Underlying Risk Preferences and Analyst Risk-Taking Behavior

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Abstract

We investigate the relation between underlying risk preferences on analysts' work-related decisions. Specifically, we examine whether facial width-to-height ratio (fWHR), an innate personal characteristic that has been linked to financial risk tolerance, is associated with analysts' stock coverage decisions and the boldness of their earnings forecasts and stock recommendations. We find that high-fWHR analysts cover firms with lower earnings predictability, and issue bolder forecasts and recommendations. Our findings shed new light on the black box of analyst decision making, assisting investment practitioners in evaluating the information content produced by different types of analysts and understanding the observed dispersion in analyst forecasts.

Key Words: *Analysts, Analysts Forecasts, Stock Recommendations, Coverage Decisions, Forecast Boldness, fWHR, Facial Width-to-Height Ratio, Innate Characteristics, Personal Characteristics, Risk-Taking Behavior, Risk Tolerance*

JEL Codes: G24, J44

1. Introduction

Most research regarding the relation of analyst characteristics to output has examined skills or variables exogenous to the analyst, such as brokerage size. Despite extensive research, Bradshaw (2011) and Ramnath et al. (2008) conclude that much is still unknown and that analyst decision making remain a black box.¹² We attempt to shed light into this black box by investigating the relation between analysts' facial masculinity, a pre-determined characteristic used as a proxy for testosterone levels associated with financial risk preferences and professional decisions (Apicella et al. 2008; Kamiya et al. 2016). Specifically, we examine two observable decisions that are likely to be affected (even if unconsciously so) by an analyst's innate risk tolerance. First, we investigate whether facial masculinity, as captured by an analyst's facial width-to-height ratio (fWHR), is associated with

his decision to cover riskier firms and more specifically, firms with less predictable earnings. Second, we investigate whether analysts' fWHR is associated with forecast boldness—defined as a deviation from a consensus earnings forecast—and with bold recommendations, defined as strong buy/sell ratings. To the best of our knowledge, the current study is the first to examine the relation between physical traits of top U.S. analysts covering U.S. firms.

Researchers investigate coverage choice and boldness because they are key components of analysts' decisions (Bradshaw 2011; Ramnath et al. 2008), particularly in regards to risk tolerance (Kadous et al. 2009). The effects of these decisions are critical to firms, peer analysts, and investors (Yu 2008; Clement and Tse 2005). Coverage choice is an essential decision, as it provides oversight and facilitates information distribution, thereby affecting the corporate production of information and a company's external financing selections (Chang et al. 2006; Yu 2008).³ We examine the relation between earnings predictability and the likelihood that a firm is covered by a high, relative to low, fWHR analyst. When an analyst covers firms with less-predictable earnings, the likelihood of inaccurate forecasts is increased, which could result in negative career consequences (Das et al. 1998). We expect that a high-fWHR analyst compared to a low-fWHR analyst is more likely to cover firms with low-earnings predictability.

Bold forecasts are commonly defined as forecasts that deviate from the consensus (Clement and Tse 2005). Such forecasts are generally considered risky, as more negative consequences exist for an inaccurate bold forecast compared to an inaccurate non-bold forecast (Kadous et al. 2009). We expect a positive relationship between fWHR and the likelihood of issuing a bold forecast.

With the benefit of hindsight, we then ask whether high-fWHR analysts, that we find to be bolder in less predictable firms, can produce forecasts that eventually turn out to be more accurate. The answer to this question is ex-ante unclear. While risk has clear implications for coverage and

boldness decisions, increased risk taking may translate into an analyst's higher or lower accuracy. To demonstrate, consider the extreme case of an analyst that only trusts a private signal and ignores the informativeness of the aggregated consensus. In such a case, a bold forecast is more likely to turn out wrong. Our results suggest that the tendency of high-fWHR analysts to go against the herd does not improve their accuracy. That said, fWHR has limited value in identifying analysts that will consistently generate more accurate forecasts. We show, for example, that high-fWHR analysts do not always display risk-taking behavior. Furthermore, our results regarding accuracy do not provide credible real-time value to market participants in evaluating individual forecasts as they are announced. Accuracy can only be measured ex-post once realized earnings are announced, typically one year after the forecast decision. We thus argue that market participants would benefit more from the ability to evaluate analyst decisions in real time. As such, we focus our hypotheses on coverage choice and boldness, both of which are observable at the time of forecast announcements.

Our sample consists of analysts honored by StarMine in their Top Stock Picker database.⁴ We focus on star analysts because they have more discretion in coverage choices and can afford to make bolder forecasts (Fang and Yasuda 2009; Clarke et al. 2007). Our sample consists of 465 star analysts nominated in 68 industries for the calendar years 2010–2015. Our first hypothesis examines whether high-fWHR analysts cover firms with less-predictable earnings. Using 26,818 analyst-firm-year observations, we find support for this prediction. Our second hypothesis examines whether high-fWHR analysts issue bolder forecasts. Using a sample of 20,128 analyst forecasts, we find evidence consistent with this hypothesis. Our results suggest that fWHR, a static facial cue associated with one's propensity for aggressive behavior, is an important factor that contributes to analyst decision making. We suggest that heterogeneity in analysts' risk preferences helps to explain the properties of their forecasts.

Because risk preferences may be correlated with the likelihood of becoming a star, we apply a two-stage methodology in which we estimate this likelihood in the first stage, and then control for it in the second stage. Our results show that implications of our study are not limited to elite (star) analysts and could be extended to the general analyst community. In particular, we argue that fWHR could be used to uncover analyst characteristics regardless of star status, which makes it relevant for investors, brokerage houses, and prospective analyst careers in general.

We also examine the behavior of up-and-coming stars. fWHR has been found to have a lower impact on behavior for high, compared to low, status individuals (Goetz et al. 2013; Welker et al. 2015). In the case of analysts selected as stars at some point in their career, we proxy for status by whether they are currently reigning. Consistent with prior studies, we find non-linearity in the relation between fWHR and risk-taking, which stems from variation in the subject's status.

Our study makes the following contributions. First, it provides further evidence for the importance of innate characteristics in evaluating information content generated by analysts and advances our understanding of observed dispersion in analysts' forecasts. Our findings help researchers and investors to better understand analyst forecasts and coverage decisions. In particular, our findings help investment managers to better weigh forecasts in making investment decisions. Importantly, our findings allow market participants to form a more informed evaluation of analysts' releases at an early stage in their career (e.g., rookie analysts) when they still lack the track record.

While prior literature has focused on acquired traits such as experience, or factors exogenous to the analyst such as broker resources, we contribute to the literature by showing that innate personal traits are associated with decision making. Recent literature has started to recognize the importance of innate analyst characteristics in explaining the variation in forecast accuracy (Luo and Xie 2012; Barron et al. 2013). While such studies largely focus on gender effects (Green et al.

2009; Kumar 2010; Li et al. 2013b), we put forth an innate characteristic that explains heterogeneity within gender, which is noteworthy given that the vast majority of analysts are male. Our findings are also useful for financial analysts by increasing their awareness to—and reducing the perils of—their own behavioral biases (De Bondt and Thaler 1990; Mokoaleli-Mokoteli et al. 2009).

Our findings also contribute to emerging interdisciplinary approaches and complement many studies in both the biology and accounting literature that find high-fWHR individuals make riskier choices in financial markets. For example, Cesarini et al. (2010) find that approximately 25% of individual variation in financial decision making is due to genetic variation. Prior literature on innate characteristics has also focused on CEOs (see for example Dikolli et al. 2012; Jia et al. 2014; Graham et al. 2013), and money managers (Brown et al. 2018; Lu and Teo 2018). The current study is one of the first to extend this literature by focusing on analysts. With regard to analysts' innate characteristics, a concurrent paper by He et al. (2019) uses data from China to test whether fWHR is associated with analyst accuracy.⁵ He et al. (2019) consider fWHR as a proxy for status seeking and achievement drive and argue that fWHR is thus correlated with an analyst's effort and employer-allocated resources. They report, for instance, that high-fWHR analysts are more likely to conduct corporate site visits, consistent with other findings relating fWHR with access to better resources (Brunell et al. 2008).⁶ The authors also report that analysts with higher fWHR are more likely to be selected as star analysts, albeit using a Chinese award, which is quite different from StarMine. We complement their findings in showing that fWHR affects the most influential analysts covering the largest U.S. firms. Our findings hold for Caucasian analysts employed by dominant U.S. brokerage houses, despite vast differences between the U.S. and Chinese markets, which include (but are not limited to) market structure, institutional details, reporting standards and disclosure regulation, and corporate governance, in addition to the domestic legal, political, and cultural environment more broadly. Importantly, by focusing on the risk-related aspect of fWHR, we show

that fWHR can provide valuable information to market participants on coverage choice and forecast boldness decisions in real time. Our sample of Caucasian U.S. analysts is particularly suitable for studying the fWHR-aggression relationship in the context of analyst risk taking, as opposed to the collaborative workplace culture in East Asia, in which aggressive behaviors are socially undesirable (Bontempo et al. 1997; Li et al. 2013a; Rule et al. 2013; Weber and Hsee 1998). Our results suggest that in markets in which fWHR does actually translate into risk taking, excessive risk taking does not improve analyst accuracy.

Although we focus on fWHR, we acknowledge that analyst risk-taking behavior may also be affected by other personal traits (e.g., I.Q., marital status, educational background, and family relations, among others). It is possible, for example, that fWHR affects the probability of getting married, and marital status affects risk taking, driving some of the total effect that we find. Nevertheless, we argue that given the direct association between fWHR and risk taking established in the literature—and the fact that fWHR is an objective measure—our focus on fWHR is informative and relevant to all market participants. In addition, fWHR is a trait which can be obtained by simply obtaining a publicly available photo.

The remainder of the study is organized as follows. In Section 2, we review related literature and develop the hypotheses in Section 3. We outline the study research design in Section 4 and discuss the results in Section 5. We report robustness tests in Section 6 and present conclusions in Section 7.

2 Literature Review

2.1 Analyst decision making

Analysts are an important focus of research in the accounting and finance literature because of their influential role in capital markets and diverse range of tasks. Prior research

regarding analysts has focused on the predictive power of analysts' forecasts and found that, due to information and timing advantages (Brown et al. 1987a), they are a better predictor of future earnings than prior earnings (Barefield and Comiskey 1975; Brown and Rozeff 1978). More recently, Bradshaw et al. (2012) reexamine analysts' superiority over time-series forecasts of annual earnings. They find that although analysts' earnings forecasts consistently beat random walk earnings forecasts over short windows, random walk forecasts (and naive extrapolation of analysts' short-horizon forecasts) are more accurate than analysts' explicit forecasts over longer horizons or when analysts forecast negative or large changes in EPS, as well as for smaller or younger firms. Extant literature also finds that in capital markets, analysts play an important role as information intermediaries because their forecasts affect market expectations (for example Schipper 1991) and share prices (Graham et al. 2005). Analyst coverage assists in monitoring firms by constraining earnings management (Yu 2008) and encouraging whistleblowing on corporate fraud (Dyck et al. 2010). Given the important roles of analysts, it is important to understand the inherent factors that influence their performances and preferences.

To explain analyst decision making, prior research has examined characteristics of analysts' skills such as experience (Hong and Kubik 2003; Clement 1999; Clement and Tse 2005; Shon and Young 2011; Mikhail et al. 1997); effort (Klettke et al. 2015); task complexity (Clement 1999); analyst incentives (Shon and Young 2011); communication with management (Chen and Matsumoto 2006; Green et al. 2014; Ke and Yu 2006); brokerage house characteristics, such as brokerage size (Clement 1999; Clement and Tse 2005); firm characteristics, such as operating performance (Shon and Young 2011) and intangibles (Amir et al. 2003); analyst following (Alford and Berger 1999; Hong et al. 2000); corporate international diversification (Duru and Reeb 2002); annual report readability (Lehavy et al. 2011) or verifiability (Bozzolan et al. 2009); and audit quality (Behn et al. 2008).

