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2010/50/DS/FIN

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July 2010

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Abstract

We study the risk-taking behavior of stock analysts under varying market conditions. We examine how the risk analysts take by providing bold forecasts that deviate from consensus depends on the degree of uncertainty in the environment as well as the analysts' skill level. We provide evidence that low-skill analysts become significantly bolder, hence taking more risk, and significantly less accurate when market uncertainty increases. These findings are consistent with previous experimental results that show that skill levels moderate differential attitudes towards uncertainty. We further provide evidence that the difference in an analyst's boldness between times of low and high uncertainty is a signal of the analyst's skill that predicts future forecasting accuracy over and above standard skill measures such as past forecasting accuracy.

Keywords: *Risk Taking; Skill; Chance; Uncertainty; Financial Analysts; Earning Forecasts.*

1. Introduction

Financial analysts are important players in the capital market. By providing earnings forecasts and stock recommendations, analysts help disseminate company information and affect the market's price-discovery process (see Womack, 1996, Barber et al., 2001, Gleeson and Lee, 2003 among others). However, the literature has shown that not all analysts are equal: some are more skilled in terms of forecasting accuracy and/or influential than others (e.g., Stickel, 1992, 1995, Jackson, 2005, Fang and Yasuda, 2009, 2010, Leone and Wu, 2007). Finding ways to distinguish ex ante which analysts will be more accurate is a question relevant to both investors and financial economists. As true accuracy skill is not observable ex ante, past literature has examined various characteristic proxies for analyst skill, such as experience or past accuracy, with mixed success.

In this paper, we explore the possibility of partly inferring an analyst's accuracy or skill level by examining behavior in addition to the characteristic traits used in the literature. In doing so, we test a specific behavior pattern that has been hitherto explored in theoretical or experimental settings. Specifically, we explore analysts' dynamic risk-taking behavior in varying market uncertainty conditions, and focus on differences in such behavior between analysts with different ex-ante characteristics (imperfectly) related to skill. We then further examine whether such behavior differences "signal" analysts' skill and can improve prediction of future analyst accuracy above and beyond characteristic traits alone.

Our work contributes to the literature in two ways. First, we examine theory and evidence that so far have been studied in theoretical or experimental settings. Our empirical findings strengthen and broaden conclusions from experimental work that is often criticized as being derived from small samples in controlled, laboratory settings that are unrepresentative of naturally occurring environments. Second, we innovate by inferring an agent's skill and future accuracy – which is generally private information in theoretical settings – from behavior patterns rather than characteristic traits and past accuracy. That is, we go beyond documenting a behavioral pattern of stock analysts. We analyze whether such a pattern can help predict future forecasting accuracy, above and beyond conventionally used skill proxies. We find that the observable behavior pattern does carry incremental predictability of future performance.

The literature in psychology examining people's perceptions of the relative roles of skill and uncertainty in action-oriented tasks has a long history (see, e.g., Atkinson, 1957, Cohen and Dearnley, 1962, Langer, 1975). Recently, Karelaia and Hogarth (in press) specifically studied how risky actions in competitive environments change depending on both people's levels of (self-assessed) skill and the relative importance of skill and luck in producing outcomes. They found that people with low self-assessed skill tend to take *riskier* actions as the role of luck increases. On the other hand, high-skill agents in that study were not sensitive to changes in the relative importance of luck and skill in producing outcomes.

Mapping these experimental findings to the context of stock analysts making earnings forecasts, we define analysts' decisions to make bold forecasts relative to other analysts as the risk-taking event. Instead of focusing on a (static) cross-sectional analysis of boldness behavior as studied previously (e.g., Scharfstein and Stein, 1990, Truman, 1994, Avery and Chevalier, 1999, Hong et al., 2000, Clark and Subramanian, 2006), we introduce a dynamic element by looking at analysts' differential risk-taking behavior in varying market conditions. Based on the aforementioned experimental findings, we expect that low-skilled analysts' risk-taking decisions are more time-varying than those of high-skilled analysts. In particular, when the market is volatile and uncertainty is high, we expect low-skilled analysts to become bolder. High-skilled analysts should maintain a relatively stable boldness over time. Using a large panel of analyst forecast data, we find strong evidence supporting these predictions thereby supporting past experimental results. Furthermore, we find evidence that this boldness differential can predict future performance above and beyond conventional measures based on analyst characteristics and past performance.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 describes our data. Sections 4 and 5 contain the main empirical analysis and Section 6 concludes.

2. Background

Our paper is related to various literatures on risk-taking and the literature in finance and economics on analysts' behavior.

While we consider the case of financial analysts, the fundamental question of how much risk a decision maker takes depending on the environment has been studied in many other settings, ranging from marketing (e.g., Gaba and Karla, 1999) to entrepreneurship (e.g. Camerer and Lovallo, 1999). For example, our set-up is remarkably similar to variants of the tournament and market-entry literatures where, as a result of taking risky actions, agents' rewards depend on how they rank on some criterion relative to competitors (e.g., Camerer and Lovallo, 1999). Tsetlin, Gaba, and Winkler (2004) compare "weak" and "strong" agents and show that in order to maximize the probability of a positive outcome, weak agents should maximize variability, while strong should minimize variability. This is similar to the behavior of mutual fund managers who, lagging behind their competitors in a given period, might increase the riskiness of their portfolios in order to outperform competitors in the next period (Chevalier and Ellison, 1997).

Of particular relevance is an experimental market-entry study by Karelaia and Hogarth (in press) who contrast agents' risky responses under different levels of uncertainty or randomness in outcomes. They compare the reactions of agents with low and high levels of ability to changes in the level of uncertainty in the environment and find that agents with low levels of ability take *more* risk when outcomes are perturbed by random events, i.e., when market outcomes are less predictable. The rationale for this behavior is that the best chance to succeed for the low-skilled agents is to take risks when the effects of market uncertainty negate the importance of ability in producing the outcomes. Unfortunately for most of these agents, however, they are not rewarded by chance and "perform" less well, on average, in conditions of high uncertainty.

