the relative revision frequencies of earnings forecasts and stock recommendation as proxies for skill utilization intensity. Relative forecast (recommendation) frequency is computed as the difference between the number of annual earnings forecasts (stock recommendations) analyst i issues for firms in industry d year t and the average number of annual earnings forecasts (stock recommendations) of all other analysts following the same industry-year, denoted as E_Freq_{idt} (S_Freq_{idt}). A relative measure is used instead of the raw number of earnings forecasts (stock recommendations) because the skill measurement is a relative one. [17] That is, if analysts are relatively more skillful in forecasting earnings (picking stocks) than their peers, I expect them to issue earnings forecasts (stock recommendations) more frequently.

Earnings Forecast Innovation ($E\_Innovation_{idt}$)

[17] Using the raw number of forecasts (recommendations) to calculate earnings forecast (stock recommendation) frequency does not change my results.

Since analysts sometimes issue earnings forecasts just to herd, I refine the measure of relative earnings forecast revision frequency (E_Freq_{idt}) by using the percentage of the innovative earnings forecast revisions from analyst i for firms in industry d year t. Following Gleason and Lee [2003], an earnings forecast revision is defined as not innovative when it is between the analyst's prior forecast and the current forecast consensus of other analysts; innovative otherwise.

4.3 Control Variables

Analyst Experience ($General\_Expr_{it}$ and Ind_Expr_{idt})

Analyst experience is included in the regressions as control variables. General experience is the number of years during which analyst i has issued forecasts in Zacks database till year t. Analysts' industry-specific experience is computed as the number of years analyst i has issued forecasts for industry d till year t.

4.4 Specific Regression Forms and Predicted Signs of the Independent Variables

As discussed at the beginning of this chapter, I use a logit regression to test H1 and H2, with detailed functional form specified below:

$$\begin{aligned}\mathrm{Special}_{idt} = \alpha &+ \beta_1 \cdot \mathrm{E\_Relevance}_{idt} + \beta_2 \cdot \mathrm{E\_Relevance}^2_{idt} + \beta_3 \cdot \mathrm{E\_Timeliness}_{idt} \\ &+ \beta_4 \cdot \mathrm{E\_Timeliness}^2_{idt} + \beta_5 \cdot \mathrm{Broker\_Size}_{it} + \beta_6 \\ &\cdot \mathrm{Broker\_Reputation}_{it} + \beta_7 \cdot \mathrm{All\_Star}_{it} + \beta_8 \cdot \mathrm{Skill\_Spillover}_{dt} + \beta_9 \\ &\cdot \mathrm{Ind\_Expr}_{idt} + \sum_t \varrho_t \cdot \mathrm{Year\_Dummy}_t + \varepsilon_{idt}\end{aligned} \tag{1}$$

where, $\mathrm{Special}_{idt}$ = 1 if analyst i specializes in earnings forecasting skill or stock picking skill in industry d year t(as defined in the variable measurement section), and zero if analyst i has non-specialization in industry d year t (as defined in the variable measurement section);

$Broker\_Size_{it}$ = The number of analysts in analyst i's brokerage house in year t.

$Broker\_Reputation_{it}$ = The strength of its underwriting business based on its Carter-Manaster ranking.

All_Star_{it} = Indicator variable that equals one if analyst i is named on the *Institutional Investor All-American Research Team* list one year before t, and zero otherwise.

$Skill\_Spillover_{dt}$ = The number of analysts covering industry d in year t.

Ind_Expr_{idt} = The number of years analyst i has issued forecasts for industry d till year t.

all other variables are defined in the variable measurement section.

As discussed in the variable measurement section, earnings relevance and earnings timeliness, which capture the information overlap between earnings and stock returns, are proxies for the economy of scope between developing earnings forecasting skill and stock picking skill. That is, if the same set of information is collected for generating earnings forecasts and stock recommendations, investing in one skill can decrease the marginal cost of investing in the other, which will lead to analysts optimally developing both skills. Since earnings relevance and timeliness also capture the usefulness of earnings for equity valuation, it is likely that investors' demand for earnings forecasting skill is high when earnings are highly relevant and timely, prompting analysts to specialize in earnings forecasting skill. In summary, I expect that when earnings relevance and earnings timeliness are sufficiently low or high, analysts will choose to specialize, while when they are between the two extremes, analysts will choose non-specialization. Therefore, I include the squared terms of earnings relevance and earnings timeliness to capture this potential non-linearity between these proxies and the choice of specialization versus non-specialization, and predict positive signs for β_2 and β_4 and negative signs for β_1 and β_3. [18]

The research strength and reputation of analysts' brokerage house, as well as analysts' star status proxy for the resources and support available to the analysts. They are expected to decrease the marginal cost of developing either skill, thus decreasing the incentive of specializing in only one skill (detailed discussion in the hypothesis development chapter). Similarly, the skill spillover phenomenon within an industry also decreases the marginal cost of developing either skill, thus prompting analysts to choose non-specialization. Therefore, I expect β_5, β_6, β_7 and β_8 to be negative.

I include analysts' industry experience as a control variable because an analyst's decision to specialize might be affected by his tenure in the industry. However, I do not have a predicted sign for this variable.

Note that, regression (1) is estimated for all the specializing and non-specializing analysts. To test H3, I focus on the subsample of analysts who self-select to have a

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[18] Results of a linear specification without the squared terms are also reported as reference (Table 5, Panel D).

specialization in either skill. To control for the potential bias caused by the self-selection problem, I use the Heckman procedure (Heckman [1979]), i.e., to include in the tests for H3 the inverse Mill's Ratio from regression (1) (IMR_{idt}) as a control variable:

$$IMR_{idt} = \varphi(z_{idt})/\Phi(z_{idt})$$

where, z_{idt} = the fitted value of the logit regression index function; $\varphi(\cdot)$ is the standard normal density function; $\Phi(\cdot)$ is the cumulative standard normal distribution function.

I use the following logit regression to test H3:

$$\begin{aligned} S\_Special_{idt} = \delta + \gamma_1 \cdot IMR_{idt} + \gamma_2 \cdot E\_Persistence_{idt} + \gamma_3 \cdot E\_Predictability_{idt} + \gamma_4 \\ \cdot E\_Fixation_{idt} + \gamma_5 \cdot Size_{idt} + \gamma_6 \cdot Brand\_Name_{idt} \\ + \sum_t \varrho_t \cdot Year\_Dummy_t + \xi_{idt} \end{aligned} \tag{2}$$

where, $S\_Special_{idt}$ = 1 if analyst i specializes in stock picking skill in industry d year t (as defined in the variable measurement section), and zero if analyst i specializes in earning forecasting skill in industry d year t(as defined in the variable measurement section);

$Brand\_Name_{idt}$ = the average value of the advertising expenditure across all the firms covered by analysts i in industry d year t.

all other variables are defined in the variable measurement section.

As discussed in the variable measurement section, earnings persistence measures the permanent component of earnings that will persist into the future, therefore it is expected to be positively correlated with investors' demand for superior earnings forecasting skill from analysts (i.e., γ_2 has a negative predicted sign). [19] Earnings predictability is expected to have a positive coefficient ($\gamma_3 > 0$) since the more unpredictable the earnings, the higher the demand from investors for analysts' earnings forecasting skill. I do not offer a predicted sign for earnings fixation since it potentially capture two things. If investors can see through earnings management, then it represents the inverse of representational faithfulness, and will be negatively related with investors' demand for "superior" earnings forecasting. Stated differently, the skill of getting closer to a manipulated and unreliable earnings number is not valued by investors. However, the reason why managers manage earnings is that: first, managers feel the pressure from investors to deliver short-term earnings; second, they believe that investors do not have the ability to detect or cannot completely undo earnings management. From this perspective, earnings management captures investors' fixation on earnings, and thus is positive correlated with their demand for analysts' earnings forecasting skill.

Investors' demand for stock picking skill is characterized by the covered firms' shareholder base. If it consists more of individual investors who lack the financial expertise or time to process and construct their own investment strategy based on earnings forecasts, they would follow analysts' recommendation directly and therefore,

[19] Although earnings relevance and earnings timeliness might also capture investors' demand for superior earnings forecasting skill from analysts, they are not included in regression (2) to avoid the collinearity problem induced by using the same variables in both the first and second stage regressions in the Heckman procedure.

demand for analysts' superior stock picking skill. I use firms' size and brand name to capture shareholder base since larger and more famous firms attract disproportionally more individual investors (Grullon et al. [2004]). Hence, the predicted signs for both γ_5 and γ_6 are positive. There is no predicted sign for IMR_{idt}, which is used to controls for the self-selection of specializing analysts.

H4 is tested with the following regression on the subsample of analysts with skill specialization:

$$E\_Freq_{idt} = \theta_0 + \theta_1 \cdot IMR_{idt} + \theta_2 \cdot Ind\_Expr_{idt} + \theta_3 \cdot General\_Expr_{idt} + \theta_4 \cdot Broker\_Size_{it} + \theta_5 \cdot Broker\_Reputation_{it} + \theta_6 \cdot S\_Special_{idt} + \sum_t \varrho_t \cdot Year\_Dummy_t + \epsilon_{idt} \quad (3)$$

$$E\_Innovation_{idt} = \rho_0 + \rho_1 \cdot IMR_{idt} + \rho_2 \cdot Ind\_Expr_{idt} + \rho_3 \cdot General\_Expr_{idt} + \rho_4 \cdot Broker\_Size_{it} + \rho_5 \cdot Broker\_Reputation_{it} + \rho_6 \cdot S\_Special_{idt} + \sum_t \rho_t \cdot Year\_Dummy_t + \varsigma_{idt} \quad (4)$$

$$S\_Freq_{idt} = \varphi_0 + \varphi_1 \cdot IMR_{idt} + \varphi_2 \cdot Ind\_Expr_{idt} + \varphi_3 \cdot General\_Expr_{idt} + \varphi_4 \cdot Broker\_Size_{it} + \varphi_5 \cdot Broker\_Reputation_{it} + \varphi_6 \cdot S\_Special_{idt} + \sum_t \rho_t \cdot Year\_Dummyt + \iota idt \quad (5)$$

where, $S\_Special_{idt}$ = 1 if analyst i specializes in stock picking skill in industry d year t (as defined in the variable measurement section), and zero if analyst i specializes in earning forecasting skill in industry d year t (as defined in the variable measurement section);

all other variables are defined in the variable measurement section.

I use relative earnings forecast (stock recommendation) frequency to proxy for the intensity of skill utilization. I expect relative earnings forecast (stock recommendation) frequency to be negative (positive) related with $S\_Special_{idt}$, an indicator variable that equals one if analyst i specializes in picking stock in industry d year t and zero if forecasting earnings. As discussed in the variable measurement section, $E\_Innovation_{idt}$ is a refined measure of E_Freq_{idt} by using the percentage of innovative earnings forecast revisions since innovative earnings forecast revisions are more likely prompted by earnings forecasting skill utilization instead of analysts' herding behavior. Analyst tenure and brokerage size are included to control for resources available to analysts.

5. Sample Selection and Empirical Results

5.1 Sample Selection

My sample covers 13 years from 1991 to 2003. My sample selection procedure is described in Table 1. I start with all available data in Zacks database during 1991 to 2003, which contains 7,746 unique analysts. 983 analysts (12.7% of the population during the sample period) are removed since they do not have either earnings forecast or stock recommendation data to measure their earnings forecasting and stock picking skills (E_Skill_{idt} and S_Skill_{idt}). Another 14.1% (1,094 analysts) are excluded because the underwriting business ranking of their brokerage houses is missing from Carter and Manaster [1990] list. [1] After excluding 722 analysts (9.3% of the Zacks analyst population during the sample period) without enough data on CRSP/COMPUSTAT Merged database in regression (1), 4,947 analysts remain in the sample. As discussed in the research design and variable measurement chapter, I only study analysts with either specialization (in either skill) or non-specialization. Therefore, I remove 444 analysts with both extremely high or extremely low skill levels (white cells in Figure 1) or with ambiguous skill strength (grey cells in Figure 1). Since I use three different measures for analysts' stock picking skill (i.e., based on raw returns, market adjusted returns, and

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[1] My results remain the same if I treat the underwriting business rankings of the missing brokerage houses as zero.

