NBER WORKING PAPER SERIES

CEO PERSONALITY AND FIRM POLICIES

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Working Paper 22435
http://www.nber.org/papers/w22435

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2016

We thank Geoff Smart, Randy Street and Alan Foster of ghSMART and Charles O'Reilly for providing the data on CEO personality. We thank discussants Christopher Parsons and Clifton Green, seminar participants at the Northwestern Law School Law and Economics Colloquium, Rice University, UC Irvine, UCLA, NBER Behavioral Finance Meeting, Wharton Business School, Miami Behavioral Finance Conference, Boston University, Duke University, INSEAD Accounting Symposium and brown bag participants at University of Chicago and Harvard Business School for helpful comments. We are grateful to Michelle Gutman, Maria Kamenetsky, Sarah Kervin, Mary Moon, Helen Park, Vincent Pham, Brian Tayan, and Robin Weiss for providing excellent research assistance. This research was funded in part by the Fama-Miller Center for Research in Finance at the University of Chicago Booth School of Business. Anastasia Zakolyukina thanks the Neubauer Family Foundation, Harry W. Kirchheimer Faculty Research Fund, IBM Corporation Faculty Research Fund and University of Chicago Booth School of Business for financial support. We acknowledge support of the University of Chicago Research Computing Center for this study. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 22435
July 2016
JEL No. D22,D23,G3,G34

ABSTRACT

Based on two samples of high quality personality data for chief executive officers (CEOs), we use linguistic features extracted from conferences calls and statistical learning techniques to develop a measure of CEO personality in terms of the Big Five traits: agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience. These personality measures have strong out-of-sample predictive performance and are stable over time. Our measures of the Big Five personality traits are associated with financing choices, investment choices and firm operating performance.

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I. Introduction

Recent research in economics and finance has started to explore the relations between individual traits of senior executives, the investment and financing choices made by these executives, and firm performance. Bertrand and Schoar (2003) use manager fixed effects to assess whether managerial "style" has an impact on various firm outcomes. While their results suggest a managerial "style" effect, they provide limited insight into the specific executive characteristics comprised by the fixed effects. Perhaps the most obvious characteristics are personality traits (Almlund et al., 2011). But, with the exception of Kaplan et al. (2012) and O'Reilly et al. (2014b), very little research examines how (or whether) differences in personality traits are associated with executive decision-making and firm performance. This gap in the literature is puzzling given the extensive literature on personality psychology (e.g., Goldberg, 1993) and the fact that personality is a predictor of work performance for different occupations, including (usually lower level) executives (e.g., Barrick, 2005, Judge et al., 2002).

A fundamental challenge for research into the effects of executive personality is the cost and difficulty of measuring personality. Measuring personality traits typically requires the administration of costly instruments or detailed interviews which are difficult to implement for large samples of top level executives. The purpose of this paper is to suggest an alternative approach. In this paper, we (i) develop and validate measures of CEO personality that can be obtained for a large sample of observations and (ii) examine the associations of these personality measures with investment choices, financing choices and firm performance.

Our approach to measuring personality is based on the so-called "Big Five" framework, which has attained a central place in psychological research (Goldberg, 1993) and identifies five broad personality traits: agreeableness, conscientiousness, extraversion (versus introversion), neuroticism (versus emotional stability), and openness to experience. Personality psychology views these personality traits as the "patterns of thoughts, feelings and behaviors that reflect the tendency to respond in certain ways in certain circumstances" (Roberts, 2009, p.140).

Rather than attempting to measure personality traits using questionnaires or interviews, we develop our measures using the linguistic features exhibited by CEOs during conference calls. That is, we develop models to score linguistic features that allow us to assess the degree to which each CEO is likely to be characterized along the Big Five dimensions of agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience. We develop this predictive scoring approach by statistically linking linguistic features of the CEOs during the question-and-answer (Q&A) portion of conference calls to their known personality traits from Kaplan et al. (2012) and Kaplan and Sorensen (2016). We validate our measures of CEO personality traits by showing that they exhibit substantial out-of-sample predictive ability using an independent sample obtained from O'Reilly et al. (2014b).

Our approach relies on research in psychology and linguistics (e.g., Pennebaker and King, 1999) that explores whether differences in the way language is used by individual executives reflects differences in personalities. This research finds that language is not only predictive of personality (e.g., Mairesse et al., 2007, Schwartz et al., 2013, Park et al., 2015), but that language-based personality scores are also stable over time (Park et al., 2015). Our findings are consistent with these studies. Using the O'Reilly et al. (2014b) sample of 28 CEOs, we find out-of-sample correlations between predicted and actual personality scores that range from 0.23 for agreeableness to 0.49 for neuroticism.[1] These out-of-sample correlations are similar to the out-of-sample correlations that range between 0.21 and 0.54 reported in prior studies linking personality to language in different contexts, such as student essays and random conversation snippets (Mairesse et al., 2007) and Facebook messages (e.g., Schwartz et al., 2013, Park et al., 2015).

Having validated these models, we apply them to 70,329 conference calls from StreetEvents, a product of ThomsonReuters, to estimate scores for Big Five personality traits for 4,591 individual CEOs and examine the associations between these estimated personality traits and investment choices, financing choices and performance for the CEOs' firms.[2] Openness is positively associated with R&D intensity and negatively with net leverage. Conscientiousness is negatively associated with growth. Extraversion is negatively associated with both contemporaneous and future return on assets and cash flows. Although our results are suggestive of possible sources of "manager effects," it is important to emphasize and caution that, like Bertrand and Schoar (2003), our paper is meant to be descriptive. We are not ascribing causality to our results.

Our study contributes to the recent literature that explores the relations between elements of "managerial style" in firm policies and performance. These studies have examined traits such

[1]Correlations for the other Big Five traits are 0.29 for openness to experience, 0.35 for extraversion, and 0.46 for conscientiousness.

[2]We exclude CEOs for which we have personality data from either Kaplan et al. (2012), Kaplan and Sorensen (2016) or O'Reilly et al. (2014b).

as overconfidence (e.g., Malmendier and Tate, 2005, Goel and Thakor, 2008, Gervais et al., 2011, Hirshleifer et al., 2012, Ben-David et al., 2013), optimism (e.g., Heaton, 2002, Hackbarth, 2009, Graham et al., 2013), risk-taking (e.g., Graham et al., 2013), and past experiences and credentials (e.g., Adams et al., 2005, Malmendier et al., 2011, Benmelech and Frydman, 2014, Falato et al., 2014). Similar to the recent work by Kaplan et al. (2012) and Green et al. (2016), we find that CEO personality is associated with organizational strategy choices and firm performance. Moreover, our linguistic measures can be easily employed in future research examining executive personality. This paper also complements Kaplan and Sorensen (2016) who use a larger sample of ghSMART assessments to study how CEO characteristics differ from those for other top executives.

The paper proceeds as follows. Section II describes prior research on personality, including research linking personality to decision-making and firm performance. Section III describes the data used in our study. Section IV describes how we develop and evaluate our measures of CEO personality. Section V studies the relationship between CEO personality and firm policies and performance. Section VI concludes.

II. Personality and firm outcomes

While the Big Five is the "most widely accepted taxonomy of personality traits" in personality psychology (Almlund et al., 2011, p.48), its use in research in economics and finance has been limited. Most of the few papers that have studied the economic consequences of personality using Big Five traits rely on either laboratory experiments (e.g., Borghans et al., 2009, Daly et al., 2009, Dohmen et al., 2010) or questionnaires (e.g., Sharpe et al., 2011). Research in economics and finance has instead focused primarily on psychological constructs such as ability, optimism, confidence, risk aversion, and time preference.

Nonetheless, there is an extensive literature in psychology examining the role of the Big Five personality traits in various decisions and dimensions of job performance. In the following discussion, we draw on this literature to describe each of the Big Five traits and to generate predictions regarding associations between the Big Five traits of CEOs and firm outcomes.

A. Agreeableness

Agreeableness is associated with tendencies to be trusting (Costa and McCrae, 1992), compliant (Hogan and Ones, 1997), to avoid conflict (Graziano et al., 1996), and to get along with others (Barrick et al., 2002). It is related to beliefs about the importance of working hard and thus positively associated with career success (e.g., Holland et al., 1993). However, Boudreau et al. (2001) suggest that agreeable individuals have a tendency to follow rather than lead. Agreeable leaders can also lack decision-effectiveness since they may easily yield to others' views (LePine and Van Dyne, 2001, Judge et al., 2009) and even be passive (Nadkarni and Herrmann, 2010). Indeed, in business settings, some find that agreeableness is not associated with leadership effectiveness (Judge et al., 2002). Because agreeable CEOs foster a cooperative (Giberson et al., 2009) and less hierarchical cultures (Peterson et al., 2003), they create a less competitive and less result-oriented environment (O'Reilly et al., 2014a). Agreeable individuals also tend to be modest, a trait not generally associated with effective leadership (e.g., Goldberg, 1990, Bass and Stogdill, 1990). For a sample of CEOs of private equity-funded companies, Kaplan et al. (2012) do not find any relation between subsequent performance and characteristics related to agreeableness. Thus prior research does not suggest an unambiguous prediction for the relation between agreeableness and performance.

While few clear predictions for the association between agreeableness and risk-taking behavior are found in prior research, Borghans et al. (2009) find that less agreeable individuals are less risk averse. Accordingly with regard to firm policies, the relation between agreeableness and risk aversion suggests that less agreeable CEOs are likely to associate with firms that are innovative (e.g., have higher levels of research and development and investment and, in turn, lower book-to-market ratios) and employ financing strategies consistent with higher levels of risk-taking (e.g., higher leverage).

B. Conscientiousness

Some studies suggest that conscientious leaders have a strong sense of direction, self-discipline, persistence, and performance motivation (Bono and Judge, 2004). They are ambitious, practical, scrupulous, and careful (Costa and McCrae, 1992). Conscientiousness is also associated with achievement and dependability (Mount and Barrick, 1995, Bono et al., 2014) and affects performance through the willingness to follow rules, to exert effort (e.g., Barrick, 2005, Barrick and Mount, 1991), and to set goals and remain committed to those goals (e.g., Barrick et al., 1993, Gellatly, 1996). Also, since they are ambitious, conscientious CEOs are likely to be attracted to outcome-oriented cultures with high expectations and norms for personal achievement (Sheridan, 1992) and to reward-oriented cultures that emphasize rewards for performance (O'Reilly et al., 1991). Consistent with both of these points, Kaplan et al. (2012) find that subsequent performance is related to characteristics associated with conscientiousness. At the same time, highly conscientious CEOs are likely to develop narrow fields of vision and a selective perception bias (Nadkarni and Herrmann, 2010). Excessive conscientiousness might even result in rigidity, inflexibility, and a focus on trivial details at the cost of more important goals and, thus, negatively relate to performance (Le et al., 2011).

Other research suggests that conscientious individuals are cautious, deliberate, and intolerant of ambiguity (e.g., Bono and Judge, 2004, McCrae and Costa Jr, 1996) and that they follow established rules rather than changing them (Peterson et al., 2003). Conscientious individuals tend to be controlled and risk-averse (Goldberg, 1990). Consistent with this, conscientiousness is negatively related to adaptability (LePine et al., 2000) and strategic flexibility (Nadkarni and Herrmann, 2010). Although conscientiousness is related to leadership in government and military settings, it is not related to leadership in business setting (Judge et al., 2002). Thus, highly conscientious CEOs are less attracted to innovative cultures that value risk-taking and inventiveness (e.g., O'Reilly et al., 1991, Judge and Cable, 1997, O'Reilly et al., 2014a).

Drawing these together, the relation between conscientiousness and performance is ambiguous. We might expect conscientious CEOs to be less attracted to innovative firms (e.g., those with higher levels of research and development and investment and, in turn, lower book-to-market ratios) and employ financing strategies consistent with lower levels of risk-taking (e.g., lower leverage).

C. Extraversion

Some research suggests that CEO extraversion is positively associated with firm performance. Extraverts are energetic and forceful in communicating their ideas (Judge et al., 2002). They have greater flexibility and thus might be more likely to initiate a strategic change (Nadkarni and Herrmann, 2010) that is helped by their ability to generate positivity and enthusiasm among employees (e.g., Judge et al., 2002, Bono and Judge, 2004). In addition, extraversion implies ambition and getting ahead (e.g., Barrick et al., 2002, Oh and Berry, 2009), and predicts both leadership emergence and effectiveness (e.g., Barrick et al., 2001, Judge et al., 2002, Ensari et al., 2011).

However, others argue that these benefits of extraversion are conditioned on obedience and submissiveness (e.g., Anderson et al., 2001, Barrick et al., 2002) and extraverted leaders view employee proactivity as a threat (Grant et al., 2011). As a result, extraversion might actually harm performance by evoking resistance (e.g., Floyd and Wooldridge, 1997, Wooldridge et al., 2008). Furthermore, extraverted CEOs may be less likely to solicit input from subordinates because they over-estimate their own abilities; and, because extreme extraverts have short-lived enthusiasm, they may pursue aggressive strategies and make premature changes if returns on such strategies do not materialize quickly (Judge et al., 2009).

As such, the predicted relation between extraversion and firm performance is unclear and thus an empirical question. With regard to firm policies, the relation between extraversion and positivity suggests that extraverts are likely to associate with firms that are innovative (e.g., have higher levels of research and development and investment and, in turn, lower book-to-market ratios) and employ financing strategies consistent with higher levels of risk-taking (e.g., higher leverage).

D. Neuroticism

Bass and Stogdill (1990) suggest that most successful leaders are emotionally stable or low on neuroticism. Emotional stability may enhance effective leadership, social interactions, and complex decision-making (e.g., Boudreau et al., 2001, Judge et al., 2002). Emotional stability is associated with optimism, self-confidence, self-assurance, decisiveness and success (see references in Boudreau et al., 2001). Emotionally stable people tend to remain calm and balanced in stressful situations (McCrae and Costa Jr, 1997). They are less threatened by uncertainties and not afraid to challenge the status quo and take risks (e.g., Judge and Bono, 2000, Peterson et al., 2003, Shimizu and Hitt, 2004, Nadkarni and Herrmann, 2010). In contrast to the positive view on emotional stability, others argue that emotional stability can lead individuals to exclude relevant cues because they are too focused (Easterbrook, 1959).

In contrast, individuals high on neuroticism tend to exhibit poor emotional adjustment and experience negative affect such as anxiety, insecurity, and hostility (e.g., Judge et al., 1995, Hogan and Ones, 1997, Watson and Clark, 1997). They can have a negative bias in the processing of information (Chan et al., 2007) and averse to uncertainty (Hirsh and Inzlicht, 2008). Neuroticism is also negatively related to beliefs about the importance of working hard (Holland et al., 1993), which is plausibly undesirable in a CEO. Consistent with this some studies find that neuroticism is negatively related to job performance and career success (e.g., Salgado, 1997, Tett et al., 1991). At the same time, neuroticism is argued to provide anticipatory ability that facilitates performance (Nettle, 2006). Furthermore, Nettle (2006) suggests that high neuroticism can serve as a motivator to achievement in competitive environments where a combination of other factors such as intelligence and conscientiousness allows for success, while low neuroticism may be related to a lack of striving.

The predictions for the association between neuroticism and performance are ambiguous and depend on the combination of other traits. With regard to organizational strategy, individuals low on neuroticism are attracted to innovative firms, as they are more flexible, adaptable, and less inclined to fear new situations and taking risks (Wiggins, 1996). Thus, neuroticism should negatively associate with firms that are innovative (e.g., have higher levels of research and development and investment and, in turn, lower book-to-market ratios) and employ financing strategies consistent with higher levels of risk-taking (e.g., higher leverage).