High-ability agents, on the other hand, should be the mirror image of the behavior of low-skilled agents, i.e., less risk taking when there is more uncertainty as "guaranteed" success is no longer "guaranteed." Instead, Karelaia and Hogarth (in press) found that high ability agents seemed to maintain a belief that their skill levels are sufficient to overcome the vagaries of chance and continue to take (or not) risky actions consistently almost independent of the level of uncertainty in the environment. Our study is primarily motivated by the findings of this experimental paper.

Separately in the finance and economics literature, there is a prominent strand of work that examines herding (or bold) behaviors by economic agents. Our work is related to and indeed consistent with this literature. Theoretical developments are represented by Scharfstein and Stein (1990), Trueman (1994), Prendergast and Stole (1996) and Avery and Chevarlier (1999). Scharfstein and Stein (1990) is the seminal paper on "reputational herding" explaining the general phenomenon of herd behavior. The central assumption is that informed agents receive correlated signals, whereas uninformed agents receive noise. Thus, to appear informed, agents have an incentive to herd. While the paper does not make cross-sectional predictions about who tends to herd and who does not, it provides theoretical underpinnings for later work to make and test such predictions. The salient idea is that agents with more reputational concerns (here reputational concerns mean the desire to be seen as talented, or, the desire to establish a good reputation), for instance younger ones, should herd more. Consistent with these predictions, empirical work such as Hong et al. (2000) and Chevalier and Ellison (1999) find that indeed less experienced agents herd more.

Trueman (1994) examines a notion of herding that refers to agents' under-weighting of private information and over-weighting of the consensus. Trueman's model predicts that in the cross-section, higher-ability analysts will be less influenced by the consensus. This is consistent with implications of Scharfstein and Stein and is empirically supported by Clement and Tse (2005). Avery and Chevalier (1999) build on Scharfstein and Stein (1990) and point out that agents only obtain private information about their own abilities over time. As a result, consistent with Scharfstein and Stein, young agents tend to herd, but older agents may be bolder. For skilled agents, bold behavior signals their superior ability; for unskilled agents, herding is a mimicking strategy to avoid being seen as having no ability.

In summary, the common conclusion emerging from past work is that experienced and skilled agents will generally be bolder. We build on this by further considering varying market conditions and arrive at the prediction that low-skill analysts should exhibit more time-varying boldness: they should become bolder in uncertain as opposed to other times.

A simple way of conceptualizing bold forecast decisions is to model each analyst's forecast for a company's earnings as a linear combination of the analyst's private information, on the one hand, and the consensus forecast of other analysts, on the other hand. Formally that is:

$$FEPS_t^{ic} = \alpha PI_t^{ic} + (1-\alpha)CS_t^c \tag{1}$$

where $FEPS_t^{ic}$ is the forecast of the i^{th} analyst ($i = 1,\ldots.I$) for the t^{th} period ($t = 1,\ldots\ldots T$) for the c^{th} company ($c = 1,\ldots\ldots C$); PI_t^{ic} is the i^{th} analyst's private information or signal for the t^{th} period for the c^{th} company; CS_t^c is the consensus forecast of other analysts for the t^{th} period for the c^{th} company; and α is the weight the analyst gives to her own private information or signal.[1] For all analysts, we assume that a common goal is to be among the most accurate in their predictions ex-post, and that they need to signal their ability by issuing bold forecasts (Prendergast and Stole, 1996).

The questions we address effectively center on how much weight (α) analysts give to their private information or signal as a function of both market conditions and personal attributes. For the former we consider the relative volatility of market conditions (stable or volatile); for the latter, we characterize analysts by their expertise (high or low). Overall, the literature relevant to the set-up in equation (1) suggests several hypotheses. First, when market uncertainty is low (stable conditions), low ability level analysts will be conservative in the sense of placing most weight on the consensus forecast, i.e., $\alpha < 0.5$, hence herd (i.e., mimic the decisions of others). Second, when market uncertainty is high (volatile conditions), low ability level agents will take more risk and weight their private information more than the consensus forecast, i.e., $\alpha > 0.5$, hence be bold. Third, high ability analysts will maintain the same weights for private information and consensus forecasts over both stable and volatile market conditions; hence for them the relation between boldness and uncertainty will not provide a strong signal about their skill.

On the empirical front, our work adds to the large literature on the behavior of financial analysts. Clarke and Subramanian (2006) study analysts' boldness depending on their past accuracy and show that analysts with high forecasting error in the recent past are on average bolder. Clement and Tse (2005) empirically test the Trueman model by focusing on how analysts' boldness changes in a sequence of forecast revisions. They find that forecasts that move away from consensus and towards the analyst's own prior tend to be more accurate and informative. Though this is different from cross-sectional studies, it suggests that boldness is positively related to analysts' private information about their own skill. Hong et al.

[1] α, of course, also varies by analyst, period, and stock. However, for the present discussion, it is simpler to drop the subscripts.

(2000) show empirically that younger analysts are more likely to be terminated for bold forecasts than their older counterparts, and consistent with career concerns, younger analysts tend to herd more. Similarly, in the mutual fund setting, Chevalier and Ellison (1999) find that job termination is more performance-sensitive for younger managers than for older ones, and consistent with career concerns, younger managers tend to hold more conventional portfolios and avoid unsystematic risk. While this past research informs our current work, it does not consider the effects of market uncertainty on the analysts' boldness decisions in a dynamic setting, which is a key contribution of this paper.