Fama-French three-factor adjusted returns to the analyst's recommendations), each measure has a different data requirement and thus, leads to a different final sample size. The combined final sample contains 4,503 analysts and 30,720 analyst-industry-years. It breaks down to a final sample of 4,174 analysts (22,544 analyst-industry-years) with S_Skill_{idt} based on raw returns; 4,185 analysts (22,451 analyst-industry-years) with S_Skill_{idt} based on market-adjusted returns; and 4,179 analysts (22,452 analyst-industry-years) with S_Skill_{idt} based on Fama-French three-factor adjusted returns. Each of these three final samples represents 54% of the Zacks analyst population during the sample period. Note that the focus of my study is analysts with a choice between specialization and non-specialization. Therefore, the study does not intend to reflect the entire analyst population. However, the data requirements on brokerage houses and covered firms might introduce bias towards analysts who cover larger firms and work for bigger brokerage houses.

Table 1: Sample Selection Procedure

	# of analysts	# of analyst-industry-years
Analysts (Analyst-industry-years) in Zacks database (1991-2003)	7,746	135,485
After excluding analyst-industry-years which do not have sufficient earnings forecasts to calculate earnings forecasting skill	7,065	89,162
After excluding analyst-industry-years which do not have sufficient stock recommendations to calculate stock picking skill	6,763	79,186
After excluding brokerages which do not have a underwriting ranking	5,669	63,630
After excluding analyst-industry-years without necessary data from CRSP/COMPUSTAT Merged database to calculate independent variables in regression (1)	4,947	47,833
After excluding analyst-industry-years not in the specialization sample	4,503	30,720
Sample size of all three recommendation profitability measurement tests combined	4,503	30,720
Less analyst-industry-years not in raw return specialization sample	329	8,176
Sample size of raw return specialization test	4,174	22,544
Less analyst-industry-years with non-specialization or without enough data from CRSP/COMPUSTAT Merged database to calculate independent variables in regression (2)	1,549	15,983
Sample size of Raw return specialization choice test	2,625	6,561
Less analyst-industry-years not in market adjusted return specialization sample	318	8,269
Sample size of market-adjusted return specialization test	4,185	22,451
Less analyst-industry-years with non-specialization or without enough data from CRSP/COMPUSTAT Merged database to calculate independent variables in regression (2)	1,564	15,934

Sample size of market-adjusted return specialization choice test	2,621	6,517
Less analyst-industry-years not in risk adjusted return specialization sample	324	8,268
Sample size of Fama-French risk-adjusted return specialization test	4,179	22,452
Less analyst-industry-years with non-specialization or without enough data from CRSP/COMPUSTAT Merged database to calculate independent variables in regression (2)	1,551	15,815
Sample size of Fama-French risk adjusted return specialization choice test	2,628	6,637

5.2 Descriptive Statistics

Table 2 provides descriptive statistics for the final sample. The mean (median) E_Skill of the sample analysts is 0.55 (0.55). As discussed in the previous chapter, E_Skill is based on the normalized rankings of earnings forecast accuracy from all the analysts covering the same firm-year, with a value of one representing the most accurate analyst and zero representing the least accurate one. Therefore, the sample mean (median) E_Skill above 0.5 means that compared with all other analysts covering the same firm-years, my sample analysts are on average slightly more accurate.

Note that all the mean and median daily returns on an investment strategy based on analysts' stock recommendations in the current year (Raw_Ret, Mkt_Ret and FF_Ret) are zero, implying that an investment strategy of simply following an average analyst's stock recommendations for a year cannot generate abnormal returns. This is consistent with the finding in the extant literature (e.g. Cowles [1933], Bidwell [1977], Diefenbach [1972], Logue and Tuttle [1973]). [2] However, a zero mean return does not imply that analysts' recommendations are uninformative, because there is substantial evidence that analysts' stock recommendations triggers market reactions and analysts exhibit differential stock picking abilities (see Womack [1996], Barber, Lehavy, McNichols and Trueman [2001], and Mikhail et al. [2004]).

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[2] Detailed review available in Womack [1996].

Table 2: Descriptive Statistics

Variables	N	Mean	Median	Std. Dev.	25%	75%
Skill variables:						
E_Skill	30,720	0.552	0.550	0.248	0.417	0.691
Raw_Ret	30,720	0.000	0.000	0.002	-0.001	0.001
Mkt_Ret	30,720	0.000	0.000	0.002	-0.001	0.001
FF_Ret	30,720	0.000	0.000	0.002	-0.001	0.001
Relevant variables for each hypothesis:						
H1:						
E_Relevance	30,720	0.145	0.123	0.105	0.071	0.194
E_Timeliness	30,720	0.468	0.473	0.209	0.331	0.609
H2:						
Broker_Size	30,720	46.769	38.000	36.078	17.000	69.000
Broker_Reputation	30,720	6.438	7.100	2.580	5.100	8.100
All_Star	30,720	0.131	0.000	0.337	0.000	0.000
Skill_Spillover	30,720	307.912	218.000	250.273	112.000	457.000
H3:						
E_Persistence	25,366	0.156	0.000	0.363	0.000	0.000
E_Predictability	25,366	-1.183	-0.886	1.682	-1.435	-0.553
E_Fixation	28,525	-0.009	-0.006	0.105	-0.038	0.025
Size	30,687	7.079	7.022	1.548	6.036	8.033
Brand_Name	30,689	57.967	0.000	208.791	0.000	13.705
H4:						
E_Freq	30,720	19.539	1.305	61.339	-12.513	31.558
E_Innovation	29,675	0.459	0.460	0.208	0.333	0.580
S_Freq	30,720	3.617	-0.342	15.222	-3.160	5.814
Control variables:						
Ind_Expr	30,720	5.554	4.000	4.641	2.000	8.000
General_Expr	30,720	7.415	6.000	5.333	3.000	11.000

See appendix for variable definitions.

Table 2 shows that mean (median) value of E_Relevance is 14.5% (12.3%), implying that earnings of the firms covered by sample analysts on average explain almost 15% of the variations in contemporaneous stock returns. The mean (median) E_Timeliness is 46.8% (47.3%), suggesting that stock returns of the firms covered by sample analysts on average explain about 47% of contemporaneous changes in earnings. A median brokerage house hires 41 financial analysts. Median Carter and Manaster underwriting business ranking is 7.1, implying that in at least half of my sample, the analysts do not work for prestigious brokerage houses (recall that the ranking above eight is regarded as prestigious brokerage by the literature (see Corwin and Schultz [2005])). Mean value of All_Star is 0.131, that is, in 13.1% of the sample observations, analysts are ranked as *Institutional Investor All-American Research Team* analysts. Skill_Spillover, number of analysts covering an industry-year, has a mean (median) value of 308 (218). Other descriptive statistics reveal the following: on average, sample analysts issue 20 more earnings forecast revisions than other analysts covering the same firm-year with 46% of earnings forecast revisions as innovative, and 3.6 more stock recommendations; their average industry-specific experience is 5.6 years, and general experience 7.4 years.

Table 3 reports the Pearson and Spearman correlation coefficients for the variables involved in the study. Panel A and B reports the correlation table for independent variables. Note that a few Pearson correlation coefficients are greater than

0.25. Analysts' all-star status (All_Star), the size of their brokerage houses (Broker_Size), and the underwriting business ranking of their brokerage house (Broker_Reputation) are highly positively correlated with each other (with Pearson correlation coefficients range from 0.24 to 0.56 with p-values < 0.01). Not surprisingly, analysts' industry experience (Ind_Expr) and general experience (General_Expr) are highly positively correlated (0.84 with p-value<0.01). The Pearson correlation between firm size (Size) and size of brokerage houses (Broker_Size) is also significantly positive (0.28 with p-value < 0.01), suggesting that larger brokerage houses tend to cover larger firms. There is a high correlation between firm size (Size) and firms' advertising expenditure (Brand_Name) (0.39 with p-value < 0.01), since larger firms tend to spend more on advertising. Panel C provides Pearson and Spearman correlation coefficients between skill measures and independent variables. No significant correlations are found in Panel C.

Table 3: Correlation Table

Panel A: Pearson Correlation

	Skill_Spillover	Ind_Expr	General_Expr	Brokerage_Size	Broker_Reputation	Size	Brand_Name	E_Relevance	E_Timeliness	E_Persistence	E_Predictability	E_Fixation
All_Star	-0.05***	0.14***	0.14***	0.35***	0.24***	0.13***	0.04***	-0.06***	0.01	-0.04***	-0.08***	0.00
Skill_Spillover		0.00	-0.07***	0.00	-0.02***	-0.07***	-0.03***	0.00	0.12***	-0.04***	0.01**	-0.12***
Ind_Expr			0.84***	0.05***	0.04***	0.06***	0.03***	-0.01*	0.02***	-0.07***	-0.05***	0.00
General_Expr				0.03***	0.03***	0.02***	0.02***	0.00	0.01**	-0.02***	-0.03***	0.01*
Brokerage_Size					0.56***	0.28***	0.06***	-0.10***	0.04***	-0.07***	-0.06***	-0.02***
Broker _Reputation						0.15***	0.03***	-0.04***	0.03***	-0.04***	-0.05***	0.01*
Size							0.39***	-0.13***	-0.05***	-0.05***	-0.13***	-0.03***
Brand_Name								-0.04***	0.01	-0.03***	-0.10***	0.01**
E_Relevance									-0.06***	0.09***	0.13***	0.00
E_Timeliness										-0.07***	-0.08***	-0.02***
E_Persistence											0.11***	0.04***
E_Predictability												0.01*

Panel B: Spearman Correlation

	All_Star	Skill_Spillover	Ind_Expr	General_Expr	Brokerage_Size	Broker_Reputation	Size	Brand_Name	E_Relevance	E_Timeliness	E_Persistence	E_Predictability
Skill _Spillover	-0.05***											
Ind_Expr	0.17***	0.02***										
General_Expr	0.16***	-0.07***	0.82***									
Brokerage_Size	0.35***	-0.01**	0.07***	0.03***								
Broker _Reputation	0.33***	-0.03***	0.06***	0.04***	0.73***							
Size	0.15***	-0.08***	0.04***	0.01	0.30***	0.21***						
Brand_Name	0.06***	-0.02***	0.10***	0.04***	0.07***	0.06***	0.25***					
E_Relevance	-0.05***	0.01	0.03***	0.01*	-0.07***	-0.05***	-0.11***	0.07***				
E_Timeliness	0.00	0.13***	0.01*	0.00	0.04***	0.03***	-0.04***	-0.05***	-0.08***			
E_Persistence	-0.04***	-0.04***	-0.06***	-0.02***	-0.07***	-0.05***	-0.06***	-0.06***	0.08***	-0.06***		
E_Predictability	-0.14***	-0.01	-0.08***	-0.03***	-0.14***	-0.13***	-0.26***	-0.06***	0.22***	-0.18***	0.24***	
E_Fixation	0.00	-0.07***	-0.02***	0.00	-0.04***	0.00	-0.01***	-0.03***	-0.01***	-0.05***	0.04***	0.05***

Panel C:

	E_Skill_Q		S_Skill_Raw_Q		S_Skill_Mkt_Q		S_Skill_FF_Q	
	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman
All_Star	0.02 ***	0.02 ***	-0.01 ***	-0.01 ***	0.01 *	0.01 *	0.00	0.00
Skill_Spillover	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
Ind_Expr	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
General_Expr	0.01	0.01	0.01	0.00	0.01	0.01	0.01 *	0.01 *
Broker_Size	0.02 ***	0.03 ***	-0.03 ***	-0.04 ***	0.00	0.00	-0.02 ***	-0.03 ***
Broker _Reputation	0.02 ***	0.02 ***	-0.02 ***	-0.03 ***	0.00	-0.01	-0.02 ***	-0.02 ***
Size	-0.02 ***	-0.02 ***	-0.01 *	-0.01 **	0.01 **	0.01 **	-0.01 *	-0.01
Brand_Name	0.00	-0.01	0.00	-0.02 ***	0.01 **	-0.01	0.00	-0.01 **
E_Relevance	0.01 *	0.01	0.00	0.00	0.00	0.00	0.00	0.00
E_Timeliness	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
E_Persistence	0.00	0.00	0.00	0.00	-0.01 *	-0.01	0.00	0.00
E_Predictability	0.00	0.02 ***	0.01 *	0.02 ***	0.00	0.00	0.01	0.01
E_Fixation	0.01 ***	0.01 **	0.01 **	0.01	0.01	-0.01	0.00	0.00

5.3 Descriptive Statistics for Subsamples of Specializing and Non-Specializing Analysts

Table 4 Panel A reports descriptive statistics for the subsample of analysts with specialization and non-specialization. The last column provides the differences between the two subsamples as well as the significance level of the differences. Examining the last column reveals some interesting facts. Specializing analysts on average issue 43 (8) fewer relative earnings forecast (stock recommendation) revisions than non-specializing analysts (significant at 0.01 level); however, there is no significant difference between their percentages of innovative earnings forecast revisions. Other significant differences (all significant at the level of 0.01) suggest that compared with non-specializing analysts, specializing analysts on average are less likely to be all-stars, cover industries with 8 less analysts following, have one year less industry experience and two quarters less general experience, work for brokerage houses with 8 fewer analysts and lower underwriting business rankings, follow smaller firms and firms with higher earnings relevance, earnings timeliness, and earnings persistence.