E. Openness to experience

Individuals who score high on openness to experience are intellectually curious, open to stimuli, value unusual thought processes, and are seen as thoughtful and creative (McCrae and Costa, 1987). Open individuals have a need for change, cope better with change, and are capable of understanding and adapting to other perspectives (e.g., Costa and McCrae, 1988, Spreitzer et al., 1997, Judge et al., 1999). In business settings, openness is positively related to leadership (Judge et al., 2002). Because open individuals are less likely to have selective perception and interpretation biases (e.g., Johnson et al., 2003, Shimizu and Hitt, 2004, Nadkarni and Narayanan, 2007), there is a positive relation between CEO openness and strategic flexibility that has a positive effect on firm performance (Nadkarni and Herrmann, 2010). Notwithstanding the indications in the literature that CEOs with high levels of openness are likely to be more successful, some research has struggled to find an empirical link with CEO success (e.g., Boudreau et al., 2001).

Open leaders seek excitement and risks (Judge et al., 2002). There is a positive relation between CEO openness and top management team intellectual flexibility and risk-taking (Peterson et al., 2003). Although openness relates to preferences for innovative cultures (e.g., Judge and Cable, 1997), Giberson et al. (2009) do not find evidence supporting this argument, while O'Reilly et al. (2014a) find that open CEOs encourage cultures that value innovation, speed, experimentation, and risk-taking.

Thus predictions for the association between high openness and performance are ambiguous. Regarding firm policies, the natural prediction is that CEOs with high openness to experience are likely be associated with firms that are innovative (e.g., have higher levels of research and development and investment and, in turn, lower book-to-market ratios) and employ financing strategies consistent with higher levels of risk-taking (e.g., higher leverage).

III. CEO personality data

We have data on personality and conference calls for 119 CEOs. The personality data come from two sources: data on 28 CEOs of U.S. technology firms from O'Reilly et al. (2014b) and data on 91 CEOs of public firms from Kaplan et al. (2012) and Kaplan and Sorensen (2016). We refer to the data from these sources as the O'Reilly and ghSMART samples, respectively. Each of these data sources relies on assessments by third-person observers, the accuracy of which has been shown to dominate that of self-assessments (e.g., Mount et al., 1994, Oh et al., 2011, Funder, 2012).

A. O'Reilly sample

As discussed in Appendix A, O'Reilly et al. (2014b) collected Big Five data from 246 current employees who completed the Ten-Item Personality Inventory (Gosling et al., 2003) for the CEOs at their respective firms. The O'Reilly et al. (2014b) data are coded on a Likert scale ranging from "disagree strongly" (1) to "agree strongly" (7) for each of the five traits. For each trait, we rescale the scores so they range from zero to one.

B. ghSMART sample

As discussed in Appendix A, the data from Kaplan et al. (2012) and Kaplan and Sorensen (2016) are sourced from assessments of CEO candidates by the management assessment firm ghSMART, which conducts 4-hour interviews with candidates for CEO positions. These interviews result in 20- to 40-page reports in which each candidate is assigned a letter grade for each of 30 characteristics.[3] The ghSMART data we have contain grades for 672 CEO candidates. These individuals are CEO candidates at firms involved in private equity and venture capital transactions (a majority of the sample) as well as other public and private companies. During our sample period, 91 of these candidates become public company executives for whom we have conference call information.

The ghSMART and O'Reilly data are based on two different approaches to personality traits. While the O'Reilly data provide assessments for the Big Five traits, the ghSMART data provide assessments for multiple characteristics that have to be translated into the Big Five traits.[4] Our primary approach to doing this uses a clustering algorithm combined with the advice and insight of Charles O'Reilly, a psychologist at Stanford University who works in the area of personality psychology. Before performing the cluster analysis, we obtained O'Reilly's view on how each characteristic maps to Big Five traits.

We first apply the hierarchical item clustering algorithm (`iclust`) from the R package `psych` (Revelle, 1979, 2015) to find groups of characteristics that capture the same underlying construct. This algorithm combines the most similar characteristics into a new composite cluster until an estimate of the unidimensionality or the presence of a single common underlying factor in a group of characteristics (Revelle's β) fails to increase. Given our focus on the Big Five personality traits, we ask the `iclust` to stop at five clusters. On this basis, the `iclust` algorithm produces the clusters depicted in Figure 1. We then compare the clustering and the mapping from ghSMART characteristics to Big Five traits suggested by Charles O'Reilly (`Expert_Mapping`).

Every characteristic in cluster `C20` was expected to be in *High openness*, so we map this cluster accordingly. Similarly, we map characteristics in cluster `C7` to `Conscientiousness` and those in cluster `C8` to *Extraversion*. Most of the characteristics in cluster `C22` were expected to be in *Conscientiousness*, except that *s_removesunderperformers* and *s_aggressive* were mapped to *Agreeableness*,

[3]We drop two characteristics (*s_writtencommunications* and *s_oralcommunication*) because values for those characteristics are missing for about half of the observations.

[4]Table I in Kaplan et al. (2012, pp.976–978) provides a detailed description of the ghSMART characteristics.

s_networkoftalentedpeople to *Extraversion* and *s_proactivity* to *High openness*. Nonetheless, we assign all characteristics in cluster `C22` to *Conscientiousness*.

With regard to cluster `C23`, we have three traits expected to be in *Agreeableness*, while two are expected to be *High openness* and one to each of *Conscientiousness*, *Extraversion*, and *Emotional stability*. We follow the plurality and map most characteristics to *Agreeableness*, in part because this is the only cluster mapping to that Big Five trait. However, because one of the eight characteristics in this cluster is the sole characteristic mapped by O'Reilly to *Emotional stability*, we assign that characteristic to that remaining Big Five trait. Our final mapping is shown in Table I.[5]

We average the letter grades of characteristics that correspond to the same Big Five dimension and normalize the scores to be between zero and one. Our Big Five classifications are related to, but different from, the factor analysis derived classifications in Kaplan and Sorensen (2016) obtained from the characteristics of executives in over 2,600 ghSMART assessments. Kaplan and Sorensen (2016) use the characteristics to create factors that explain the variation in characteristics, but are uncorrelated with each other. The second factor in Kaplan and Sorensen (2016) is positively related to agreeableness characteristics and negatively related to some of those for conscientiousness; the third factor is positively related to some conscientiousness characteristics and negatively related to those for extraversion; while the fourth factor is positively related to openness characteristics and, again, negatively to some conscientiousness characteristics.

C. *CEO personality samples: Descriptive statistics*

Table II presents descriptive statistics on CEO personality for the 28 CEOs in the O'Reilly sample and for the 91 CEOs in the ghSMART sample for whom we have conference call data from StreetEvents. Although the scores in both samples range from zero to one, these scores are not directly comparable between the two samples because these are constructed using very different methodologies.[6] If a median score for agreeableness is closer to one, half of the CEOs are closer

[5]One alternative approach would rely exclusively on the `iclust` mapping. This would mean mapping *s_calmunderpressure* to agreeableness, increasing the out-of-sample correlation for that trait from 0.23 to 0.29, but would mean the loss of a measure of emotional stability. The `iclust` mapping implies two conscientiousness clusters with out-of-sample correlations of 0.21 and 0.41 compared to that of our final mapping of 0.46. A second alternative would use `Expert_Mapping`, but the out-of-sample performance is no better, and generally worse than that of our final mapping. We believe our final mapping utilizes the strength of the statistical relationships from `iclust` and the advice from O'Reilly from `Expert_Mapping` to combine ghSMART characteristics into meaningful clusters that correspond to the Big Five traits better than either of these approaches alone.

[6]This is also the reason we use the two samples separately—estimating the model using the ghSMART sample and validating using the O'Reilly sample.

in agreeableness to the most agreeable CEO on a given scale and, thus, we can loosely say that CEOs are generally more agreeable than disagreeable. In both samples, CEOs are generally more agreeable, conscientious, extraverted, emotionally stable, and open on the corresponding scale. From 2001 to early 2013, we have an average of 13 earnings conference calls for each ghSMART CEO resulting in 1,186 calls and an average of 27 conference calls for each O'Reilly CEO resulting in 771 calls.

Firm characteristics in these two samples are substantially different. Because we use ghSMART data to estimate personality prediction models and O'Reilly data to evaluate their accuracy, these differences ensure that firm-specific features are not the primary determinants of our personality measures. Table III presents descriptive statistics on industry composition for the personality CEOs sample. As expected, the O'Reilly sample is dominated by technology firms in computer software and hardware industries, represented by 16 and 7 firms, respectively. In contrast, the ghSMART sample has an equal number of CEOs from computer software and pharmaceuticals industries, both represented by 11 firms. Overall, the ghSMART data cover 28 industries out of 49 Fama-French industries; whereas the O'Reilly sample covers only 7 industries.

Table IV compares characteristics of firms with ghSMART CEOs, firms with O'Reilly CEOs and all other firms with no CEO personality data. Because the sample of firms with CEO personality data is significantly smaller than the sample with no personality data, extreme observations are potentially more important when computing average values in this sample. Accordingly, we focus our comparisons on median differences. The ghSMART sample firms are similar to the sample of firms with no personality data. For ghSMART firms and firms with no personality data, median total assets are, respectively, \$0.93 and \$0.75 billion; the book-to-market ratios are 48.58% and 44.66%; return on assets are 11.45% and 12.42%; cash flows deflated by lagged total assets are 8.07% and 9.05%; and the net leverage is 5.94% and 3.35%. Both samples have lower R&D intensity compared to the O'Reilly sample. The O'Reilly firms are larger with median assets of \$7.44 billion; higher-growth firms with book-to-market of 24.89%; more profitable, with return on assets of 15.95% and cash flow of 18.85%; higher-R&D, with R&D intensity of 14.79%; and lower-net-leverage firms with the net leverage of -24.51%.

IV. Measuring personality

A. Prior research on personality and language

Because interviews and questionnaires of executives are not feasible for a large sample of public company executives, we follow prior research in psychology and linguistics (e.g., Pennebaker and King, 1999) in exploring whether differences in the way individual executives use language reflect differences in personality. For example, an early study in this literature, Pennebaker and King (1999), applies the Linguistic Inquiry and Word Count (LIWC) categories to examine a variety of sources, including diaries from substance abuse inpatients, daily writing assignments from students, and journal abstracts from social psychologists, and finds that these demonstrate internal consistency and out-of-sample classification power. The study concludes "that linguistic style is an independent and meaningful way of exploring personality."

Much of this research relies on written text, such as e-mail messages (Oberlander and Gill, 2006), essays (Mairesse et al., 2007), self-narratives (Hirsh and Peterson, 2009), and text messages (Holtgraves, 2011). Some studies have focused on written language used in less formal settings, such as Twitter and blogs. Qiu et al. (2012) examine the tweets of 142 participants to study how Big Five personality traits are associated with linguistic markers in posts on Twitter and find evidence of associations between use of words (in terms of LIWC categories) and Big Five traits. Yarkoni (2010) analyses the blogs of 576 personality survey respondents to derive mappings from LIWC categories and individual words to Big Five traits. Overall, a number of studies find significant associations between LIWC categories and Big Five traits (see also Hirsh and Peterson, 2009, Holtgraves, 2011).[7] A challenge with using written text in our setting is that published writing by CEOs likely involves the active participation of other managers and advisers such as lawyers and communication specialists which would reduce our ability to discern personality traits from such text. Relatively informal writing such as that used by Qiu et al. (2012) and Yarkoni (2010) is difficult to obtain or identify for a large sample of CEOs.

Other research relies on spoken language, but generally focuses on features observable from transcripts. For instance, Mehl et al. (2006) follow 96 participants over two days using electronic recorders. While they use elements relying on third-party assessments of audible properties, such

[7] Mairesse and Walker (2010) reverse the process by applying results from psycholinguistic studies to develop a system that produces utterances matching particular personality profiles. They find that human judges perceive the personality of system utterances in the intended fashion.

as mood, they focus on features observable from transcripts (e.g., talking more or using shorter words). Mehl et al. (2006) find evidence of Big Five traits manifesting in features of recorded language. Mairesse et al. (2007) use two corpora, the first corpus contains 2,479 essays from psychology students (1.9 million words); the second contains recorded speech of 96 students (97,468 words) from Mehl et al. (2006) . Even though they use speech and include some voice features, their focus is on features observable in transcripts, such as word categories from LIWC, features from the MRC Psycholinguistic database, and utterance type (command, question, etc.). They find that linguistic markers are helpful in classifying participants Big Five personality traits. While some research has focused on audible properties of spoken language, e.g., Hobson et al. (2012), this research has focused on a limited set of cues, such as vocal dissonance, with a view to detecting deception.

In recent work, Green et al. (2016) apply models provided by Mairesse et al. (2007) to CEO comments in the Q&A portion of earnings conference calls to construct a measure of extraversion. Because the Mairesse et al. (2007) algorithms were developed in a very different context (i.e., student essays and random conversation snippets), Green et al. (2016) validate their measure using student assessments of CEO extraversion from 100 audio excerpts of conference calls. They show that the correlation between the listener-based assessments of extraversion and the linguistic-based measure is 0.40 and the agreement rises to 75% for the binary measure when listeners are more confident in their assessments. In contrast to Green et al. (2016), we leverage unique data on CEO personality to develop our own mapping between linguistic features and personality traits. We also measure all Big Five traits and evaluate out-of-sample predictive performance of our models against high-quality personality assessments.

B. Selection of linguistic features

The first task in our analysis is to construct linguistic features from conference calls. Our source of conference calls transcripts is StreetEvents. We parse these transcripts into individual utterances. For each utterance, we have data on its relative position, the name of the speaker who made it, his or her employer and title, and whether the utterance was part of the corporate presentation or Q&A portion of the call. For each CEO-call observation, we aggregate all utterances made by a CEO during Q&A. We require a minimum of 150 words.[8] This provides us with linguistic data on 4,710 CEOs—119 with data on Big Five and 4,591 with no data on Big Five—participating in 72,286 earnings conference calls.

B.1. Features considered

We follow Pennebaker and King (1999) in using counts of words from categories as the primary features for our analysis. Most of the word categories we use come from LIWC. According to Pennebaker and King (1999, p.1297), LIWC's "subjective dictionaries were independently rated by judges. In addition to careful construction of language categories, most LIWC dimensions were subsequently validated by having judges rate hundreds of files of written text." We use the most recent version of the LIWC, LIWC2007 (Pennebaker et al., 2007). While LIWC has 64 word-list categories, we omit several categories unlikely to be common in the context of corporate conference calls (e.g., categories grouped under "social processes," which include words such as *daughter*, *baby*, and *neighbor* and those under "biological processes," which include words such as *spit*, *love*, and *eat*).

We further augment LIWC features with two additional sets of word categories. The first set of word categories comes from Larcker and Zakolyukina (2012). These additional categories modify LIWC categories by breaking them into smaller subcategories, such as extreme and non-extreme positive emotion words. The second set of word categories comprises four categories constructed for this paper that add dimensions missing from LIWC, but hypothesized to be related to the Big Five traits in prior research. These are thanks (e.g., *thank you*, *you're welcome*), vague quantifiers (e.g., *a load of*, *a lot of*), qualifiers (e.g., *arguably*, *as a whole*), and generalizations (e.g., *all that stuff*, *almost*).