Despite research that documents innate characteristics influence the decision making of corporate managers (Graham et al. 2013; Dikolli et al. 2012; Jia et al. 2014) and investors (Cesarini et al. 2010; Cronqvist et al. 2016), the effect of innate characteristics on analysts has not been sufficiently explored.⁷ Some exceptions include Jiang et al. (2016), who find that U.S. analysts that donate to the Republican party issue less-bold forecasts than those that donate to the Democratic party. Political preferences are considered innate because they are a product not only one's environment, but also of genetics (Alford et al. 2005). Furthermore, Kumar (2010) finds that female analysts make more accurate forecasts; however, he attributes this result to self-selection rather than to higher innate ability. We extend the literature on innate characteristics that affect analysts' decision making by considering the relation to fWHR, which has been found to be associated with underlying risk preference (Apicella et al. 2008; Kamiya et al. 2016).

Given that the focus of this paper is on analyst risk-taking behavior, we adhere to analyst features that can be directly related to risk. As we demonstrate in the following section, we find that *bold* coverage choice, forecasts, and stock recommendation decisions are the most relevant. Although many studies examine other analyst features (e.g., investment profitability), we do not include such features that cannot be directly attributed to analyst risk-taking behavior in the scope of this paper.

2.2 fWHR, testosterone, and risk preferences

In using facial width-to-height ratio as a metric, we first note its limitations. We acknowledge that fWHR is a noisy and imperfect proxy for individual risk preferences. fWHR may be correlated with other omitted factors such as ethnic origin, and its estimation is subject to measurement error. To minimize these concerns, we focus only on one gender and ethnicity, namely, Caucasian male analysts. We then use raw fWHR figures to classify analysts to high- and

low-fWHR relative to the median. To minimize measurement error and the effect of outliers, we use this dichotomous variable in our main empirical tests. In addition, we rely on Apicella et al. (2008), who confirm that fWHR is highly correlated with alternative metrics of innate risk preferences, such as testosterone in saliva and finger ratio, and show that these traits are associated with decision-making with real monetary outcomes.

The facial width-to-height ratio is affected by testosterone levels due to the hormone's effect on lateral cheekbone growth during puberty, with such growth increasing the width of the face and thus the fWHR (Pound et al. 2009; Lefevre et al. 2013; Carré et al. 2013; Verdonck et al. 1999). A higher fWHR is associated with higher baseline and reactive testosterone levels in men (Lefevre et al. 2013; Pound et al. 2009).

Testosterone has been found to affect decision-making and behavior through its effect on neural mechanisms (Mehta and Beer 2010). Despite not knowing the exact neuroendocrinological mechanisms that drive the effect of testosterone on behavior (Jia et al. 2014), the hormone has consistently been found to affect risk-taking behavior (Apicella et al. 2008; Kamiya et al. 2016; Sapienza et al. 2009; Booth et al. 1999).⁸ Such behaviors include a higher propensity to engage in activities such as smoking, alcohol, drug abuse, and having multiple sexual partners (Booth et al. 1999), as well as the pursuit of risky careers (Sapienza et al. 2009).

Studies have found that testosterone levels are associated with financial risk-taking behavior. Using data from the Swedish Twin Registry, Cronqvist et al. (2016) find that differences in individuals' exposure to prenatal testosterone explain heterogeneity in financial decisions later in life. In a study of 98 men in an investment game, Apicella et al. (2008) investigate the effect of testosterone levels on decision making with real monetary outcomes. They find that men with higher levels of testosterone, as measured by fWHR and through saliva, have a greater tendency to take financial risks. The authors also show that the second-to-fourth digit length ratio (2D:4D), which

has been proposed as a proxy for prenatal testosterone exposure, did not correlate significantly with risk preferences. Kamiya et al. (2016) find that firms with high-fWHR CEOs take on more debt, engage in more M&A activity, and experience greater stock return volatility.⁹

The main fWHR-induced behavior of interest in our study is financial risk preferences.¹⁰ We thus focus on two analyst decisions that are likely to be affected by risk tolerance: coverage choice and forecast boldness (Kadous et al. 2009).¹¹

3. Hypothesis Development

3.1 fWHR and coverage choice

Covering firms with less-predictable earnings is risky for an analyst. Dichev and Tang (2009) show that firms with higher earnings volatility are associated with economically large analyst forecast errors. Bradshaw et al. (2012) find that analysts' earnings forecasts are less accurate when they forecast large changes in EPS. If firms with less-predictable earnings are more likely to lead to inaccurate forecasts, then analysts covering such firms face riskier career prospects (Hong and Kubik 2003; Groysberg et al. 2011; Mikhail et al. 1999). For example, Mikhail et al. (1999) document higher analyst turnover when forecast accuracy is lower. Groysberg et al. (2011) find that analyst accuracy correlates with tenure. The large potential downside, in the form of lower credibility and diminished career outcomes from inaccurate forecasts, may deter risk-averse analysts from covering firms with low-earnings predictability. Given that high fWHR is associated with increased financial risk tolerance (Apicella et al. 2008; Kamiya et al. 2016), we expect that high-fWHR analysts are more likely to cover firms with low-earnings predictability compared with low-fWHR analysts. This leads to:

H1: Analysts with high fWHR are more likely to cover firms with low-earnings predictability.

We note that brokerage houses typically assign stocks to its analysts, with no need to provide any incentive for covering less-desirable stocks. One may argue that a brokerage house may allocate stocks based on analysts' masculinity whether the managers are conscious of this bias or not. If so, it is then difficult to attribute the association between fWHR and coverage choice to the analysts themselves rather than to their employers. That said, study the impact of star analyst job changes on their coverage choices, and find that unlike ordinary analysts, star analysts rarely revise their coverage portfolio when they switch brokerage houses. Therefore, the focus of this paper is on star analysts, who, given their status have more discretion in coverage choices.

One may argue that high-fWHR analysts are more likely to choose stocks that generate bonuses regardless of risk. Investor demand for analysts' forecasts may be higher for firms with lower ex-ante earnings predictability, because information on these firms is more valuable (Chung et al. 1995). Bhushan (1989) models the supply and demand for analysts' forecasts and predicts that an increase in forecast demand in a particular company will lead more analysts to cover the stock. When an analyst meets the demand for coverage, it may result in increased brokerage revenue for his employer that may in turn lead to higher compensation for the analyst. Groysberg et al. (2011) find that analyst compensation is positively related to star recognition, investment-banking contributions, and the size of analysts' portfolios. On the other hand, they find analyst turnover to be related to forecast accuracy, suggesting that analyst forecasting incentives are primarily based on termination. That is, although covering more risky firms can potentially indirectly lead to higher compensation, such a benefit is dominated by an increased termination risk, which is significantly larger than the risk of any bonus for increased trading.

3.2 fWHR, bold earnings forecasts, and stock recommendations

A bold forecast is commonly defined as a forecast that is different from a consensus forecast (Hong et al. 2000; Clement and Tse 2005). That is, bold forecasts stand out from the crowd, but they are also riskier. Bernhardt et al. (2006) find that analysts systematically issue bold forecasts, and in nearly 60% of the time, their contrarian forecasts overshoot actual EPS. Scharfstein and Stein (1990) suggest that a herding forecast may increase the perception of an analyst's skill level. They argue that analysts who forecast similar earnings must have received the same informative signal, and thus investors perceive these analysts to be highly skilled. However, when a bold forecast turns out to be wrong, investors infer that the analyst received a noisy signal and therefore has low skills. Bold forecasts can thus undermine an analyst's reputation, leading to lower compensation and higher termination risk (Groysberg et al. 2011). The same logic applies to stock recommendations, wherein we assume that a more extreme recommendation is a bolder move with more severe consequences. Given that high fWHR is associated with an increased financial risk tolerance (Apicella et al. 2008; Kamiya et al. 2016), and issuing bold forecasts are considered risk-taking behavior for analysts, we predict that:

H2: Analysts with a greater fWHR are more likely to issue bolder earnings forecasts and stock recommendations.

It is possible that high-fWHR analysts actually tend to systematically over- or under-estimate earnings, rather than distance themselves from the pack regardless of direction. Such a one-way bias (signed deviation from consensus) can mechanically result in a significant forecast boldness (absolute deviation from consensus). We therefore explore not only forecast boldness and strong recommendations, but also forecast bias as well as buy and sell recommendations separately. Finding a significant result for absolute boldness and an insignificant one in the signed/directional variables will further support our risk-taking argument.

One may argue that high-fWHR analysts issue bolder forecasts simply because they are either more informed or incorporate more of their private information (Clement and Tse 2005; Hong et al. 2000; Scharfstein and Stein 1990; Trueman 1994; Welch 2000; Desai et al. 2000). The notion that bold forecasts are more informative to investors is supported by a higher share price reaction to bold earnings-forecast revisions compared to herding forecast revisions (Clement and Tse 2003; Gleason and Lee 2003). Even if more informed analysts have an incentive to issue bolder forecasts, it seems that the downside prevails.¹²

Nevertheless, we complement our empirical tests by examining in hindsight whether high-fWHR analysts result in higher accuracy. We examine both the absolute forecast error and the signed error. The latter is typically interpreted as a measure for analyst optimism.

3.3 fWHR and relative status

Risk taking is often used as a means of enhancing one's position in a social hierarchy (see Ellis et al. 2012, for a review) or at least a means of dissuading future challenges directed at oneself (Fessler et al. 2014). Having low status or experiencing an acute drop in status should motivate an individual to prefer risk-seeking strategies that can recover or close the gap. Under conditions of high social status, on the other hand, risk taking is suboptimal, as further gains have diminishing returns (Ermer et al. 2008).

Recent studies highlight the importance of considering relative social status when examining the link between fWHR and risk-taking behavior. For example, Goetz et al. (2013) find fWHR to be positively correlated with reactive aggression, but only in men who reported low subjective social status. Welker et al. (2015) extend these findings with experimental evidence that fWHR is only an indicator of risk-taking behaviors in individuals that perceive themselves as having low status. The authors suggest that fWHR may specifically promote risk taking in situations where

risk taking is advantageous, such as low social status. We therefore test whether the non-linearity in the relation between fWHR and risk-taking stems from variation in the subject's status. In particular, we distinguish between high-status and low-status analysts. We proxy for relative status by the current ranking of an analyst. That is, for analysts selected as stars at some point in their career, we proxy for status by whether they are currently reigning. This allows us to examine the boldness decision for incumbent vs. aspiring former and future stars separately.

4. Research Design

4.1 Sample collection

We draw our data from several sources. The data on analysts' characteristics, consensus and management guidance comes from the Institutional Brokers' Estimate System (I/B/E/S) files. To include firm characteristics, we merge our data with CompuStat and CRSP.

For the period 2010–2015, we identify 3,958,699 firm earnings forecasts for more than 9,497 U.S. firms, which are generated by 10,926 analysts employed by 797 brokerage houses. We focus on a specific group of analysts across all industries, namely “celebrity” analysts (also known as star analysts) that are objectively ranked as top analysts by fund managers, journalists, and others.¹³ Such celebrity analysts are more visible, and their photos can be collected from outlets external to the analyst such as the financial press and brokerage websites, which mitigate self-selection issues of choosing whether and which photo to include on one's personal online profile. This allows us to construct an unbiased sample of analysts' photos in order to measure their fWHR.

To identify star analysts, we use the StarMine's Top Stock Picker database.¹⁴ This database is based purely on the excess return from investment recommendations over the preceding calendar year. StarMine ratings are widely used by industry, and top Wall Street firms use the ratings in determining analyst compensation (Beyer and Guttman 2011; Ertimur et al. 2011).¹⁵

The sample collection procedure is as follows. For the years 2010–2015, we obtain 715 analysts from the StarMine ratings database. We match the vast majority of StarMine analysts with the I/B/E/S recommendations file, which includes family name and first initial, as well as the name of the brokerage house. We then try to source a photo from the financial press, business channels, industry publications, and brokerage websites. In some instances, we source photographs from LinkedIn, an employment-oriented social networking service. We can crosscheck in some cases that the photo is similar to that on TipRanks (a website providing information about financial analysts, bloggers, and insider trading).

The effect of testosterone on craniofacial growth varies between genders and ethnicities (Lefevre et al. 2013; Kramer 2015). Consistent with prior literature, including Lefevre et al. (2013) and Wong et al. (2011), we focus on only one gender and ethnicity and eliminate female analysts and non-Caucasian analysts.¹⁶ We also drop seven analysts that are ranked by StarMine in more than one sector.