Table 4: Descriptive Statistics for Subsamples of Specializing and Non-Specializing Analysts

Panel A: Descriptive statistics for non-specializing analysts ($Special_{idt}$ = 0), specializing analysts ($Special_{idt}$ = 1) and the difference between the two groups.

Variables	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	Difference
	Special=0				*Special=1*				*(Special=1) −(Special=0)*
E_Freq	13,310	38.66	15.83	72.02	9,142	-4.15	-8.62	32.93	-42.81***
E_Innovation	13,094	0.46	0.46	0.18	8,594	0.46	0.46	0.24	-0.00
S_Freq	13,310	7.28	2.21	18.34	9,142	-0.87	-2.01	8.87	-8.15***
All_Star	13,310	0.16	0.00	0.37	9,142	0.10	0.00	0.30	-0.06***
Skill_Spillover	13,310	312.45	219.00	254.31	9,142	304.47	216.00	245.71	-7.98***
Ind_Expr	13,310	6.09	5.00	4.84	9,142	4.83	3.00	4.24	-1.26***
General_Expr	13,310	7.63	6.00	5.37	9,142	7.12	6.00	5.28	0.52***
Broker_Size	13,310	49.88	43.00	36.23	9,142	42.11	31.00	34.91	-7.78***
Broker _Reputation	13,310	6.63	7.10	2.52	9,142	6.15	7.10	2.64	-0.48***
Size	13,304	7.25	7.19	1.42	9,120	6.76	6.67	1.64	-0.49***
Brand_Name	13,305	62.27	0.33	197.26	9,121	50.42	0.00	213.89	-11.84***
E_Relevance	13,310	0.14	0.12	0.09	9,142	0.15	0.12	0.12	0.01***
E_Timeliness	13,310	0.47	0.47	0.19	9,142	0.47	0.48	0.23	0.01***
E_Persistence	11,728	0.13	0.00	0.34	6,778	0.19	0.00	0.39	0.05***
E_Predictability	11,728	-1.19	-0.92	0.95	6,778	-1.17	-0.82	2.74	0.02
E_Fixation	12,475	-0.01	-0.01	0.10	8,393	-0.01	-0.01	0.11	0.00

See appendix for variable definitions.

Panel B: Descriptive statistics for analysts specializing in earnings forecasting skill (S_Skill$_{idt}$ = 0), analysts specializing in stock picking skill (S_Skill$_{idt}$ = 1), and the difference between the two groups.

Variables	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	Difference
	S_Skill=0				*S_Skill=1*				*(S_Skill=1) −(S_Skill=0)*
E_Freq	4,549	-1.94	-7.44	35.42	4,593	-6.34	-9.87	30.11	-4.40***
E_Innovation	4,274	0.48	0.48	0.23	4,320	0.45	0.45	0.25	-0.03***
S_Freq	4,549	-0.66	-1.93	9.24	4,593	-1.08	-2.12	8.49	-0.42**
All_Star	4,549	0.10	0.00	0.30	4,593	0.09	0.00	0.29	-0.01
Skill_Spillover	4,549	306.37	218.00	245.58	4,593	302.60	212.00	245.85	3.77
Ind_Expr	4,549	4.78	3.00	4.19	4,593	4.87	3.00	4.28	0.09
General_Expr	4,549	7.07	6.00	5.23	4,593	7.16	6.00	5.33	0.09
Broker_Size	4,549	43.40	33.00	34.88	4,593	40.83	28.00	34.91	-2.56***
Broker_Reputation	4,549	6.21	7.10	2.65	4,593	6.10	7.10	2.63	-0.11**
Size	4,536	6.70	6.63	1.62	4,584	6.82	6.73	1.66	0.12***
Brand_Name	4,537	45.68	0.00	206.37	4,584	55.11	0.00	221.01	9.43**
E_Relevance	4,549	0.15	0.12	0.12	4,593	0.15	0.12	0.12	0.00
E_Timeliness	4,549	0.47	0.48	0.23	4,593	0.47	0.48	0.23	0.00
E_Persistence	3,315	0.20	0.00	0.40	3,463	0.18	0.00	0.38	-0.02**
E_Predictability	3,315	-1.19	-0.80	3.76	3,463	-1.15	-0.85	1.09	0.04
E_Fixation	4,203	-0.01	0.00	0.12	4,190	-0.01	-0.01	0.11	-0.00**

See appendix for variable definitions.

Table 4 Panel B provides descriptive statistics of specializing analysts. The last column reports the differences between analysts specializing in earnings forecasting skill and analysts in stock picking skill. As we can see from the last column, analysts specializing in stock picking skill issue significantly fewer earnings forecasts and innovative earnings forecast revisions than analysts with earnings forecasting specialization. Compared with analysts with earnings forecasting specialization, analysts specializing in stock picking skill cover larger and more visible companies, companies with less timely and less persistent earnings, as well as companies with less earnings fixation.

5.4 Main Results

Table 5 through Table 7 present the main results for H1 to H4. I present results using analysts' stock picking skill measure based on Fama-French three-factor adjusted returns ($S\_Skill\_FF\_Q_{idt}$) in Panel A of these tables. Results based on raw returns and market adjusted returns, presented in Panel B and C of Table 5 to Table 7 are qualitatively similar and hence, for brevity, are not discussed. Panel D of Table 5 presents results of regression (1) without the squared terms. Since the regressions are estimated for the pooled sample, all significance levels reported are after analyst level clustered controls. [1] Year dummies in the regressions are estimated but not reported.

[1] Cluster control at the brokerage level yields the same results.

Table 5: Logit Regression of Specialization versus Non-Specialization

Panel A: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns

$$\begin{aligned}\mathrm{Special}_{idt} = \alpha &+ \beta_1 \cdot \mathrm{E\_Relevance}_{idt} + \beta_2 \cdot \mathrm{E\_Relevance}^2_{idt} + \beta_3 \cdot \mathrm{E\_Timeliness}_{idt} \\ &+ \beta_4 \cdot \mathrm{E\_Timeliness}^2_{idt} + \beta_5 \cdot \mathrm{Broker\_Size}_{it} + \beta_6 \cdot \mathrm{Broker\_Reputation}_{it} \\ &+ \beta_7 \cdot \mathrm{All\_Star}_{it} + \beta_8 \cdot \mathrm{Skill\_Spillover}_{dt} + \beta_9 \cdot \mathrm{Ind\_Expr}_{idt} \\ &+ \sum_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \varepsilon_{idt}\end{aligned} \tag{1}$$

Dependent Variable: $\mathrm{Special}_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept		1.3057	<.0001	
E_Relevance	–	-3.9963	<.0001	-0.098
E_Relevance^2	+	11.4079	<.0001	0.144
E_Timeliness	–	-3.6958	<.0001	-0.175
E_Timeliness^2	+	4.1756	<.0001	0.205
Broker_Size	–	-0.0046	<.0001	-0.037
Underwrite_Rank	–	-0.0234	0.0014	-0.016
All_Star	–	-0.2272	<.0001	-0.054
Skill_Spillover	–	-0.0001	<.0001	-0.050
Ind_Expr		-0.0488	<.0001	-0.049
N ($\mathrm{Special}_{idt}$=1)	22,452 (9,142)			
Pseudo R^2	7.57%			
Likelihood Ratio (Chi-Square)	1,296.54			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Panel B: Stock Picking Ability Measured Using Raw Returns

$$\begin{aligned}\text{Special}_{idt} = {} & \alpha + \beta_1 \cdot \text{E\_Relevance}_{idt} + \beta_2 \cdot \text{E\_Relevance}^2_{idt} + \beta_3 \cdot \text{E\_Timeliness}_{idt} \\ & + \beta_4 \cdot \text{E\_Timeliness}^2_{idt} + \beta_5 \cdot \text{Broker\_Size}_{it} + \beta_6 \cdot \text{Broker\_Reputation}_{it} \\ & + \beta_7 \cdot \text{All\_Star}_{it} + \beta_8 \cdot \text{Skill\_Spillover}_{dt} + \beta_9 \cdot \text{Ind\_Expr}_{idt} \\ & + \sum_t \rho_t \cdot \text{Year\_Dummy}_t + \varepsilon_{idt}\end{aligned} \quad (1)$$

Dependent Variable: Special_{idt}	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept		1.2862	<.0001	
E_Relevance	−	-3.8135	<.0001	-0.094
E_Relevance^2	+	10.1031	<.0001	0.127
E_Timeliness	−	-3.9235	<.0001	-0.184
E_Timeliness^2	+	4.4446	<.0001	0.218
Broker_Size	−	-0.0045	<.0001	-0.036
Underwrite_Rank	−	-0.0233	0.0010	-0.016
All_Star	−	-0.1862	0.0002	-0.045
Skill_Spillover	−	-0.0001	0.0225	-0.013
Ind_Expr		-0.0471	<.0001	-0.047
N (Special_{idt}=1)	22,544 (9,188)			
Pseudo R^2	7.13%			
Likelihood Ratio (Chi-Square)	1,224.87			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Panel C: Stock Picking Ability Measured Using Market Model Adjusted Returns

$$\begin{aligned} \mathrm{Special}_{idt} = \alpha &+ \beta_1 \cdot \mathrm{E\_Relevance}_{idt} + \beta_2 \cdot \mathrm{E\_Relevance}^2_{idt} + \beta_3 \cdot \mathrm{E\_Timeliness}_{idt} \\ &+ \beta_4 \cdot \mathrm{E\_Timeliness}^2_{idt} + \beta_5 \cdot \mathrm{Broker\_Size}_{it} + \beta_6 \cdot \mathrm{Broker\_Reputation}_{it} \\ &+ \beta_7 \cdot \mathrm{All\_Star}_{it} + \beta_8 \cdot \mathrm{Skill\_Spillover}_{dt} + \beta_9 \cdot \mathrm{Ind\_Expr}_{idt} \\ &+ \sum_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \varepsilon_{idt} \end{aligned} \tag{1}$$

Dependent Variable: $\mathrm{Special}_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept		1.2842	<.0001	
E_Relevance	−	-3.6594	<.0001	-0.091
$\mathrm{E\_Relevance}^2$	+	10.3666	<.0001	0.132
E_Timeliness	−	-3.5489	<.0001	-0.171
$\mathrm{E\_Timeliness}^2$	+	4.0692	<.0001	0.200
Broker_Size	−	-0.0053	<.0001	-0.043
Underwrite_Rank	−	-0.0273	0.0002	-0.019
All_Star	−	-0.1937	0.0001	-0.047
Skill_Spillover	−	-0.0001	0.0020	-0.013
Ind_Expr		-0.0500	<.0001	-0.050
N ($\mathrm{Special}_{idt}$=1)	22,451 (9,240)			
Pseudo R^2	7.58%			
Likelihood Ratio (Chi-Square)	1,299.59			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Panel D: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns – Linear Specification

$$\text{Special}_{idt} = \alpha + \beta_1 \cdot \text{E\_Relevance}_{idt} + \beta_3 \cdot \text{E\_Timeliness}_{idt} + \beta_5 \cdot \text{Broker\_Size}_{it} + \beta_6 \cdot \text{Broker\_Reputation}_{it} + \beta_7 \cdot \text{All\_Star}_{it} + \beta_8 \cdot \text{Skill\_Spillover}_{dt} + \beta_9 \cdot \text{Ind\_Expr}_{idt} + \sum_t \rho_t \cdot \text{Year\_Dummy}_t + \varepsilon_{idt} \quad (1)$$