Alternative approaches to feature selection common in finance and accounting tend to use significantly larger sets of features (e.g., measures of the presence or absence of individual words as in Antweiler and Frank, 2004, Li, 2010, Balakrishnan et al., 2010) or significantly fewer features (e.g., Loughran and McDonald, 2011, propose the six alternative single-feature measures of the "tone" of 10-K filings using the proportion of words falling into specific categories, namely, positive tone, negative tone, uncertainty, litigious, strong modal words, and weak modal words).

While feature selection and the approach used to develop classification models using those

[8]This requirement reduces the number of calls by 3% and the number of CEOs by less than 1%

features are, in principle, distinct, they are often closely related. Models that use a large number of features often use the Naive Bayes algorithm, which Hastie et al. (2009, pp.210–211) point out is "especially appropriate when the dimension p of the feature space is high, making [other approaches] unattractive." Following prior research on personality, we have chosen a much smaller feature set. Accordingly, issues of high-dimensionality should not be as problematic for our approach.

Papers that construct models using a smaller number of features tend not to examine the performance of their models directly. For example, Loughran and McDonald (2011) propose six alternative single-feature measures of the "tone" of 10-K filings, but have no benchmark measure of tone to evaluate the performance of their measures. Instead, they examine the stock market reaction at the time of 10-K filings, which amounts to a test of joint hypotheses that the market reacts to the tone of 10-K filings and that their measures successfully capture tone.[9] Similarly, Li (2008) proposes "fog" as a single-feature measure of managerial obfuscation, but also has no benchmark measure against which to evaluate it. Our approach differs in that we have benchmark measures of personality with which to evaluate the classification performance of the models we estimate.

We draw on prior research on the relation between personality and language to identify linguistic features for our analysis. Based on Qiu et al. (2012), Gill and Oberlander (2003), and Iacobelli et al. (2011), we consider *Self-references*, measured as the number of uses of the words "I" and "we" by the speakers. Based on Qiu et al. (2012), Mairesse and Walker (2010), and Pennebaker and King (1999), we consider linguistic markers of *Negative emotion* (e.g., *absurd*, *adverse*), *Positive emotion* (e.g., *fantastic*, *nice*), *Agreement* (e.g., *agree*, *thanks*), *Certainty* (e.g., *always*, *a lot*), markers of *Cognitive processes* (e.g., *admitting*, *except*), and use of *Hesitation and fillers* phrases (e.g., *you know*). Finally, we consider markers of *Linguistic processes* such as the use of conjunctions, adverbs, and words with more than six letters (e.g. Qiu et al., 2012), as well as measures of the number of times spoken relative to others on the conference call. We consider 33 linguistic features in total.

We standardize all features so that they are comparable across calls with different lengths of CEOs' comments. For word categories, we divide the raw word count by the words spoken by the CEO and multiply by the median words spoken by CEOs, i.e., 1,950. For times spoken, we divide the raw number of times the CEO spoke by the number of times all speakers spoke and multiply by the median number of times all speakers spoke on a call, i.e., 15. For words spoken,

[9] An alternative explanation is that a common underlying cause determines both tone and market reaction.

we divide the raw word count of the CEO by the total word count of all speakers and multiply by the median word count of all speakers on a call, i.e., 5,650.

B.2. Feature selection and prediction models

We use gradient boosting of regression trees (Freund and Schapire, 1997, Friedman, 2001) to relate linguistic features to personality traits.[10] Boosting methods have proved remarkably successful in producing highly accurate out-of-sample predictive performance by combining many relatively inaccurate models such as regression trees (Schapire and Freund, 2012). A regression tree partitions the feature space into a set of regions and uses the mean of the dependent variable as the fitted value for each partition.[11] For instance, a tree can split CEOs by *Words spoken* and use the average neuroticism score in each region as the estimate for CEOs. The algorithm can further split these regions by, for instance, *Adverbs*. The second split produces a regression tree with an interaction depth of two because both *Words spoken* and *Adverbs* define a region.

As discussed in Hastie et al. (2009) (Section 10.7), of all of the predictive methods, trees are the best candidates for the off-the-shelf predictive algorithms because they are fast to construct, interpretable, invariant to strictly monotone transformations of features, and immune to the effects of outliers in features. Regression trees also perform internal feature selection and, as a result, are resistant to the inclusion of irrelevant predictor features. Thus, when we include all 33 linguistic features, the algorithm tends to ignore features that are irrelevant for predicting personality. However, a single tree is inaccurate and a gradient boosted model often dramatically improves its accuracy while maintaining desirable properties. The boosted tree model is essentially a weighted sum of trees that minimizes a loss function. Each iteration adds a new tree that maximally improves the fit to the data given the already existing model and its fit (Friedman, 2001). This procedure divides the feature space with much higher granularity than a single tree. We choose the squared error criterion as our loss function. This is a standard choice for prediction problems with continuous outcomes.

The gradient boosting algorithm depends on three meta-parameters. The first parameter is

[10] We use gradient boosting of regression trees as implemented in the `gbm` R package by Ridgeway (2015) with the following parameters: `distribution = "gaussian", n.trees = 60,000, interaction.depth = 2, shrinkage = 0.01`.

[11] Strictly speaking, this is the approach that minimizes squared error; other loss functions will yield different estimators, such as the median.

the interaction depth of the regression trees, which is the number of splits considered for each tree. As the optimal value of interaction depth is low in most problems (Hastie et al., 2009), we set this parameter equal to two (i.e., each tree involves two splits).[12] The second parameter is the shrinkage or learning parameter, which scales the contribution of each new tree that is added to the model. This parameter controls the learning rate with smaller values reducing over-fitting and thus improving out-of-sample performance (Friedman, 2001). We set the shrinkage parameter to 0.01, which James et al. (2013, p. 323) identifies as a "typical value." The third parameter is the number of trees in the model. There is a trade-off between shrinkage and the optimal number of trees in the model. Smaller values of shrinkage require correspondingly larger values for the number of trees. We set the maximum number of trees to 60,000. Because the algorithm starts with a single tree and grows the model one tree at a time, this means we fit 60,000 models and select among these the model that minimizes mean squared error when applied out of sample to the O'Reilly data.

B.3. Results

We estimate models for predicting personality based on the ghSMART data without using information from the O'Reilly data. We use the O'Reilly data to choose the best model among those estimated and to evaluate the classification performance of the model selected for each trait.

Figure 2 depicts the basic elements of this analysis. For each Big Five personality trait, Figure 2 includes a pair of plots. The top plot of each pair depicts the out-of-sample mean squared error (MSE) calculated after applying the model estimated using the ghSMART data at each step of the boosting algorithm (represented by the number of trees included at that step) to the O'Reilly data. For each CEO, we compute the fitted personality scores as the median predicted scores over all conference calls. We then compare the fitted personality scores with the actual personality scores to calculate MSE. For each Big Five trait, we select the model (i.e., the number of trees) that minimizes the out-of-sample MSE for that trait. The final models are depicted by vertical lines on the MSE plots.

The size of the final models varies by trait. Extraversion and conscientiousness correspond

[12]In untabulated analysis, we examine the sensitivity of out-of-sample performance to setting this parameter equal to one (a single-split regression tree) or three. For some traits, increasing the interaction depth improves the out-of-sample performance, while for others decreasing it improves performance. To optimize performance across traits while minimizing the risk of over-fitting, we chose a single value of two.

to the smallest models with under 500 trees, and agreeableness corresponds to the largest model close to 50,000 trees. Relatively large models are not surprising because the shrinkage parameter is small. The small shrinkage parameter allows for slower learning that improves the out-of-sample performance at the cost of computing larger models. Indeed, smaller models for extraversion and conscientiousness indicate the importance of slow learning as fast learning causes rapid deterioration in the predictive performance. As the top plots consistently show, there are a large number of models that correspond to the MSE that is close to the minimum MSE of the best performing models; the performance of the final models is not driven by an isolated drop in the MSE. Because we do not use the O'Reilly sample for estimating these models, the predictive performance on these CEOs is an unbiased estimate of how the final models would perform on the new sample of CEOs.

The bottom plot of each pair depicts the relation between the value of the respective Big Five trait assigned to each CEO in the O'Reilly data with the predicted value of that trait for the model selected. Underneath the plot is the regression equation for that relation. Because the regressor (actual Big Five score) and regressand (predicted Big Five score) have been standardized to have mean zero and unit standard deviation, the slope coefficient from this univariate regression represents the correlation between the actual and predicted Big Five scores, which is also the square root of the R^2 for the regression. The lowest correlations are 0.23 for agreeableness and 0.29 for openness with both being statistically insignificant. The lack of statistical significance could be due to the small sample of 28 CEOs in the O'Reilly data. The remaining three correlations are larger and statistically significant. The correlations are 0.35 for extraversion, 0.46 for conscientiousness and 0.49 for neuroticism. Because of concerns about outliers in the estimated scores, we also examine the impact of winsorizing these outliers on the regression analysis. This impact is depicted in the bottom plots by the dashed regression lines. As can be seen, winsorizing standardized predicted personality scores at 3 generally does not materially affect the correlation between the actual and predicted personality scores for the O'Reilly sample.

These out-of-sample correlations are consistent with prior findings. Similar to this paper, a number of recent studies (e.g., Mairesse et al., 2007, Schwartz et al., 2013, Park et al., 2015) used linguistic features to predict continuous Big Five scores in different contexts. Schwartz et al. (2013) analyzed Facebook messages of 75,000 volunteers to predict their Big Five traits. Large sample allows them to use phrases and topics with LIWC providing a lower bound on the predictive performance. When the authors use LIWC, the correlation is 0.25 for agreeableness and 0.29 for openness, and 0.27 for extraversion, 0.29 for conscientiousness, and 0.21 neuroticism. In contrast, when the authors combine LIWC, phrases, and topics, the highest correlation is 0.42 for openness, similar to the highest value in our sample of 0.49 for neuroticism. Again based on a large Facebook sample, Park et al. (2015) report similar correlations for self-reported and observer-assessed Big Five traits. The out-of-sample correlations with the actual self-reported personality range from 0.35 for neuroticism and agreeableness to 0.43 for openness. The out-of-sample correlations with observer-assessed personality are, on average, 0.32 and statistically similar to correlations with self-reported personality. Finally, using the sample of student essays from Pennebaker and King (1999), random conversation snippets from Mehl et al. (2006), and the expanded set of linguistic and prosodic features, Mairesse et al. (2007) report the highest out-of-sample correlation of 0.33 for openness based on the student essay data and 0.54 for extraversion based on the conversation data.

C. Relation between features and personality

While the tree-based boosting approach appears to provide robust predictive models, one potential disadvantage relative to regression-based or simpler tree-based approaches is lower model interpretability. Nonetheless, it is possible to gain some understanding of the relation between features and predicted personality by considering the relative importance of various features and examining partial dependence plots. Figure 3 depicts, for each Big Five trait, the importance of each predictor (i.e., linguistic feature) in the model relative to the most important feature for that model. Importance is computed as the reduction of the squared error attributable to this predictor as described in Friedman (2001).

For the five most important predictors for each Big Five trait, we also examine partial dependence plots to understand the relation between linguistic features and estimated personality (Friedman, 2001). Figure 4 depicts, for each Big Five trait, single-variable partial dependence plots for that trait on the most important features. Each partial dependence plot depicts the relation between the given linguistic feature and the estimate of the given Big Five trait averaged over all other linguistic features in the ghSMART sample.[13] Because the tree-based boosting approach

[13]The plot is produced by averaging estimated Big Five traits over the training (ghSMART) sample as the given feature is varied while the other features are held at their observed values. Because the tree-based models are not

allows for discontinuities, the partial dependence plots need not be smooth.

In the following discussion, we highlight some general patterns of the fitted specifications and relate these to prior research on the relation between linguistic features and personality. We note that relative importance is not based on the statistical significance of the linguistic features selected by the boosting algorithm. As discussed in Shmueli (2010), the statistical significance of regression coefficients plays little or no role in assessing the out-of-sample predictive performance. Specifically, a variable that is not significantly associated with an outcome in a model estimated using training data can nonetheless provide useful information for predicting outcomes out of sample.

While we relate our models to predictions based on prior research, we make a number of caveats in doing so. First, prior research does not yield sharp predictions and associations documented appear to vary from one study to the other (Ireland and Mehl, 2014).

Second, the context that we study—corporate earnings conference calls—is arguably different from those studied in prior research which examine relatively informal or personal settings such as tweets (Qiu et al., 2012), everyday speech (Mehl et al., 2006), email (Oberlander and Gill, 2006), psychology students' essays and students' recorded speech (Mairesse et al., 2007), self-narratives of undergraduate students (Hirsh and Peterson, 2009), blogs (Yarkoni, 2010), text messages (Holtgraves, 2011), and Facebook posts (Schwartz et al., 2013). At the same time, word use is highly contextual and many of the findings may not hold in a wide range of settings (e.g., Tausczik and Pennebaker, 2010, Park et al., 2015). One advantage of our setting, however, is that the circumstances of communication are narrower, meaning that variations in speech patterns are more likely to be attributable to personality differences than they would be when the situation of speech varies more widely. One disadvantage of our setting is that its constrained nature may lead to speech being less personal and, hence, less revealing of personality.

Third, the goal of our study is to classify CEOs' personality based on language features. This goal differs from that of most prior research which has generally focused on predicting language features using measures of personality rather than using language to classify individuals in terms of their Big Five traits.

constrained to be linear, this is not equivalent to the estimates that would result from holding the other features at the mean of their observed values.

C.1. Agreeableness

Based on Goldberg (1992) and John and Srivastava (1999), agreeableness is associated with adjectives such as appreciative, considerate, gentle, and trustful. The most important predictors for agreeableness are *Words spoken*, *Adverbs*, *Words per sentence*, *Vague quantifiers*, and *Quantifiers*. A relation between the number of words and agreeableness is consistent with Mairesse and Walker (2010). In a blog context, agreeable individuals have shorter posts than disagreeable individuals because they are more considerate of others. Indeed, when the number of words per sentence is high, the agreeableness score is low.

C.2. Conscientiousness

Based on Goldberg (1992) and John and Srivastava (1999), conscientiousness is associated with adjectives such as careful, deliberate, dependable, disciplined, planning, and thorough. The most important predictors for conscientiousness are *General knowledge references*, *Hesitations*, *Words > 6 letters*, *Qualifiers*, and *Words per sentence*. *General knowledge references* and *Hesitations* can capture fillers and there is a negative association between fillers and conscientiousness (Schwartz et al., 2013). Indeed, the conscientiousness score decreases in the highest values of *General knowledge references* and *Hesitations*. The complexity of comments as captured by *Words per sentence* is also negatively related to conscientiousness.

C.3. Extraversion

Based on Goldberg (1992) and John and Srivastava (1999), extraversion is associated with adjectives such as adventurous, aggressive, confident, sociable, and vigorous. The most important predictors for extraversion are *Words per sentence*, *Quantifiers*, *Adverbs*, *Anxiety*, and *Discrepancy*. These results are similar to Hirsh and Peterson (2009), Holtgraves (2011), and Schwartz et al. (2013). Extraverts are more talkative than introverts (Mehl et al., 2006) and produce more complex utterances (Oberlander and Gill, 2006) and, thus, extraverts should have higher *Words per sentence*. In contrast, *Words per sentence* have a negative relation to extraversion in our study. Extraverts also have a lower preference for precision than introverts and, thus, use less *Quantifiers* (Oberlander and Gill, 2004), and a lower preference for explicitness and less formal style of speaking (e.g., Oberlander and Gill, 2006, Mairesse and Walker, 2010) and, thus, use more *Adverbs*. Indeed, *Quantifiers* are negatively and *Adverbs* are positively associated with extraversion. Extraverts are also predisposed to positive affect and, thus, use fewer anxiety words (Schwartz et al., 2013). However, the other findings on this are mixed with some studies (e.g., Mairesse et al., 2007, Yarkoni, 2010, Qiu et al., 2012) reporting a positive association between positive emotion words and extraversion, and Holtgraves (2011) reporting no association between positive emotion words and extraversion. The use of *Anxiety* words is positively associated with extraversion in our study.