Finally, we note that our work is distinct from the literature of agents' behavioral biases. In the analyst context, Hilary and Menzly (2006), for example study the short-term dynamics of analysts' behavior and provide evidence that analysts become overconfident after a series of accurate forecasts, leading to bolder and less accurate behavior in the short-term. Our work differs from this literature in two ways. First, we consider analysts' performance using past accuracy over a long time period, as opposed to the recent past. The long-term track record is more likely to reflect analysts' skill independent of short-term behavioral biases such as over-confidence or over-reaction. Second, we do not appeal to any notion of irrationality in deriving our predictions. In other words, our time-varying pattern may be due to agents taking rational, calculated risks in different environments. Third, as noted above, unlike past work on the behavior of analysts, we consider how behavior changes with market conditions.

3. Empirical Setup

3.1 Data

We use quarterly Earnings per Share (EPS) forecast data from I/B/E/S for the period of January 1, 1990 to December 31, 2009. We perform data pre-processing steps common in the literature (see for example Hong et al., 2000, Clement and Tse, 2005, Hilary and Menzly, 2006): we only keep forecasts made during the same quarter of the company announcement; to remove possible errors we remove forecasts reported after the company announcement; all actual and predicted quarterly EPS are divided by the average stock price of the company during the quarter – to also avoid heteroscedasticity issues in the regressions, as typically done in the literature – and multiplied by 100 – hence all EPS, forecasted and actual, are "dollars earned/lost per 100 dollars"; we only use company quarters if the average stock price during the quarter is more than 5 dollars; we only use the last EPS forecast of each analyst in each quarter and we control for the number of days left from the time of this last company forecast of the analyst in the quarter till the company announcement date; finally, we remove outliers defined as company quarters for which at least one analyst had a forecast error larger than 40 (hence more than 40 dollars per 100 dollars) – this is the 99th percentile of the maximum forecast error during a calendar quarter.

All variables used in the models below are defined in Table 1. We define boldness as the absolute difference between the forecasted EPS of an analyst and the average forecasted EPS of all *other* analysts during the quarter for the company. To have reliable estimates of boldness we only consider company quarters where we have at least 5 analysts, as also done in the literature (e.g., Hilary and Menzly, 2006, Hong et al., 2000) – varying this threshold does not alter the results qualitatively. We define the forecast error of an analyst for a company in a quarter to be the absolute difference between the forecasted and actual EPS. Table 2 presents summary statistics for the main variables used in the analysis below.

3.2 Measures of Skill

As we cannot directly observe how analysts assess their own skill, we use a proxy for it. Our proxy for self-assessed skill is based only on past accuracy (Clement and Tse, 2005).

Specifically, we measure the skill of an analyst as the negative of the mean absolute forecast error (so the higher the more skill) of the analyst over the previous twelve quarters available for this analyst[2], namely $SKILL_t^i = - MEAN\_FRR_{(t-12)(t-1)}^i$. Using longer lengths of time, including the average error since the very first time an analyst appears in the dataset, namely $SKILL_{2t}^i = - MEAN\_FERR_{0(t-1)}^i$, leads to similar results. Using a twelve month time window, we consider a rolling window of performance to allow for changes of skill over time. The correlation between consecutive non-overlapping twelve-quarter windows of SKILL is 0.32, which is sufficiently high (Clement and Tse, 2005). In the analysis we use data only from analysts for whom we have at least twelve quarters of data (to have enough data to calculate SKILL) as well as at least one quarter of data for each particular company (to have enough data to use past short-term company specific performance and boldness as control variables). However, all analysts are considered when calculating boldness.

3.3 Measures of Uncertainty

Much as in the case of skill, we cannot directly measure how much uncertainty an analyst perceives for a particular company at a particular quarter, and we can only develop proxies for this. There are many candidate proxies such as the dispersion of all analysts' forecasts for a company during a quarter, the overall market volatility, or firm characteristics. We would like the proxy to be exogenous and to change across quarters and firms. Clearly a market level volatility, such as the VIX index, cannot differentiate among firms, while firm characteristics do not change frequently across quarters. Using the dispersion of analysts'

[2] While we consider the average forecast error of an analyst as a proxy for the analyst's self-assessed skill, other ways to conceptualize self-assessed past accuracy are possible. For example, it is possible that when assessing their skills, analysts overweight peak or/and end performance in the sequence relative to other pieces of evidence regarding their skill level. However, Cojuharenco and Ryvkin (2008) showed that the co-called "peak-end rule" often produces similar evaluations of streams of experiences as simple averaging, especially when the impressions generated by past experiences are relatively persistent.

forecasts is subject to endogeneity issues. We therefore choose to measure the uncertainty perceived about a firm during a quarter as the standard deviation of the daily stock returns of that company during the quarter.[3] Moreover, to allow an analysis of the analysts' behavior under low or high-uncertainty environments, we define as high-uncertainty company quarters those when the standard deviation of the daily returns of the company's stock is within the top 20% of the standard deviations of quarterly daily returns for that company in all previous quarters.[4]

4. Skill, Uncertainty, and Boldness

4.1. Baseline findings

We begin with a simple univariate analysis of the relation between self-assessed skill (proxied by past accuracy), uncertainty (proxied by stock-level return volatility), and analysts' forecast boldness. First we note that in high-uncertainty times, the overall variance across forecasts is higher: the average across companies and quarters of the standard deviation of the analysts' (company-quarter) forecasts[5] *FEPS* is 0.16 for low-uncertainty quarters and 0.34 for high-uncertainty. The larger variance across forecasts in high-volatility periods indicates that analysts exhibit more divergent opinions in such times.