Dependent Variable: Special_{idt}	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept		0.2771	<.0003	
E_Relevance	?	0.6588	<.0001	0.017
E_Timeliness	?	0.2533	0.0004	0.013
Broker_Size	–	-0.0048	<.0001	-0.038
Underwrite_Rank	–	-0.0227	0.0017	-0.015
All_Star	–	-0.2207	<.0001	-0.053
Skill_Spillover	–	-0.0002	0.0016	-0.011
Ind_Expr		-0.0572	<.0001	-0.057
N (Special_{idt}=1)	22,452 (9,142)			
Pseudo R^2	4.69%			
Likelihood Ratio (Chi-Square)	794.71			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Table 5 Panel A reports the results from estimating logistic regression based on equation (1). Recall that in equation (1), the dependent variable is an indicator variable, $Special_{idt}$, that equals one when analyst i specializes in either forecasting earnings or picking stocks in industry d year t; zero when analyst i has non-specialization in industry d year t. H1 predicts a negative relation between specialization and the economies of scope of developing both skills. As discussed in the previous chapter, earnings relevance and earnings timeliness potentially not only capture the economies of scope of developing both skills but also the demand from investors for earnings forecasting skills when earnings quality is sufficiently high. Therefore, I include the squared terms of earnings relevance and earnings timeliness to control for potential nonlinearity. The coefficient on E_Relevance is significantly negative; the coefficient on $E\_Relevance^2$ is significantly positive, both consistent with predicted signs, suggesting a U-shaped relation between specialization and earnings relevance. Examining the magnitude of the coefficients reveals that, when E_Relevance is below 0.18 (which is close to the sample mean of 0.15), specialization decreases with earnings relevance; when E_Relevance is above 0.18, specialization increases with earnings relevance. The results are consistent with H1 that earnings relevance captures the economies of scope of developing both skills when it is lower than 18%. The positive relation between specialization and earnings relevance when earnings relevance is above 18% is consistent with investors' demand for earnings forecasting skill is higher when earnings quality is higher. Similar U-shaped relation is found between specialization and earnings timeliness. The coefficients on E_Timeliness and its squared term are significantly different from zero (at the level of 0.01). The magnitude and the sign of the coefficients suggest that when E_Timeliness is lower than 0.44 (compared with the sample mean of 0.47), the specialization decreases (increases) with earnings timeliness. The results support H1 that earnings timeliness captures economies of scope of developing both skills when it is sufficiently low. When earnings timeliness is high, the incentive for analysts to specialize in earnings forecasting skill kicks in and dominates the effect of economies of scope.

Table 5 Panel A shows that the coefficients on brokerage size and brokerage reputation are significantly negative (at the level of 0.01), consistent with H2 that specialization likelihood decreases with the resources and support available to analysts. Note that, as discussed before, the brokerage size and underwriting business ranking are not proxies for analysts' innate abilities since all sample analysts are along the dash lines in Figure 1, and arguably exhibit the same level of innate abilities. Also consistent with H2, the coefficient on All_Star is significantly negative (at the level of 0.01). Skill_Spillover has a negative coefficient significant at the level of 0.01, which supports H2 that analysts tend to develop both skills when there are more analysts covering the industry and thus greater skill spillover effects. Note that the coefficient on Ind_Expr is significantly negative, indicating that analysts with a longer tenure will be more likely to develop non-specialization, consistent with analyst tenure serving as a proxy for the amount of resources available to analysts.

Table 6: Logit Regression of Specializing in Stock Picking versus Earnings Forecasting

Panel A: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns

$$\begin{aligned} \mathrm{S\_Special}_{idt} = \delta + \gamma_2 \cdot \mathrm{IMR}_{idt} + \gamma_2 \cdot \mathrm{E\_Persistence}_{idt} + \gamma_3 \cdot \mathrm{E\_Predictability}_{idt} + \gamma_4 \\ \cdot \mathrm{E\_Fixation}_{idt} + \gamma_5 \cdot \mathrm{Size}_{idt} + \gamma_6 \cdot \mathrm{Brand\_Name}_{idt} \\ + \sum_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \xi_{idt} \end{aligned} \quad (2)$$

Dependent Variable: $\mathrm{S\_Special}_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept	?	-1.1566	<.0001	
IMR	?	0.0782	0.3597	0.007
E_Persistence	−	-0.0978	0.0645	-0.021
E_Predictability	+	0.0150	0.0794	0.007
E_Fixation	?	-0.4979	0.0307	-0.014
Size	+	0.1394	<.0001	0.055
Brand_Name	+	-0.0000	0.4086	0.000
N ($\mathrm{S\_Special}_{idt}$=1)	6,637 (3,466)			
Pseudo R^2	1.97%			
Likelihood Ratio (Chi-Square)	96.92			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Panel B: Stock Picking Ability Measured Using Raw Returns

$$S\_Special_{idt} = \delta + \gamma_2 \cdot IMR_{idt} + \gamma_2 \cdot E\_Persistence_{idt} + \gamma_3 \cdot E\_Predictability_{idt} + \gamma_4 \cdot E\_Fixation_{idt} + \gamma_5 \cdot Size_{idt} + \gamma_6 \cdot Brand\_Name_{idt} + \sum_t \rho_t \cdot Year\_Dummy_t + \xi_{idt} \quad (2)$$

Dependent Variable: $S\_Special_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept	?	-0.9638	<.0001	
IMR	?	0.0646	0.4466	0.006
E_Persistence	–	-0.0911	0.1067	-0.019
E_Predictability	+	0.0291	0.0739	0.008
E_Fixation	?	-0.1595	0.0809	-0.004
Size	+	0.1247	<.0001	0.049
Brand_Name	+	0.0000	0.4694	0.001
N ($S\_Special_{idt}$=1)	6,561 (2,773)			
Pseudo R^2	1.58%			
Likelihood Ratio (Chi-Square)	61.86			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Panel C: Stock Picking Ability Measured Using Market Model Adjusted Returns

$$\begin{aligned} \mathrm{S\_Special_{idt}} = {} & \delta + \gamma_2 \cdot \mathrm{IMR_{idt}} + \gamma_2 \cdot \mathrm{E\_Persistence_{idt}} + \gamma_3 \cdot \mathrm{E\_Predictability_{idt}} + \gamma_4 \\ & \cdot \mathrm{E\_Fixation_{idt}} + \gamma_5 \cdot \mathrm{Size_{idt}} + \gamma_6 \cdot \mathrm{Brand\_Name_{idt}} \\ & + \sum_t \rho_t \cdot \mathrm{Year\_Dummy_t} + \xi_{idt} \end{aligned} \quad (2)$$

Dependent Variable: $S\_Special_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept	?	-1.0718	<.0001	
IMR	?	0.0904	0.2239	0.009
E_Persistence	−	-0.1434	0.0296	-0.033
E_Predictability	+	0.0272	0.0678	0.013
E_Fixation	?	-0.2441	0.0755	-0.007
Size	+	0.1359	<.0001	0.055
Brand_Name	+	-0.0001	0.2693	-0.004
N ($S\_Special_{idt}$=1)		6,517 (2,675)		
Pseudo R^2		1.80%		
Likelihood Ratio (Chi-Square)		68.74		
Pr > ChiSq		<.0001		

See appendix for variable definitions.

Table 6 Panel A presents the results for H3 based on estimating equation (2). The coefficient on E_Persistence is significantly negative (at the level of 0.1), suggesting that analysts who cover firms with high earnings persistence have a higher likelihood of specializing in earnings forecasting skill, consistent with H3 that analysts develop a skill when the demand for the skill is high. The coefficient on E_Predictability is significantly positive (at the level of 0.1). The result is consistent with H3 that the more unpredictable the earnings (i.e. smaller values of E_Predictability), the higher the market's demand for analysts' earnings forecasting skill, and thus the higher the likelihood of observing analysts' specializing in earnings forecasting skill. E_Fixation has a negative coefficient significant at the level of 0.05. As discussed in the previous chapters, E_Fixation likely captures investors' fixation on earnings, and such earnings fixation creates demand for superior earnings forecasting skill; in this case, a negative coefficient on E_Fixation is predicted. However, if investors are both sophisticated and rational such that they can detect earnings management, there should not be a demand for "superior" earnings forecasting skill as defined in my study. Since it is a joint test of both H3 and the economic nature of the proxy E_Fixation, the empirical results can be interpreted as consistent with both E_Fixation captures investors' fixation on earnings and analysts optimally choose to specialize in forecasting earnings when covered firms engage more in earnings management. Also consistent with H3 that the likelihood of specializing in stock picking skill is positively correlated with the size of the firms covered by analysts (significant at the level of 0.01), which proxies for the number of individual investors owning the firms covered by the analyst. Brand_Name, however, is not siginifcant probably due to the high correlation between Brand_Name and Size. In an untabulated test, I include only Brand_Name but not Size in the regression, and find significant positive coefficient on Brand_Name, which is consistent with H3.

Table 7: Testing Skill Specialization and Skill Utilization

Panel A: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns

$$\mathrm{E\_Freq}_{idt} = \theta_0 + \theta_1 \cdot \mathrm{IMR}_{idt} + \theta_2 \cdot \mathrm{Ind\_Expr}_{idt} + \theta_3 \cdot \mathrm{General\_Expr}_{idt} + \theta_4 \cdot \mathrm{Broker\_Size}_{it} + \theta_5 \cdot \mathrm{Broker\_Reputation}_{it} + \theta_6 \cdot \mathrm{S\_Special}_{idt} + \sum_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \epsilon_{idt} \qquad (3)$$

$$\mathrm{E\_Innovation}_{idt} = \rho_0 + \rho_1 \cdot \mathrm{IMR}_{idt} + \rho_2 \cdot \mathrm{Ind\_Expr}_{idt} + \rho_3 \cdot \mathrm{General\_Expr}_{idt} + \rho_4 \cdot \mathrm{Broker\_Size}_{it} + \rho_5 \cdot \mathrm{Broker\_Reputation}_{it} + \rho_6 \cdot \mathrm{S\_Special}_{idt} + \sum_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \varsigma_{idt} \qquad (4)$$

$$\mathrm{S\_Freq}_{idt} = \varphi_0 + \varphi_1 \cdot \mathrm{IMR}_{idt} + \varphi_2 \cdot \mathrm{Ind\_Expr}_{idt} + \varphi_3 \cdot \mathrm{General\_Expr}_{idt} + \varphi_4 \cdot \mathrm{Broker\_Size}_{it} + \varphi_5 \cdot \mathrm{Broker\_Reputation}_{it} + \varphi_6 \cdot \mathrm{S\_Special}_{idt} + \sum_t \rho_t \cdot \mathrm{Year\_Dummyt} + \iota\mathrm{idt} \qquad (5)$$

Dependent Variable:	E_Freq			E_Innovation			S_Freq		
	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value
Intercept		-34.0864	<.0001		0.5224	<.0001		-8.2219	<.0001
IMR		27.1834	<.0001		-0.0263	0.0384		7.2792	<.0001
Ind_Expr	+	1.4416	<.0001	+	-0.0002	0.4507	+	0.3178	<.0001
General_Expr	+	-1.1616	<.0001	+	-0.0012	0.1861	+	-0.3072	<.0001
Broker_Size	+	0.0364	0.0129	+	0.0011	<.0001	+	0.0154	0.0003
Broker_Reputation	+	0.3302	0.0442	+	-0.0097	<.0001	+	-0.0670	0.0780
S_Special	−	-3.6792	<.0001	−	-0.0370	<.0001	+	-0.2806	0.1082
N		7,061			6,614			7,061	
Adjusted R^2		9.76%			2.60%			8.31%	

See appendix for variable definitions.