C.4. Neuroticism

Based on Goldberg (1992) and John and Srivastava (1999), neuroticism is associated with adjectives such as anxious, fearful, nervous, and worrying. The most important predictors for neuroticism are *Words spoken*, *Adverbs*, *Words per sentence*, *Conjunctions*, and *Certainty*. That *Words spoken* is an important predictor is consistent with Mehl et al. (2006) and that for *Conjunctions* is consistent with Oberlander and Gill (2004) and Qiu et al. (2012). Prior research has found both negative (e.g., Mehl et al., 2006, Mairesse et al., 2007) and no association (Holtgraves, 2011) of neuroticism with the number of words. The relation we find is U-shaped. The importance of *Adverbs* is consistent with the implicit nature of neurotics (Oberlander and Gill, 2006). However, Oberlander and Gill (2006) report a negative association between the use of adverbs and neuroticism, and Schwartz et al. (2013) report a positive association; while we find a generally negative relation.

C.5. Openness

Based on Goldberg (1992) and John and Srivastava (1999), openness is associated with adjectives such as artistic, curious, innovative, insightful, philosophical, and witty. The most important predictors for openness are *Conjunctions*, *Words* $>$ *6 letters*, *Numbers*, *Words spoken*, and *Generalizations*. Schwartz et al. (2013) report a positive association between *Conjunctions*, *Numbers* and openness. While we find a generally positive association between *Conjunctions* and openness, the association between *Numbers* and openness is negative which is consistent with Yarkoni (2010). The result for *Words* $>$ *6 letters* is in line with Pennebaker and King (1999) and Mairesse et al. (2007). Both papers find a positive association between *Words* $>$ *6 letters* and being high on openness. Similarly, we find a generally positive association for *Words* $>$ *6 letters*.

D. *Calculating the personality measure*

Our Big Five personality models map linguistic features into personality scores. Thus we can apply these models to linguistic features extracted from the transcripts of CEO utterances on the Q&A portion of quarterly earnings conference calls to estimate personality traits for the full sample of CEOs drawn from StreetEvents. For a given CEO i, we measure each Big Five personality trait for the fiscal year t as the median score over all quarterly earnings conference calls up to (and including) the last call for the fiscal year t. Because the overwhelming majority of conference calls for the first quarter start four months after the fiscal year-end, we allow for a three-month lag after the fiscal year end for the last call. To compute our final measures, we require at least three quarterly conference calls.[14] Table V reports descriptive statistics for the linguistic features for the samples of CEOs with and without personality data.

As discussed in Section IV.B.1, most of our word categories are from LIWC by Pennebaker et al. (2007) supplemented by categories drawn from Larcker and Zakolyukina (2012). We construct an additional four categories for this paper; these are described in Table VI. Descriptive statistics of linguistic features are very similar for CEOs from ghSMART, O'Reilly, and CEOs with no personality data. The most frequently used word categories are inclusive words (e.g., *each*, *including*), first-person plural pronouns (e.g., *we*, *us*, *our*), non-extreme positive emotion words (e.g., *nice*, *accept*), and quantifiers (e.g., *all*, *a lot*, *bit*). Two categories in hesitations and fillers—hesitations (e.g., *ah*, *um*) and general knowledge references (e.g., *you know*, *investors well know*)—and two categories in negative emotion words—anxiety (e.g., *worried*, *fearful*) and anger (e.g., *hate*, *annoyed*)—are the most rare.

E. *Personality measure: Descriptive statistics*

Research in personality psychology shows that Big Five personality traits change relatively slowly over an individual's lifetime with the least change in the middle adulthood (ages 40-60) (e.g. Srivastava et al., 2003, Roberts and Mroczek, 2008). Accordingly, we expect the true underlying personality to be relatively stable over our sample period because most CEOs fall into the late middle adulthood cohort—the median CEO is 55 years old and has 5 years of tenure. We evaluate the stability of our measures using the ratio of between-CEO to within-CEO variability and the

[14]This requirement reduces the number of CEOs by 6.82% from 4,591 to 4,278.

correlation between personality measured in two different firms for the CEOs who changed firms.

Table VII presents the ratios of between-CEO to within-CEO mean squared error for the measures based on quarterly conference calls and our final measures. For both types of measures, the between-CEO variation is greater than the within-CEO variation. The lowest ratio is 3.45 (14.93) for neuroticism and the highest ratio is 5.74 (22.45) for extraversion for the quarterly (final) measures. These ratios are consistently higher for our final measures by construction. In addition, Panel B of Table VII reports correlations between personality measured at two different firms for the 41 CEOs who changed firms in our sample. All correlations are positive and statistically significant. The lowest correlation is for openness of 0.23 and the highest correlation is for extraversion and conscientiousness of 0.55. For Facebook messages, Park et al. (2015) also find that language-based personality scores are stable across 6-month intervals with the lowest correlation for neuroticism and the highest for conscientiousness. Overall, our measures are stable and, thus, plausibly capture relatively stable personality traits.

Table VII shows that CEOs score high on conscientiousness (median of 0.76), openness (median of 0.74), extraversion (median of 0.73) and agreeableness (median of 0.71) while scoring low on neuroticism (median of 0.23). Agreeableness has the highest standard deviation (0.045) while conscientiousness has the lowest (0.008). It is not possible to assign a meaning to these values, as they merely reflect the grades assigned (e.g., A or B+) by ghSMART to the characteristics that map to the Big Five traits. However, this is not essential for our task, which only requires cross-sectional variation in personality scores and the ability to rank CEOs on these traits.

Table VIII reports the correlations of the Big Five personality traits. This allows us to compare our results to those in Van der Linden et al. (2010) who provide a meta-analysis of 212 Big Five studies that report intercorrelations among Big Five traits. The signs of the correlations in Table VIII are identical to those in Van der Linden et al. (2010) except for the correlation between openness and extraversion (-0.12). As in Ones et al. (1996), neuroticism has the strongest average (and negative) correlation with the other Big Five traits. Agreeableness has a positive correlation with conscientiousness (0.18), extraversion (0.28), and openness (0.16); and negative with neuroticism (-0.51). Conscientiousness has a positive correlation with extraversion (0.19) and openness (0.16); and negative with neuroticism (-0.26). Whereas extraversion has a negative correlation with both neuroticism (-0.28) and openness (-0.12). Finally, the correlation between openness and neuroticism is negative (-0.16).

V. Firm policies and performance

In this section, we examine the association of CEO personality with firm policies and performance measures that prior research in psychology suggests might be associated with Big Five traits. We consider four firm policy variables (labels in parentheses are Compustat data codes): *R&D intensity*, *Investment*, *Book-to-market*, and *Net leverage*. *R&D intensity* is R&D expense (XRD) divided by sales (SALE). *Investment* is capital expenditure (CAPX) scaled by lagged net property plant and equipment (PPENT). The two performance variables are *Return on assets* and *Cash flow*. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT). *Cash flow* equals cash from operations (OANCF or, if this is missing, computed using balance sheet method as in Klein and Marquardt (2006)) divided by lagged total assets (AT).

We include the following control variables in our analyses: *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the book-to-market ratio where book equity is computed as in Cohen et al. (2003). *Net leverage* equals total debt (DLTT + DLC) minus cash and cash equivalents (CHE) divided by total assets (AT).[15]

We winsorize all variables at the 1st and 99th percentiles and present descriptive statistics in Table IX. We exclude financial firms (SIC codes 6000–6999) and utilities (SIC codes 4900–4999). When estimating the regressions, we scale Big Five measures and control variables by their interquartile ranges to facilitate the assessment of the economic magnitudes of the coefficients.

An important qualification for our analyses is that CEOs may not be randomly assigned to firms, making it difficult to ascribe causal explanations to the associations we document. It seems plausible that personality affects the type of firm at which an executive chooses to work, the type of CEO that a firm chooses to hire, as well as the policies that a CEO pursues once he or she is hired. It is difficult to distinguish among these alternative explanations. Accordingly, we follow the approach of Bertrand and Schoar (2003), who argue that because "there is no such thing as a random allocation of top executives to firms . . . we are not hoping . . . to estimate the causal effect of managers on firm practices."

[15]In our regressions, we examine the following permutations of controls and fixed effects: year fixed effects only, industry fixed effects and year fixed effects, and industry fixed effects and year fixed effects with controls. We do not include firm fixed effects because the limited number of observations where CEOs change for any given firm means that introducing such effects would mean that the effect of personality would be largely limited to year-to-year changes in these measures. Given the stability of personality in middle adulthood, this would largely limit our analyses to measurement error in personality. We cluster standard errors by industry which is conservative relative to the two-way clustering by industry and year.

A. *Firm policies*

Table X presents results for firm policies. We find a positive relation between openness and R&D intensity and between conscientiousness and book-to-market ratio, as well as a negative relation between net leverage and openness. An increase in openness by its interquartile range (i.e., from 0.71 to 0.76) is associated with an increase of between 2.10 and 14.87 percentage points in *R&D intensity* (relative to a mean of 13.60 percentage points and a median of 0.33 percentage points) and with a decrease of between -2.24 and -9.25 percentage points in *Net leverage* (relative to a mean of -0.58 percentage points and a median of 3.96 percentage points) depending on the specification. An increase in conscientiousness by its interquartile range (i.e., from 0.76 to 0.77) is associated with an increase of between 4.45 and 6.24 percentage points in *Book-to-market* (relative to a mean of 62.49 and a median of 44.70 percentage points).

The positive association between openness and *R&D intensity* is intuitive and consistent with the characterization of CEOs who score high on openness as creative (McCrae and Costa, 1987) and open to change (e.g., Costa and McCrae, 1988, Spreitzer et al., 1997, Judge et al., 1999). Similarly, Judge and Cable (1997) argue that openness relates to preferences for innovative cultures and O'Reilly et al. (2014a) find that open CEOs encourage cultures that value innovation, speed, experimentation, and risk-taking. CEOs high on openness have a preference for risk (Judge et al., 2002, Peterson et al., 2003, O'Reilly et al., 2014a) and the negative association between openness and *Net leverage* is not consistent with these CEOs having a preference for riskier debt financing. At the same time, the choice of leverage is endogenous to profitability and business risk. For instance, industry leverage tends to be lower when profitability and business risk are high (Myers, 2001). The sign of association between openness and *Net leverage* is consistent with these firms being exposed to a greater business risk, e.g., through higher R&D, and, thus, lower leverage.

The positive association between conscientiousness and *Book-to-market* (i.e., low growth) is consistent with these CEOs having a preference for rules and low adaptability (LePine et al., 2000, Nadkarni and Herrmann, 2010). Several extant studies argue that highly conscientious CEOs are less attracted to innovative cultures that value risk-taking and inventiveness (e.g., O'Reilly et al., 1991, Judge and Cable, 1997, O'Reilly et al., 2014a), which is likely to result in lower growth.

To examine the robustness of these results, we also estimate regressions of firm policies from Table X when we include Big Five traits with 1-, 2-, and 3-year lags. We expect the lags of Big

Five traits to be associated with future firm policies because personality is relatively stable over time. In addition, these tests reduce the possibility that our personality measures capture dimensions of contemporaneous firm policies reflected in linguistic features rather than personality traits of CEOs. The results (untabluated) are very similar to Table X both in terms of the statistical significance and magnitude of the coefficients. Conscientiousness is positively associated with *Book-to-market* (i.e., negatively associated with growth), and openness is positively associated with *R&D intensity* and negatively associated with *Net leverage*. The only exception is the association between openness and *R&D intensity*, which while similar in magnitude, is no longer statistically significant in the specification that omits industry fixed effects.

B. Performance

Table XI presents results for current and future return on assets; Table XII presents results for current and future cash flow. Because Big Five traits are relatively stable, we expect them to be associated with current and future firm outcomes. For this reason, in Tables XI and XII, we report results using profitability measured contemporaneously and up to three years in the future. When interpreting the coefficients, we focus on associations that are robust beyond the year in which Big Five traits are measured.

There is a robust negative association between extraversion and return on assets and cash flow. The increase in extraversion by an interquartile range (i.e., from 0.72 to 0.73) is associated with a decrease of between -0.39 and -2.27 (between -0.24 and -0.28) percentage points in *Return on assets* for year t ($t+3$) (relative to a mean of 11.96 percentage points and a median of 13.03 percentage points) and with a decrease of between -1.09 and -1.64 (between -0.31 and -0.50) percentage points in *Cash flow* (relative to a mean of 9.32 percentage points and a median of 10.01 percentage points). Similarly, openness is negatively associated with profitability. However, the statistical significance of coefficients is not as robust across different horizons. An increase in openness by its interquartile range (i.e., from 0.71 to 0.76) is associated with a decrease of between -0.34 and -3.52 (between -0.17 and -0.34) percentage points in *Return on assets* for year t ($t+2$) and with a decrease of between -1.00 and -2.68 (between -0.28 and -0.57) percentage points in *Cash flow* for year t ($t+3$).

The negative association between extraversion and performance is consistent with the argument that extraverts like to dominate and the benefits of extraversion are conditioned on obedience and submissiveness (e.g., Anderson et al., 2001, Barrick et al., 2002) that may not help decision-making in the corporate setting. Moreover, short-lived enthusiasm of extreme extraverts can result in aggressive strategies that tend to be prematurely terminated (Judge et al., 2009). The negative results on extraversion are also suggestive of the negative results on overconfidence in Malmendier and Tate (2005) and Malmendier et al. (2011). At the same time, however, Kaplan et al. (2012) find no correlation between extraversion (enthusiasm and persuasiveness) in the subsequent performance of private equity-funded companies.

VI. Conclusion

Recent research in economics and finance has started to explore the relations between individual senior executive traits, investment and financing choices made by these executives, and firm performance. Very few papers, however, examine how (or whether) differences in personality traits are associated with executive decision-making and firm performance. We develop and validate measures of Big Five personality traits for CEOs and examine the associations between these measures and investment and financing choices and firm performance.

Our measures are based on a statistical learning approach linking linguistic features of CEO speech during Q&A portion of conference calls with known personality traits drawn from data used in Kaplan et al. (2012) and Kaplan and Sorensen (2016). We validate our measures of CEO personality traits by showing that they exhibit substantial out-of-sample predictive ability using an independent sample obtained from O'Reilly et al. (2014b).

Finally, we examine associations between CEO personality traits with observed investment and financing choices and firm performance. We find that openness is positively associated with R&D intensity and negatively with net leverage; whereas conscientiousness is negatively associated with growth. In performance tests, extraversion is negatively associated with both contemporaneous and future return on assets and cash flow. However, our results are descriptive and further work is necessary to understand the nature of the causal relations, if any, between personality and firm policies and performance.