Second, each quarter t we sort all analysts according to their past skill proxy ($SKILL_t^i$) and split them into five low-to-high quintiles (quintile 1 contains the bottom 20% and quintile 5 the top 20%). An analyst may be in different quintiles in different quarters. We then measure the average boldness of analysts in each skill quintile, focusing on the boldness differential

[3] Using the volatility of daily returns of the previous quarter or an average over the past two quarters does not change the results.
[4] The results are robust to changes of this 20% threshold. All results below also hold if we use the actual, real-valued, stock returns standard deviation in the models below instead of the dummy variable measure (*UNC*).
[5] This is the average across all company-quarters of the standard deviation of the forecasts for each company-quarter. It is not the standard deviation of all forecasts (across companies and quarters) reported in Table 2.

between times of high and low-uncertainty for each of the quintiles. Our hypothesis is that low-skill analysts should exhibit larger boldness differentials between high and low-uncertainty periods.

Table 3 shows the results. Several observations can be made. First, in high-uncertainty times, overall boldness increases. Since boldness is measured as absolute deviations from consensus, this likely reflects the larger variance in high-uncertainty company quarters noted above. Second, the most salient observation is that, consistent with our prediction, the results indicate that change in boldness by low-skill analysts from low to high-uncertainty times is much larger (at an average of 0.36) than the same change for high-skill analysts (at an average of 0.06).

We next re-examine the same relation in a multi-variate setting. We consider a number of controls studied in the literature that relate to analysts' boldness behavior. As discussed above, previous studies suggest that boldness depends on career and reputation concerns (e.g., Hong et al., 2000) as well as reactions to recent performance (e.g., Clarke and Subramanian, 2006, Hilary and Menzly, 2006). To control for the first, we use EXP_t^{ic} as in Hong et al. (2000) and Clement and Tse (2005). [6] Analysts with more quarters of experience are expected to be bolder as they face less career and reputational concerns (Hong et al., 2000). To control for recency effects we include previous quarter accuracy and boldness, $FERR_{t-1}^{ic}$ and $BOLD_{t-1}^{ic}$. We also include as further controls the variables SN_t^i, $DAYS_t^{ic}$, $LSIZE_t^c$, N_t^c (see Table 1 for definitions), and a full set of year dummies. Clement and Tse (2005) find that bold forecasts are less likely to be issued by analysts with large portfolios, hence the introduction of the number of companies the analysts follow, SN_t^i, as a control. The earlier a forecast, $DAYS_t^{ic}$, the less information is available to the analyst hence possibly the larger the

[6] Using company specific experience instead does not alter the results.

deviation from consensus. Both the size of the firm $LSIZE_t^c$ as well as the number of analysts following a firm N_t^c are related to the amount of information available to the market for a particular firm (e.g., Hilary and Menzly, 2006). Although we estimate analyst-firm fixed effects models, we use $LSIZE_t^c$ since over the 20 years period we consider the size of the companies changes. Size is known to be related to a number of factors beyond the amount of information available to the market for a particular firm.

We estimate analyst-company fixed-effect regressions to study the effects of these factors on boldness. The full model tested is:

$$\begin{aligned} BOLD_t^{ic} = \alpha + \beta_1 SKILL_t^i + \beta_2 UNC_t^c + \beta_3 (SKILL_{1t}^i * UNC_t^c) + \beta_4 EXP_t^i + \beta_5 FERR_{t-1}^{ic} + \\ \beta_6 BOLD_{t-1}^{ic} + \beta_7 SN_t^i + \beta_8 N_t^c + \beta_9 DAYS_t^{ic} + \beta_{10} LSIZE_t^c + \beta_{11} DTIME_t + \alpha^{ic} + \varepsilon_t^{ic} \end{aligned} \tag{2}$$

where *DTIME* is a dummy for each year (from 1990 to 2009), α^{ic} is the analyst-firm fixed effect, and ε_t^{ic} is the error term. In all models, standard errors are adjusted for clustering by analysts and firms since observations are independent across clusters but not necessarily independent within clusters.[7]

An underlying assumption of the specification used is that analysts treat each stock independently. Although this may be a limitation, such a specification has been often used and justified (e.g. Barberis and Huang, 2001) in the past. Moreover, as the uncertainty is stock-specific, aggregating the results across all stocks would not allow the test of our hypotheses. Using a market-wide measure of uncertainty, such as the VIX index, does not provide enough information and only allows for few quarters where overall market uncertainty was high.

The estimated coefficients of all models are shown in Table 4. The results are in agreement with the uni-variate tests in Table 3. Boldness increases as uncertainty increases, and the coefficient β_3 of the $(SKILL_{1t}^i * UNC_t^c)$ interaction is negative (-0.227) and significant

[7] Estimating Fama-Macbeth regressions (Fama-MacBeth, 1973), instead, does not alter the results.

supporting the hypothesis that as uncertainty increases less skilled analysts become relatively bolder. Thus, both uni-variate and multi-variate analysis yield the same conclusion that low-skill analysts become relatively bolder in highly uncertain times, consistent with our prediction and the prior experimental results.

One question is whether the boldness exhibited by low-skilled analysts in uncertain times actually "pays off" in the sense that these forecasts are accurate. Our prediction is that they should not because low-skilled analysts are unlikely to suddenly become more skilled in uncertain times. Even if at the individual level the observed behavior may be rational – which we cannot infer – it may be inefficient in the sense that no additional information is incorporated in these bold forecasts, as argued by Scharftein and Stein (1990).

To formally test this, we examine ex-post accuracy of forecasts, and focus on whether accuracy drops during highly uncertain times. Table 5 shows the uni-variate test. This table is similar to Table 3 except that instead of reporting boldness we report forecast error. As expected, when uncertainty is high everyone becomes less accurate. More importantly, the accuracy of low-skill analysts drops by 0.98 in high- compared to low-uncertain times, a much larger drop than that exhibited by high-skill analysts (0.17).