Panel B: Stock Picking Ability Measured Using Raw Returns

$$\text{E\_Freq}_{idt} = \theta_0 + \theta_1 \cdot \text{IMR}_{idt} + \theta_2 \cdot \text{Ind\_Expr}_{idt} + \theta_3 \cdot \text{General\_Expr}_{idt} + \theta_4 \cdot \text{Broker\_Size}_{it} + \theta_5 \cdot \text{Broker\_Reputation}_{it} + \theta_6 \cdot \text{S\_Special}_{idt} + \sum_t \rho_t \cdot \text{Year\_Dummy}_t + \epsilon_{idt} \tag{3}$$

$$\text{E\_Innovation}_{idt} = \rho_0 + \rho_1 \cdot \text{IMR}_{idt} + \rho_2 \cdot \text{Ind\_Expr}_{idt} + \rho_3 \cdot \text{General\_Expr}_{idt} + \rho_4 \cdot \text{Broker\_Size}_{it} + \rho_5 \cdot \text{Broker\_Reputation}_{it} + \rho_6 \cdot \text{S\_Special}_{idt} + \sum_t \rho_t \cdot \text{Year\_Dummy}_t + \varsigma_{idt} \tag{4}$$

$$\text{S\_Freq}_{idt} = \varphi_0 + \varphi_1 \cdot \text{IMR}_{idt} + \varphi_2 \cdot \text{Ind\_Expr}_{idt} + \varphi_3 \cdot \text{General\_Expr}_{idt} + \varphi_4 \cdot \text{Broker\_Size}_{it} + \varphi_5 \cdot \text{Broker\_Reputation}_{it} + \varphi_6 \cdot \text{S\_Special}_{idt} + \sum_t \rho_t \cdot \text{Year\_Dummyt}+\iota\text{idt} \tag{5}$$

Dependent Variable:	E_Freq			E_Innovation			S_Freq		
	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value
Intercept		-25.4153	<.0001		0.5181	<.0001		-6.5395	<.0001
IMR		15.1573	<.0001		-0.0102	0.3764		4.7445	<.0001
Ind_Expr	+	1.9692	<.0001	+	-0.0010	0.2443	+	0.4672	<.0001
General_Expr	+	-1.2208	<.0001	+	-0.0004	0.4151	+	-0.3264	<.0001
Broker_Size	+	0.0766	0.0001	+	0.0010	<.0001	+	0.0244	<.0001
Broker_Reputation	+	0.4950	0.0126	+	-0.0101	<.0001	+	-0.0349	0.2567
S_Special	−	-4.1367	<.0001	−	-0.0394	<.0001	+	-0.2846	0.1376
N		5,607			5,232			5,607	
Adjusted R^2		8.42%			2.52%			7.69%	

See appendix for variable definitions.

Panel C: Stock Picking Ability Measured Using Market Model Adjusted Returns

$$E\_Freq_{idt} = \theta_0 + \theta_1 \cdot IMR_{idt} + \theta_2 \cdot Ind\_Expr_{idt} + \theta_3 \cdot General\_Expr_{idt} + \theta_4 \cdot Broker\_Size_{it} + \theta_5 \cdot Broker\_Reputation_{it} + \theta_6 \cdot S\_Special_{idt} + \sum_t \rho_t \cdot Year\_Dummy_t + \epsilon_{idt} \quad (3)$$

$$E\_Innovation_{idt} = \rho_0 + \rho_1 \cdot IMR_{idt} + \rho_2 \cdot Ind\_Expr_{idt} + \rho_3 \cdot General\_Expr_{idt} + \rho_4 \cdot Broker\_Size_{it} + \rho_5 \cdot Broker\_Reputation_{it} + \rho_6 \cdot S\_Special_{idt} + \sum_t \rho_t \cdot Year\_Dummy_t + \varsigma_{idt} \quad (4)$$

$$S\_Freq_{idt} = \varphi_0 + \varphi_1 \cdot IMR_{idt} + \varphi_2 \cdot Ind\_Expr_{idt} + \varphi_3 \cdot General\_Expr_{idt} + \varphi_4 \cdot Broker\_Size_{it} + \varphi_5 \cdot Broker\_Reputation_{it} + \varphi_6 \cdot S\_Special_{idt} + \sum_t \rho_t \cdot Year\_Dummyt + \iota idt \quad (5)$$

Dependent Variable:	E_Freq			E_Innovation			S_Freq		
	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value
Intercept		-20.6444	<.0001		0.5176	<.0001		-4.6152	<.0001
IMR		5.6031	0.0002		-0.0147	0.0911		1.6099	<.0001
Ind_Expr	+	2.3399	<.0001	+	-0.0007	0.3309	+	0.5547	<.0001
General_Expr	+	-1.3216	<.0001	+	-0.0008	0.2302	+	-0.3520	<.0001
Broker_Size	+	0.0969	<.0001	+	0.0012	<.0001	+	0.0264	<.0001
Broker_Reputation	+	0.8305	<.0001	+	-0.0114	<.0001	+	0.0891	0.0398
S_Special	−	-3.5075	0.0001	−	-0.0328	<.0001	+	-0.2016	0.2009
N		5,484			5,114			5,484	
Adjusted R^2		7.32%			2.65%			5.96%	

See appendix for variable definitions.

Table 7 Panel A reports the results for H4. When relative earnings forecast frequency (E_Freq) is the dependent variable, it is significantly negatively correlated with S_Special (significant at level of 0.01) after controlling for analysts' industry experience, general experience, brokerage size as well as brokerage reputation (all significant at level of 0.05), suggesting that analysts who specialize in earnings forecasting skill issue earnings forecasts more frequently. The result is consistent with H4 that after an analyst specializes in earnings forecasting skill, he would utilize the skill intensively to maximize its return. When the dependent variable is the percentage of innovative earnings forecasts, it is also significantly positively correlated with S_Special (significant at level of 0.01) after controlling for analysts' industry experience, general experience, brokerage size and brokerage reputation. Together, results of Equation (3) and (4) suggest that analysts who specialize in earnings forecasting skills not only issue relatively more earnings forecasts but also have a higher percentage of innovative earnings forecasts, consistent with the prediction of H4.

The last three columns of Table 7 Panel A report the results for Equation (5) with relative stock recommendation frequency (S_Freq) as the dependent variable. After controlling for analysts' industry experience, general experience, brokerage size and brokerage reputation, S_Freq is not significantly correlated with S_Special (p-value >0.10). The insignificance could be due to the fact that stock recommendations are much more discrete than earnings forecasts, thus analysts in general update stock recommendations less frequently than earnings forecasts. Therefore, even if an analyst who specializes in stock picking skill utilizes the skill intensively, we might not observe a higher frequency of stock recommendation revisions since the utilization of the skill does not necessarily trigger a stock recommendation revision.

6. Sensitivity Tests

6.1 Analysts' Incentives

It is documented in the literature that analysts can have incentive to issue biased reports due to their conflict of interest. For example, there is evidence that analysts issue systematically optimistic forecast (O'Brien [1990]), that analysts issue pessimistic forecasts so that managers can beat their forecasts more easily (Bartov, Givoly and Hayn [2002], Burgstahler and Eames [2002], DeGeorge, Patel and Zeckhauser [1999], Kasznik and McNichols [2002], Matsumoto [2002], and Richardson, Teoh and Wysocki [1999]), and that affiliated analysts issue more optimistic growth forecasts and stock recommendations (Lin and McNichols [1998]).

It is ex ante unclear which of these incentives, i.e., among currying favor with management for information (Francis and Philbrick [1993], Lim [2001], Ke and Yu [2006], and Huang, Willis and Zang [2005]), competing for investment banking relationship, maintaining current investment banking relationship, and signaling proprietary information, dominates in the analysts' utility function. Admittedly, existence of these analyst biases might add measurement errors to my skill specialization proxies, since some analysts have incentives not to minimize the forecasting error or maximize recommendation profitability, and therefore, reduces the power of my tests. However, it is not obvious from the evidence in the extant literature whether these incentives make analysts more biased in one output but not the other one and thus biased my specialization measure systematically.

I conduct several sensitivity tests to address the concern that analysts' incentives might bias my empirical results. First, I base earnings forecast skill measurement on the last forecast issued by analysts in the fiscal year. As shown in Figure 1 in Richardson et al. [2004], from 1992 to 2001, which covers my sample period, analysts' forecast errors three months before the earnings announcement date are closest to zero in all the sub-periods (from eleven months before earnings announcement till the month of earnings announcement), indicating that the incentives for all analysts to bias forecast either favorably or unfavorably are minimal towards the end of the fiscal year.

Second, I treat all the "hold" recommendation as "sell" recommendations in order to mitigate analysts' favorable biases in stock recommendations. (Sensitivity based on treating all hold recommendation as holding neither long nor short position yield the same result).

Third, earnings forecasting and stock picking skill are measured relative to analysts' peers covering the same stocks. The problem of analyst incentives is mitigated if all the analysts covering the same stock are subject to same conflict of interest.

Fourth, I replicate the main tests excluding affiliated analysts identified following Malmendier and Shanthikumar [2007]. Specifically, I download all the initial public offering (IPO), secondary equity offering (SEO), and bond underwriting data from SDC Platinum Database and manually match the brokerage names in the IPO underwriter lists provided by SDC to the brokerage names in Zacks brokerage list. I define analysts as affiliated if their brokerage house was the lead underwriter or co-underwriter in an IPO of the covered stock in the past five years, an SEO in the past two years, or an SEO in the next one or two years, or the lead underwriter of bonds in the past year.

After excluding affiliated analysts, the correlation between earnings forecast accuracy and stock recommendation profitability remains low (0.020), indicating that analyst biases induced by affiliation does not explain the low correlation between the two skills. I also estimate the logistic regressions excluding all affiliated analyst-firms, and the inferences are unaltered.

6.2 Internet Bubble and Bust Periods

My sample period encompasses the internet bubble and bust periods. During these periods, analysts' biases may be quite distinct. As a sensitivity check, I separately estimate the regressions for the pre and post internet bubble periods, 1991-2000 and 2001-2003 respectively and report the results in Table 8 and 9 below. The results from the pre-bubble period (1991-2000) are mostly the same as those from the full sample. The results from the post-bubble period (2001-2003) are weaker than those from the full sample, especially in the logit regression of specializing in stock picking versus earnings forecasting, perhaps due to the decreased sample size (1,536 observations, less than one fourth of the full sample size) or the change of analyst incentives after the internet bubble burst. Since analysts' skill specialization is unlikely to be affected by their incentives (as discussed in section 6.1), it is more likely that the weaker results from post-bubble period (2001-2003) are due to the decrease in sample size.

Table 8: Logit Regression of Specialization versus Non-Specialization – Internet Bubble and Bust Periods

Panel A: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns (1991-2000)

$$\begin{aligned}\text{Special}_{\text{idt}} = \alpha &+ \beta_1 \cdot \text{E\_Relevance}_{\text{idt}} + \beta_2 \cdot \text{E\_Relevance}^2_{\text{idt}} + \beta_3 \cdot \text{E\_Timeliness}_{\text{idt}} \\ &+ \beta_4 \cdot \text{E\_Timeliness}^2_{\text{idt}} + \beta_5 \cdot \text{Broker\_Size}_{\text{it}} + \beta_6 \cdot \text{Broker\_Reputation}_{\text{it}} \\ &+ \beta_7 \cdot \text{All\_Star}_{\text{it}} + \beta_8 \cdot \text{Skill\_Spillover}_{\text{dt}} + \beta_9 \cdot \text{Ind\_Expr}_{\text{idt}} \\ &+ \sum_t \rho_t \cdot \text{Year\_Dummy}_t + \varepsilon_{\text{idt}}\end{aligned} \tag{1}$$

Dependent Variable: $\text{Special}_{\text{idt}}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept		1.3516	<.0001	
E_Relevance	−	-3.6405	<.0001	-0.091
E_Relevance^2	+	10.3952	<.0001	0.134
E_Timeliness	−	-3.4456	<.0001	-0.159
E_Timeliness^2	+	3.9289	<.0001	0.198
Broker_Size	−	-0.0047	<.0001	-0.037
Underwrite_Rank	−	-0.0337	0.0004	-0.018
All_Star	−	-0.2329	<.0001	-0.055
Skill_Spillover	−	-0.0001	0.1596	-0.004
Ind_Expr		-0.0543	<.0001	-0.054
N ($\text{Special}_{\text{idt}}$=1)	17,017 (6,877)			
Pseudo R^2	7.82%			
Likelihood Ratio (Chi-Square)	1,014.98			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Panel B: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns (2001-2003)

$$\begin{aligned} \mathrm{Special}_{idt} = \alpha &+ \beta_1 \cdot \mathrm{E\_Relevance}_{idt} + \beta_2 \cdot \mathrm{E\_Relevance}^2_{idt} + \beta_3 \cdot \mathrm{E\_Timeliness}_{idt} \\ &+ \beta_4 \cdot \mathrm{E\_Timeliness}^2_{idt} + \beta_5 \cdot \mathrm{Broker\_Size}_{it} + \beta_6 \cdot \mathrm{Broker\_Reputation}_{it} \\ &+ \beta_7 \cdot \mathrm{All\_Star}_{it} + \beta_8 \cdot \mathrm{Skill\_Spillover}_{dt} + \beta_9 \cdot \mathrm{Ind\_Expr}_{idt} \\ &+ \sum\nolimits_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \varepsilon_{idt} \end{aligned} \quad (1)$$

Dependent Variable: $\mathrm{Special}_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept		1.3910	<.0001	
E_Relevance	−	-5.8034	<.0001	-0.125
E_Relevance^2	+	17.0708	<.0001	0.173
E_Timeliness	−	-4.4414	<.0001	-0.187
E_Timeliness^2	+	4.9183	<.0001	0.221
Broker_Size	−	-0.0045	0.0001	-0.044
Underwrite_Rank	−	-0.0087	0.2536	-0.006
All_Star	−	-0.1876	0.0498	-0.045
Skill_Spillover	−	-0.0001	0.1420	-0.008
Ind_Expr		-0.0327	<.0001	-0.037
N ($\mathrm{Special}_{idt}$=1)	5,435 (2,265)			
Pseudo R^2	7.34%			
Likelihood Ratio (Chi-Square)	304.67			
Pr > ChiSq	<.0001			

See appendix for variable definitions.