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Appendix A Personality data

A.1 ghSMART data

The data from Kaplan et al. (2012) and Kaplan and Sorensen (2016) are sourced from the assessments of CEO candidates by the management assessment firm ghSMART. Smart and Street (2008), Kaplan et al. (2012), and Kaplan and Sorensen (2016) contain details on the assessment methodology. Because ghSMART does not receive a fee contingent on hiring, Kaplan and Sorensen (2016) conclude that it has no incentives to bias assessments since its main objective is to sustain its reputation.

These assessments are based on interviews in which a candidate answers questions about his or her past behavior. The interviewers generally hold doctoral or MBA degrees and have worked at top consulting firms. ghSMART reports a high degree of consistency of assessments across interviewers. Interviewers do not ask the same questions, but they use the same methodology. Based on the description of the candidate's past behavior, interviewers then provide an assessment on 30 individual characteristics placed into five general categories: Leadership, Personal, Intellectual, Motivational, and Interpersonal as described in Table 1 in Kaplan et al. (2012).

A.2 O'Reilly data

O'Reilly et al. (2014b) rely on observer ratings of CEO personality, which have been shown to be more accurate than self-assessments (e.g., Funder, 2012, Mount et al., 1994). In spring 2011, the authors contacted 648 current employees at 32 technology firms. Of these 648, 250 individuals completed a survey asking them to assess their CEO's personality using the Ten-Item Personality Inventory. This instrument was developed by Gosling et al. (2003) and has been shown to be reliable and valid (e.g, Ehrhart et al., 2009, Muck et al., 2007).

After requiring at least five responses per firm, O'Reilly et al. (2014b) have data from 246 respondents from 29 firms. There are between 5 and 25 observers per CEO personality assessment with a mean of 8.48 and a standard deviation of 4.73. O'Reilly et al. (2014b) report that 34% of the respondents are female with the average tenure of 7.19 years. All had earned a bachelors degree and 69% of respondents had earned an MBA.

The scale ranges from "disagree strongly" (score of 1) to "agree strongly" (score of 7) and the ten items are (1) extraverted, enthusiastic; (2) critical, quarrelsome; (3) dependable, self-disciplined; (4) anxious, easily upset; (5) open to new experiences, complex; (6) reserved, quiet; (7) sympathetic, warm; (8) disorganized, careless; (9) calm, emotionally stable; (10) conventional, uncreative. Extraversion corresponds to (1) and the reverse of (6). Agreeableness corresponds to (7) and the reverse of (2). Conscientiousness corresponds to (3) and the reverse of (8). Emotional stability corresponds to (9) and the reverse of (4). High openness to experience corresponds to (5) and the reverse of (10).

Figure 1. Results of clustering analysis of ghSMART data

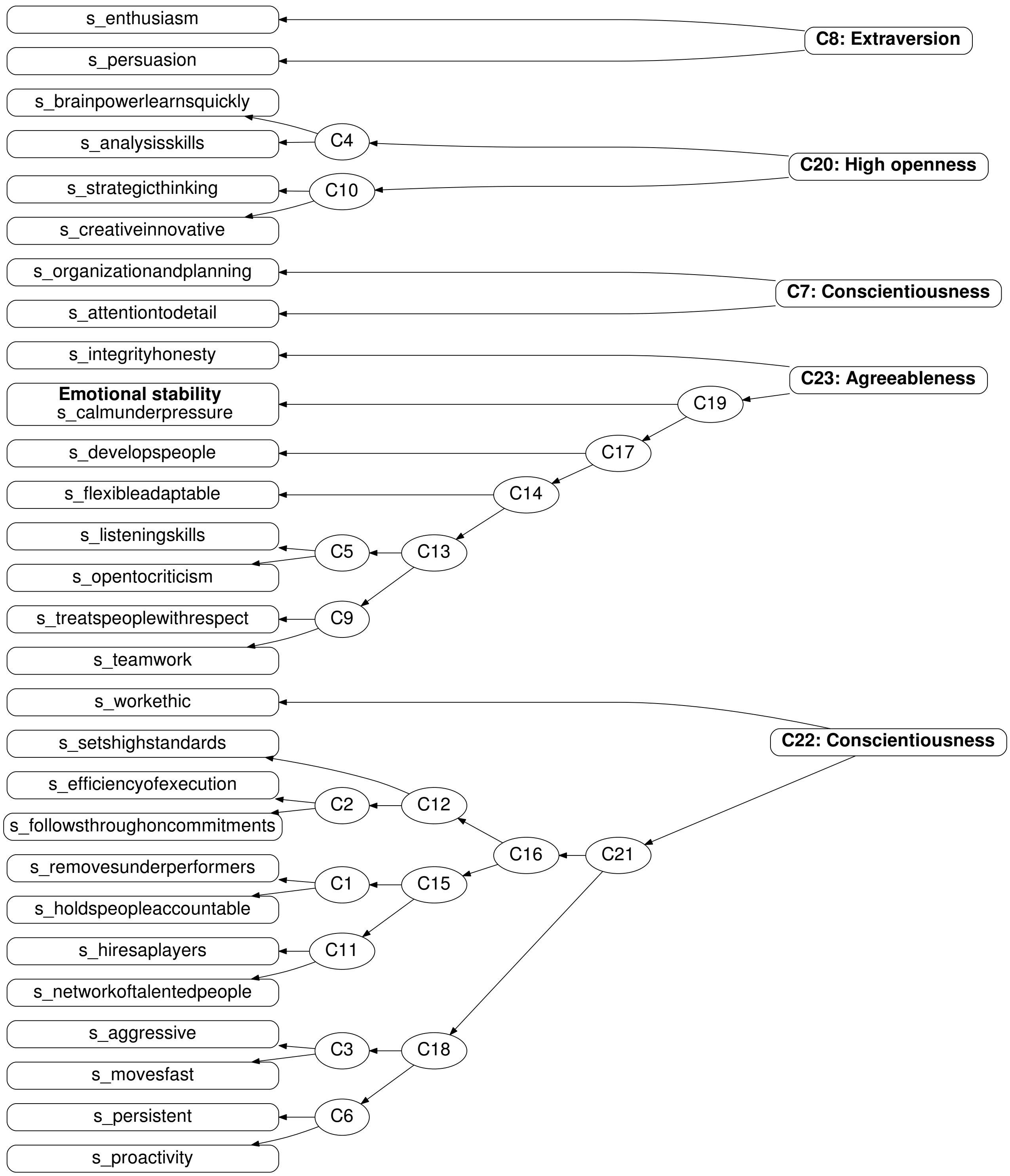
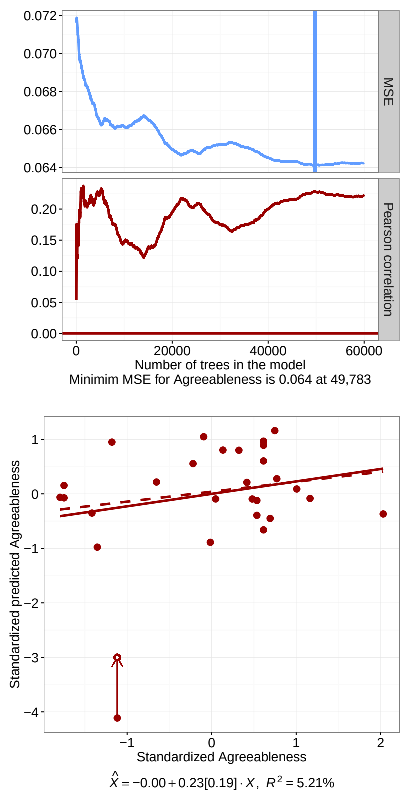


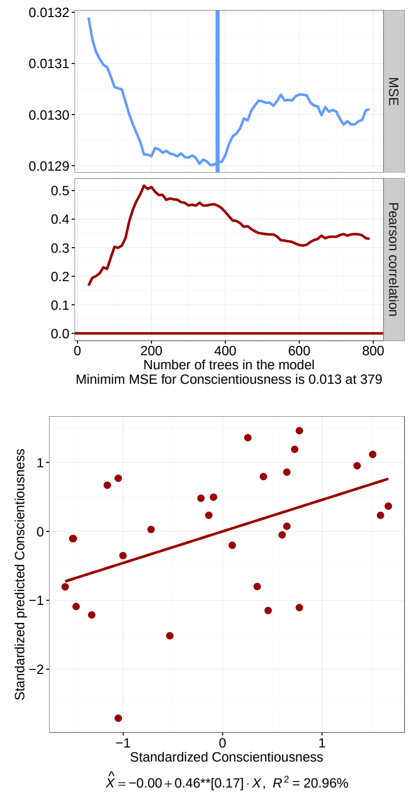
Figure 2. Model Selection for the Big Five Personality Traits

The top panels depict the out-of-sample mean squared error (MSE) and Pearson correlation for the O'Reilly data against the number of trees for the models estimated using the ghSMART data. The trees involve up to two splits. The vertical lines show the number of trees in our final models—the minimum-MSE models. The bottom panels depict the actual personality scores versus predicted personality scores for each CEO and a regression line of predicted scores on actual scores for the minimum-MSE models applied to the O'Reilly data. For each CEO, we compute predicted personality as the *median* predicted personality over all conference calls for the CEO. Actual and predicted scores are standardized. If a predicted score is more than three standard deviations away from the mean, we replace the corresponding score with the three-standard-deviations value (depicted by an empty circle) and re-estimate the regression line (depicted by a dashed line). The arrows show the replacement score.

(a) Agreeableness



(b) Conscientiousness



(c) Extraversion

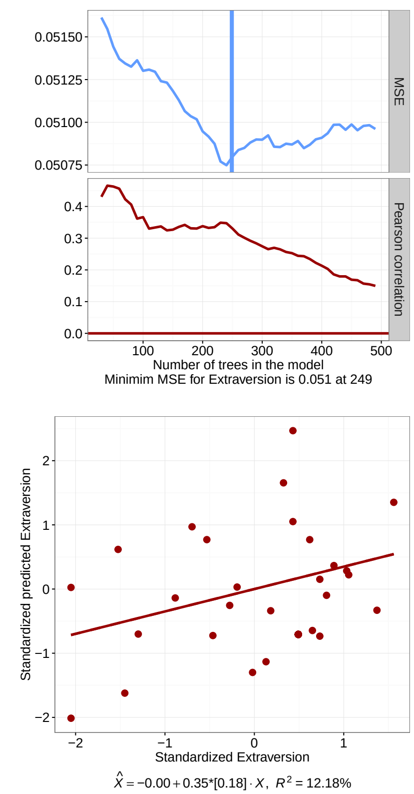
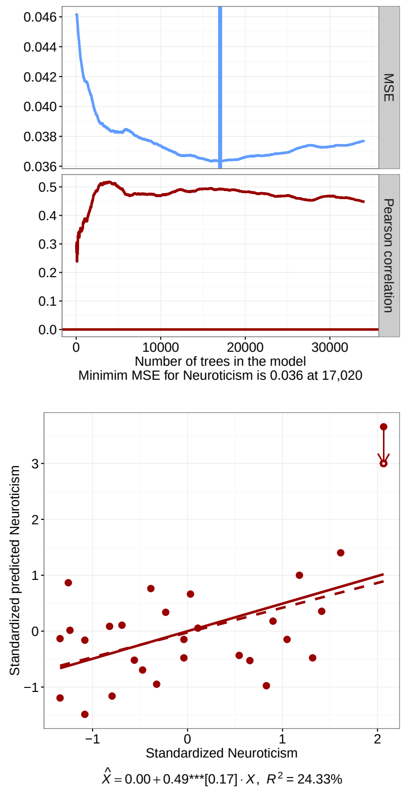


Figure 2. —*Continued*

(d) Neuroticism



(e) Openness

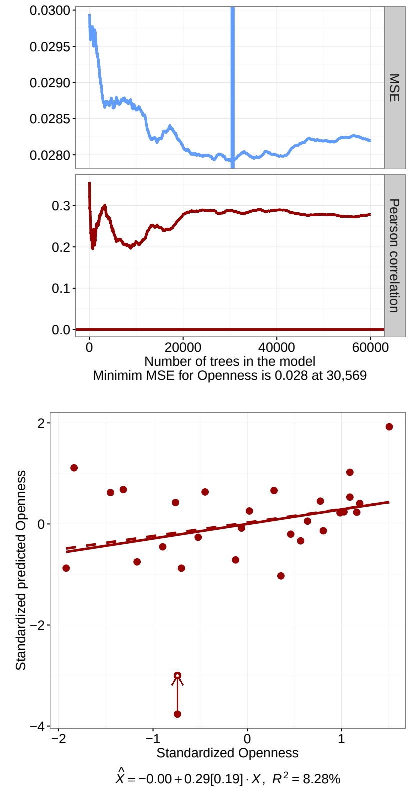


Figure 3. Importance of Linguistic Features for Predicting Big Five Personality Traits

This figure depicts the relative importance of the top fifteen linguistic features for predicting Big Five traits. For each linguistic feature, importance is computed as the reduction of the squared error attributable to this feature as described in Friedman (2001) using the training (ghSMART) sample. The bars indicate the relative importance of each linguistic features normalized by the relative importance of the most influential linguistic feature (on the bottom).

(a) Agreeableness **(b)** Conscientiousness **(c)** Extraversion

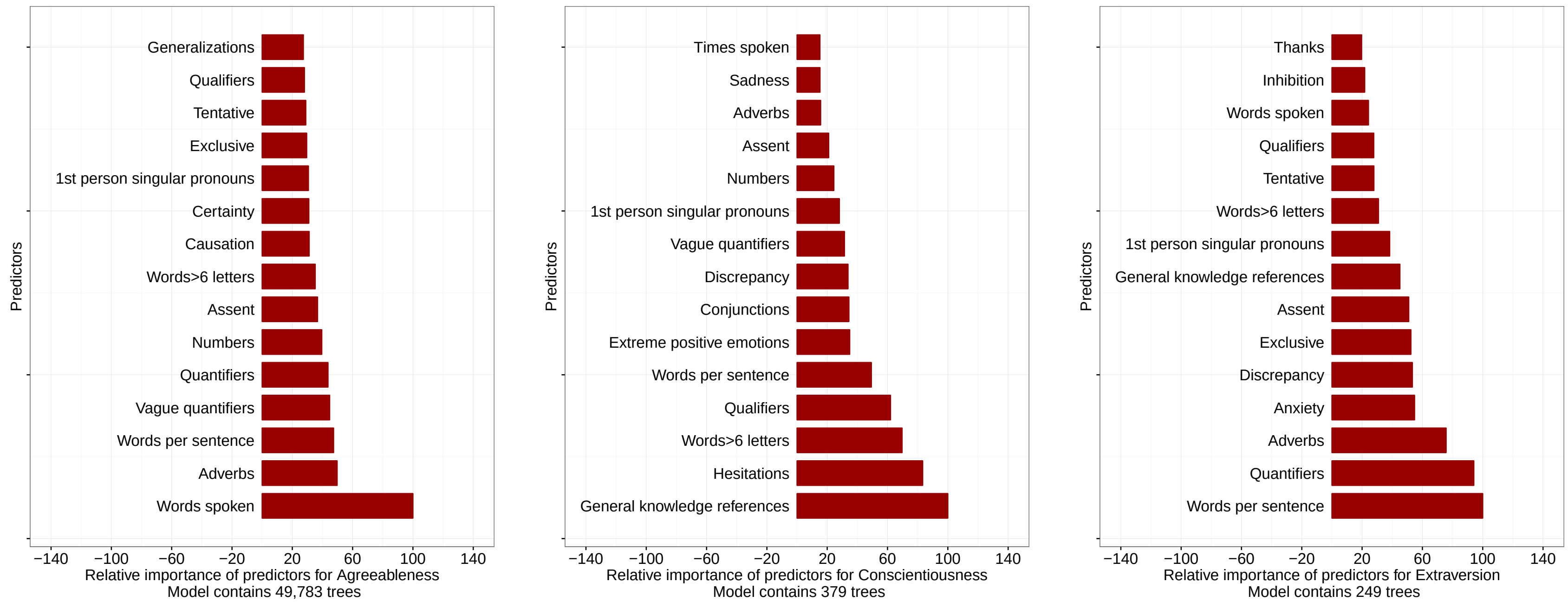
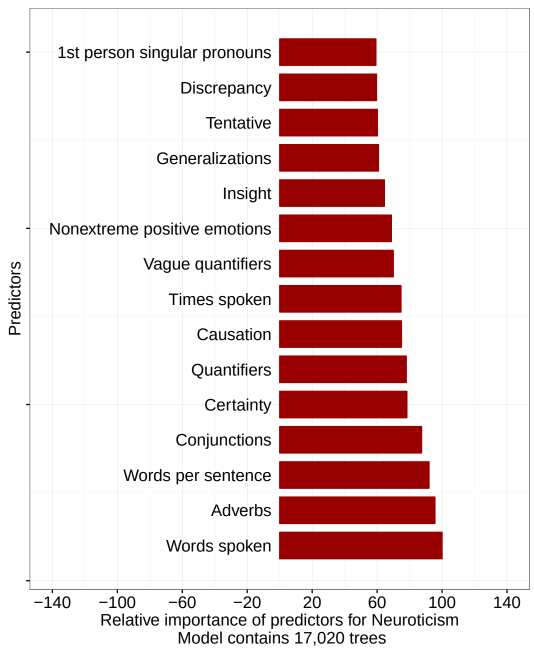