Table 6 further confirms this finding in a multi-variate setting. We estimate analyst-firm fixed-effects regressions using $FERR_t^{ic}$ as the dependent variable. We use the same control variables as for boldness in Table 4, except that we also add the boldness $BOLD_t^{ic}$ of the analyst *i* for company *c* during the same quarter *t* as a dependent variable. As in Table 4, in all models, standard errors are adjusted for clustering by analysts and firms since observations are independent across clusters but not necessarily independent within clusters.[8]

From this table we observe that overall forecast error increases as uncertainty increases, but more importantly, the coefficient β_3 of the $(SKILL_{1t}^i * UNC_t^c)$ interaction is negative (-0.43)

[8] Estimating Fama-Macbeth regressions (Fama-MacBeth, 1973) does not alter the results.

and significant. This means that the reduction in accuracy as uncertainty increases is significantly smaller among high than low-skill analysts, consistent with the uni-variate result in Table 5. Thus, we conclude that the selective boldness exhibited by low-skill analysts in highly uncertain time-periods on average does not "pay off".

4.2. The Role of Experience

So far we have documented that, consistent with experimental evidence, low-skill analysts exhibit a greater boldness differential when uncertainty increases. An interesting question is how this pattern is affected by analyst experience. Is it more pronounced among younger or older analysts? The question is relevant as much existing literature has pointed out differences in herding behavior between the young and the old.

Existing work (e.g. Hong et al., 2000, Clement and Tse, 2005) shows that, having greater career concerns, young analysts generally herd more that their older counterparts. This is supported by the positive (0.006 in model (2)) and significant coefficient of *EXP* in Table 4. Young analysts' overall desire to herd more out of career concerns may attenuate the opportunistic behavior of selective boldness in uncertain times. In addition, selective boldness in uncertain times requires that the analysts have private information about their own skills. Young analysts, as pointed out by Avery and Chevalier (1999), have little private information about their own type. For these two reasons, we expect that the time-varying pattern documented in our baseline analysis should be more pronounced among the older analysts.

Tables 7 and 8 investigate this issue. In Table 7 we define four types of analysts: a) low experience and low skill; b) low experience and high skill; c) high experience and low skill; d) high experience and high skill. We define low and high as the bottom and top quintiles for both experience and skill. We estimate a model analogous to model (2) in Table 4 adding dummies for each of the four types (YOUNG_UNSKILL, YOUNG_SKILL, OLD_UNSKILL, OLD_SKILL) of analysts and their interactions with uncertainty (YOUNG_UNSKILL*UNC, YOUNG_SKILL*UNC, OLD_UNSKILL*UNC, OLD_SKILL*UNC).

First, regardless of experience, skilled analysts exhibit less time-varying boldness than unskilled analysts, as shown above: the coefficients of both YOUNG_SKILL*UNC (-0.25) and OLD_SKILL*UNC (-0.23) are negative and significant indicating that relative to old unskilled analysts (the omitted group), skilled analysts, young and old, exhibit less selective boldness in uncertain times. Moreover, the coefficient of YOUNG_UNSKILL*UNC (-0.08) is also negative (but insignificant with a p-value = .076) indicating that unskilled analysts generally exhibit time-varying boldness, but at least in terms of magnitude, it seems that the effect is stronger for the most experienced analysts than it is for the least experienced ones.

To further investigate the last point, we estimate separate regressions for young and old analysts. The results are shown in Table 8. For both populations the coefficient of $(SKILL_{1t}^{i} * UNC_{t}^{c})$ is negative and significant supporting the previous results. Moreover, consistent with our prediction and suggestive result in Table 7, the coefficient of the interaction is smaller (0.18) for the young sample than for the old sample (0.28).

5. Relationship between past boldness behavior and future performance

If low-skill analysts become relatively bolder when there is higher uncertainty, then we may be able to infer analyst skill by observing how they behave as uncertainty varies. For this purpose, we replicate the accuracy analysis above but this time using the following indicator of skill:

$$BSKILL_{t}^{i} = LMEAN\_BOLD_{0(t-1)}^{i} - HMEAN\_BOLD_{0(t-1)}^{i} \tag{3}$$

That is, we observe how much bolder each analyst has become in the past when uncertainty was high. As in Tables 3 and 5, high-uncertainty company quarters are defined as those where the standard deviation of the daily returns of the company's stock is within the top 20% of the standard deviations of quarterly daily returns for that company in all previous quarters. Notice that BSKILL only uses past information based solely on the effect we study.

As in Table 5, we first study the uni-variate relation between the new skill measure, BSKILL, and forecast error. For this purpose, as before, each quarter *t* we sort all analysts according to their new skill ($BSKILL_t$) and split them into five low-to-high skill quintiles (from the bottom 20% to the top 20%). An analyst may be in different quintiles in different quarters. We then measure the average forecast error, separately across all high- and low-uncertainty company quarters, of the analysts in each of these quintiles. Table 9 shows the uni-variate relation between *BSKILL* and forecast error as in Table 5. The new skill measure does differentiate low-skill analysts, especially, the lower quintile, from the rest.

We further examine whether the new measure of skill, *BSKILL,* can provide additional information regarding the future accuracy of an analyst beyond that indicated by the past accuracy based measure *SKILL* and *EXP*. The correlation between the two measures of skill is 0.28. We first report the average forecast error of analysts double-sorted according to both the accuracy based skill measure *SKILL* and the new measure *BSKILL*. Table 10 shows the results. The results indicate that *BSKILL* further differentiates the low-skill analysts: for the analysts in the lowest *SKILL* quintile, the average forecast error diminishes from 1.04 to 0.70 when these analysts are further ranked according to *BSKILL*.