Table 9: Logit Regression of Specializing in Stock Picking versus Earnings Forecasting – Internet Bubble and Bust Periods

Panel A: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns (1991-2000)

$$\begin{aligned} \mathrm{S\_Special}_{idt} = {} & \delta + \gamma_2 \cdot \mathrm{IMR}_{idt} + \gamma_2 \cdot \mathrm{E\_Persistence}_{idt} + \gamma_3 \cdot \mathrm{E\_Predictability}_{idt} + \gamma_4 \\ & \cdot \mathrm{E\_Fixation}_{idt} + \gamma_5 \cdot \mathrm{Size}_{idt} + \gamma_6 \cdot \mathrm{Brand\_Name}_{idt} \\ & + \sum_t \rho_t \cdot \mathrm{Year\_Dummy}_t + \xi_{idt} \end{aligned} \quad (2)$$

Dependent Variable: $S\_Special_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept	?	-0.1437	0.4759	
IMR	?	-0.1940	0.0478	-0.016
E_Persistence	–	-0.1970	0.0039	-0.049
E_Predictability	+	0.0026	0.4578	0.000
E_Fixation	?	-0.4275	0.0863	-0.014
Size	+	0.0565	0.0051	0.023
Brand_Name	+	0.0000	0.4325	0.001
N ($S\_Special_{idt}$=1)		5,101 (2,707)		
Pseudo R^2		0.74%		
Likelihood Ratio (Chi-Square)		26.26		
Pr > ChiSq		0.0354		

See appendix for variable definitions.

Panel B: Stock Picking Ability Measured Using Fama-French Three-Factor Model Adjusted Returns (2001-2003)

$$S\_Special_{idt} = \delta + \gamma_2 \cdot IMR_{idt} + \gamma_2 \cdot E\_Persistence_{idt} + \gamma_3 \cdot E\_Predictability_{idt} + \gamma_4 \cdot E\_Fixation_{idt} + \gamma_5 \cdot Size_{idt} + \gamma_6 \cdot Brand\_Name_{idt} + \sum_t \rho_t \cdot Year\_Dummy_t + \xi_{idt} \quad (2)$$

Dependent Variable: $S\_Special_{idt}$	Pred. Sign	Coef.	P-Value	Marginal Eff.
Intercept	?	-0.0995	0.7581	
IMR	?	-0.0342	0.8408	-0.002
E_Persistence	−	0.1370	0.1680	0.034
E_Predictability	+	0.0186	0.0856	0.020
E_Fixation	?	-0.2029	0.3231	-0.007
Size	+	-0.0031	0.4679	-0.001
Brand_Name	+	0.0002	0.1938	0.012
N ($S\_Special_{idt}$=1)		1,536 (759)		
Pseudo R^2		0.51%		
Likelihood Ratio (Chi-Square)		5.9272		
Pr > ChiSq		0.6554		

See appendix for variable definitions.

6.3 Persistence of Analysts' Skills

An implicit assumption of my paper is that the analyst makes skill specialization decisions in each period. However, one can argue that analysts' skills are developed over time and their specialization decisions become permanent after a point. If this conjecture is true, then the results of the tests are inflated. In order to test the validity of this conjecture, I examine the persistence of analysts' skill specialization over time. The autocorrelation coefficients of analyst specialization (i.e. whether they specialize or not) and the type of their specialization (i.e. which skill the specializing analysts choose) are 0.26 and 0.24, respectively, indicating that analysts' skill specialization decisions are not highly persistent over time. I regress the autocorrelation coefficients of analyst specialization and the type of their specialization on analysts' industry experience and find that the coefficients on experience are statistically insignificant, inconsistent with the argument that analysts maintain fixed skill specialization after a certain point.

6.4 Absence of Analyst Efforts

In my paper, analysts' placement on the skill matrix is determined by their innate ability and their choice of skill specializations. As illustrated in the skill matrix (Figure 1), different dash lines represent analysts with different level of innate ability and their specialization choices determine their placement on the dash lines.

An alternative explanation for analysts' placement in Figure 1 is that there is no role for analyst innate ability or skill specialization choices, and that the distribution of analysts on the grid is solely determined by the characteristics of the firms they follow. Such alternative hypothesis predicts that if analysts cover firms with perfect complementarities between information needed for earnings forecasts and for stock recommendations, analysts' earnings forecast accuracy and stock recommendation profitability are mechanically correlated, and we should observe analysts distributed along the diagonal cells in Figure 1. For example, if an analyst following such firms receives low (high) quality earnings information in this year, he is likely to receive low (high) quality stock price information as well, and therefore he will appear in cell (1, 1) ((5, 5)) in Figure 1. If analysts cover firms with no complementarities between information needed for earnings forecasts and for stock recommendations, there is no correlation between analyst earnings forecast accuracy and stock recommendation profitability and we should expect analysts to be evenly distributed on the grid.

If such alternative hypothesis is valid, we should expect the firms covered by analysts in the white cells (i.e. those with good or bad performance in both earnings forecasting and stock picking) offer higher complementarities between information needed for earnings forecasts and stock recommendations (proxied by earnings relevance and earnings timeliness) than firms covered by analysts in the off-diagonal cells.

In the sensitivity test, I find no significant difference in earnings timeliness of the firms covered by analysts in the white cells and firms followed by analysts in the lower left and upper right corners (analysts in top (bottom) two earnings forecasting skill quintiles and bottom (top) two stock picking skill quintiles). The firms covered by analysts in the white cells have higher earnings relevance (significant at 10% level) than the analysts in the lower left and upper right corners. However, this result is sensitive to the definition of extreme skills. If I define the top (bottom) skills as the top (bottom) one quintile instead of the top (bottom) two quintiles, there is no significant difference in the earnings relevance and earnings timeliness of the firms covered by these two groups of analysts.

Overall, there is little support for the alternative explanation that firms covered by analysts in the white cells offer higher complementarities for earnings forecasts and stock recommendations than firms covered by analysts in off-diagonal cells. Therefore, it is unlikely that analyst distribution on the grid can be explained by the characteristics of the firms covered without considering analysts' efforts and choices of skill specialization.

6.5 Multinomial Logit Analysis

In my empirical test, I identify and separately test two different sets of determinants: one set for analysts' choice between specializing and non-specializing, and the other for specializing analysts' choice between specializing in earnings forecasting skill and stock picking skill. In testing the determinants for specializing analysts' choice between specializing in earnings forecasting skill and stock picking skill, I control for the effect of their self-selecting to be specializing in one skill using inverse Mill's Ratio from the first test.

An alternative empirical specification is to use the multinomial logit model where the two sets of determinants are combined to explain the decisions among non-specialization, specializing in earnings forecasting skill and specializing in stock picking skill. Although such specification is econometrically feasible, it is less appropriate than the specification in my main test since the two choices, specializing in earnings forecasting skill and specializing in stock picking skill, are not comparable to the choice of non-specializing. By not comparable, I mean they have different determinants. An analogue is that the choice of not drinking alcohol is not comparable to the choices of drinking red wine or drinking white wine; not drinking alcohol may be determined by the person's age, whether he drinks alcohol, whether he needs to drive, and his budget; the choices between red and white wine are likely determined by his taste, and whether he is having steak or fish, etc. Therefore, although the specification is econometrically feasible, it is difficult to interpret some of the coefficients.

The results of the multinomial logistic analysis are reported in Table 10. I do not have predictions for some of the independent variables for the reasons discussed above. For the independent variables with predictions, the signs of their estimated coefficients are consistent with the predictions, and the significance of them is stronger than that is reported by Table 5 and 6. Therefore, my empirical results are not sensitive to the multinomial logistic specification.

Table 10: Multinomial Logit Analysis for Non-Specializing, Specializing in Earnings Forecasting Skill, and Specializing in Stock Picking Skill

	S_Special = 0 versus No Specialty			S_Special = 1 versus No Specialty			S_Special = 1 versus S_Special = 0		
	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value	Pred. Sign	Coef.	P-Value
Intercept		0.1598	0.7029		1.2189	0.0049		1.0591	0.0401
E_Relevance	−	-5.0617	<.0001	−	-4.9064	<.0001		0.1553	0.8115
E_Relevance^2	+	13.3657	<.0001	+	13.0402	<.0001		-0.3255	0.8119
E_Timeliness	−	-3.8777	<.0001	−	-4.3616	<.0001		-0.4839	0.2726
E_Timeliness^2	+	4.4733	<.0001	+	4.8552	<.0001		0.3819	0.3959
Broker_Size	−	-0.0021	0.0081	−	-0.0040	<.0001		-0.0019	0.0656
Underwrite_Rank	−	-0.0216	0.0081	−	-0.0360	0.0003		-0.0144	0.2489
All_Star	−	-0.2013	0.0208	−	-0.1970	0.0028		0.0043	0.9620
Skill_Spillover	−	-0.0002	0.0135	−	-0.0002	0.0028		-0.0000	0.6708
Ind_Expr	?	-0.0400	<.0001	?	-0.0393	<.0001		0.0007	0.9009
E_Persistence		0.2971	<.0001		0.1618	0.0044	−	-0.1353	0.0213
E_Predictability		-0.0453	0.0102		-0.0339	0.0560	+	0.0114	0.0754
E_Fixation		0.1275	0.5762		-0.2531	0.2360	?	-0.3806	0.0767
Size		-0.2213	<.0001		-0.1643	<.0001	+	0.0570	0.0022
Brand_Name		-0.0005	0.0135		-0.0004	0.0004	+	0.0001	0.2526
	No Specialty (N=10,996), S_Special=0 (N=3,083), S_Special=1 (N=3,195)								
Likelihood Ratio (Chi-Square)	30,140.07								
Pr > Chisq	<.0001								

See appendix for variable definitions.

7. Conclusion

My dissertation examines individual analysts' specialization in earnings forecasting skill and stock picking skill. I analyze analyst utility maximization process and predict that non-specialization is optimal for analysts when there is considerable economy of scope between the two skills' development; that specialization is optimal when the costs of skill development are high; and that the marginal benefit of each skill is positively correlated with the chance that analysts choose to develop that particular skill. Consistent with my hypotheses, I find empirical evidence that an analyst's choice of non-specialization is positively correlated with his brokerage size, brokerage reputation, his all-star status, the industry skill spillover effect, all of which capture the inverse of the costs associated with skill development. I show that the economy of scope in skill development, measured with earnings relevance and earnings timeliness, can explain an analyst's choice of skill specialization versus non-specialization, albeit in a non-linear manner. Using earnings persistence, earnings predictability, and earnings fixation to measure investors' demand for analysts' earnings forecasting skill, and firms' shareholder base to measure the demand for analysts' stock picking skill, I show that these firm characteristics explain analysts' choices between the two skill specializations. I also find analysts who specialize in earnings forecasting utilize the skill more intensively than analysts who do not by issuing more frequent and more innovative earnings forecast revisions. However, there is no significant relation between relative stock recommendation frequency and stock picking specialization probably due to the highly discrete nature of stock recommendations. My study not only empirically tests the theories of labor specialization but also improves our understanding of analyst utility maximization process and skill development.

Appendix I: A Model of Analyst Skill Specialization

In this appendix, I follow Rosen [1983] and develop a simple analytical model to show the circumstances where an analyst will choose to specialize in one of the two skills in order to maximize the return to his human capital.

For simplicity, let us assume that forecasting earnings and picking stocks, or portions of these two tasks, involve two different skills: k_1 and k_2. k_1 and k_2 are efficiency units representing an analyst's efficiency in forecasting earnings and picking stocks, respectively. A higher k_1 means that the analyst is more skillful in forecasting earnings; a higher k_2 means the analyst is more skillful in picking stocks. The level of k_1 and k_2 are chosen by the analyst.

