CEO Personality and Firm Policies

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March 24, 2015

ABSTRACT

We use linguistic features extracted from conferences calls and statistical learning techniques to develop a measure of CEO personality in terms of Big Five factors: Extraversion (versus Introversion), Emotional Stability (versus Neuroticism), Agreeableness, Conscientiousness, and Openness to Experience. We find that our linguistic measures have strong out-of-sample classification performance and are stable over time, consistent with them measuring individual traits that are relatively persistent. We find that our measures of the Big Five personality factors are associated with organizational strategy choices, investment and financial policy, and firm performance.

PRELIMINARY DRAFT

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Recent research in finance and economics has explored the relations between executive traits and firm policies. One stream of research, led by Bertrand and Schoar (2003), has used manager fixed effects to discern the effect that managerial "style" has on firm outcomes without a limited focus on specific executive characteristics. Another stream of research has taken a more direct approach to executive characteristics, with a focus on risk aversion, time preference, ability, and optimism or overconfidence. For example, Malmendier et al. (2005) and Malmendier and Tate (2008) study the relation between overconfidence, investment-cash flow sensitivities, and merger activity. Graham et al. (2013) provide evidence that CEO behavior is related to measures of overconfidence, optimism, and risk aversion.

At the same time, psychology research has somewhat converged on a model that posits the existence of five personality factors, which provide a basis for more thoroughgoing analysis of the relations between executive traits and firm outcomes. Personality psychology views traits as the "relatively enduring patterns of thoughts, feelings and behaviors that reflect the tendency to respond in certain ways in certain circumstances." (Roberts, 2009, p.140). Psychologists have examined many different ways of measuring personality traits, but much research and practice has converged on the Big Five traits, which are derived from factor analysis and were originally related to lexical analysis of terms used to describe personal traits (Goldberg, 1993).[1]

One challenge to examining the relation between executives' personality traits and firm outcomes is that measurement of such traits typically involves administration of costly instruments or detailed interviews, which is unlikely to be feasible even if executives were in principle willing to share such information with researchers. In this paper, we leverage—and link—two data sets to create a measure of executive personality in terms of Big Five traits. The first data set is detailed information on personalities. We obtain such data on 84 CEOs from two sources: O'Reilly et al. (2014) and Kaplan, Klebanov, and Sorensen (2012). O'Reilly et al. (2014) collected data from surveys of 246 current employees at the U.S. high-tech firms who completed the Ten-Item Personality Inventory (Gosling, Rentfrow, and Swann, 2003) for the CEOs at their respective firms. The Kaplan, Klebanov, and Sorensen (2012) sample covers CEOs of public firms and is based on data

[1]While the psychology literature often refers to these as Big Five factors or dimensions, to emphasize their relation with individual traits, we use these as Big Five traits.

provided by the management assessment firm ghSMART. ghSMART data conducts lengthy interviews with CEO candidates involved in buyout and venture capital transactions and prepares 20-40-page reports which assign a letter grade to each CEO on each of 30 characteristics. We map these characteristics into Big Five dimensions.[2]

The second data set we employ is ThomsonReuters StreetEvents, which provides transcripts of corporate conference calls. StreetEvents provides for each utterance on a call the following data: the name, employer, and title of the speaker who made it (title is generally "analyst" for speakers not working for the subject firm), whether the utterance was part of the corporate presentation or the question-and-answer portion of the call, and the position of the utterance relative to other utterances. We code the StreetEvent data into linguistic features (e.g., "proportion of words over 6 letters," or "proportion of words expressing anger") drawn from prior research on personality and linguistics.

We use linguistic features, including those identified in prior research on language and personality, along with the personality data from O'Reilly et al. (2014) and Kaplan, Klebanov, and Sorensen (2012), as training data for a statistical learning algorithm that seeks to classify CEOs in terms of personality traits. We follow approaches from the statistics literature to enhance the out-of-sample classification ability of our models (Fawcett, 2006). We apply the lasso approach to logit regressions of personality traits on linguistic features to identify candidate feature sets for evaluation and follow approaches from statistical learning (Friedman et al., 2010) to select a single model for each Big Five trait. For example, our final model for unconscientiousness uses 19 features (7 from the presentation portion of the call and 12 from the Q&A portion). This model assigns a higher probability that an individual CEO is unconscientious if he or she uses more first person singular pronouns (e.g., "I") and fewer first person plural pronouns (e.g., "we"). In cross-validation analyses, we find that the classification performance of our models is excellent, with AUC statistics between 79% and 96% for the five traits.

Having developed a model for each Big Five trait, we then use data on linguistic features of CEOs' utterances on conference calls to extend our measure of personality to 65,759 conference-

[2]Table I contains our mapping between ghSMART categories and Big Five dimensions and Table I in Kaplan, Klebanov, and Sorensen (2012, pp.976–978) provides a detailed description of the ghSMART characteristics.

call-level observations on 4,372 CEOs for whom we do not have personality data. We then examine relations between this measure of personality and a variety of firm policies and outcomes. The policies and outcomes we consider follow Bertrand and Schoar (2003), who examine the effect of managerial style of firm policies.