For a photograph to be considered as suitable for the fWHR measurement, the analyst must be forward-facing and have a neutral expression (Kramer 2016; Jia et al. 2014).¹⁷ A researcher and a research assistant obtained the photographs, which were then validated by other co-researchers on the project. Once we dropped cases in which we were unable to source a photo that would lead to a reliable fWHR measurement, we arrive at a final sample of 465 (Caucasian male) star analysts, covering 22,521 analyst-firm-years, and generating 119,917 annual earnings forecasts. For this sample, we measured analysts' faces using ImageJ software provided by the National Institutes of Health. The manual measurement of fWHR (as opposed to a software-based approach) can handle photos that include other cues (such as glasses, a mustache, or a beard) and photos with a fake smile. fWHR is the distance between the left and right zygion (bizygomatic width) divided by the distance between the upper lip and mid-brow (height) (Carré et al. 2009).¹⁸ Both the mean and

median fWHR in our star-analyst sample are around 2, which is very similar to studies among CEOs (Jia et al. 2014) and the general male population (Lefevre et al. 2013). Please refer to Appendix A for an example and a detailed description of the measurement process.

In both the forecast and recommendation analyses, we include only the latest announcement per analyst-firm-year combination. That is, we do not include any early announcements that are later revised, which could result in multiple forecasts by the same analyst for the same firm but with different horizons. This scenario could introduce problems related to the choice of revision timing and mechanistic relations between accuracy and forecast horizon. We choose the latest rather than the earliest announcement, as boldness only becomes meaningful once one deviates from an established view by the analyst community. In addition, the latest announcements are likely clustered towards the end of the fiscal year and are thus more homogenous in terms of horizon. Therefore, for each firm an analyst covers, we maintain only the latest stock recommendation and the latest EPS forecast for the next fiscal year as long as it is made before the end of the fiscal year.

4.3 Empirical methodology

Because risk preferences may be correlated with the likelihood of becoming a star, we apply a two-stage methodology, in which we estimate the propensity of being selected as a star in the first stage and control for it in the second stage. In fact, several of our control variables have been shown to be associated with star status, such as analyst general experience (*GenExp*), analysts from larger brokerage houses (*BSize*), average firm size (*FSize*) and analysts covering larger portfolios (*FCovered*) (e.g., Rees et al. 2015; Bradley et al. 2017, 2019). The latter is anticipated in light of the explicit qualification criteria in the StarMine rankings. Specifically, an analyst must cover a minimum number of stocks in a given industry throughout the year to qualify for the Industry Stock Picking

Award.¹⁹ We thus use the number of firms in the analyst's portfolio (*FCovered*) as an exclusion variable. As the number of firms covered does not seem to have any association with analyst risk-taking behavior, *FCovered* meets the exclusion restriction and we do not include it in the second stage.

4.3.1 Model for Hypothesis 1: Coverage choice

The first hypothesis studies the association between a firm's earnings predictability and the characteristics of analysts covering it. We predict that star analysts with high fWHR are more likely to cover firms with low earnings predictability. We use earnings volatility as a proxy to earnings predictability. Dichev and Tang (2009) show that earnings predictability is negatively correlated with earnings volatility. They find that the effect of earnings volatility on earnings predictability exceeds that of several plausible benchmarks, including cash flow volatility, the accrual effect, and the extreme-earnings, mean-reversion effect. They further show that current earnings volatility information allows for the identification of predictable and economically large analyst forecast errors.

One may argue that a more risk-tolerant analyst can choose to cover firms with low-earnings persistence rather than firms with higher earnings volatility. These two earnings features are highly (negatively) correlated and the negative effect of earnings volatility on earnings persistence reinforces the base negative relation between earnings volatility and earnings predictability (Dichev and Tang 2009). For the purpose of our study, we therefore do not distinguish between these two highly correlated channels, but rather capture earnings predictability using earnings volatility (*EV*) (Graham et al. 2005; Dichev and Tang 2009). Thus, a higher value of *EV* indicates lower earnings predictability.

We examine the relation between $fWHR$ and a set of firm, analyst, and broker characteristics. Our independent variable of interest, $dfWHR$, is equal to 1 if the analyst covering the firm possesses an $fWHR$ above the sample median and 0 otherwise. This binary approach helps limit the potential for human error in measurement (Greene 2012; Jia et al. 2014).²⁰ Intuitively, $dfWHR$ indicates coverage by an analyst with high, rather than low, $fWHR$.

To capture the marginal relation between an analyst's $fWHR$ and earnings volatility of firms he chooses to cover, we control for firm-level characteristics identified by prior literature. We include firm size ($FSize$), as large firms enjoy high analyst and media coverage as well as better and more stable information environments (Lui et al. 2007) and therefore more predictable earnings. We include analyst coverage ($ACoverage$) and voluntary disclosure ($VolDisc$), because a larger analyst following and the provision of more voluntary disclosures increase the firm's information environment, thus increasing earnings predictability (Duru and Reeb 2002). We further control for firm characteristics including trading volume ($Volume$) (Liang et al. 2008; Barth et al. 2001; Tehranian et al. 2013; Shon and Young 2011), sales growth ($GrowthSales$) (Barth et al. 2001), market-to-book ratio (MTB) (Krigman et al. 2001; Tehranian et al. 2013; Liang et al. 2008), and share returns ($Return$) (Tehranian et al. 2013; Shon and Young 2011; Liang et al. 2008). The higher a firm's growth, the more its earnings are sensitive to growth opportunities. The market-to-book ratio is a proxy for a firm's unrecognized intangible assets. When a firm has significant unrecognized intangible assets, their accounting system is generally less informative (Barth et al. 2001). Firms that trade more actively or had previously performed better may garner more interest and monitoring by both institutional and retail investors.

Analyst characteristics include experience ($GenExp$) (Liang et al. 2008; O'Brien and Tan 2015), as experienced analysts may be able to cover more complex firms because of their greater skills (Liang et al. 2008). As for broker characteristics we control for the number of analysts the

brokerage house employs (*BSize*) as it may be correlated with a tendency to focus on specific types of stocks (Liang et al. 2008; Barth et al. 2001; Tehranian et al. 2013). We also include year and industry fixed effects to ensure that our results are not driven by cross-sectional variation across years or between different industries, respectively.

Measurement of all variables is defined in Appendix B. The following two-stage specification is estimated at the analyst-firm-year level:

$$\begin{aligned} Star = & \alpha + \beta_1 FSize + \beta_2 ACoverage + \beta_3 VolDisc + \beta_4 Volume + \beta_5 GrowthSales + \\ & \beta_6 MTB + \beta_7 Return + \beta_8 GenExp + \beta_9 BSize + \beta_{10} FCovered + \\ & Year\ and\ Industry\ Fixed\ Effects + \varepsilon \end{aligned} \quad (1)$$

$$\begin{aligned} EV = & \alpha + \beta_1 dfWHR + \beta_2 Mills + \beta_3 FSize + \beta_4 ACoverage + \beta_5 VolDisc + \\ & \beta_6 Volume + \beta_7 GrowthSales + \beta_8 MTB + \beta_9 Return + \beta_{10} GenExp + \\ & \beta_{11} BSize + Year\ and\ Industry\ Fixed\ Effects + \varepsilon \end{aligned} \quad (2)$$

A significant positive coefficient on *dfWHR* will provide support for H1, which posits that high-fWHR analysts are more likely to cover firms with less-predictable earnings.

4.3.2 Model for Hypothesis 2: Forecast boldness

Our first dependent variable is forecast boldness, measured as the deviation of the forecast from consensus and consistent with Hong et al. (2000), Clement and Tse (2005), and Bernhardt et al. (2006). Specifically, we measure boldness as the absolute deviation of analyst *i*'s forecast for firm *j* from the median outstanding forecast of firm *j* for period *t* scaled by stock price. We note that from the point of view of investors, the median of all publicly available forecasts on firm *j* represents the relevant reference point for the firm. It seems highly unlikely that investors compute analyst-specific consensus by dropping analyst *i* from his benchmark set. Econometrically, the median forecast—rather than the mean forecast—further minimizes any potential effect of analyst *i*'s own previous

forecast. That is, while one's own outstanding forecast by definition affects the mean, it almost surely does not tip the scales of the median. By using the median forecast, we also alleviate concerns regarding stocks covered by very few analysts. In addition, following O'Neill et al. (2011), we exclude firms with less than three analysts following the firm for the current period to remove the effect of the analyst's forecast unduly influencing the consensus.

Because boldness is measured in terms of earnings-per-share, we scale it by the concurrent market price per share. Consider, for example, a firm characterized by a very small number of outstanding shares. Such firm would exhibit high price-per-share, high EPS, and thus high deviations from the consensus EPS. As such, scaling facilitates our cross-sectional analysis across firms that can differ significantly in the number of outstanding shares.

Our independent variable of interest is fWHR, measured using a binary variable (*dfWHR*) that equals 1 if the analyst's fWHR is greater than median, and 0 otherwise. This binary approach helps limit the potential for human error in measurement (Greene 2012; Jia et al. 2014).²¹

Following Clement and Tse (2005), we include analyst-related characteristics such as the size of the broker (*BSize*), the number of firm forecasts the analyst generated in the previous period (*FcastFreq*), the earliness of the forecast (*Horizon*), the number of years the analyst has been following the firm (*FirmExp*), and the number of years in which the analyst has been covering any firm (*GenExp*), as control variables.

Analysts are more likely to herd when there is limited information about the firm (Welch 2000). We thus include measures used in prior literature that proxy for the firm's information environment including firm size (*FSize*) (Brown et al. 1987b; Duru and Reeb 2002), number of analysts following the firm (*ACoverage*) (Duru and Reeb 2002; Alford and Berger 1999), and the level of voluntary disclosure (*VolDisc*) (Lang and Lundholm 1996; Barron et al. 1999; Hope 2003). We

further control for firm characteristics including trading volume (*Volume*) (Liang et al. 2008; Barth et al. 2001; Tehranian et al. 2013; Shon and Young 2011). In doing so, we also ensure that the level of boldness of high-fWHR analysts is not merely driven by high-fWHR analysts choosing to cover a certain type of stock.

We include year and industry (based on 2-digit SIC) fixed effects to ensure that our results are not driven by cross-sectional variation across years or between different industries, respectively. We define measurement of all variables in Appendix B. To test H2, we estimate the following two-stage specification using analyst-firm-year-forecast observations in our sample:

$$\begin{aligned} Star = & \alpha + \beta_1 BSize + \beta_2 FcastFreq + \beta_3 Horizon + \beta_4 FirmExp + \beta_5 GenExp + \\ & \beta_6 FSize + \beta_7 ACoverage + \beta_8 VolDisc + \beta_9 FCovered + \\ & Year\ and\ Industry\ Fixed\ Effects + \varepsilon \end{aligned} \quad (2)$$

$$\begin{aligned} Boldness = & \alpha + \beta_1 dfWHR + \beta_2 mills + \beta_3 BSize + \beta_4 FcastFreq + \beta_5 Horizon + \\ & \beta_6 FirmExp + \beta_7 GenExp + \beta_8 FSize + \beta_9 ACoverage + \beta_{10} VolDisc + \\ & \beta_{11} Volume + \beta_{12} GrowthSales + \beta_{13} FCoverage + \\ & Year\ and\ Industry\ Fixed\ Effects + \varepsilon \end{aligned} \quad (3)$$

As previously discussed, we include only one observation per analyst and firm-year, specifically the latest announcement. Furthermore, because bolder analysts may be consistently bold over time and across all their covered firms, we use standard errors clustered by analyst.

A significant positive coefficient on *dfWHR* would provide support for H2, which posits that high fWHR analysts produce bolder forecasts. Our data further allows us to study the non-linearity in the relation between fWHR and risk taking. In particular, we distinguish between high- and low-status analysts. For analysts that have been selected as stars at some point in their career, we proxy for status by whether they are currently reigning. This allows us to examine the boldness decision for current vs. former-and-future stars, separately.