Multi-variate tests like those in Table 6, including only *BSKILL* or both *BSKILL* and *SKILL*, are shown in Table 11 – the results with only *SKILL* are as in Table 6. All previous control variables except the uncertainty related ones are used. Model (2) in Table 11, as well as the coefficient of *BSKILL* in models (1) and (3), indicates that the new measure of skill does add information to the past-error based measure of skill, *SKILL*. Both *SKILL* and *BSKILL* are significant in model (3) in Table 11.

5. Discussion

Given their importance in the functioning of the financial markets and the plethora of data capturing their behavior, the work of financial analysts has provided a fertile ground for research. A number of researchers have used analysts' forecast data to test theories developed in theoretical or experimental settings (Easterwood and Nutt, 1999, Clarke and Subramanian, 2006, Friesen and Weller, 2006, Hilary and Menzly, 2006). Such work has had at least two major benefits. It has tested possibly competing theories in naturally occurring environments, and increased our understanding of the behavior of financial analysts as key participants in financial markets.

This paper contributes to the literature by using analysts' forecast data to test a specific behavioral pattern that has been studied in theoretical or experimental settings in the past. Our findings both shed light on the risk-taking behavior of stock analysts and provide further proxies of analysts' accuracy skill that go beyond those existing in the literature. Consistent with past experimental findings, we provide evidence that as compared to high-skill financial analysts, low-skill analysts take more risk by being bolder when uncertainty in the market is high. The prediction error of such analysts also significantly increases in these circumstances. Moreover, observing how much bolder an analyst becomes during high-uncertainty times can provide a signal of the skill, and future accuracy, of the analyst. Indeed, we show that such a signal can explain future accuracy of an analyst beyond traditional measures of skill based on past forecast accuracy. These results are robust to a number of control variables, alternative econometric estimations, and measures of skill and market uncertainty.[9]

In common with many other professions, the tasks of financial analysts are competitive and outcomes depend on both skill and luck. Stimulated by experimental work in

[9] All such robustness tests have been indicated across the analysis.

analogous environments where low-ability agents are seen to increase their level of risk taking as the weight of luck becomes more important relative to that of skill, we find similar behavior among a population of financial analysts. At one level, such increases in risk taking can be seen as rational – it may be the only way that people with low ability can succeed. On the other hand, for most analysts of low ability – as well as most experimental participants – success is far from guaranteed and the behavior resembles that of buying lottery tickets with highly skewed payoffs. As to high-skill analysts – as well as high-skill experimental participants – there seems to be little evidence of hedging against increased luck in outcomes as they both act as though their skills are impervious to the vagaries of chance. Having made the link about ability and chance in experiments as well as one naturally occurring environment (i.e., the world of financial analysts), we can naturally ask questions about the boundary conditions of our findings. Do the same types of skill-risk-chance interactions occur in other competitive environments in the financial world (e.g., portfolio and fund managers) or elsewhere (e.g., launching new products or services, competitions in sports or for jobs, places in educational institutions, etc.)? Our paradigm provides a useful framework for illuminating risk taking in many applied areas.

Table 1: Definitions of the variables used.

EPS_t^c	Actual EPS announced by company *c* at the end of quarter *t*. This is divided by the average stock price of company *c* during quarter *t*, and multiplied by 100.
N_t^c and SN_t^i	The number of analysts forecasting for company *c* in calendar quarter *t*, and the number of companies analyst *i* follows in quarter *t*, respectively
UNC_t^c	A dummy that is one if uncertainty is high and 0 otherwise. Uncertainty is the standard deviation of the daily stock returns of company *c* during quarter *t*. VOL_t^c is 1 if the standard deviation is in the top 20% of the standard deviations of all previous quarters of company *c*.
$LSIZE_t^c$	The logarithm of the market capitalization (average quarterly stock price x number of shares outstanding) of company *c* in quarter *t*.
$FEPS_t^{ic}$	The last forecasted EPS of analyst *i* for company *c* at calendar quarter *t*. This is scaled by the average stock price of company *c* during quarter *t*, and multiplied by 100.
$DAYS_t^{ic}$	The number of days between the last forecast of analyst *i* for company *c* in calendar quarter *t*, (namely $FEPS_t^{ic}$) and the date of the company announcement, EPS_t^c, that quarter.
$FERR_t^{ic}$	The absolute forecast error of analyst *i* for company *c* in calendar quarter *t* defined as $FERR_t^{ic} = \left\| FEPS_t^{ic} - EPS_t^c \right\|$. Note that both $FEPS_t^{ic}$ and EPS_t^c have been scaled by the average stock price of company's *c* during quarter *t*.
$BOLD_t^{ic}$	The absolute boldness of analyst *I* in calendar quarter *t* for company *c* defined as $BOLD_t^{ic} = \left\| FEPS_t^{ic} - \frac{1}{N_t^c - 1}\sum_{j \neq i} FEPS_t^{jc} \right\|$.
$MEAN\_FERR_{ts}^i$	The average forecast error across all companies followed by analyst *i* between calendar quarters *t* and *s*, including quarters *t* and *s*. Time index 0 is for the very first quarter and *T* for the very last quarter (of the analyst in this case). For example $MEAN\_FERR_{(t-1)(t-1)}^i$ is the average error across companies followed of analyst *i* during quarter *(t-1)*.
$MEAN\_BOLD_{ts}^i$, $LMEAN\_BOLD_{ts}^i$, $HMEAN\_BOLD_{ts}^i$	$MEAN\_BOLD_{tt}^i$ is the average absolute boldness across all companies followed by analyst *i* between calendar quarters *t* and *s* including quarters *t* and *s*. For example $MEAN\_BOLD_{tt}^i$ is the average across companies followed of analyst *i* during quarter *t*. $LMEAN\_BOLD_{ts}^i$ is the same but averaged only across low-uncertainty (*UNC*) quarters, while $HMEAN\_BOLD_{ts}^i$ is averaged only across high-uncertainty (*UNC*) quarters.
EXP_t^i	Calendar quarters of total experience of an analyst at time *t*: This is the number of calendar quarters for which analyst *i* has been in the data until time *t*.