Figure 3. —*Continued*

(d) Neuroticism



(e) Openness

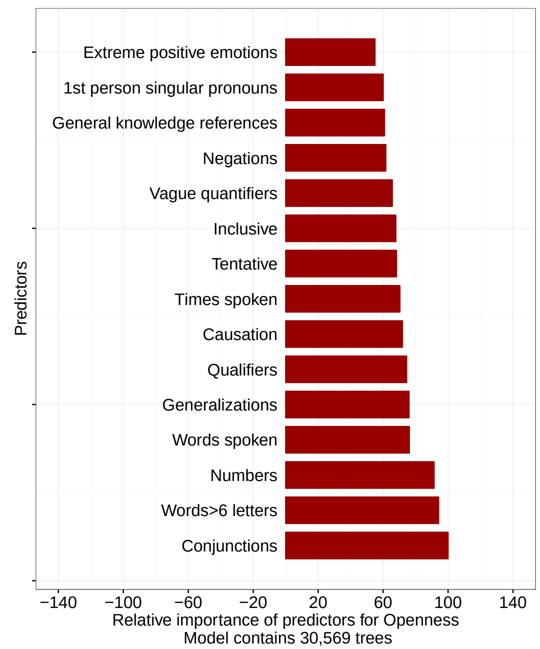


Figure 4. Partial Dependence Plots of Linguistic Features for Predicting Big Five Personality Traits

This figure depicts partial dependence plots (Friedman, 2001) for the five most important linguistic features for each of the Big Five traits. Each partial dependence plot is produced by averaging estimated Big Five traits over the training (ghSMART) sample as the given linguistic feature is varied while the other features are held at their observed value. The vertical gridlines and the hash marks at the base of the plot represent the deciles of the linguistic feature distribution from the ghSMART data with the median depicted by the dashed line.

(a) Agreeableness | **(b)** Conscientiousness | **(c)** Extraversion

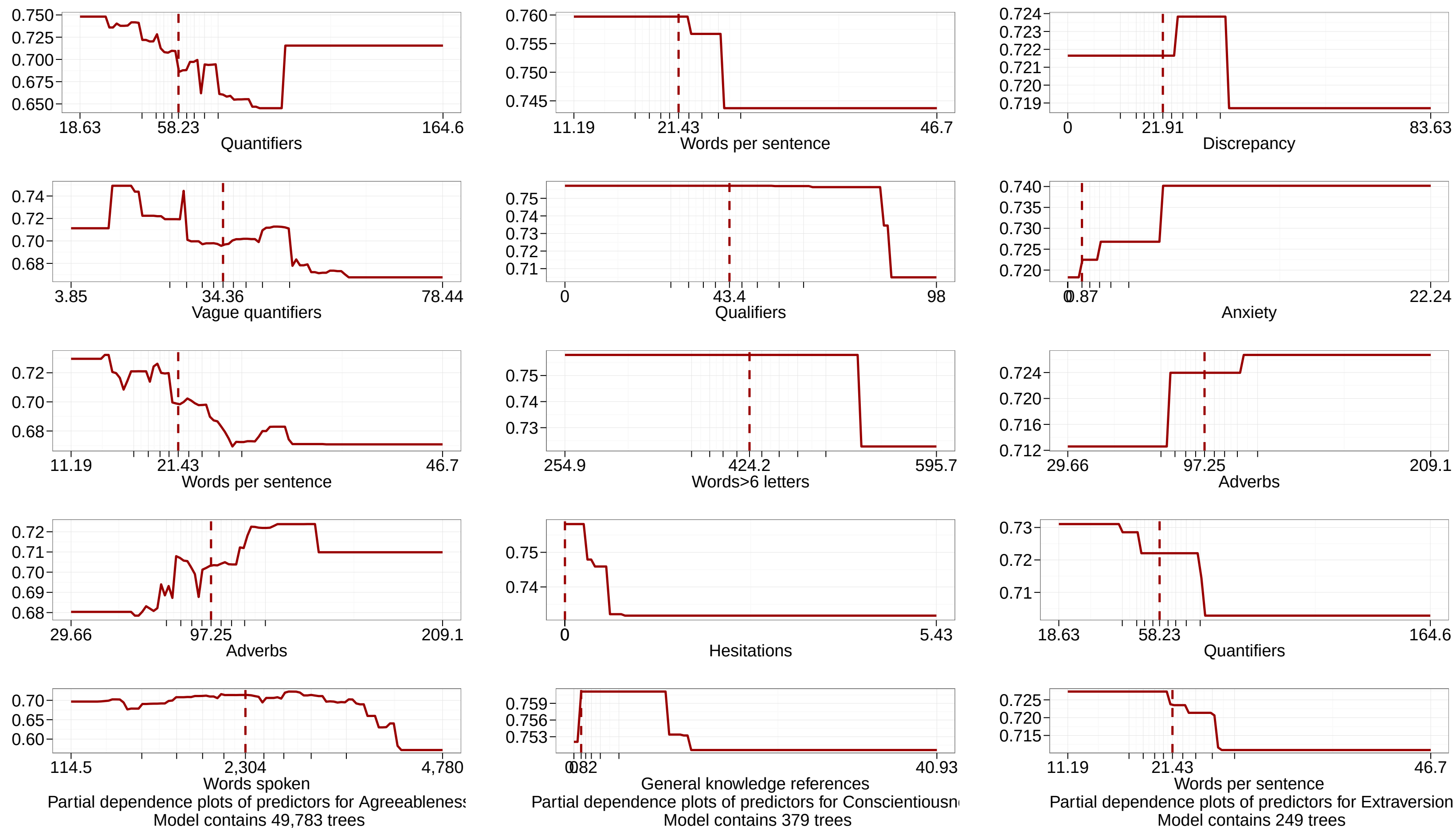


Figure 4. —*Continued*

(d) Neuroticism **(e)** Openness

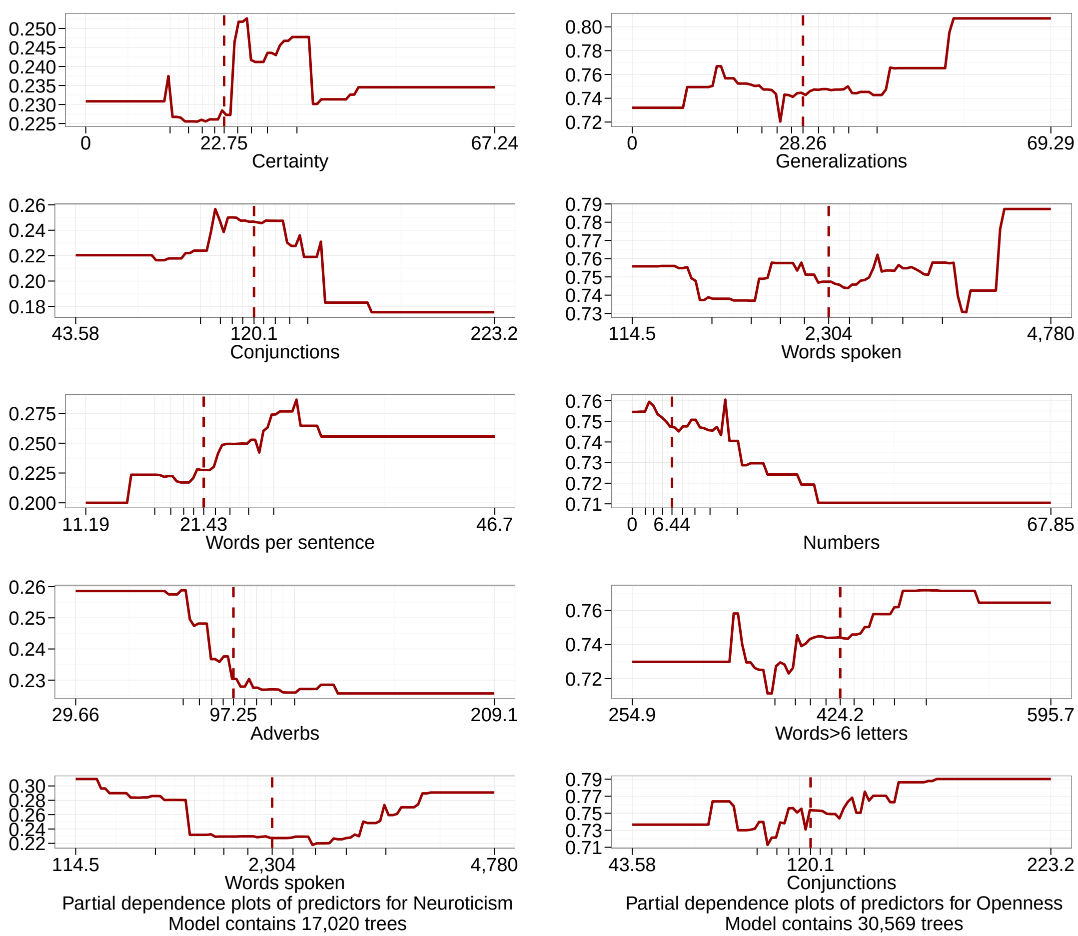


Table I
Mapping of ghSMART characteristics to Big Five traits

This table contains details on the mapping of the ghSMART data to Big Five traits The ghSMART characteristics are described in Table 1 of Kaplan, Klebanov, and Sorensen (2012, pp. 976–978). Mapping `iclust` refers to the raw output of the clustering algorithm from the `psych` package. Mapping `Expert_Mapping` refers to the mapping provided by Charles O'Reilly, as described in the text. The mapping used in our analysis is labeled "Final Mapping" below.

Characteristic	`iclust`	`Expert_Mapping`	Final Mapping
s_developspeople	C23	Agreeableness	Agreeableness
s_treatspeoplewithrespect	C23	Agreeableness	Agreeableness
s_listeningskills	C23	Agreeableness	Agreeableness
s_integrityhonesty	C23	Conscientiousness	Agreeableness
s_teamwork	C23	Extraversion	Agreeableness
s_flexibleadaptable	C23	High openness	Agreeableness
s_opentocriticism	C23	High openness	Agreeableness
s_removesunderperformers	C22	Agreeableness	Conscientiousness
s_aggressive	C22	Agreeableness	Conscientiousness
s_hiresaplayers	C22	Conscientiousness	Conscientiousness
s_efficiencyofexecution	C22	Conscientiousness	Conscientiousness
s_movesfast	C22	Conscientiousness	Conscientiousness
s_followsthroughoncommitments	C22	Conscientiousness	Conscientiousness
s_persistent	C22	Conscientiousness	Conscientiousness
s_workethic	C22	Conscientiousness	Conscientiousness
s_setshighstandards	C22	Conscientiousness	Conscientiousness
s_holdspeopleaccountable	C22	Conscientiousness	Conscientiousness
s_networkoftalentedpeople	C22	Extraversion	Conscientiousness
s_proactivity	C22	High openness	Conscientiousness
s_organizationandplanning	C7	Conscientiousness	Conscientiousness
s_attentiontodetail	C7	Conscientiousness	Conscientiousness
s_calmunderpressure	C23	Emotional stability	Emotional stability
s_enthusiasm	C8	Extraversion	Extraversion
s_persuasion	C8	Extraversion	Extraversion
s_brainpowerlearnsquickly	C20	High openness	High openness
s_analysisskills	C20	High openness	High openness
s_strategicthinking	C20	High openness	High openness
s_creativeinnovative	C20	High openness	High openness

Table II
Descriptive Statistics for CEOs with Data on Big Five Traits

This table provides descriptive statistics on personality scores for our sample of CEOs with data on Big Five traits from the Kaplan et al. (2012), Kaplan and Sorensen (2016) and O'Reilly et al. (2014b) samples. We label these samples as ghSMART and O'Reilly respectively.

	ghSMART					O'Reilly				
	Mean	Std. Dev.	Min	50th	Max	Mean	Std. Dev.	Min	50th	Max
Agreeableness	0.70	0.13	0.21	0.73	0.88	0.54	0.21	0.16	0.61	0.97
Conscientiousness	0.76	0.09	0.49	0.78	0.88	0.81	0.11	0.64	0.82	0.98
Extraversion	0.72	0.14	0.31	0.75	0.94	0.65	0.22	0.20	0.71	1.00
Neuroticism	0.24	0.13	0.12	0.19	0.50	0.34	0.19	0.08	0.32	0.74
Openness high	0.75	0.12	0.41	0.75	1.00	0.68	0.16	0.37	0.70	0.92
Number of calls	13.03	10.03	1.00	12.00	41.00	27.54	13.96	1.00	29.50	52.00
CEO obs.	91					28				
CEO–call obs.	1,186					771				

Table III
Descriptive Statistics for CEOs with Data on Big Five Traits: Industry

This table provides descriptive statistics on industry for our sample of CEOs with data on Big Five traits from the Kaplan et al. (2012), Kaplan and Sorensen (2016) and O'Reilly et al. (2014b) samples. We label these samples as ghSMART and O'Reilly respectively. We classify firms into the 49 Fama-French industries.