We then employ the same specification for forecast accuracy. Unlike forecast boldness, which is measured as relative to the consensus at announcement date, accuracy is only realized when actual earnings are announced almost a year later by the firm, and is measured as relative to earnings that may be subject to earnings management (Degeorge et al. 1999). Specifically, we measure an ex-post forecast error as the absolute deviation of the analyst's forecast from the actual earnings of the firm, normalized by actual earnings. We also explore the signed forecast error, typically interpreted as analyst optimism.

As another aspect of analyst boldness, we look at the boldness of analyst recommendations. As with earnings forecasts, we assume that a more extreme recommendation is a bolder move with more severe consequences. Confirming common intuition, Loh and Mian (2006) suggest that analysts issuing bold forecasts likely overlap with those making bold recommendations. That said, given the very limited number of choices available for an analyst in making a stock recommendation (five at most), their risk-taking behavior may differ between the two outputs. We define an indicator variable *Strong Buy/Sell* as equal to 1 for strong buy or strong sell and 0 otherwise. We note that given the discrete nature of stock recommendation, we assume that extreme recommendations are bold irrespective of the consensus. That is, a strong buy is considered bold even if the mean/median recommendation is buy. To test H2 using stock recommendations, we redefine forecast frequency to count the number of recommendations by the analyst for the firm during the same year. We also drop forecast horizon as a control (as it can only be identified in the context of earnings forecasts). The following two-stage specification is estimated using analyst-firm-year-recommendation observations in our sample:

$$\begin{aligned} Star = & \alpha + \beta_1 BSize + \beta_2 FcastFreq + \beta_3 Horizon + \beta_4 FirmExp + \beta_5 GenExp + \\ & \beta_6 FSize + \beta_7 ACoverage + \beta_8 VolDisc + \beta_9 FCovered + \\ & Year \text{ and Industry Fixed Effects} + \varepsilon \end{aligned} \quad (4)$$

$$\begin{aligned}
\text{Strong Sell / Buy} = & \alpha + \beta_1 dfWHR + \beta_2 mills + \beta_3 BSize + \beta_4 FcastFreq + \beta_5 Horizon + \\
& \beta_6 FirmExp + \beta_7 GenExp + \beta_8 FSize + \beta_9 ACoverage + \beta_{10} VolDisc + \\
& \beta_{11} Volume + \beta_{12} GrowthSales + \beta_{13} FCoverage + \\
& \text{Year and Industry Fixed Effects} + \varepsilon
\end{aligned} \tag{5}$$

To study whether our results for strong recommendations are driven by either direction, we also employ the same specification, but use it to explore strong buy and strong sell recommendations separately. We create an indicator variable *Strong Buy (Strong Sell)* defined as 1 for strong buy (strong sell) recommendations and 0 otherwise.

5. Results

5.1 Results for Hypothesis 1: Coverage choice

We present descriptive statistics of the sample used to test the first hypothesis in Table 1. Panel A reports descriptive statistics for the full sample. Panel B presents descriptive statistics when the analyst's fWHR is smaller or equal to the median and above the median. The mean of *EV* for the high-fWHR subsample is 1.640 and 1.557 for the low-fWHR subsample.²²

(Insert Table 1 here)

The first hypothesis assesses whether high-fWHR analysts are more likely to cover firms with low earnings predictability. For the Heckman first-stage sample ($N = 254,065$), we find (untabulated) that *FCovered* has a mean (median) of 21.28 (19) and 17.44 (17) for star analysts and non-stars, respectively. Column 1 in Table 2 presents the results of the first-stage Heckman selection model. Consistent with our expectations, *FCovered* is significant and positively associated with becoming a star analyst ($p < 0.001$). The second stage results (Column 2) include the inverse mills ratio computed from the first stage. The main variable of interest is *dfWHR*. Consistent with our expectations, we find a significant positive

coefficient on $dfWHR$ ($p < 0.10$), which is consistent with high-fWHR analysts covering firms with less- predictable earnings.

As expected, we find that earnings volatility is also related to some of the control variables. Specifically, higher earnings volatility is associated with less analyst coverage ($ACoverage$), smaller firm size ($FSize$), less general experience ($GenExp$), and greater share turnover ($Volume$). Higher earnings volatility is also associated with lower growth ($GrowthSales$) and market-to-book ratio (MTB). We do not find level of voluntary disclosures ($VolDisc$), market return ($Return$), or working in a larger brokerage firm ($BSize$) to be associated with earnings volatility of the firm covered. Overall, our results are consistent with high-fWHR analysts covering firms with higher earnings volatility, while holding fixed other firm characteristics that star analysts consider when deciding which stocks to cover.

(Insert Table 2 here)

5.2 Results for Hypothesis 2: Forecast boldness

Table 3 reports descriptive statistics for the sample used for the second hypothesis. Panel A reports descriptive statistics for the Heckman model. For the Heckman first-stage sample ($n = 225,741$), we find (untabulated) that $FCovered$ has a mean (median) of 21.31 (19) and 16.65 (16) for stars and non-stars respectively. Panel B reports descriptive statistics for the full sample. Panel C presents univariate statistics that split the sample by whether the analyst's fWHR is smaller or equal to the median.

(Insert Table 3 here)

Table 4 presents results for the second hypothesis in which we test whether high- fWHR analysts issue bolder forecasts. Column 1 in Table 4 presents the results of the first-stage Heckman

selection model. Consistent with expectations, *FCovered* is significant and positively associated with the likelihood of being selected as a star analyst ($p < 0.001$).

The second-stage results include the inverse mills ratio computed from the first stage. Column 2 reports results for the sample consisting of all career-star analysts, Column 3 reports results for the subsample consisting of former/future star analyst, and Column 4 reports results for the subsample consisting of reigning star analysts. In the sample consisting of all career-star analysts (Column 2), we find a significant positive coefficient on *dfWHR* ($p < 0.10$). Results are consistent with the second hypothesis—i.e., high-fWHR analysts issue bolder forecasts. Our control variables are generally consistent across the subsamples. We also find that consistent with prior literature, forecast boldness is significantly lower when more analysts cover the firm (*ACoverage*) ($p < 0.05$), and a negative association exists between forecast boldness and analyst experience in covering the firm ($p < 0.10$). We find a positive association between forecast boldness and firm size (*FSize*), as well as with firms with greater share turnover (*Volume*), which are both significant at the 5% level.

We next examine whether the relation between fWHR and forecast boldness varies by star status. As reported in Columns 3 and 4, we find that the relation between *dfWHR* and forecast boldness holds for former/future star analysts ($p < 0.05$), but not for reigning star analysts ($p > 0.10$). This is consistent with prior literature, which finds that fWHR has a lower impact on behavior for high, compared to low, status individuals (Goetz et al. 2013; Welker et al. 2015).

(Insert Table 4 here)

According to our risk-taking argument, high-fWHR analysts try to distance themselves from the pack regardless of direction. It is also possible that high-fWHR analysts tend to systematically over- or under-estimate earnings, which mechanically drives the absolute boldness. We therefore examine the relation between fWHR and forecast bias. The dependent variable, *Bias*, is the deviation

of the analyst's forecast from the median consensus forecast for that firm's earnings, scaled by stock price. As with the previous analyses, the model includes the inverse mills ratio (Eq. 3) and all other controls in Eq. 4. As reported in Table 5, we do not find *dfWHR* to be associated with forecast bias in all the samples. That is, we find that boldness (absolute deviation from consensus) is significant while bias (signed deviation from consensus) is not. This further establishes *fWHR* as an unconscious risk tolerance rather than a strategic one.

(Insert Table 5 here)

In Table 6, we report our results examining analysts' recommendations and their *fWHR*. Panel A reports descriptive statistics for the Heckman model. For the Heckman first-stage sample ($n = 66,455$), we find (untabulated) that *FCovered* has a mean (median) of 11.09 (10) and 10.84 (9) for stars and non-stars, respectively. Panel B and C provide descriptive statistics and univariate, respectively. Similar to our previous analyses, we obtain the inverse mills ratio.

(Insert Table 6 here)

We present our regression results in panel A, Table 7, in which Column 1 shows the results of the first-stage Heckman selection model. Consistent with expectations, *FCovered* is significant and positively associated with the likelihood of being selected as a star analyst ($p < 0.05$). We find that *dfWHR* has a positive association with issuing a bolder stock recommendation (i.e., strong buy or strong sell) ($p < 0.10$). Turning to our control variables, we find that analysts are less likely to issue a bolder recommendation when the brokerage size is bigger ($p < 0.10$) and when the firm has a lower share turnover (*Volume*) ($p < 0.01$). Examining strong buy and sell separately, we find a positive association between *dfWHR* and analysts giving a strong buy recommendation ($p < 0.10$), but do not find *dfWHR* to be associated with a strong sell recommendation.

We next examine whether the relation between *fWHR* and forecast boldness varies by star status. As shown in panel B of Table 7, we find that the relation between *dfWHR* and boldness of recommendation holds for reigning star analysts ($p < 0.10$ or better), but not for former/future star analysts ($p > 0.10$).

(Insert Table 7 here)

Taken together, our results support H2: high-*fWHR* analysts produce bolder forecasts compared to low-*fWHR* analysts while holding fixed other factors related to forecast boldness.

5.3 Results for forecast error

We next test whether high-*fWHR* analysts issue forecasts that result in higher accuracy. We examine two dependent variables related to forecast errors. The first dependent variable is forecast error, defined as the absolute deviation of the analyst's forecast from the actual earnings of the firm normalized by actual earnings. Finding that accuracy does not improve with boldness, will further establish *fWHR* as an innate risk tolerance rather than a rational one. The second dependent variable is signed forecast error, computed as the deviation of the analyst's forecast from the actual earnings of the firm normalized by actual earnings. The latter is typically interpreted as a measure for analyst optimism.

To address sample selection bias between star and non-star analyst, our model specifications include the inverse mills ratio (a transformation of the predicted likelihood of becoming a star analyst based on the first-stage probit model) as discussed above. Results for the absolute forecast error (signed forecast error) are reported in Table 8, Panel A (B). In both panels, Column 1 reports results for all career-star analysts, Column 2 reports results for former/future star analysts, and Column 3 reports results for reigning star analysts. In all the samples, we do not find

dfWHR to be associated with forecast error. Our results suggest that the excessive risk taking by high-*fWHR* analysts is not detrimental to their forecast accuracy.

(Insert Table 8 here)

6. Entropy Balancing

In our main results, we use a Heckman selection model to address selection issues that may confound our results. We note that our multivariate regressions already control for a battery of variables that may be correlated with *fWHR*. In order to facilitate our interpretation, attributing analyst risk-taking behavior to their *fWHR*, rather than to other firm characteristics. That said, a limitation of the linear model is that it does not properly account for differences in covariate distributions between firms covered by high- vs. low-*fWHR* analysts. As an alternative model specification, we apply entropy balancing, a preprocessing technique to achieve covariate balance within a binary treatment (Hainmueller 2012). The treatment (control) group is $dfWHR=1(=0)$. Using entropy balancing, we adjust the inequalities in the covariate distributions with respect to the first (mean) and second (variance) moments. Untabulated results indicate that our results remain consistent, albeit slightly less significant.

7. Conclusions

In this study we examine the effect of one innate analyst characteristic, the facial width-to-height ratio (*fWHR*), on coverage decisions and the boldness of earnings forecast and stock recommendations. *fWHR* has been found to be associated with increased risk-taking behavior (Apicella et al. 2008; Kamiya et al. 2016). Using a sample of star analysts, we examine two observable decisions likely to be a function of analyst risk tolerance: analysts' coverage choice of firms and earnings forecast boldness.

We first hypothesize that firms with low-earnings predictability are riskier to cover. We predict and find that high-fWHR analysts are more likely to select firms with low-earnings predictability. In the second hypothesis, we posit that high-fWHR analysts issue bolder forecasts. This follows prior literature suggesting that issuing bold forecasts is risky, as forecasts that deviate from the consensus are attributed to the analysts themselves, whereas non-bold forecasts are attributed to external factors (Kadous et al. 2009). Our results support this prediction by finding that high-fWHR analysts issue forecasts that deviate from the consensus more than low-fWHR analysts. Furthermore, we find that the forecasts made by high-fWHR analysts are less accurate than those of low-fWHR analysts. The findings from this study are robust to alternative model specifications and alternate measurement of variables.