Table 2: Mean, median, standard deviation, 25th and 75th percentiles of the main variables in Table 1 for all the data used after the data pre-processing steps. There is a total of 448,672 unique analyst-company-quarter observations, 72,482 unique company-quarter observations, 76,178 unique analyst-quarter observations, and 4,756 unique analysts.

Variable	Mean	Median	Std. Dev.	25th Percentile	75th Percentile
EPS_t^c	.9304279	1.005011	4.153732	.4275096	1.643764
$FEPS_t^{ic}$	1.038153	1.033739	3.553862	.4757407	1.634565
$FERR_t^{ic}$	.3952537	.0959106	1.489068	.0300551	.2799681
$BOLD_t^{ic}$	.1656673	.0421835	.6420146	.013626	.1226241
EXP_t^i	26.88075	23	13.14133	17	34

Table 3: Average boldness $BOLD_t^{ic}$ depending on the analyst's skill $SKILL_t^i$ for low and high-uncertainty firm quarters. All differences between high and low-uncertainty – in bold – are significant (p<.05).

	Mean Absolute Boldness $BOLD_t^{ic}$			
	Low Uncertainty	High Uncertainty	Difference	Mean
Low 20% of skill $SKILL_t^i$	0.28	0.64	**0.36**	0.35
20-40%	0.16	0.31	**0.15**	0.19
40-60%	0.11	0.21	**0.10**	0.13
60-80%	0.08	0.16	**0.08**	0.09
High 20% of skill $SKILL_t^i$	0.05	0.11	**0.06**	0.06
Mean	0.14	0.29	0.15	0.16

Table 4: Dependent variable is boldness $BOLD_t^{ic}$. Fixed-effect (analyst-company) regressions. Standard errors are deflated for autocorrelation and heteroscedasticity. Time dummies are included. Results without (first column) and with (second column) considering uncertainty with all the data are shown.

	(1)	(2)
$SKILL_{1t}^{i}$	-0.119**	-0.065**
	[8.20]	[4.68]
UNC_t^c		7.21**
		[11.40]
$SKILL_{1t}^{i} * UNC_t^c$		-0.227**
		[11.30]
EXP_t^i	0.007**	0.006**
	[6.26]	[5.69]
$FERR_{t-1}^{ic}$	0.071**	0.068**
	[10.26]	[9.93]
$BOLD_{t-1}^{ic}$	-0.028**	-0.028
	[10.09]	[10.12]
SN_t^i	-0.0003	-0.0003
	[1.15]	[1.17]
N_t^i	0.004**	0.004**
	[12.90]	[11.49]
$DAYS_t^{ic}$	-0.0004**	-0.0004**
	[8.13]	[7.22]
$LSIZE_t^c$	-0.202**	-0.190**
	[33.81]	[33.15]
Intercept	6.73**	4.85**
	[14.17]	[10.76]
Observations	448,672	448,672
R-squared	0.447	0.451

Robust t statistics in brackets
** significant at 5%

Table 5: Forecast error $FERR_t^{ic}$ depending on the analyst's skill $SKILL_t^i$ for low and high-uncertainty firm quarters. All differences between high and low-uncertainty – in bold – are significant (p<.05).

	Mean Absolute Forecast Error $FERR_t^{ic}$			
	Low Uncertainty	High Uncertainty	Difference	Mean
Low 20% of skill $SKILL_t^i$	0.65	1.63	**0.98**	0.84
20-40%	0.35	0.78	**0.43**	0.43
40-60%	0.26	0.56	**0.30**	0.31
60-80%	0.19	0.45	**0.26**	0.23
High 20% of skill $SKILL_t^i$	0.13	0.30	**0.17**	0.16
Mean	0.32	0.74	0.43	0.39

Table 6: Dependent variable is forecast error $FERR_t^{ic}$. Fixed-effect (analyst-company) regressions. Standard errors are deflated for autocorrelation and heteroscedasticity. Time dummies are included. Results without considering uncertainty (first column) and after including uncertainty (second column) are shown.

	(1)	(2)
$SKILL_{1t}^{i}$	-0.195**	-0.09**
	[6.81]	[3.67]
UNC_t^c		13.72**
		[10.15]
$SKILL_{1t}^{i} * UNC_t^c$		-0.43**
		[10.04]
EXP_t^i	0.024**	0.02**
	[16.76]	[16.44]
$BOLD_t^{ic}$	0.87**	0.86**
	[37.69]	[37.19]
$FERR_{t-1}^{ic}$	0.02	0.017
	[1.90]	[1.59]
$BOLD_{t-1}^{ic}$	0.003	0.003
	[0.58]	[0.51]
SN_t^i	-0.001**	0.001**
	[2.30]	[2.24]
N_t^i	0.007**	0.006**
	[9.78]	[8.37]
$DAYS_t^{ic}$	0.001**	0.001**
	[13.36]	[14.47]
$LSIZE_t^c$	-0.4**	-0.38**
	[34.41]	[33.78]
Intercept	12.06**	8.50**
	[13.23]	[10.60]
Observations	448,672	448,672
R-squared	0.5378	0.5408

Robust t statistics in brackets
** significant at 5%

Table 7: Dependent variable is boldness $BOLD_t^{ic}$. Fixed-effect (analyst-company) regressions using only the lowest and highest quintile analysts in terms of skill and years of experience. Standard errors are deflated for autocorrelation and heteroscedasticity. Time dummies are included. Dummies for the lowest and highest (quintile) analysts in terms of skill and quarters of experience (four types of analysts) and their interactions with uncertainty are included.