	CEO-firm observations				Conference calls			
	ghSMART		O'Reilly		ghSMART		O'Reilly	
	Num.	%	Num.	%	Num.	%	Num.	%
Computer Software	11	11.46	16	48.48	129	11.91	342	44.36
Computer Hardware	3	3.12	7	21.21	12	1.11	155	20.10
Electronic Eq.	2	2.08	5	15.15	21	1.94	143	18.55
Control Eq.	1	1.04	2	6.06	8	0.74	78	10.12
Retail	9	9.38	1	3.03	149	13.76	1	0.13
Communication	4	4.17	1	3.03	27	2.49	11	1.43
Machinery	3	3.12	1	3.03	73	6.74	41	5.32
Pharmaceuticals	11	11.46			93	8.59		
Food Products	7	7.29			109	10.06		
Wholesale	6	6.25			58	5.36		
Business Services	5	5.21			39	3.60		
Trading	5	5.21			48	4.43		
Banking	4	4.17			86	7.94		
Medical Equipment	4	4.17			53	4.89		
Transportation	4	4.17			21	1.94		
Chemicals	3	3.12			23	2.12		
Insurance	3	3.12			43	3.97		
Auto. and Trucks	2	2.08			25	2.31		
Agriculture	1	1.04			3	0.28		
Business Supplies	1	1.04			12	1.11		
Candy and Soda	1	1.04			7	0.65		
Entertainment	1	1.04			9	0.83		
Personal Services	1	1.04			1	0.09		
Petroleum and Gas	1	1.04			14	1.29		
Recreation	1	1.04			2	0.18		
Rubber and Plastic Products	1	1.04			17	1.57		
Steel Works Etc	1	1.04			1	0.09		
Obs.	96		33		1083		771	
CEO obs.	80		28		80		28	

Table IV
Descriptive Statistics: Firm Characteristics

This table provides descriptive statistics on firm characteristics for our sample of CEOs with data on Big Five traits from the Kaplan et al. (2012), Kaplan and Sorensen (2016) and O'Reilly et al. (2014b) and the sample of CEOs with no data on Big Five traits. Each observation corresponds to the CEO-firm pair with median firm characteristics over the period from January 1, 2001 to December 31, 2013. We require three years of non-missing data. *Size* is the total assets (AT), in billions of 2013 dollars. *Book-to-market* is the book-to-market in percentage points. Book equity is computed as in Cohen et al. (2003). *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT) in percentage points. *Cash flow* equals cash from operations (OANCF or, if missing, computed using balance sheet method) divided by lagged total assets (AT) in percentage points. *R&D intensity* equals R&D expense (XRD) divided by sales (SALE) in percentage points. *Net leverage* equals total debt (DLTT + DLC) minus cash and cash equivalents (CHE) divided by total assets (AT) in percentage points. All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses.

Panel A: ghSMART sample

	Mean	Std.Dev.	5th	25th	50th	75th	95th
Size	7.91	22.01	0.09	0.23	0.93	3.16	49.76
Book-to-market	117.40	338.31	11.09	31.41	48.58	78.71	284.32
Return on assets	11.84	16.49	−14.90	4.68	11.45	19.85	35.17
Cash flow	8.05	13.16	−13.74	4.02	8.07	14.65	24.30
R&D intensity	19.84	94.13	0.00	0.00	0.00	6.02	55.21
Net leverage	4.04	33.02	−46.86	−17.80	5.94	26.89	55.43
CEO-firm obs.	87						
CEO obs.	73						

Panel B: O'Reilly sample

	Mean	Std.Dev.	5th	25th	50th	75th	95th
Size	21.18	26.34	2.07	4.00	7.44	33.43	76.47
Book-to-market	27.65	11.88	14.49	19.58	24.89	34.91	46.62
Return on assets	18.05	7.29	7.88	12.34	15.95	24.86	29.19
Cash flow	18.30	6.80	9.05	12.74	18.85	22.61	29.72
R&D intensity	15.97	7.59	3.69	12.45	14.79	20.01	30.37
Net leverage	−25.69	17.45	−52.54	−38.38	−24.51	−16.77	3.44
CEO-firm obs.	32						
CEO obs.	28						

Panel C: Sample of CEOs without Big Five traits

	Mean	Std.Dev.	5th	25th	50th	75th	95th
Size	4.25	13.57	0.04	0.22	0.75	2.66	18.83
Book-to-market	53.80	45.75	11.75	28.15	44.66	68.70	118.13
Return on assets	9.83	17.45	−25.52	7.17	12.42	17.93	29.17
Cash flow	7.38	14.42	−20.09	4.73	9.05	13.82	23.61
R&D intensity	23.92	128.89	0.00	0.00	0.41	7.97	52.09
Net leverage	−0.99	33.38	−61.78	−22.79	3.35	22.95	49.35
CEO-firm obs.	3,222						
CEO obs.	3,185						

Table V
Descriptive Statistics: Linguistic Features

This table reports descriptive statistics for the linguistic features that we include in our Big Five traits classification models. Panel A contains descriptive statistics for the sample of conference calls of CEOs with data on Big Five traits and Panel B for the sample of conference calls of CEOs without these data. LIWC is the Linguistic Inquiry and Word Count psychosocial dictionary by James W. Pennebaker, Roger J. Booth, and Martha E. Francis Pennebaker et al. (2007). We provide the names of the corresponding LIWC categories in the second column. LZ categories are from Larcker and Zakolyukina (2012). The lists of words in self-constructed word categories are in Table VI. We standardize all features across conference calls. For word categories, we divide the raw word count by the words spoken by the CEO and multiply by 1,950 (the median words spoken by CEOs). For times spoken, we divide the raw number of times the CEO spoke by the number of times all speakers spoke and multiply by 15 (the median number of times all speakers spoke on a call). For words spoken, we divide the raw word count of the CEO by the total word count of all speakers and multiply by 5,650 (the median word count of all speakers on a call). For each CEO-call observation, we require a minimum of 150 words in the question-and-answer portion of the call.

Feature	Description	**Panel A:** CEOs with data on Big Five				**Panel B:** Without Big Five	
		ghSMART		O'Reilly			
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
		Personal pronouns					
First per. singular	LIWC "I": I, me, mine, etc.	29.05	13.04	29.88	11.69	29.72	13.52
First per. plural	LIWC "we": we, us, our, etc.	97.21	23.48	85.33	18.45	93.75	22.87
		Negative emotion words					
Sadness	LIWC "sad": devastat*, disadvantage*, etc.	2.21	2.35	2.41	2.19	2.55	2.76
Anxiety	LIWC "anx": worried, fearful, nervous, etc.	1.48	2.08	1.37	1.47	1.69	2.24
Anger	LIWC "anger": hate, kill, annoyed, etc.	1.36	1.92	1.65	1.79	1.40	2.01
Extreme negative	LZ using LIWC "negemo": absurd, adverse, awful, etc.	3.58	3.37	3.70	2.66	3.64	3.24
		Positive emotion words					
Extreme positive	LZ using LIWC "posemo": fantastic, great, definitely, etc.	10.00	5.62	12.29	5.50	9.17	5.86
Nonextreme positive	LZ using LIWC "posemo": love, nice, accept, etc.	53.69	14.61	48.40	11.84	53.22	15.75
		Agreement					
Negations	LIWC "negate": no, not, never, etc.	18.52	8.01	18.12	6.92	21.02	9.14
Assent	LIWC "assent": agree, OK, yes, etc.	5.18	4.76	3.47	2.55	5.11	4.43
Thanks	Self-constructed: thank you, thanks, you're welcome, etc.	3.71	4.63	1.59	1.94	3.95	4.93

Table V—*Continued*

Feature	Description	**Panel A:** CEOs with data on Big Five				**Panel B:** Without Big Five	
		ghSMART		O'Reilly			
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
			Certainty				
Certainty	LIWC "certain": always, never, etc.	23.71	8.49	24.22	8.10	23.09	8.60
Numbers	Number of numbers	7.92	7.07	8.62	7.22	10.32	8.93
Quantifiers	LIWC "quant": all, a lot, bit, etc.	58.88	12.99	59.67	11.47	58.67	13.51
Tentative	LIWC "tentat": maybe, perhaps, guess, etc.	47.70	15.05	44.15	11.70	50.20	14.89
Vague quantifiers	Self-constructed: a load of, a lot of, etc.	35.13	9.94	32.99	8.79	35.16	10.65
Qualifiers	Self-constructed: arguably, as a whole, etc.	44.70	14.21	42.12	13.23	45.70	14.37
Generalizations	Self-constructed: all that stuff, almost, etc.	28.88	9.46	29.84	8.44	28.93	9.57
			Cognitive process				
Insight	LIWC "insight": admitting, analy*, etc.	42.17	14.31	42.89	11.55	41.37	13.53
Causation	LIWC "cause": allow*, attribut*, based, etc.	30.90	10.28	34.51	9.18	29.35	10.69
Discrepancy	LIWC "discrep": besides, could, etc.	22.85	9.28	21.23	7.11	24.38	9.78
Inhibition	LIWC "inhib": abandon*, abstain*, etc.	5.21	3.75	5.42	3.54	5.66	4.27
Inclusive	LIWC "incl": each, inclu*, inside, etc.	149.26	24.44	140.91	20.25	143.36	24.22
Exclusive	LIWC "excl": either, except, exclu* , etc.	43.26	12.64	41.79	10.14	44.60	12.82
			Hesitations and fillers				
Hesitations	LZ using LIWC "filler": ah, um, etc.	0.08	0.36	0.23	2.32	0.21	1.32
Gen. knowledge	LZ: you know, investors well know, etc.	2.10	4.30	1.97	3.61	2.53	4.75
			Linguistic process				
Times spoken	Number of times spoken	3.75	1.38	3.40	1.18	4.01	1.53
Words spoken	Number of words spoken ignoring articles	2290.63	934.30	2422.13	854.10	2411.02	1009.34
Words per sentence	Words per sentence	22.05	4.36	23.44	4.78	21.47	4.44
Words>6 letters	Words longer than 6 letters	428.29	47.37	433.43	41.88	420.97	50.61
Articles	LIWC "article": a, an, the	122.12	18.83	124.93	14.84	121.28	18.77
Conjunctions	LIWC "conj": although, and, as, etc.	120.39	19.09	123.12	16.26	117.37	18.26
Adverbs	LIWC "adverb": about, absolutely, etc.	98.48	19.70	100.22	17.58	95.94	18.71
Calls obs.		1,186		771		70,329	

Table VI
Self-Constructed Word Categories

This table presents the word categories and individual words that we construct to use in estimation of Big Five traits classification models.

Thanks	thank you, thanks, you're welcome, youre welcome, you are welcome
Vague quantifiers	*ish, a bit of, a couple of, a few, a load of, a lot of, a scrap of, a touch of, about, almost, always, approximately, around, at least, billions, few, fewer, fewest, hundreds, hundreds of billions, hundreds of millions, hundreds of thousands, like, lots of, many, masses of, millions, millions of billions, more than, most, only a few, oodles of, or less, or so, over, probably, quite a few, round, seldom, several, so many, some, sometimes, tens of billions, tens of millions, tens of thousands, thousands, thousands of billions, thousands of millions, tons of, umpteen, unabashedly, usually, a tidbit of, less, less than, tons of
Qualifiers	a bit, a couple of, a tidge, a touch, about, all things being equal, almost, anticipate, anticipated, appears, arguably, as a whole, believe, broadly, could be, expect, expected, fairly, few months, few quarters, few weeks, few years, for the time being, generally, guesstimate, guesstimating, guestimate, guestimating, hopefully, I am guessing, i am guessing, I believe, i believe, I guess, i guess, i think, I think, I'm guessing, i'm guessing, in general, in that territory, in the meantime, in the range of, in the range off, in the region of, in the same range of, kind of, largely, likely, luck, mainly, marginally, may be, maybe, more or less, most, mostly, no big, no critical, no key, no major, on the whole, ought, overall, possibility, possibly, potential, potentially, presumably, pretty much, pretty regular, pretty similar, pretty soon, pretty well, probably, quite, range, relatively, roughly, seems, should, slightly, some, sort of, thinks, undeniably
Generalizations	a couple, a few, a whole range of things, all that, all that crap, all that junk, all that stuff, almost, and all, and all that, and all that sort of thing, and crap, and everything, and junk like this, and so on, and stuff, and stuff like that, anybody like that, anyone like that, anywhere like that, area, as a whole, broadly, bundle, bundled, chunk, close to, etc, etcetera, evenly, eventually, few, flat, generally, gradual improvement, gradual improvements, in many respects, in many ways, in the future, in the near future, insignificant, it can, it may, kind of, less than more, long term, long-term, medium term, medium-term, more or less, more than less, near to, not significant, nothing big, nothing huge, nothing major, on the whole, one of, or so forth, overall, package of, part of, partially, possibly, potential, pretty much, probably, proliferation, quantity, quite, relatively, seems, set of, short term, short-term, slice, slightly, somebody like that, someone like that, something like that, something of that kind, something of that sort, something of that type, sometime, sometimes, somewhere like that, soon, spread, stuff, stuff like that, suite of, territory, the whole bit, thing, things, thingy, very open, watchmacallit, what, what do you call it, what have you, whatchamacallit, whatever you prefer, whatnot, what-not, wherever, who, whole range of things

Table VII
Descriptive Statistics: Big Five Traits

This table provides descriptive statistics for measures of Big Five traits for our sample of CEOs with no personality data. We compute personality scores for each CEO using the CEO's utterances from the question-and-answer portion of quarterly earnings conference calls. We further aggregate these scores and define our final measures for the year t as the *median* scores over all quarterly earnings conference calls up to (and including) the last call for the fiscal year t. We require at least three quarterly conference calls. B/W denotes the ratio of between-CEO mean squared error to within-CEO mean squared error. In Panel A, Quarterly B/W are for the Big Five traits scores estimated using quarterly conference calls. In Panel B, Final B/W are for our final measures. Panel B also presents Pearson correlations for our final scores when CEOs change firms, i.e., between the scores for the same CEO in the new and the old firm. These scores are computed as the median score over all calls for the CEO-firm pair with at least two years of data. The alternative hypothesis for the Pearson correlation test is that the correlation is greater than zero. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Quarterly Big Five traits scores

	Quarterly B/W	Big Five traits based on quarterly conference calls						
		Mean	Std.Dev.	5th	25th	50th	75th	95th
Agreeableness	3.661	0.702	0.083	0.561	0.652	0.707	0.758	0.830
Conscientiousness	3.460	0.759	0.016	0.726	0.752	0.760	0.769	0.780
Extraversion	5.740	0.725	0.017	0.695	0.715	0.726	0.736	0.750
Neuroticism	3.453	0.235	0.072	0.120	0.187	0.233	0.280	0.357
Openness high	4.169	0.732	0.074	0.604	0.688	0.736	0.781	0.844
Obs.	70,329							

Panel B: Final Big Five traits scores

	Final B/W	CEOs change firms	Big Five traits						
			Mean	Std.Dev.	5th	25th	50th	75th	95th
Agreeableness	16.213	0.413^{***}	0.703	0.045	0.627	0.678	0.706	0.731	0.770
Conscientiousness	15.102	0.545^{***}	0.760	0.008	0.748	0.756	0.761	0.765	0.772
Extraversion	22.451	0.552^{***}	0.725	0.010	0.707	0.719	0.726	0.732	0.741
Neuroticism	14.934	0.240^{*}	0.234	0.039	0.174	0.210	0.233	0.257	0.300
Openness high	18.388	0.230^{*}	0.734	0.041	0.667	0.710	0.736	0.759	0.799
Obs.	19,011	41							

Table VIII
Correlations: Big Five Traits

This table reports pairwise Pearson correlations between our Big Five trait measures. Big Five trait measures are standardized. t-statistics based on robust standard errors clustered by CEO are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness high
Agreeableness	1.000				
Conscientiousness	0.184^{***}	1.000			
Extraversion	0.280^{***}	0.188^{***}	1.000		
Neuroticism	-0.511^{***}	-0.258^{***}	-0.275^{***}	1.000	
Openness high	0.157^{***}	0.155^{***}	-0.120^{***}	-0.157^{***}	1.000

Table IX
Descriptive Statistics

This table provides descriptive statistics for firm outcomes regressions. Big Five traits correspond to the personality scores calculated as the *median* scores over all quarterly earnings conference calls up to (and including) the last call for the fiscal year *t*. *R&D intensity* is R&D expense (XRD) divided by sales (SALE) in percentage points. *Investment* is the capital expenditures (CAPX) scaled by lag of net property plant and equipment (PPENT) in percentage points. *Book-to-market* is the natural logarithm of book-to-market in percentage points. Book equity is computed as in Cohen et al. (2003). *Net leverage* equals total debt (DLTT + DLC) minus cash and cash equivalents (CHE) divided by total assets (AT) in percentage points. *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT) in percentage points. *Cash flow* equals cash from operations (OANCF or, if missing, computed using balance sheet method as in Klein and Marquardt (2006)) divided by lagged total assets (AT) in percentage points. Compustat data codes are included in parentheses. We exclude financial firms (SIC in 6000 - 6999) and utilities (SIC in 4900 - 4999). All variables are winsorized at the 1st and 99th percentiles.