The findings from this study contribute to the analyst-forecasting literature and add to a growing body of research that investigates the effect of innate characteristics on decision making. In finding that fWHR is associated with forecast boldness and coverage choice, we address calls by scholars (for example Ramnath et al. 2008; Brown et al. 2015; Bradshaw 2011) to better understand the black box of analyst decision making. Specifically, in finding that fWHR is associated with coverage choice and forecast boldness, investment practitioners are better able to evaluate the information content generated by different types of analysts and weigh their individual forecasts in making investment decisions. By focusing on analysts' risky decisions, we provide further validation of fWHR as an indicator of risk tolerance. Together, our results provide a catalyst to better understand how innate individual heterogeneity affects analysts' work.

A remaining open question is whether the increased risk-taking of high-fWHR analysts is beneficial or detrimental to their employer and clients. While we find no significant relation between fWHR and accuracy, we acknowledge that this has limited value to market participants, as accuracy is measured only ex-post against realized earnings. Furthermore, an association between fWHR and

accuracy does not necessarily inform market participants with regards to analyst behavior. Rather, accuracy may be driven by a brokerage house that allocates resources based on masculinity. He et al. (2019), for example, find that high-fWHR analysts are more likely to conduct corporate site visits, consistent with other findings relating fWHR with access to better resources (Brunell et al. 2008).

Directions for future research include investigating other innate or personal analyst characteristics and their effects on decisions such as target price forecasting, investment recommendations profitability, and investment banking business for employers.

Appendix A: Example of fWHR measurement

fWHR, the facial width-to-height ratio, is the distance between the left and right zygion (bizygomatic width) divided by the distance between the upper lip and top of the eyelid (height) (Carré et al. 2009).

In the example shown, we find the fWHR of the United States' 44th President Barack Obama to be 1.95. Using the Obama image, the fWHR is equal to the distance between lines 1 and 2 (the bizygomatic width) divided by the distance between lines 3 and 4 (the facial height).

To do this on the Image J software, we first built a box around the analyst's face with lines 1–4. Line 1 is at the inner edge of the left earlobe and is the left-most point of the face (as looked at from the front). Line 2 is the right-most point, which is at the inner edge of the right earlobe. Line 3 is the highest point of the face, which is at the top of the eyelids, whereas Line 4 is the lowest part of the face and is at the top of the lip.

The width of the face is the horizontal dotted line in the example below and is the distance between lines 1 and 2. The height of the face, shown as the vertical dotted line, is the distance between lines 3 and 4. Dividing the length of the horizontal dotted line by the length of the vertical dotted line calculates the fWHR.

Appendix B: Variable Definitions

Variable Name	Source	Definition
<i>Star</i>	StarMine	A binary variable indicating whether an analyst is ranked in the top 3 places in the Top Stock Picker rankings in any of the calendar years 2010–2015.
<i>ACoverage</i>	I/B/E/S	Number of analysts issuing forecasts for firm j in period t .
<i>FcastErr</i>	I/B/E/S	The absolute deviation of the analyst's forecast from the actual earnings of the firm, scaled by actual earnings.
<i>FcastErr (Signed)</i>	I/B/E/S	The deviation of the analyst's forecast from the actual earnings of the firm, scaled by actual earnings.
<i>Boldness</i>	I/B/E/S	Calculated as the absolute deviation of analyst i 's EPS forecast for firm j for period t , from the median consensus EPS forecast for firm j for period $t-1$,

		scaled by stock price
<i>Strong Buy/Sell</i>	I/B/E/S	A dichotomous variable assigned a value of 1 for strong buy or strong sell, 0 otherwise.
<i>Strong Sell</i>	I/B/E/S	A dichotomous variable assigned a value of 1 for strong sell, 0 otherwise.
<i>Strong Buy</i>	I/B/E/S	A dichotomous variable assigned a value of 1 for strong buy, 0 otherwise.
<i>Bias</i>	I/B/E/S	The deviation of the analyst's forecast from the median consensus forecast for that firm's earnings, scaled by stock price.
<i>BSize</i>	I/B/E/S	Brokerage house size as measured by the number of analysts from a brokerage house issuing a forecast for a firm in the previous financial year.
<i>dfWHR</i>	Hand Collected	A dichotomous variable assigned a value of 1 if analyst <i>i</i> 's fWHR is greater than the median fWHR, and 0 otherwise.
<i>EV</i>	Compustat	Earnings volatility is measured as the standard deviation of firm <i>j</i> 's annual net income for years 2010–2014, divided by the mean annual net income for firm <i>j</i> for the period 2010–2014.
<i>FcastFreq</i>	I/B/E/S	Forecast frequency. Number of forecasts including revisions the analyst <i>i</i> released for firm <i>j</i> in the previous financial year.
<i>FCovered</i>	I/B/E/S	Firms the analyst covers measured as the number of firms analyst <i>i</i> releases forecasts for in the previous financial year.
<i>FirmExp</i>	I/B/E/S	Analyst experience covering firm <i>j</i> calculated as the number of years that analyst <i>i</i> has issued forecasts for firm <i>j</i> .
<i>FSize</i>	Compustat	Firm size measured as the natural log of firm <i>j</i> 's total assets from the annual report in the previous financial year.
<i>fWHR</i>	Hand Collected	Facial width-to-height ratio as

		calculated by the bizygomatic width (facial width) divided by facial height (between upper lip and top of eyelids) of analyst <i>i</i> . Refer to Appendix A for a worked example.
<i>GenExp</i>	I/B/E/S	General experience of the analyst. Number of years that analyst <i>i</i> has issued forecasts for any firm by the end of the previous financial year.
<i>GrowthSales</i>	Compustat	Compound annual growth rate of firm <i>j</i> 's sales between 2010–2014.
<i>Horizon</i>	I/B/E/S	Months between analyst <i>i</i> releasing forecast for firm <i>j</i> to firm the releasing of firm <i>j</i> 's earnings for period <i>t</i> .
<i>MTB</i>	CRSP & Compustat	Firm <i>j</i> 's market-to-book ratio measured as the market capitalization of firm <i>j</i> in January of each year, divided by the most recent total equity value.
<i>Return</i>	CRSP	The percentage change in market capitalization for firm <i>j</i> between January and the following January.
<i>Volume</i>	CRSP	The monthly trading volume of firm <i>j</i> in January divided by the number of shares outstanding.
<i>VolDisc</i>	I/B/E/S	The level of voluntary disclosure measured as the total number of management forecasts firm <i>j</i> released in the previous financial year.

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Table 1: Descriptive Statistics for Heckman and Coverage Choice Samples

Panel A: Descriptive statistics for Heckman model

	N	mean	p25	p50	p75	sd
<i>Star</i>	254,065	0.187	0.000	0.000	0.000	0.390
<i>FSize</i>	254,065	8.421	7.182	8.404	9.656	1.926
<i>ACoverage</i>	254,065	19.233	10.000	18.000	27.000	11.616
<i>VolDisc</i>	254,065	4.061	0.000	4.000	6.000	3.489
<i>Volume</i>	254,065	225.312	100.200	155.423	245.492	651.751
<i>GrowthSales</i>	254,065	0.069	0.002	0.048	0.111	0.162
<i>MTB</i>	254,065	3.257	1.321	2.215	3.761	39.768
<i>Return</i>	254,065	0.223	-0.084	0.116	0.357	0.904
<i>GenExp</i>	254,065	12.664	4.000	10.000	21.000	9.818
<i>BSize</i>	254,065	65.705	19.000	48.000	99.000	56.659
<i>FCovered</i>	254,065	18.160	12.000	17.000	23.000	10.987

Panel B: Descriptive statistics for coverage model

	N	mean	p25	p50	p75	sd
<i>fWHR</i>	26,818	2.054	1.931	2.034	2.156	0.171
<i>dfWHR</i>	26,818	0.489	0.000	0.000	1.000	0.500
<i>Mills</i>	26,818	0.643	0.600	0.649	0.692	0.065
<i>EV</i>	26,818	1.597	0.213	0.411	1.056	4.414
<i>FSize</i>	26,818	8.460	7.282	8.425	9.597	1.784
<i>ACoverage</i>	26,818	19.106	10.000	18.000	26.000	10.898

<i>VolDisc</i>	26,818	4.532	2.000	4.000	6.000	3.428
<i>Volume</i>	26,818	201.872	101.571	149.771	227.085	330.336
<i>GrowthSales</i>	26,818	0.056	0.002	0.043	0.096	0.123
<i>MTB</i>	26,818	3.509	1.474	2.431	4.154	44.313
<i>Return</i>	26,818	0.176	-0.076	0.107	0.313	0.788
<i>GenExp</i>	26,818	15.734	8.000	14.000	25.000	9.543
<i>BSize</i>	26,818	69.068	21.000	49.000	103.000	59.957

Panel C: Univariate statistics for coverage model

	<i>dfWHR</i> =0	<i>N</i> 1	<i>dfWHR</i> =1	<i>N</i> 2	<i>t-stat</i>	<i>p-value</i>
<i>fWHR</i>	1.924	13,705	2.189	13,113	-201.516	0.000
<i>EV</i>	1.557	13,705	1.640	13,113	-1.529	0.126
<i>FSize</i>	8.425	13,705	8.496	13,113	-3.273	0.001
<i>ACoverage</i>	19.169	13,705	19.041	13,113	0.963	0.336
<i>VolDisc</i>	4.608	13,705	4.452	13,113	3.723	0.000
<i>Volume</i>	214.430	13,705	188.746	13,113	6.369	0.000
<i>GrowthSales</i>	0.056	13,705	0.056	13,113	-0.416	0.677
<i>MTB</i>	3.335	13,705	3.690	13,113	-0.654	0.513
<i>Return</i>	0.169	13,705	0.183	13,113	-1.383	0.167
<i>GenExp</i>	15.868	13,705	15.594	13,113	2.357	0.018
<i>BSize</i>	73.375	13,705	64.571	13,113	12.052	0.000

The table presents descriptive statistics and univariate results for the models used in Table 4. Panel A presents the descriptive statistics for the Heckman model. Panel B presents the descriptive statistics for the coverage choice model. Panel C reports univariate tests results for differences between the high- and low-*fWHR* star analysts. The variables *Star*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, *GrowthSales*, *MTB*, *Return*, *GenExp*, *BSize*, *FCovered*, *fWHR*, *dfWHR*, *mills*, and *EV* stand for star analyst, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, sales growth rate, market to book ratio, change in market capitalization, analyst experience, brokerage house size, number of firms covered by an analyst, Facial width-to-height ratio, a dummy for high *fWHR*, inverse *mills* ratio (from first step), and earnings volatility, respectively. See Appendix B for variable definitions.

Table 2: Two-stage Regression of Firms' Earnings Volatility by fWHR

	(1)	(2)
	First stage - <i>Star</i>	Second stage - <i>EV</i>
<i>dfWHR</i>		0.138*
		(1.809)
<i>mills</i>		-2.132
		(-1.534)
<i>FSize</i>	0.007***	-0.115***
	(3.028)	(-3.769)
<i>ACoverage</i>	-0.002***	-0.020***
	(-5.591)	(-4.089)
<i>VolDisc</i>	0.017***	0.007
	(17.084)	(0.624)
<i>Volume</i>	0.000**	0.000**
	(2.533)	(2.169)
<i>GrowthSales</i>	-0.129***	-1.299**
	(-6.121)	(-2.120)
<i>MTB</i>	-0.000	-0.001**
	(-0.843)	(-2.134)
<i>Return</i>	-0.000	0.079
	(-0.061)	(1.616)
<i>GenExp</i>	0.017***	-0.011*
	(52.621)	(-1.764)
<i>BSize</i>	0.000***	-0.000
	(5.697)	(-0.285)
<i>FCovered</i>	0.014***	
	(53.700)	
Constant	-1.393***	4.051***
	(-17.240)	(3.691)
Year dummies	Y	Y
Industry dummies	Y	Y
<i>N</i>	254,065	26,818
Pseudo R ²	0.077	
Adj. R ²		0.048

This table reports results of the association of fWHR on the coverage choice of the earnings volatility of firms. Column 1 presents the results of the first-stage Heckman selection model with the dependent variable being an indicator equals 1 being a star analyst and 0 otherwise (*Star*). Column 2 reports results for the second stage with the dependent variable being earnings volatility (*EV*). The main variable of interest is *dfWHR*; a dichotomous variable equal to 1 if the analyst's fWHR is above the sample median or 0 otherwise. For each variable, a coefficient is reported, with the corresponding *t*-stat reported in parentheses. The dependent variables *FSize*, *ACoverage*, *VolDisc*, *Volume*, *GrowthSales*, *MTB*, *Return*, *GenExp*, *BSize*,

FCovered, and *mills* stand for firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, sales growth rate, market to book ratio, change in market capitalization, analyst experience, brokerage house size, number of firms covered by an analyst, and inverse mills ratio (from first step), respectively. See Appendix B for variable definitions. Standard errors are clustered at the analyst-level. *, **, *** denote differences that are significant at the 0.10, 0.05 and 0.01 level, respectively. A full list of variable definitions is provided in Appendix B.