$YOUNGSKILL_{1t}^{i}$	0.114**
	[2.27]
$YOUNGUNSKILL_{1t}^{i}$	0.114**
	[2.10]
$OLDSKILL_{1t}^{i}$	-0.019
	[0.62]
UNC_t^{c}	0.25
	[7.42]
$YOUNGSKILL_{1t}^{i} * UNC_t^{c}$	-0.25**
	[7.18]
$YOUNGUNSKILL_{1t}^{i} * UNC_t^{c}$	-0.08*
	[1.78]
$OLDUNSKILL_{1t}^{i} * UNC_t^{c}$	-0.23**
	[6.84]
$FERR_{t-1}^{ic}$	0.032**
	[2.79]
$BOLD_{t-1}^{ic}$	-0.051**
	[5.54]
SN_t^{i}	-0.001
	[0.08]
N_t^{i}	0.003**
	[3.45]
$DAYS_t^{ic}$	-0.0003*
	[1.77]
$LSIZE_t^{c}$	-0.34**
	[13.50]
Intercept	4.68**
	[14.16]
Observations	94,920
R-squared	0.5492

Robust t statistics in brackets
** significant at 5% , * significant at 10%

Table 8: Dependent variable is boldness $BOLD_t^{ic}$. Fixed-effect (analyst-company) regressions. Standard errors are deflated for autocorrelation and heteroscedasticity. Time dummies are included. Results for only the lowest (first column) and highest (second column) experienced analysts are provided.

	(1)	(2)
$SKILL_{1t}^i$	0.022	-0.12**
	[0.66]	[3.03]
UNC_t^c	5.38**	8.82**
	[4.72]	[6.16]
$SKILL_{1t}^i * UNC_t^c$	-0.17**	-0.28**
	[4.72]	[6.11]
$FERR_{t-1}^{ic}$	0.004	0.06**
	[0.29]	[4.61]
$BOLD_{t-1}^{ic}$	-0.064**	-0.025**
	[10.83]	[4.89]
SN_t^i	-0.0001	-0.000
	[0.19]	[0.13]
N_t^i	0.004**	0.003**
	[4.94]	[4.87]
$DAYS_t^{ic}$	-0.0003**	-0.0004**
	[2.85]	[3.05]
$LSIZE_t^c$	-0.24**	-0.24**
	[15.58]	[18.50]
Intercept	2.87**	7.26**
	[2.64]	[5.84]
Observations	128,501	115,198
R-squared	0.584	0.446

Robust t statistics in brackets
** significant at 5%

Table 9: Forecast error $FERR_t^{ic}$ depending on the analyst's new skill measure $BSKILL_t^i$ for low and high-uncertainty firm quarters. All differences between high and low-uncertainty – in bold – are significant (p<.05).

	Mean Absolute Forecast Error $FERR_t^{ic}$			
	Low Uncertainty	High Uncertainty	Difference	Mean
Low 20% of skill $SKILL_t^i$	0.44	1.52	**1.08**	0.63
20-40%	0.28	0.76	**0.48**	0.37
40-60%	0.24	0.53	**0.29**	0.29
60-80%	0.25	0.46	**0.21**	0.29
High 20% of skill $SKILL_t^i$	0.39	0.64	**0.25**	0.43
Mean	0.32	0.78	0.46	0.40

Table 10: Forecast error $FERR_t^{ic}$ depending on the analyst's skill measure $SKILL_t^i$ as well as the new skill measure $BSKILL_t^i$.

	BSKILL Quintile					
	1	2	3	4	5	Mean
SKILL Quintile:						
1	1.04	0.79	0.64	0.64	0.70	0.84
2	0.46	0.43	0.41	0.41	0.41	0.43
3	0.32	0.34	0.30	0.29	0.33	0.31
4	0.24	0.23	0.24	0.22	0.24	0.23
5	0.16	0.16	0.16	0.15	0.17	0.16
Mean	0.63	0.37	0.29	0.29	0.43	

Table 11: Dependent variable is forecast error $FERR_t^{ic}$. Fixed-effect (analyst-company) regressions are shown. Standard errors are deflated for autocorrelation and heteroscedasticity. Time dummies are included. Results with only one measure of skill, *SKILL* (column 1 – same as column 1 in Table 7) and *BSKILL* (column 2), as well as with both measures of skill (column 3) are shown.

	(1)	(2)	(3)
$SKILL_{1t}^{i}$	-0.195**		-0.16**
	[6.81]		[5.46]
$BSKILL_{1t}^{i}$		-0.18**	-0.15**
		[5.69]	[4.92]
EXP_t^{i}	0.024**	0.02**	0.023**
	[16.76]	[15.48]	[16.45]
$BOLD_t^{ic}$	0.87**	0.87**	0.87**
	[37.69]	[37.23]	[37.21]
$FERR_{t-1}^{ic}$	0.02	0.02	0.02
	[1.90]	[1.93]	[1.60]
$BOLD_{t-1}^{ic}$	0.003	0.003	0.003
	[0.58]	[0.58]	[0.55]
SN_t^{i}	-0.001**	0.001**	0.001**
	[2.30]	[2.12]	[2.09]
N_t^{i}	0.007**	0.006**	0.007**
	[9.78]	[9.95]	[9.82]
$DAYS_t^{ic}$	0.001**	0.001**	0.001**
	[13.36]	[13.38]	[13.33]
$LSIZE_t^{c}$	-0.4**	-0.4**	-0.4**
	[34.41]	[34.34]	[34.06]
Intercept	12.06**	11.76**	15.07**
	[13.23]	[11.28]	[12.37]
Observations	448,672	448,672	448,672
R-squared	0.5378	0.5415	0.5419

Robust t statistics in brackets
** significant at 5%

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