Assume that the amount of time an analyst spends in task 1 and 2 are t_1 and t_2 respectively, i.e. t_1 and t_2 are also analysts' choice variables. Therefore, the amount of work the analyst accomplish in task 1 and 2 are: t_1k_1 and t_2k_2. Note that, t_1 and t_2 do *not* represent the time analysts spend in *developing* skills k_1 and k_2 but the time analysts spend in *utilizing* these skills. An implicit assumption here is that once a certain level of skill is acquired, utilizing the skill does not result in costs or increase the skill level. [1]

Assume that the wage rates for task 1 and 2 are w_1 and w_2, are set by competitive labor market driven by various forces such as the market demand for the earnings

[1] Analysts can develop skills by self-studying, learning from their peers, obtain training from the brokerage house, and etc. However, in my paper, I do not model the different ways analysts develop their skills.

forecasting skill and stock picking skill, and are considered exogenous. Therefore, w_1/w_2 captures the relative benefit of developing earnings forecasting skill versus stock picking skill for analysts. The total returns to task 1 and 2 are $w_1k_1t_1$ and $w_2k_2t_2$, respectively.

Assume the cost function of developing the two skills is a convex function with strictly positive marginal cost of development in both skills:

$$C(k_1, k_2) = \frac{1}{2} \cdot a_1 \cdot k_1^2 + \frac{1}{2} \cdot a_2 \cdot k_2^2 + \rho \cdot k_1 \cdot k_2.$$

$C_1 = a_1 \cdot k_1 + \rho \cdot k_2$ is the marginal cost of developing k_1; $C_2 = a_2 \cdot k_2 + \rho \cdot k_1$ is the marginal cost of developing k_2. Assume a_i is sufficiently large that $C_i > 0$. $\rho < 0$ captures the economy of scope in developing skills, i.e., the extent of the decrease in the marginal cost of developing one skill due to the development of the other skill. Note that t_1 and t_2 determine the returns to task 1 and 2 but are not part of the cost function of developing skills, $C(k_1, k_2)$, since they are the time analysts spend on utilizing but not developing the skills.

An analyst with one unit of available market time, i.e. $t_1 + t_2 = 1$, has a human capital value of

$$V = w_1k_1t_1 + w_2k_2(1 - t_1) - C(k_1, k_2). \tag{1}$$

The analyst chooses k_1, k_2 and t_1 to maximize V. First-order conditions for maximizing (1), subject to the constraints of $k_i \geq 0$, $0 \leq t_1 \leq 1$, are

$$\begin{cases} (w_1k_1 - w_2k_2)\cdot t_1 = 0 \\ (w_2k_2 - w_1k_1)\cdot(1-t_1) = 0. \\ (w_it_i - C_i)\cdot k_i = 0, \;\; i = 1,2. \end{cases}$$

First, let us consider the interior solution, where the analyst invests in both skills (i.e., $k_i > 0$ and $0 < t_1 < 1$). The optimal allocation of time is such that the marginal value of a unit of time spent on each skill must be equal. Therefore, the relative skill level developed is constrained by

$$k_1 = (w_2/w_1)k_2 \equiv \gamma k_2 \tag{2}$$

Note that (2) suggests that if the analyst invests in both skills, the optimal allocation of time implies that $w_1k_1t_1 + w_2k_2(1-t_1) = w_1k_1 = w_2k_2$,

Let V^{12} denote the value of (1) under the optimal allocation of time when the analyst invests in both skills. From (2) we have $w_1k_1 = w_2k_2$, therefore:

$$V^{12}(k_1,k_2) = w_2k_2 - C(\gamma k_2, k_2) = w_1k_1 - C(k_1, k_1/\gamma).$$

Second, let us consider the corner solution where the analyst chooses to specialize in one skill. If the analyst specializes in task 1, i.e. $k_2 = 0$, (1) becomes

$$V^1(k_1) = w_1k_1 - C(k_1, 0);$$

Similarly, if the analyst specializes in task 2, i.e. $k_1 = 0$, (1) becomes

$$V^2(k_2) = w_2k_2 - C(0, k_2);$$

Therefore, non-specialization (i.e., interior solution) is optimal (i.e. the maximum utility of the interior solution is higher than the maximum utility under the corner solution) if both following conditions are satisfied for all conceivable values of k_1 and k_2:

$$\begin{cases} V^{12}(k_1, k_2) - V^1(k_1) > 0 \Rightarrow -C(k_1, k_1/\gamma) + C(k_1, 0) > 0, \forall k_1 & (3) \\ V^{12}(k_1, k_2) - V^2(k_2) > 0 \Rightarrow -C(\gamma k_2, k_2) + C(0, k_2) > 0, \forall k_2 & (4) \end{cases}$$

Expanding the cost terms in (3) and (4) yields:

$$\begin{cases} -\frac{1}{2} \cdot a_2 \cdot \left(\frac{k_1}{\gamma}\right)^2 - \rho \cdot k_1 \cdot \frac{k_1}{\gamma} > 0, \forall k_1 \\ -\frac{1}{2} \cdot a_1 \cdot (\gamma \cdot k_2)^2 - \rho \cdot \gamma \cdot k_2 \cdot k_2 > 0, \forall k_2 \end{cases}$$

Further simplification yields:

$$\rho < min\left\{-\frac{a_2}{2} \cdot \frac{1}{\gamma}, -\frac{a_1}{2} \cdot \gamma\right\}$$

That is, the non-specialization solution exists if $\rho < 0$, and a_1 and a_2 are sufficiently small.

One of the corner solutions (i.e., specializing in task 1 or task 2) is optimal for the analyst, when $\rho > 0$, or $\rho < 0$ but a_1 and a_2 are sufficiently large (i.e., $V^{12}(k_1, k_2) - V^1(k_1) < 0$ and $V^{12}(k_1, k_2) - V^2(k_2) < 0$ for all conceivable values of k_1 and k_2).

When corner solutions is optimal, the analyst determines which skill to specialize by comparing $V^1(k_1)$ and $V^2(k_2)$, both of which are maximized by picking the optimal level of k_i^* satisfying the constraint that marginal benefit equals marginal cost (i.e., $w_i = a_i \cdot k_i^*$):

$$V^1(k_1) = \frac{w_1^2}{2 \cdot a_1}, \tag{14}$$

$$V^2(k_2) = \frac{w_2^2}{2 \cdot a_2}. \tag{15}$$

Specializing in k_1 is optimal when $V^1(k_1) > V^2(k_2)$; specializing in k_2 is optimal when $V^1(k_1) < V^2(k_2)$.

Appendix II: Alternative Model with b Capturing the Benefit of Earnings Forecasting Skill for Picking Stocks

For simplicity, my model in Appendix I does not incorporate the role of earnings forecasting skill in picking stocks in the benefit function of stock picking skill. As shown later, incorporating the correlation between the two skills in the benefit function of stock picking skill does not change the implications from the model.

Presumably, stock picking skill increases with earnings forecasting skill, since forecasted earnings are important inputs to the valuation functions analysts use to generate target prices, which they use to generate stock recommendations. Therefore, we can think of the skill for picking stocks as having two components; one is related to earnings forecasting skill (k_1); the other is all other skills beyond forecasting earnings required to generate stock recommendations (k_2). Therefore, the stock picking skill is $b \cdot k_1 + k_2$, with b capturing the benefit of earnings forecasting skills for picking stocks. Incorporating b into my model, analysts' objective function becomes the following:

$$\max_{k_1, k_2, t_1} V = w_1 k_1 t_1 + w_2(b \cdot k_1 + k_2)(1 - t_1) - C(k_1, k_2). \tag{5}$$

The analyst chooses k_1, k_2 and t_1 to maximize V. First-order conditions for maximizing (5), subject to the constraints of $k_i \geq 0$, $0 \leq t_1 \leq 1$, are

$$\begin{cases} [w_1k_1 - w_2(b \cdot k_1 + k_2)] \cdot t_1 = 0 \\ [w_2(b \cdot k_1 + k_2) - w_1k_1] \cdot (1 - t_1) = 0 \\ (w_1t_1 - C_1) \cdot k_1 = 0 \\ [w_2(1 - t_1) - C_2] \cdot (b \cdot k_1 + k_2) = 0 \end{cases}.$$

First, let us consider the interior solution, where the analyst invests in both skills (i.e., $k_i > 0$ and $0 < t_1 < 1$). The optimal allocation of time is such that the marginal value of a unit of time spent on each skill must be equal. Therefore, the relative skill level developed is constrained by:

$$k_1 = \frac{w_2}{w_1 - b \cdot w_2} k_2 \equiv \gamma k_2 \tag{6}$$

Note that (6) suggests that if the analyst invests in both skills, the optimal allocation of time implies that $w_1k_1t_1 + w_2(b \cdot k_1 + k_2)(1 - t_1) = w_1k_1 = w_2(b \cdot k_1 + k_2)$,

Let V^{12} denote the value of (5) under the optimal allocation of time when the analyst invests in both skills. From (6) we have $w_1k_1 = w_2(b \cdot k_1 + k_2)$, therefore:

$$V^{12}(k_1, k_2) = w_2(b \cdot k_1 + k_2) - C(\gamma k_2, k_2) = w_1k_1 - C(k_1, k_1/\gamma).$$

Second, let us consider the corner solution where the analyst chooses to specialize in one skill. Also assume that $w_1 > b \cdot w_2$, which requires that the benefit from more accurate earnings forecasts due to a higher earnings forecasting skill is greater than the benefit from more accurate stock recommendations due to the higher earnings forecasting skill. If the analyst specializes in task 1, i.e. $k_2 = 0$, (5) becomes

$$V^1(k_1) = w_1k_1 - C(k_1, 0);$$

Similarly, if the analyst specializes in task 2, i.e. $k_1 = 0$, (5) becomes

$$V^2(k_2) = w_2 k_2 - C(0, k_2);$$

Therefore, non-specialization (i.e., interior solution) is optimal (i.e. the maximum utility of the interior solution is higher than the maximum utility under the corner solution) if both following conditions are satisfied for all conceivable values of k_1 and k_2:

$$\begin{cases} V^{12}(k_1, k_2) - V^1(k_1) > 0 \Rightarrow -C(k_1, k_1/\gamma) + C(k_1, 0) > 0, \forall k_1 & (7) \\ V^{12}(k_1, k_2) - V^2(k_2) > 0 \Rightarrow w_2 \cdot b \cdot k_1 - C(\gamma k_2, k_2) + C(0, k_2) > 0, \forall k_2 & (8) \end{cases}$$

Expanding the cost terms in (7) and (8) yields:

$$-\frac{1}{2} \cdot a_2 \cdot \left(\frac{k_1}{\gamma}\right)^2 - \rho \cdot k_1 \cdot \frac{k_1}{\gamma} > 0, \forall k_1$$

$$w_2 \cdot b \cdot \gamma \cdot k_2 - \frac{1}{2} \cdot a_1 \cdot (\gamma \cdot k_2)^2 - \rho \cdot \gamma \cdot k_2 \cdot k_2 > 0, \forall k_2$$

Further simplification yields:

$$\rho < min\left\{-\frac{a_2}{2} \cdot \frac{1}{\gamma}, -\frac{a_1}{2} \cdot \gamma + \frac{w_2 \cdot b}{k_2}\right\}$$

That is, the non-specialization solution exists if $\rho < 0$, a_1 and a_2 are sufficiently small, and b is sufficiently large.

One of the corner solutions (i.e., specializing in task 1 or task 2) is optimal for the analyst, when $\rho > 0$, or $\rho < 0$ but a_1 and a_2 are sufficiently large, and b is sufficiently small (i.e., $V^{12}(k_1, k_2) - V^1(k_1) < 0$ and $V^{12}(k_1, k_2) - V^2(k_2) < 0$ for all conceivable values of k_1 and k_2).

When corner solutions is optimal, he determines which skill to specialize by comparing $V^1(k_1)$ and $V^2(k_2)$, both of which are maximized by picking optimal level of k_i^* satisfying the constraint that marginal benefit equals marginal cost (i.e., $w_i = a_i \cdot k_i^*$):

$$V^1(k_1) = \frac{(w_1 + b \cdot w_2)^2}{2 \cdot a_1},$$

$$V^2(k_2) = \frac{w_2^2}{2 \cdot a_2}.$$

Specializing in k_1 is optimal when $V^1(k_1) > V^2(k_2)$; specializing in k_2 is optimal when $V^1(k_1) < V^2(k_2)$. When b is larger, the analyst is more likely to specialize in earnings forecasting skill. The result is intuitive since larger b means that improving earnings forecasting skill helps the analyst with picking stocks more, and thus providing him with greater incentive to specialize in forecasting earnings. This intuition is hypothesized in H3, where b is considered as positively correlated with w_1.