Table 3: Descriptive Statistics for Forecast Boldness and Accuracy Samples

Panel A: Descriptive statistics for Heckman model

	<i>N</i>	mean	p25	p50	p75	sd
<i>Star</i>	225,741	0.186	0.000	0.000	0.000	0.389
<i>BSize</i>	225,741	66.023	19.000	48.000	100.000	57.080
<i>GenExp</i>	225,741	12.491	4.000	10.000	21.000	9.751
<i>ACoverage</i>	225,741	19.660	10.000	18.000	27.000	11.717
<i>FirmExp</i>	225,741	4.253	1.000	3.000	6.000	4.516
<i>FcastFreq</i>	225,741	4.446	2.000	4.000	6.000	3.088
<i>Horizon</i>	225,741	3.608	1.433	3.233	3.933	2.924
<i>FSize</i>	225,741	8.413	7.181	8.400	9.647	1.926
<i>GrowthSales</i>	225,741	0.070	0.004	0.049	0.112	0.159
<i>Volume</i>	225,741	227.706	99.316	154.960	246.194	688.107
<i>VolDisc</i>	225,741	4.088	0.000	4.000	6.000	3.532
<i>FCovered</i>	225,741	18.265	12.000	17.000	23.000	10.991

Panel B: Descriptive statistics

	<i>N</i>	mean	p25	p50	p75	sd
<i>fWHR</i>	20,128	2.054	1.930	2.034	2.156	0.171
<i>dfWHR</i>	20,128	0.489	0.000	0.000	1.000	0.500
<i>Boldness</i>	20,128	6.992	0.000	0.001	0.004	360.293
<i>FcastErr</i>	20,079	0.040	0.005	0.017	0.048	1.477
<i>FcastErr (Signed)</i>	20,079	1.821	-0.002	0.000	0.001	198.530
<i>Bias</i>	20,128	4.070	-0.002	0.000	0.001	360.338

<i>BSize</i>	20,128	68.799	21.000	49.000	103.000	60.096
<i>FcastFreq</i>	20,128	4.615	3.000	4.000	6.000	2.429
<i>Horizon</i>	20,128	3.112	1.533	3.200	3.700	2.096
<i>FirmExp</i>	20,128	5.456	2.000	4.000	8.000	5.066
<i>GenExp</i>	20,128	15.272	7.000	13.000	24.000	9.378
<i>FSize</i>	20,128	8.437	7.217	8.373	9.611	1.801
<i>ACoverage</i>	20,128	19.975	11.000	19.000	27.000	11.076
<i>VolDisc</i>	20,128	4.670	2.000	4.000	7.000	3.485
<i>Volume</i>	20,128	205.331	104.161	152.819	231.866	249.009
<i>GrowthSales</i>	20,128	0.057	0.004	0.043	0.096	0.130

Panel C: Univariate analysis

	<i>dfWHR</i> =0	<i>N</i> 1	<i>dfWHR</i> =1	<i>N</i> 2	<i>t-stat</i>	<i>p-value</i>
<i>fWHR</i>	1.925	10,286	2.190	9,842	-173.243	0.000
<i>Boldness</i>	2.925	10,286	11.242	9,842	-1.637	0.102
<i>FcastErr</i>	0.029	10,264	0.051	9,815	-1.023	0.306
<i>FcastErr (Signed)</i>	3.225	10,264	0.352	9,815	1.025	0.305
<i>Bias</i>	1.133	10,286	7.140	9,842	-1.182	0.237
<i>BSize</i>	73.263	10,286	64.132	9,842	10.806	0.000
<i>FcastFreq</i>	4.627	10,286	4.603	9,842	0.708	0.479
<i>Horizon</i>	3.113	10,286	3.110	9,842	0.086	0.931
<i>FirmExp</i>	5.433	10,286	5.479	9,842	-0.642	0.521
<i>GenExp</i>	15.248	10,286	15.296	9,842	-0.367	0.713
<i>FSize</i>	8.407	10,286	8.469	9,842	-2.417	0.016
<i>ACoverage</i>	20.030	10,286	19.917	9,842	0.724	0.469
<i>VolDisc</i>	4.767	10,286	4.567	9,842	4.071	0.000
<i>Volume</i>	214.540	10,286	195.706	9,842	5.368	0.000

<i>GrowthSales</i>	0.058	10,286	0.056	9,842	1.137	0.256
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The table presents descriptive statistics and univariate results for the models used in Table 4. Panel A presents the descriptive statistics for the Heckman selection model. Panel B reports univariate tests results for differences between high and low fWHR star analysts. The variables *Star*, *fWHR*, *dfWHR*, *Boldness*, *FcastErr*, *FcastErr (Signed)*, *Bias*, *BSize*, *FcastFreq*, *Horizon*, *FirmExp*, *GenExp*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, *GrowthSales*, and *FCovered* stand for star analyst, facial width-to-height ratio, a dummy for high fWHR, boldness, absolute forecasts error, signed forecast error, bias, brokerage house size, forecast frequency, time between forecast and release of earnings, analyst experience covering a firm, analyst experience, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, sales growth rate, and number of firms covered by an analyst, respectively. See Appendix B for variable definitions.

Table 4: Regression of Forecast Boldness Model

	(1)	(2)	(3)	(4)
	First Stage - <i>Star</i>	All star analyst	Former/future star analyst	Reigning star analyst
<i>dfWHR</i>		10.374*	12.081**	-0.769
		(1.928)	(2.026)	(-0.734)
<i>mills</i>		-128.050	-153.563	4.954
		(-1.204)	(-1.227)	(0.444)
<i>BSize</i>	0.000***	0.005	0.010	-0.009
	(4.412)	(0.135)	(0.232)	(-1.307)
<i>FcastFreq</i>	0.000	-0.569	-0.832	0.822
	(0.258)	(-0.691)	(-0.830)	(1.041)
<i>Horizon</i>	-0.020***	3.211**	3.968**	0.178
	(-15.415)	(2.066)	(2.142)	(0.909)
<i>FirmExp</i>	0.010***	-1.498*	-1.864*	-0.081
	(13.324)	(-1.809)	(-1.804)	(-1.387)
<i>GenExp</i>	0.014***	-0.063	-0.129	0.095
	(36.768)	(-0.134)	(-0.236)	(0.926)
<i>FSize</i>	0.002	10.194**	12.071**	1.095
	(0.875)	(2.446)	(2.417)	(1.357)
<i>ACoverage</i>	-0.002***	-1.656**	-2.003**	-0.109
	(-5.653)	(-2.159)	(-2.157)	(-1.393)
<i>VolDisc</i>	0.016***	1.286	1.679	-0.234
	(15.422)	(1.232)	(1.307)	(-1.456)
<i>Volume</i>	0.000***	0.081**	0.108**	0.002
	(2.876)	(2.015)	(2.068)	(1.155)
<i>GrowthSales</i>	-0.115***	-25.495	-28.758	2.308
	(-5.024)	(-1.152)	(-1.096)	(1.067)
<i>FCovered</i>	0.014***			
	(51.351)			
<i>Constant</i>	-1.282***	-10.194	-12.452	-14.976
	(-14.825)	(-0.152)	(-0.156)	(-0.908)
Year dummies	Y	Y	Y	Y

Industry dummies	Y	Y	Y	Y
Pseudo / Adj. R ²	0.079	0.013	0.015	0.031
N	225,741	20,128	16,634	3,494

This table reports results of the association of *fWHR* on forecast boldness. Column 1 presents the results of the first stage Heckman selection model with the dependent variable being an indicator equals 1 being a star analyst and 0 otherwise. Columns (2)–(4) report results for the second stage with the dependent variable being *Boldness* for the full star analysts sample, the former/future star analysts subsample, and the reigning star analysts subsample, respectively. *Boldness* is the absolute deviation of the analyst's forecast from the median consensus forecast for that firm's earnings, scaled by stock price. The main variable of interest is *dfWHR*; a dichotomous variable equal to 1 if the analyst's *fWHR* is above the sample median, or 0 otherwise. *Mills* is the inverse mills ratio (from first step). The dependent variables *BSize*, *FcastFreq*, *Horizon*, *FirmExp*, *GenExp*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, *GrowthSales*, and *FCovered* stand for brokerage house size, forecast frequency, time between forecast and release of earnings, analyst experience covering a firm, analyst experience, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, sales growth rate, and number of firms covered by an analyst, respectively. See Appendix B for variable definitions. For each variable, a coefficient is reported, with the corresponding *t*-stat reported in parentheses. Standard errors are clustered at the analyst-level. *, **, *** denote differences that are significant at the 0.10, 0.05 and 0.01 level, respectively.

Table 5: Regression of Forecast Bias Model

	(1)	(2)	(3)
	All star analyst	Former/future star analyst	Reigning star analyst
<i>dfWHR</i>	6.380	7.112	0.689
	(1.296)	(1.301)	(0.691)
<i>mills</i>	-104.710	-124.058	-5.163
	(-1.174)	(-1.186)	(-0.469)
<i>BSize</i>	0.039	0.049	0.009
	(1.135)	(1.133)	(1.298)
<i>FcastFreq</i>	-0.663	-0.615	-0.812
	(-0.974)	(-0.751)	(-1.047)
<i>Horizon</i>	2.196	2.758	-0.191
	(1.337)	(1.394)	(-0.919)
<i>FirmExp</i>	-1.406*	-1.779*	0.076

	(-1.687)	(-1.706)	(1.421)
<i>GenExp</i>	0.083	0.091	-0.088
	(0.201)	(0.190)	(-0.902)
<i>FSize</i>	5.515	6.763	-1.012
	(1.378)	(1.398)	(-1.338)
<i>ACoverage</i>	-1.047	-1.279	0.096
	(-1.370)	(-1.372)	(1.301)
<i>VolDisc</i>	1.729	2.126	0.217
	(1.491)	(1.479)	(1.466)
<i>Volume</i>	0.036	0.048	-0.001
	(0.958)	(0.961)	(-0.514)
<i>GrowthSales</i>	-36.585	-41.717	-2.675
	(-1.561)	(-1.507)	(-1.139)
<i>Constant</i>	8.784	7.921	14.525
	(0.155)	(0.117)	(0.908)
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Adj. R ²	0.002	0.002	0.005
<i>N</i>	20,128	16,634	3,494

This table reports results of the association of *fWHR* on forecast bias. Columns (1)-(3) report results for the second stage with the dependent variable being *Bias* for the full star analysts sample, the former/future star analysts subsample, and the reigning star analysts subsample, respectively. *Bias* is the deviation of the analyst's forecast from the median consensus forecast for that firm's earnings, scaled by stock price. The main variable of interest is *dfWHR*; a dichotomous variable equal to 1 if the analyst's *fWHR* is above the sample median, or 0 otherwise. *Mills* is the inverse mills ratio (from first step). The dependent variables *BSize*, *FcastFreq*, *Horizon*, *FirmExp*, *GenExp*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, and *GrowthSales* stand for brokerage house size, forecast frequency, time between forecast and release of earnings, analyst experience covering a firm, analyst experience, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, and sales growth rate, respectively. See Appendix B for variable

definitions. For each variable, a coefficient is reported, with the corresponding *t*-stat reported in parentheses. Standard errors are clustered at the analyst-level. *, **, *** denote differences that are significant at the 0.10, 0.05 and 0.01 level, respectively.