	Obs.	Mean	Std.Dev.	5th	25th	50th	75th	95th
Agreeableness	14,028	0.702	0.042	0.626	0.677	0.704	0.729	0.768
Conscientiousness	14,028	0.761	0.007	0.749	0.756	0.761	0.765	0.772
Extraversion	14,028	0.725	0.010	0.707	0.719	0.725	0.732	0.741
Neuroticism	14,028	0.236	0.037	0.174	0.211	0.235	0.258	0.301
Openness high	14,028	0.734	0.039	0.666	0.711	0.736	0.759	0.799
R&D intensity	14,006	13.595	54.097	0.000	0.000	0.333	7.171	38.932
Investment	14,008	31.351	30.531	5.059	12.829	21.893	38.469	89.849
Book-to-market	14,028	62.489	62.346	8.933	25.704	44.696	76.473	173.867
Net leverage	14,028	-0.579	33.458	-63.013	-22.347	3.960	23.529	48.942
Size	14,028	6.888	1.718	4.080	5.673	6.828	8.022	9.919
Return on assets	14,028	11.963	15.877	-16.870	7.251	13.029	19.422	34.368
Cash flow	14,028	9.316	13.393	-13.509	4.879	10.005	15.822	28.385
ΔReturn on assets	12,035	-0.281	8.336	-14.010	-3.078	0.075	2.825	12.000
ΔCash flow	12,035	-0.287	9.047	-14.602	-4.151	-0.201	3.579	13.935

Table X
Firm Policies

This table reports results of the regressions of firm policy variables on Big Five traits of CEOs with no personality data and controls measured at the end of the fiscal year t, unless noted otherwise. Big Five traits correspond to the predicted personality scores calculated as the *median* scores over all quarterly earnings conference calls up to (and including) the last call for the fiscal year t, unless noted otherwise. *R&D intensity* is R&D expense (XRD) divided by sales (SALE) in percentage points. *Book-to-market* is the book-to-market ratio in percentage points. Book equity is computed as in Cohen et al. (2003). *Investment* is the capital expenditures (CAPX) scaled by lag of net property plant and equipment (PPENT) in percentage points. *Net leverage* equals total debt (DLTT + DLC) minus cash and cash equivalents (CHE) divided by total assets (AT) in percentage points. *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT). *Cash flow* equals cash from operations (OANCF or, if missing, computed using balance sheet method as in Klein and Marquardt (2006)) divided by lagged total assets (AT). Compustat data codes are included in parentheses. We exclude financial firms (SIC in 6000 - 6999) and utilities (SIC in 4900 - 4999) from this analysis. All variables are winsorized at the 1st and 99th percentiles. Big Five trait measures and control variables are scaled by the corresponding interquartile ranges, i.e., the difference between the 75th and 25th percentiles. The dependent variables are not scaled. Industry fixed effects are based on the 49 Fama-French industries. Robust standard errors clustered by the 49 Fama-French industries are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	R&D intensity			Investment			Book-to-market			Net leverage		
Agreeableness	−1.354	−1.659	0.609	0.310	0.214	0.485	−1.603	−2.020*	−0.339	1.359*	0.831	−0.408
	(0.921)	(1.218)	(0.659)	(0.570)	(0.502)	(0.546)	(1.138)	(1.149)	(0.997)	(0.773)	(0.671)	(0.432)
Conscientiousness	1.597	0.563	0.536	−1.816*	−1.009	−0.866	6.239***	5.793***	4.451***	2.036**	0.768	1.371*
	(2.293)	(1.139)	(1.267)	(0.950)	(0.661)	(0.531)	(1.085)	(0.855)	(0.814)	(0.971)	(0.685)	(0.716)
Extraversion	5.538**	2.367***	−0.680	−0.063	−0.581	−0.916	−0.514	0.807	−0.818	−3.034**	−1.303*	−0.219
	(2.722)	(0.864)	(0.848)	(0.772)	(0.652)	(0.694)	(1.330)	(1.041)	(1.061)	(1.397)	(0.769)	(0.577)
Neuroticism	1.639	2.021*	1.844**	0.878	0.187	0.519	0.729	0.231	0.068	0.430	0.603	−0.028
	(1.097)	(1.044)	(0.734)	(0.872)	(0.649)	(0.637)	(1.164)	(0.844)	(0.818)	(1.239)	(0.602)	(0.592)
Openness high	14.867*	5.718**	2.094***	2.981***	1.287*	0.607	−4.299**	−1.048	−1.700	−9.252***	−3.189***	−2.235***
	(8.972)	(2.696)	(0.692)	(1.040)	(0.662)	(0.640)	(1.761)	(1.226)	(1.264)	(2.413)	(0.829)	(0.557)
Size			1.202			−6.667***			−8.157***			17.049***
			(1.565)			(0.767)			(2.079)			(1.566)
Book-to-market			−6.590***			−3.675***						4.360***
			(1.747)			(0.551)						(0.514)
Return on assets			−18.786**			0.882			−15.855***			7.223***
			(7.616)			(1.423)			(4.254)			(1.715)
Cash flow			−6.020***			0.940			1.748			−6.447***
			(1.316)			(1.276)			(1.901)			(1.672)
Net leverage			−12.545***			−7.373***			17.502***			
			(3.394)			(0.758)			(1.857)			
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.090	0.318	0.517	0.514	0.564	0.601	0.555	0.580	0.626	0.048	0.323	0.460
Obs.	14,006	14,006	14,006	14,008	14,008	14,008	14,028	14,028	14,028	14,028	14,028	14,028

Table XI
Performance: Return on Assets

This table reports results of the regressions of firm outcome variables on Big Five traits of CEOs with no personality data and controls measured at the end of the fiscal year t, unless noted otherwise. Big Five traits correspond to the predicted personality scores calculated as the *median* scores over all quarterly earnings conference calls up to (and including) the last call for the fiscal year t, unless noted otherwise. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT) in percentage points. *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the book-to-market. Book equity is computed as in Cohen et al. (2003). *Cash flow* equals cash from operations (OANCF or, if missing, computed using balance sheet method as in Klein and Marquardt (2006)) divided by lagged total assets (AT). *Net leverage* equals total debt (DLTT + DLC) minus cash and cash equivalents (CHE) divided by total assets (AT). Compustat data codes are included in parentheses. We exclude financial firms (SIC in 6000 - 6999) and utilities (SIC in 4900 - 4999) from this analysis. All variables are winsorized at the 1st and 99th percentiles. Big Five trait measures and control variables are scaled by the corresponding interquartile ranges, i.e., the difference between the 75th and 25th percentiles. The dependent variables are not scaled. Industry fixed effects are based on the 49 Fama-French industries. Robust standard errors clustered by the 49 Fama-French industries are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Return on assets			ΔReturn on assets$_{t+1}$ Big Five measured at t			ΔReturn on assets$_{t+1}$ Big Five measured at $t-1$			ΔReturn on assets$_{t+1}$ Big Five measured at $t-2$		
Agreeableness	1.367^{***}	1.317^{***}	0.520^{***}	0.137	0.142	0.160	0.191	0.187	0.187	0.075	0.060	0.065
	(0.378)	(0.279)	(0.165)	(0.123)	(0.108)	(0.103)	(0.165)	(0.152)	(0.140)	(0.174)	(0.173)	(0.174)
Conscientiousness	-0.618^{***}	-0.472^{**}	0.253^{*}	-0.055	-0.061	0.010	0.045	0.031	0.110	-0.111	-0.105	-0.045
	(0.211)	(0.186)	(0.142)	(0.087)	(0.088)	(0.094)	(0.110)	(0.113)	(0.103)	(0.128)	(0.130)	(0.118)
Extraversion	-2.272^{***}	-1.532^{***}	-0.390^{***}	-0.513^{***}	-0.458^{***}	-0.425^{***}	-0.355^{**}	-0.299^{**}	-0.234^{*}	-0.276^{**}	-0.236^{**}	-0.169
	(0.554)	(0.346)	(0.121)	(0.159)	(0.152)	(0.139)	(0.146)	(0.139)	(0.124)	(0.115)	(0.108)	(0.105)
Neuroticism	-0.203	-0.179	0.131	-0.158	-0.173	-0.159	0.023	-0.010	0.002	0.062	0.033	0.041
	(0.365)	(0.372)	(0.143)	(0.113)	(0.116)	(0.124)	(0.131)	(0.134)	(0.140)	(0.134)	(0.152)	(0.148)
Openness high	-3.522^{**}	-1.446^{***}	-0.341^{**}	-0.346^{***}	-0.165	-0.115	-0.341^{***}	-0.165^{*}	-0.105	-0.126	0.028	0.065
	(1.544)	(0.489)	(0.165)	(0.133)	(0.102)	(0.119)	(0.130)	(0.095)	(0.107)	(0.136)	(0.101)	(0.106)
Size			0.758^{**}			0.347^{*}			0.122			-0.068
			(0.338)			(0.200)			(0.174)			(0.192)
Book-to-market			-1.442^{***}			-0.304^{***}			-0.298^{**}			-0.163
			(0.220)			(0.097)			(0.127)			(0.143)
Return on assets				-2.309^{***}	-2.566^{***}	-4.498^{***}	-2.252^{***}	-2.511^{***}	-4.390^{***}	-2.086^{***}	-2.329^{***}	-4.048^{***}
				(0.330)	(0.327)	(0.314)	(0.432)	(0.442)	(0.401)	(0.399)	(0.415)	(0.424)
Cash flow			9.971^{***}			2.059^{***}			2.060^{***}			1.987^{***}
			(0.230)			(0.315)			(0.403)			(0.360)
Net leverage			2.637^{***}			1.178^{***}			1.226^{***}			1.150^{***}
			(0.581)			(0.265)			(0.300)			(0.259)
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.375	0.466	0.840	0.131	0.139	0.167	0.126	0.133	0.161	0.114	0.120	0.144
Obs.	14,028	14,028	14,028	12,035	12,035	12,035	9,267	9,267	9,267	6,957	6,957	6,957

Table XII
Performance: Cash Flow

This table reports results of the regressions of firm outcome variables on Big Five traits of CEOs with no personality data and controls measured at the end of the fiscal year t, unless noted otherwise. Big Five traits correspond to the predicted personality scores calculated as the *median* scores over all quarterly earnings conference calls up to (and including) the last call for the fiscal year t, unless noted otherwise. *Cash flow* equals cash from operations (OANCF or, if missing, computed using balance sheet method as in Klein and Marquardt (2006)) divided by lagged total assets (AT) in percentage points. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT). *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the book-to-market. Book equity is computed as in Cohen et al. (2003). *Net leverage* equals total debt (DLTT + DLC) minus cash and cash equivalents (CHE) divided by total assets (AT). Compustat data codes are included in parentheses. We exclude financial firms (SIC in 6000 - 6999) and utilities (SIC in 4900 - 4999) from this analysis. All variables are winsorized at the 1st and 99th percentiles. Big Five trait measures and control variables are scaled by the corresponding interquartile ranges, i.e., the difference between the 75th and 25th percentiles. The dependent variables are not scaled. Industry fixed effects are based on the 49 Fama-French industries. Robust standard errors clustered by the 49 Fama-French industries are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Cash flow			ΔCash flow$_{t+1}$ Big Five measured at t			ΔCash flow$_{t+1}$ Big Five measured at $t-1$			ΔCash flow$_{t+1}$ Big Five measured at $t-2$		
Agreeableness	0.712^{**}	0.702^{***}	-0.246	0.272^{*}	0.293^{**}	0.076	0.304	0.326^{*}	0.170	0.254	0.286	0.140
	(0.343)	(0.245)	(0.162)	(0.156)	(0.135)	(0.156)	(0.212)	(0.192)	(0.202)	(0.199)	(0.202)	(0.164)
Conscientiousness	-0.825^{***}	-0.612^{***}	-0.192	-0.192^{**}	-0.157^{**}	-0.192^{**}	-0.097	-0.063	-0.139	-0.013	0.023	-0.087
	(0.182)	(0.200)	(0.160)	(0.084)	(0.079)	(0.082)	(0.102)	(0.095)	(0.094)	(0.122)	(0.128)	(0.108)
Extraversion	-1.638^{***}	-1.090^{***}	-0.016	-0.751^{***}	-0.673^{***}	-0.473^{***}	-0.487^{***}	-0.405^{***}	-0.268^{*}	-0.495^{***}	-0.442^{***}	-0.308^{**}
	(0.491)	(0.324)	(0.111)	(0.173)	(0.162)	(0.159)	(0.139)	(0.133)	(0.139)	(0.186)	(0.162)	(0.151)
Neuroticism	-0.364	-0.392	-0.261^{**}	-0.223^{*}	-0.235^{*}	-0.306^{**}	0.052	0.047	-0.027	0.047	0.058	0.032
	(0.364)	(0.332)	(0.131)	(0.125)	(0.130)	(0.135)	(0.117)	(0.116)	(0.134)	(0.147)	(0.155)	(0.148)
Openness high	-2.682^{**}	-0.996^{**}	-0.087	-0.682^{***}	-0.350^{***}	-0.152^{*}	-0.615^{***}	-0.301^{***}	-0.156	-0.566^{**}	-0.282^{**}	-0.135
	(1.302)	(0.392)	(0.154)	(0.230)	(0.108)	(0.087)	(0.186)	(0.086)	(0.118)	(0.246)	(0.137)	(0.136)
Size			0.903^{***}			0.246			0.046			-0.075
			(0.330)			(0.247)			(0.220)			(0.257)
Book-to-market			0.148			0.035			0.012			0.115
			(0.164)			(0.131)			(0.159)			(0.188)
Cash flow				-3.013^{***}	-3.381^{***}	-6.614^{***}	-3.023^{***}	-3.391^{***}	-6.578^{***}	-2.974^{***}	-3.314^{***}	-6.499^{***}
				(0.359)	(0.311)	(0.389)	(0.416)	(0.385)	(0.477)	(0.436)	(0.417)	(0.545)
Return on assets			9.287^{***}			4.079^{***}			4.071^{***}			4.131^{***}
			(0.360)			(0.444)			(0.465)			(0.435)
Net leverage			-2.193^{***}			0.229			0.251			0.069
			(0.368)			(0.330)			(0.337)			(0.291)
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.R^2	0.331	0.420	0.817	0.157	0.172	0.254	0.154	0.168	0.251	0.141	0.152	0.236
Obs.	14,028	14,028	14,028	12,035	12,035	12,035	9,267	9,267	9,267	6,957	6,957	6,957