Appendix III: Variable Definition

Skill Variables:	
AFE_{ijt}(Absolute Forecast Error)	Absolute difference between the last forecasted annual earnings per share issued by analyst i for firm j in year t and the realized annual earnings per share: $AFE_{ijt} = \lvert Forecast_{ijt} - Actual_{ijt} \rvert$.
E_Skill_{idt}	Average normalized rankings analyst i receives for all firms within industry d in year t to measure his earnings forecasting skill for this specific industry-year, where normalized ranking is defined as the following: The analyst with the largest AFE for firm j in year t receives a ranking that equals to zero; the analyst with the next largest AFE receives a ranking that equals to one. Continue to assign ranks until the most accurate analyst receives the highest rank. Analysts with the same AFE are assigned the same rank. In order to normalize ranking, I divide all raw rankings with the number of analysts following firm j in year t minus one so that all rankings are between 0 and 1.
$E\_Skill\_Q_{idt}$	The quintile ranking of analyst i's E_Skill in industry d year t. A higher $E\_Skill\_Q_{idt}$ indicates analyst i has relatively higher earnings forecasting skill among all the analysts who cover industry d in year t.
$S\_Skill\_Q_{idt}$ ($E\_Skill\_Raw\_Q_{idt}$, $E\_Skill\_Mkt\_Q_{idt}$, and $E\_Skill\_FF\_Q_{idt}$)	I treat all strong buy and buy recommendations (1 and 2 in the Zacks database) as buy recommendations (hereafter BUY), and all hold, sell and strong sell recommendations (3, 4 and 5 in Zacks database) as sell recommendations (hereafter SELL). For analyst i, I calculate his recommendation profitability for firm j year t as the average daily buy-and-hold returns from the following investment strategy. From the first recommendation analyst i issues for firm j in calendar year t, long stock j when the most recent recommendation is BUY, and short it when the most recent recommendation is SELL until the last recommendation issued in calendar year t. If analyst i's last recommendation for firm j in year t is a BUY (SELL), I continue to long (short) stock j until twelve months after the last recommendation in year t or when analyst i changes his recommendation to SELL (BUY), whichever comes first. Basically, the average daily buy-and-hold returns of this investment strategy capture the raw daily returns

	from following all analyst i's recommendations for firm j in calendar year t (Raw_Ret_{ijt}). Market adjusted returns (Mkt_Ret_{ijt}) are computed as subtracting the average daily value-weighted returns of all NYSE, AMEX, and NASDAQ stocks for the same period (i.e., the value-weighted CRSP index) from the raw returns (Raw_Ret_{ijt}). Fama-French three-factor adjusted returns (FF_Ret_{ijt}) are computed as subtracting the expected daily returns from the Fama-French three-factor model estimated over each long/short period for each firm. For each measure of returns (Raw_Ret_{ijt}, Mkt_Ret_{ijt} and FF_Ret_{ijt}), I calculate the mean value across all the firms analyst i covers in industry d year t and use it to rank all the analysts covering this industry-year into quintiles. This quintile ranking (denoted as $S\_Skill\_Raw\_Q_{idt}$, $S\_Skill\_Mkt\_Q_{idt}$ and $S\_Skill\_FF\_Q_{idt}$, or simply called $S\_Skill\_Q_{idt}$) of analyst i measures his stock picking skill relative to his peers in industry d year t.
$S\_Special_{idt}$ and $Special_{idt}$	I first assign analysts in each industry year into a 5×5 matrix (illustrated by Figure 1) base on the quintile rankings of their relative earnings forecast and stock picking skills for industry d year t, i.e., ($E\_Skill\_Q_{idt}$, $S\_Skill\_Q_{idt}$). The number in each cell of Figure 1 stands for the absolute difference between analysts' E_Skill quintile and S_Skill quintile, and it proxies for his relative strength in either skill (denoted as Strength). I define that an analyst has a specialization when the absolute difference between his two skills (hereafter, Strength) is greater than two, i.e. there is substantial difference between the levels of his two skills. Therefore, the cells with horizontal lines (in the bottom left corner) contain analysts who specialize in forecasting earnings; the cells with vertical lines (in the upper right corner) contain analysts who specialize in picking stocks. I define an analyst as having non-specialization when his Strength is 0 or 1, i.e. the levels of his earnings forecasting skill and stock picking skill are indistinguishable. To reduce measurement errors, I do not define analysts with Strength 2 (denoted by the grey cells in Figure 1) as having specialization or non-specialization. Note that, only the analysts in the cells along the three dash lines in Figure 1 have the choices between specialization and non-specialization. The analysts in the top-left white cells do not have a choice because their innate ability is too

	low or they have not developed enough skills in either task. Therefore, their choice of specialization or non-specialization is unobservable in my research design. Similarly, the analysts in the bottom-right white cells have high innate abilities so that even if they specialize in one skill, the weaker skill is still better than most peers, which makes their choice between specialization and non-specialization unobservable in this research design. Therefore, only the analysts have a choice between specialization and non-specialization and whose two skills are not distinguishable are considered as having non-specialization (denoted by cells in the middle with grids in Figure 1). $S\_Special_{idt}$ is an indicator variable that equals one when analyst i covering industry d in year t specializes in picking stocks; zero if he specializes in forecasting earnings. $Special_{idt}$ is an indicator variable that equals one when analyst i covering industry d in year t specializes in either forecasting earnings or picking stocks, zero if he has non-specialization.
Independent Variables	
$E\_Relevance_{idt}$	I run the following firm specific regression for all a rolling ten year window and use the adjusted R^2 to proxy for the earnings relevance for firm j in year t: $RET_{j\tau} = \alpha_{0jt} + \beta_{1jt} \cdot \Delta EARN_{j\tau} + \beta_{2jt} \cdot EARN_{j\tau} + \varepsilon_{j\tau}$, where, $RET_{j\tau}$ = firm j's 5-month return ending two months after the end of fiscal quarter τ; $EARN_{j\tau}$ = firm j's income before extraordinary items in quarter τ, scaled by market value at the end of quarter $\tau - 1$ = data69/(data61×data14); $\Delta EARN_{j\tau}$ = firm j's change in NIBE in quarter τ, scaled by market value at the end of quarter $\tau - 1$ = Δdata69/(data61×data14). $E\_Relevance_{idt}$ is the mean value of earnings relevance across all the firms covered by analyst i in industry d year t.
$E\_Timeliness_{idt}$	The mean value of the adjust R^2's from the following firm-specific reverse regression estimated in a rolling ten year window across all the firms covered by analyst i in industry d year t: $EARN_{j\tau} = \alpha_{0jt} + \beta_{1j} \cdot NEG_{j\tau} + \beta_{2j} \cdot RET_{j\tau} + \beta_{3j} \cdot RET_{j\tau} \cdot NEG_{j\tau} + \varepsilon_{j\tau}$ where, $EARN_{j\tau}$ = firm j's income before extraordinary items in quarter τ, scaled by market value at the end of quarter $\tau - 1$ = data69/(data61×data14); $RET_{j\tau}$ = firm j's 5-month return ending two months after the end of fiscal quarter τ; $NEG_{j\tau}$ = 1 if $RET_{j\tau} < 0$, and 0 otherwise.

$Broker\_Size_{it}$	The number of analysts in analyst i's brokerage house in year t.
$Broker\_Reputation_{it}$	The strength of its underwriting business based on its Carter-Manaster ranking. Carter-Manaster rankings are based on the relative placement of underwriter names in IPO tombstones (Carter and Manaster [1990]) and range from zero to nine with scores above eight considered highly prestigious (e.g. Corwin and Schultz [2005]).
All_Star_{it}	Indicator variable that equals one if analyst i is named on the *Institutional Investor All-American Research Team* list one year before t, and zero otherwise.
$Skill\_Spillover_{dt}$	The number of analysts covering industry d in year t.
$E\_Persistence_{idt}$	Mean value of the earnings autocorrelation coefficients across all the firms covered by analyst i in industry d in year t. Earnings autocorrelation is the slope coefficient estimate from an autoregressive model of order one (AR1) for annual earnings per share over a rolling ten year window: $$EPS_{j\tau} = \alpha_j + \beta_j \cdot EPS_{j\tau-1} + \varepsilon_{j\tau}$$ where, $EPS_{j\tau}$ = firm j's net income before extraordinary items in year τ divided by the average number of outstanding shares at the beginning and the end of year τ.
$E\_Predictability_{idt}$	The negative square root of the error variance $(-\sqrt{\sigma^2(\hat{\varepsilon}_{j\tau})})$ from the following autoregressive model of order one (AR1) for annual earnings per share over a rolling ten year window: $$EPS_{j\tau} = \alpha_j + \beta_j \cdot EPS_{j\tau-1} + \varepsilon_{j\tau}$$ where, $EPS_{j\tau}$ = firm j's net income before extraordinary items in year τ divided by the average number of outstanding shares at the beginning and the end of year τ. The mean value across all the firms covered by analyst i in industry d in year t is used as predictability of earnings for the firms covered by him for industry d year t.
$E\_Fixation_{idt}$	I use a modified version of Jones [1991] model developed by Dechow, Richardson and Tuna's [2003] to estimate the normal level of total accruals (i.e., nondiscretionary accruals): $$\frac{TAC_{jt}}{A_{jt-1}} = \frac{\alpha_{0d}}{A_{jt-1}} + \beta_{1d} \cdot \frac{(1+k_{dt})\cdot\Delta S_{jt} - \Delta REC_{jt}}{A_{jt-1}} + \beta_{2d} \cdot \frac{PPE_{jt}}{A_{jt-1}} + \beta_{3d} \cdot \frac{TAC_{jt-1}}{A_{jt-1}} + \beta_{4d} \cdot \frac{\Delta S_{jt+1}}{S_{jt}} + \varepsilon_{jt},$$ where, TAC_{jt} = total accruals of firm j in year t = Data 123 – Data 308; ΔS_{jt} = $Sales_t$ – $Sales_{t-1}$; ΔREC_{jt} = change in account receivable = ΔData 2; k_{dt} = estimated slope coefficient from a regression of

	ΔREC_{jt} on ΔS_{jt} for each 2-digit SIC industry-year grouping, i.e., $\Delta REC_{jt} = a_{dt} + k_{dt} \cdot \Delta S_{jt} + \varepsilon_{jt}$; PPE_{jt} = property, plant and equipment (Data 8). The above regression is estimated cross-sectionally for all 2-digit SIC industry-years with at least 15 observations. I use the absolute value of the residual from the above regression ($\lvert\hat{\varepsilon}_{jt}\rvert$) to measure earnings management by firm j in year t. I take the average of all $\lvert\hat{\varepsilon}_{jt}\rvert$ across all the firms covered by analyst i for industry d in year t and obtain $E\_Fixation_{idt}$.
$Brand\_Name_{idt}$	The average value of the advertising expenditure across all the firms covered by analysts i in industry d year t.
$Size_{idt}$	The average log of market value of equity across all the firms covered by analysts i in industry d year t.
E_Freq_{idt}	The difference between the number of annual earnings forecasts analyst i issues for firms in industry d year t and the average number of annual earnings forecasts of all other analysts following the same industry-year.
S_Freq_{idt}	The difference between the number of stock recommendations analyst i issues for firms in industry d year t and the average number of stock recommendations of all other analysts following the same industry-year.
$S\_Innovation_{idt}$	The percentage of the innovative earnings forecast revisions from analyst i for firms in industry d year t. Following Gleason and Lee [2003], an earnings forecast revision is defined as not innovative when it is between the analyst's prior forecast and the current forecast consensus of other analysts; innovative otherwise.
Control Variables	
$General\_Expr_{it}$	The number of years during which analyst i has issued forecasts in Zacks database till year t.
Ind_Expr_{idt}	The number of years analyst i has issued forecasts for industry d till year t.

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Biography

Allen Hao Huang was born in Wuhan, China on October 27th, 1979. He earned his Bachelor of Science degree in Electronics in 2001 from Peking University, Beijing, China. Allen also studied in the Electrical Engineering Master of Science program in George Mason University from 2001 to 2002.

From 2002 to 2007, Allen attended the Ph.D program in Accounting at the Fuqua School of Business, Duke University in the United States of America. During this period, his paper titled "CEO Reputation and Earnings Quality.", which is co-authored with Jennifer Francis, Shivaram Rajgopal and Amy Y. Zang, was accepted for publication by one of the top accounting academic journals—Contemporary Accounting Research.

Allen enjoys playing basketball, watching movies, playing poker and travelling with his wife, Amy.