Table 6: Descriptive Statistics for Recommendation Sample

Panel A: Descriptive statistics for Heckman model

	<i>N</i>	mean	p25	p50	p75	sd
<i>Star</i>	66,455	0.170	0.000	0.000	0.000	0.375
<i>BSize</i>	66,455	32.579	12.000	23.000	43.000	28.896
<i>GenExp</i>	66,455	12.062	4.000	9.000	20.000	9.861
<i>ACoverage</i>	66,455	9.474	5.000	8.000	13.000	6.109
<i>FirmExp</i>	66,455	3.578	0.000	2.000	5.000	4.461
<i>FcastFreq</i>	66,455	1.312	1.000	1.000	1.000	0.651
<i>FSize</i>	66,455	8.177	6.923	8.144	9.423	1.940
<i>GrowthSales</i>	66,455	0.072	0.003	0.052	0.119	0.167
<i>Volume</i>	66,455	240.049	104.895	164.367	265.413	553.204
<i>VolDisc</i>	66,455	4.026	0.000	4.000	6.000	3.498
<i>FCovered</i>	66,455	10.886	6.000	9.000	14.000	7.374

Panel B: Descriptive statistics for recommendation sample

	<i>N</i>	mean	p25	p50	p75	sd
<i>dfWHR</i>	7,413	0.478	0.000	0.000	1.000	0.500
<i>fWHR</i>	7,413	2.059	1.931	2.032	2.158	0.176
<i>Strong Buy/Sell</i>	7,413	0.229	0.000	0.000	0.000	0.421
<i>Strong Buy</i>	7,413	0.210	0.000	0.000	0.000	0.407
<i>Strong Sell</i>	7,413	0.020	0.000	0.000	0.000	0.139
<i>BSize</i>	7,413	34.225	14.000	25.000	43.000	28.519
<i>FcastFreq</i>	7,413	1.267	1.000	1.000	1.000	0.585
<i>FirmExp</i>	7,413	4.473	1.000	3.000	7.000	4.861
<i>GenExp</i>	7,413	14.769	6.000	12.000	24.000	9.772

<i>FSize</i>	7,413	8.124	6.823	8.036	9.268	1.868
<i>ACoverage</i>	7,413	8.938	4.000	8.000	12.000	5.743
<i>VolDisc</i>	7,413	4.242	1.000	4.000	6.000	3.367
<i>Volume</i>	7,413	223.217	106.266	162.661	250.940	397.106
<i>GrowthSales</i>	7,413	0.062	0.002	0.049	0.110	0.138

Panel C: Univariate statistics

	<i>dfWHR</i> =0	<i>N</i> 1	<i>dfWHR</i> =1	<i>N</i> 2	<i>t-stat</i>	<i>p-value</i>
<i>fWHR</i>	1.931	3872	2.199	3,541	-101.431	0.000
<i>Strong Buy/Sell</i>	0.203	3872	0.259	3,541	-5.734	0.000
<i>Strong Buy</i>	0.180	3872	0.242	3,541	-6.570	0.000
<i>Strong Sell</i>	0.023	3872	0.017	3,541	1.871	0.061
<i>BSize</i>	36.696	3872	31.524	3,541	7.831	0.000
<i>FcastFreq</i>	1.276	3872	1.258	3,541	1.343	0.179
<i>FirmExp</i>	4.620	3872	4.313	3,541	2.719	0.007
<i>GenExp</i>	15.342	3872	14.131	3,541	5.287	0.000
<i>FSize</i>	8.055	3872	8.200	3,541	-3.364	0.001
<i>ACoverage</i>	9.180	3872	8.674	3,541	3.796	0.000
<i>VolDisc</i>	4.279	3872	4.200	3,541	1.005	0.315
<i>Volume</i>	245.502	3872	198.848	3,541	5.061	0.000
<i>GrowthSales</i>	0.064	3872	0.061	3,541	0.879	0.379

The table presents descriptive statistics and univariate results for the models used in Table 7. Panel A presents the descriptive statistics for the Heckman selection model. Panel B reports descriptive statistics for the recommendation sample. Panel C reports univariate tests results for differences between high- and low-*fWHR* star analysts. The variables *Star*, *fWHR*, *dfWHR*, *Strong Buy/Sell*, *Strong Sell*, *Strong Buy*, *BSize*, *FcastFreq*, *FirmExp*, *GenExp*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, *GrowthSales*, and *FCovered* stand for star analyst, facial width-to-height ratio, a dummy for high *fWHR*, boldness, absolute forecasts error, signed forecast error, bias, brokerage house size, forecast frequency, analyst experience covering a firm, analyst experience, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, sales growth rate, and number of firms covered by an analyst, respectively. See Appendix B for variable definitions.

Table 7: Regression of Bold Stock Recommendations Model

Panel A: Full sample

	(1)	(2)	(3)	(4)
	First stage - <i>Star</i>	Second stage - <i>Strong Buy/Sell</i>	Second stage - <i>Strong Buy</i>	Second stage - <i>Strong Sell</i>
<i>dfWHR</i>		0.054 [*]	0.054 [*]	0.001
		(1.740)	(1.837)	(0.133)
<i>mills</i>		-1.259	-1.048	-0.211
		(-0.931)	(-0.850)	(-0.478)
<i>BSize</i>	0.001 ^{***}	-0.001 [*]	-0.001	-0.000 ^{***}
	(2.750)	(-1.967)	(-1.365)	(-3.057)
<i>FcastFreq</i>	-0.056 ^{***}	-0.014	-0.024 [*]	0.010 [*]
	(-5.672)	(-0.912)	(-1.744)	(1.732)
<i>FirmExp</i>	0.012 ^{***}	-0.004	-0.004	0.001
	(8.541)	(-1.160)	(-1.413)	(0.492)
<i>GenExp</i>	0.015 ^{***}	-0.002	-0.001	-0.001
	(22.912)	(-0.597)	(-0.399)	(-0.759)
<i>FSize</i>	-0.021 ^{***}	0.009	0.010	-0.001
	(-4.867)	(1.397)	(1.609)	(-0.613)
<i>ACoverage</i>	-0.006 ^{***}	-0.000	-0.002	0.002 ^{**}
	(-4.606)	(-0.127)	(-0.972)	(2.497)
<i>VolDisc</i>	0.014 ^{***}	-0.005	-0.004	-0.002
	(6.929)	(-1.524)	(-1.198)	(-1.256)
<i>Volume</i>	0.000	-0.000 ^{**}	-0.000 ^{***}	0.000
	(1.439)	(-2.364)	(-2.971)	(0.397)
<i>GrowthSales</i>	-0.111 ^{***}	0.067	0.047	0.020

	(-2.783)	(1.197)	(0.901)	(1.261)
<i>FCovered</i>	0.002 ^{**}			
	(2.155)			
<i>Constant</i>	-0.668 ^{***}	1.000	0.856	0.145
	(-4.357)	(1.133)	(1.062)	(0.505)
Year dummies	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y
Pseudo / Adj. R ²	0.061	0.059	0.057	0.044
<i>N</i>	66,455	7,413	7,413	7,413

Panel B: Former/Future stars vs. reigning stars

	(1)	(2)	(3)	(4)	(5)	(6)
	Strong Buy/Sell		Strong Buy		Strong Sell	
	Former/future	Reigning	Former/future	Reigning	Former/future	Reigning
<i>dfWHR</i>	0.042	0.144 ^{***}	0.043	0.129 ^{***}	-0.001	0.015
	(1.318)	(3.268)	(1.449)	(3.019)	(-0.171)	(1.532)
<i>mills</i>	-1.117	-1.971	-0.988	-0.185	-0.129	-1.786
	(-0.806)	(-0.746)	(-0.785)	(-0.079)	(-0.263)	(-1.548)
<i>BSize</i>	-0.001 [*]	-0.001	-0.001	-0.001	-0.000 ^{**}	-0.001 ^{**}
	(-1.804)	(-1.648)	(-1.305)	(-0.778)	(-2.565)	(-2.242)
<i>FcastFreq</i>	-0.014	-0.005	-0.022	-0.037	0.008	0.032 [*]
	(-0.962)	(-0.133)	(-1.584)	(-1.131)	(1.258)	(1.698)
<i>FirmExp</i>	-0.003	-0.010	-0.003	-0.009	0.000	-0.001
	(-0.797)	(-1.449)	(-0.890)	(-1.464)	(0.092)	(-0.320)
<i>GenExp</i>	-0.002	-0.000	-0.002	0.004	-0.001	-0.005
	(-0.643)	(-0.057)	(-0.529)	(0.702)	(-0.484)	(-1.459)
<i>FSize</i>	0.006	0.028 ^{**}	0.007	0.029 ^{**}	-0.001	-0.001

	(0.912)	(2.132)	(1.073)	(2.280)	(-0.423)	(-0.297)
<i>ACoverage</i>	0.000	-0.002	-0.001	-0.007*	0.001*	0.005*
	(0.077)	(-0.465)	(-0.569)	(-1.690)	(1.915)	(1.850)
<i>VolDisc</i>	-0.006	-0.002	-0.005	0.003	-0.001	-0.005*
	(-1.611)	(-0.220)	(-1.389)	(0.408)	(-0.952)	(-1.909)
<i>Volume</i>	-0.000**	0.000	-0.000***	0.000	0.000	-0.000
	(-2.515)	(0.259)	(-2.914)	(0.385)	(0.517)	(-0.037)
<i>GrowthSales</i>	0.041	0.261*	0.023	0.169	0.018	0.092*
	(0.729)	(1.785)	(0.430)	(1.275)	(1.020)	(1.888)
<i>Constant</i>	0.958	1.118	0.864	-0.072	0.094	1.190
	(1.053)	(0.665)	(1.043)	(-0.049)	(0.295)	(1.630)
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
<i>N</i>	6,272	1,141	6,272	1,141	6,272	1,141
Adj. R ²	0.049	0.088	0.046	0.092	0.027	0.115

This table reports results of the association of *fWHR* on boldness recommendation. Panel A, Column 1 presents the results of the first stage Heckman selection model with the dependent variable being an indicator equals 1 being a star analyst and 0 otherwise. Columns (2)–(4) report results for the second stage with the dependent variable being *Strong Buy/Sell*, *Strong Buy* and *Strong Sell* for the full star analysts sample, respectively. In panel B, Columns (1), (3) and (5) report results for the former/future star analysts subsample, Columns (2), (4) and (6) report results for the reigning star analysts subsample. The main variable of interest is *dfWHR*; a dichotomous variable equal to 1 if the analyst's *fWHR* is above the sample median, or 0 otherwise. *Mills* is the inverse mills ratio (from first step). The dependent variables *BSize*, *FcastFreq*, *FirmExp*, *GenExp*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, *GrowthSales*, and *FCovered* stand for brokerage house size, forecast frequency, analyst experience covering a firm, analyst experience, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, sales growth rate, and number of firms covered by an analyst, respectively. See Appendix B for variable definitions. For each variable, a coefficient is reported, with the corresponding *t*-stat reported in parentheses. Standard errors are clustered at the analyst-level. *, **, *** denote differences that are significant at the 0.10, 0.05 and 0.01 level, respectively.

Table 8: Regression of Forecast Error Model

Panel A: Absolute forecast error

	(1)	(2)	(3)
	All star analyst	Former/future star analyst	Reigning star analyst
<i>dfWHR</i>	0.008	0.019	-0.054
	(0.340)	(0.681)	(-1.273)
<i>mills</i>	0.416	0.721	-1.331
	(0.730)	(1.142)	(-0.626)
<i>BSize</i>	-0.000	-0.000	-0.000
	(-0.133)	(-0.393)	(-0.189)
<i>FcastFreq</i>	0.000	-0.002	0.015 ^{**}
	(0.004)	(-0.283)	(2.081)
<i>Horizon</i>	0.006	0.012	-0.011
	(0.771)	(1.433)	(-0.632)
<i>FirmExp</i>	0.001	-0.000	-0.000
	(0.357)	(-0.036)	(-0.011)
<i>GenExp</i>	0.001	0.002	-0.001
	(0.515)	(0.683)	(-0.135)
<i>FSize</i>	0.015	0.021	-0.019
	(1.027)	(1.230)	(-1.016)
<i>ACoverage</i>	-0.003 ^{**}	-0.003 [*]	0.001
	(-1.990)	(-1.853)	(0.161)
<i>VolDisc</i>	0.005	0.005	0.001
	(1.299)	(1.150)	(0.198)
<i>Volume</i>	-0.000 [*]	-0.000 [*]	-0.000
	(-1.944)	(-1.707)	(-0.748)
<i>GrowthSales</i>	0.176 ^{***}	0.149 ^{***}	0.188
	(2.621)	(2.955)	(0.908)
<i>Constant</i>	-0.404	-0.690	1.068
	(-0.838)	(-1.263)	(0.635)
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Adj. R ²	0.006	0.005	0.106
<i>N</i>	20,079	16,596	3,483

Panel B: Signed forecast error

	(1)	(2)	(3)
	All star analyst	Former/future star analyst	Reigning star analyst
<i>dfWHR</i>	-2.048	-2.332	-0.595
	(-0.997)	(-1.011)	(-1.320)
<i>mills</i>	644.139	629.435	-178.716
	(0.735)	(0.691)	(-0.413)
<i>BSize</i>	0.011	0.016	-0.002
	(0.791)	(0.882)	(-1.317)
<i>FcastFreq</i>	-0.323	-0.438	-0.025
	(-1.110)	(-1.127)	(-1.150)
<i>Horizon</i>	2.548	3.062	-0.082
	(1.117)	(1.132)	(-0.924)
<i>FirmExp</i>	-0.191	-0.249	-0.025
	(-1.296)	(-1.295)	(-1.275)
<i>GenExp</i>	0.172	0.203	0.050
	(1.112)	(1.107)	(1.463)
<i>FSize</i>	2.459	2.889	0.064
	(1.300)	(1.278)	(0.199)
<i>ACoverage</i>	-0.223	-0.269	-0.009
	(-1.068)	(-1.013)	(-0.203)
<i>VolDisc</i>	-0.289	-0.346	-0.030
	(-0.590)	(-0.591)	(-0.555)
<i>Volume</i>	0.006	0.008	0.000
	(0.366)	(0.363)	(0.198)
<i>GrowthSales</i>	4.385	6.650	-1.603
	(0.574)	(0.654)	(-1.130)
<i>Constant</i>	-463.271	-458.316	128.876
	(-0.769)	(-0.729)	(0.415)
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Adj. R ²	0.005	0.006	0.002
N	20,091	16,606	3,485

This table reports results of the association of *fWHR* on absolute forecast error and signed forecast error in panels A and B, respectively. In both panels Columns (1)–(3) report results for the second stage with the dependent variable being *FcastErr* for the full star analysts sample, the former/future star analysts subsample, and the reigning star analysts subsample, respectively. *FcastErr* is the absolute difference between the analyst's forecast and actual firm's earnings, normalized by stock price. The main variable of interest is *dfWHR*; a dichotomous variable equal to 1 if the analyst's *fWHR* is above the sample median, or 0 otherwise. *Mills* is the inverse mills ratio (from first step). The dependent variables *BSize*, *FcastFreq*, *Horizon*, *FirmExp*, *GenExp*, *FSize*, *ACoverage*, *VolDisc*, *Volume*, and *GrowthSales* stand for brokerage house size, forecast frequency, time between forecast and release of earnings, analyst experience covering a

firm, analyst experience, firm size, number analyst's forecasts for a firm, level of voluntary disclosure, monthly trading volume, and sales growth rate, respectively. See Appendix B for variable definitions. For each variable, a coefficient is reported, with the corresponding *t*-stat reported in parentheses. Standard errors are clustered at the analyst-level. *, **, *** denote differences that are significant at the 0.10, 0.05 and 0.01 level, respectively.

¹ Luo and Xie (2012) support their concerns that after controlling for commonly used forecast accuracy determinants such as general and firm experience, task complexity, analyst following, the forecast horizon and broker resources, much is still unknown about how analysts form their forecasts. Specifically, without analyst fixed effects, the explanatory power of their regression model is 12.17%, while including analyst fixed effect increases it to 26.11% (Luo and Xie 2012). Their findings suggest that despite efforts to identify analyst characteristics that affect forecasts, much is as yet unexplained and the black box is still very much opaque.

² In a more recent study, Brown et al. (2015) address the “Black-Box” problem using surveys and interviews with sell-side analysts. They focus on a broad range of factors affecting analysts’ decisions but do not cover innate characteristics that have been found to play an important role in individuals in financial markets.

³ For example, Yu (2008) finds that firms covered by more analysts have less discretionary accruals. Easley and O'hara (2004) find that firms with greater analyst coverage leads to greater abnormal returns and have a lower cost of capital, as investor uncertainty is decreased. Analyst coverage also affects external financing decisions since firms with lower analyst coverage have higher leverage, and issue equity less often, but in greater amounts (Chang et al. 2006).

⁴ Thomson Reuters produces the StarMine rankings of the top 3 analysts across 59 industries based on I/B/E/S data (Thomson Reuters 2015).

⁵ Chan et al. (2016) seem to have a similar flavor. They report that analysts with greater fWHR are more likely to issue a “lowball” forecast right before earnings announcements. The market reacts less to the forecast revisions they issue, particularly when the date of a forecast is close to the date of an earnings announcement.

⁶ Relatedly, Cao et al. (2019) find that attractive analysts attain better job performance through privileged access to information from firm management.

⁷ A recent stream of literature finds that innate characteristics of corporate managers affect their decision making. For example, Graham et al. (2013) use psychometric tests of CEOs to assess psychological traits and find that certain psychological traits are associated with certain behaviors. For instance, they find more optimistic CEOs rely more on short-term debt to finance the firm (Graham et al. 2013). Other research into personal characteristics on corporate outcomes finds CEOs and CFOs with a legal record are more likely to perpetrate fraud (Davidson et al. 2013). Dikolli et al. (2012) find that firms with CEOs of greater integrity, as measured linguistically from shareholder

letters, have greater earnings quality. CEOs that exhibit overconfidence are more likely to intentionally misreport financial statements (Schrand and Zechman 2012), as are CEOs with a greater fWHR (Jia et al. 2014). Likewise, it can be expected that innate traits of analysts affect their decision making.

⁸ In addition, extant psychology and neuroscience studies find that increased testosterone levels are associated with increased aggression (Carré and McCormick 2008), egocentrism (Wright et al. 2012), and desire to cheat (McIntyre et al. 2006).

⁹ fWHR is used by others to attribute expected behaviors related to testosterone such as aggression and risk taking. This is shown by Carré et al. (2009) who find that people use fWHR as a visual cue to predict behavior in others, and those with a high fWHR are expected to behave as if they had high levels of testosterone. Those with high fWHR may feel pressure to behave in ways that testosterone would otherwise lead them to even if fWHR is not associated with testosterone, resulting in a self-fulfilling prophecy (Haselhuhn et al. 2013). In other words, fWHR may be a reliable indicator of behavior even if fWHR is not affected by testosterone (Haselhuhn et al. 2013).

¹⁰ A related study by Harlow and Brown (1990) similarly argue that an individual's financial risk tolerance is related to certain biochemical and psychological influences. They examine this by testing a neuroregulating enzyme, platelet MAO, and find that biological traits are associated with financial risk tolerance.

¹¹ Two key tasks that an analyst undertakes include deciding which firms to cover and how bold to make their forecasts for these firms (Ramnath et al. 2008; Bradshaw 2011).

¹² For example, Kadous et al. (2009) design an experiment and find an asymmetric payoff function for analysts who issue bold forecasts. The authors postulate that bold forecasts have an asymmetric payoff function, in terms of perceived competence and trustworthiness, because a wrong bold forecast is punished more harshly than accurate bold forecasts are rewarded. This is because when a bold forecast turns out to be accurate, investors attribute the realization of earnings that the consensus did not anticipate to external factors. Because the issuance of inaccurate bold forecasts, relative to inaccurate herding forecasts, affects the perceived credibility of the analyst more—and bold forecasts have an asymmetric value function for analysts—Kadous et al. (2009) conclude that bold forecasts are risky for analysts.

¹³ In the literature, the use of star analysts is a common subset of analysts because they are a particularly important group. Recommendations by star analysts generate higher abnormal returns than other analysts (Fang and Yasuda 2014) and recommendation changes by star analysts result in greater turnover than changes by non-star analysts (Loh and Stulz 2011). Because of the increased returns and turnover, star analysts have a high profile (relatively to non-star analysts). They appear frequently in the media, increasing the likelihood of having a public photo. A potential downside of using star analysts as a sample is that fWHR has been found to have a lower impact on behavior for high, compared to low, status individuals (Goetz et al. 2013; Welker et al. 2015). Using star analysts, who are arguably of higher status than non-star analysts, would then bias against finding a significant association with fWHR. Another potential downside of using star analysts for the second hypothesis is

that they issue more bold forecasts (Stickel 1990), which biases against finding significant variation in boldness within this subgroup.

¹⁴ StarMine has two classes of star analysts, Top Earnings Estimators and Top Stock Pickers, which are based on earnings estimates and investment recommendations, respectively. To qualify for the Top Earnings Estimator award, the forecast must be different from other analysts' estimates. That is, the earnings estimate measure requires bold forecasts (Thomson Reuters 2015). Using star analysts from the Top Earnings Estimators would make testing the second research hypothesis unsuitable because by default, all forecasts will be bold, limiting the ability to assess whether fWHR helps determine forecast boldness.

¹⁵ Kucheev et al. (2015) identify two other main sources of analyst rankings: The Wall Street Journal's Best on the Street and Institutional Investor Magazine's All-America Research Team. The Wall Street Journal's Best on the Street is awarded every year to 5 analysts per industry in 44 industries. The ranking is based on analysts who have the highest cumulative one-day returns if an investor were to follow the analyst's recommendation on the day the recommendation change is released (Wall Street Journal 2012). This methodology may lead to higher ratings for analysts who coincidentally released their recommendation change on the same day after a significant price reaction has already occurred rather than analysts who are most skilled (Kucheev et al. 2015). The mean reversion for the Best on the Street star analysts, as their luck in timing their recommendations runs out, is supported by Emery and Li (2009). Accordingly, we chose not to use The Wall Street Journal's Best on the Street as the sample for star analysts. Institutional Investor's All-America Research Team is based on surveys sent to buy-side money managers who rate the sell-side analysts (Institutional Investor 2015). Based on the survey score, *Institutional Investor* places the first, second, and third highest ranked analyst per industry in the All-America first, second, and third teams, respectively. Emery and Li (2009) find that the forecast accuracy and recommendations of the All-America Research Team in the year following being ranked are not significantly different from non-star analysts. Further, they find that recognition (as measured by brokerage house size and past star status) is more important in getting rated a star than performance, and conclude that the All-American Research team is a "popularity contest" (Emery and Li 2009). Accordingly, we choose not to use this database as the sample of star analysts.

¹⁶ We focus on males rather than females because testosterone has a greater impact on the fWHR of men than women (Lefevre et al. 2013), making fWHR a better proxy for testosterone in men than women. fWHR has been found to be statistically different between different ethnicities (Kramer 2015), therefore we focus only on one ethnicity, Caucasian men, the majority in our sample. Categorization of race/ethnicity is defined by the government, following Kramer (2015). In the U.S., the census provides the following race/ethnicity categories: White, Black or African American, American Indian or Alaskan Native, Asian, and/or Native Hawaiian or Other Pacific Islander. Definitions can be found at: <https://www.census.gov/topics/population/race/about.html>. Caucasian for the purposes of this study is treated as White.

¹⁷ A neutral expression includes "fake" smiles (Jia et al. 2014).

¹⁸ A worked example of the measurement of fWHR is provided in Appendix A.

¹⁹ The Thomson Reuters Analyst Awards: Methodology: Qualification Criteria: (<http://www.analystawards.com/methodology.php>)

²⁰ As a robustness test, we measure fWHR as a continuous variable and our results are qualitatively unchanged for all model specifications.

²¹ As a robustness test, we measure fWHR as a continuous variable and our results are qualitatively unchanged for all model specifications.

²² We assess multicollinearity issues by examining variance inflationary factors (VIFs). For Model 2, the mean VIF is 1.13, and *ACoverage* has the highest VIF of 1.51. All VIFs reported are well below levels associated with multicollinearity, indicating that multicollinearity is not likely to be an issue.

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