While in personality psychology, the "most widely accepted taxonomy of personality traits is the Big Five" (Almlund et al., 2011, p.48), its use in research in economics and finance has been limited. In particular, research in behavioral finance has mostly focused on psychological dimensions such as ability, optimism, confidence, risk aversion, and time preference. Therefore, to relate our findings to prior research in economics and finance, we draw on prior research (primarily in psychology) to map these dimensions to the Big Five traits that we study. Having done so, we find that a number of our findings are consistent with results from the conjunction of prior research in psychology and behavioral finance. For instance, we find that disagreeableness and introversion are negatively associated with R&D intensity, consistent with prior research on the effect of optimism and overconfidence, and we find that introversion is negatively associated with net stock issuance, consistent with prior research on the effect of overconfidence. Consistent with prior research on risk aversion, we find that disagreeableness and neuroticism are negatively associated with measures of firm volatility.

While a number of our findings are consistent with predictions derived from prior research in economics, finance, and psychology, others seem less so. For example, we find positive associations between introversion and disagreeableness and operating performance and between introversion and growth. We believe that plausible explanations exist for these findings. First, the mapping provided by research in psychology from the traits studies in prior research in behavioral finance (such as risk aversion, ability, optimism, and overconfidence) to Big Five traits is likely imperfect and incomplete. As the Big Five traits we study are plausibly broader and more complete measures of CEO personality, it seems possible that some associations we find are driven by relations not yet explored in finance and economics. Additionally, the implications of executive traits such as overconfidence for some firm policies, such as financial policy, are unclear and our proxies for these policies are imperfect. In summary, our results suggest that further work is

necessary to explore the possibility that our measures of personality are capturing executive traits beyond risk aversion, ability, optimism, and overconfidence that also have implications for firm policies.

The paper proceeds as follows. Section I describes prior research on personality. Section II describes the data used in our study. Section III describes how we develop and evaluate our measures of CEO personality. Section IV studies the relationship between CEO personality and firm policies. Section V concludes.

I. Prior literature

The study of personality is a major sub-discipline of psychology. An important perspective in personality psychology is based on traits, which can be viewed as persistent styles of individual behavior. Research has shown that personality traits have a significant hereditary component, are generally stable or slowly changing over an individual's lifetime, and predict important life outcomes.

A. The Big Five factor structure

An early perspective on understanding personality was the lexical hypothesis, which holds that "the most important individual differences in human transactions will come be encoded as single terms in some or all of the world's languages" (Goldberg, 1993, p.26). Early studies used personality-related terms from standard dictionaries and asked raters to describe people they knew (e.g. Thurstone, 1934). From these long lists, many researchers have found that they can be reduced to five factors (see Goldberg, 1993, p.27) listed in Table I. The precise content and labels applied to the five dimensions varies by study. A frequently used nomenclature has them as follows: Extraversion (versus Introversion), Emotional Stability (versus Neuroticism), Agreeableness, Conscientiousness, and High Openness to Experience.

B. *Personality in economics*

While in personality psychology, the "most widely accepted taxonomy of personality traits is the Big Five" (Almlund et al., 2011, p.48), its use in research in economics and finance has been limited. There are few papers that have studied economic consequences of personality measured using the Big Five traits. Most of these studies 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). Instead, research has mostly focused on narrower psychological dimensions such as ability, optimism, confidence, risk aversion, and time preference. Therefore, in interpreting prior research in economics and finance in terms of the Big Five, it is necessary to link the dimensions considered to the Big Five traits.

One area of focus has been risk aversion (e.g., Borghans et al., 2009, Dohmen et al., 2010, Anderson et al., 2011) and time preference (e.g., Daly et al., 2009, Dohmen et al., 2010, Anderson et al., 2011). Risk aversion is negatively associated with disagreeableness (e.g., Borghans et al., 2009) and positively associated with neuroticism (e.g., Borghans et al., 2009, Anderson et al., 2011). Daly et al. (2009) report that conscientious individuals are more patient with respect to monetary outcomes, and extraverted individuals are less patient. Patience is also positively correlated with openness (e.g., Anderson et al., 2011). At the same time, Dohmen et al. (2010) find no association between personality traits and risk aversion or impatience. Another area of focus has been optimism (e.g., Sharpe et al., 2011) and overconfidence (e.g., Schaefer et al., 2004). Neuroticism and introversion tend to have the strongest negative associations with optimism, with disagreeableness and unconscientiousness explaining the residual variance (Sharpe et al., 2011). People are generally overconfident when assessing their performance (e.g., Budescu et al., 1997). Schaefer et al. (2004) find that extraversion is the strongest predictor of overconfidence.

Some research has compared the explanatory power of personality traits with that of cognitive ability. In terms of educational outcomes, conscientiousness is the best predictor of overall attainment and achievement with openness to experience predicting finer measures such as course difficulty (see Almlund et al., 2011, Vedel, 2014). Conscientiousness is comparable to SAT scores in its ability to predict college grades. Borghans et al. (2008) find that individual performance on

cognitive tests depends on non-cognitive skills, and argue that the latter skills might affect effort. For instance, for individuals high on emotional stability and conscientiousness, monetary rewards have little effect on the time spent on a test. As summarized by Almlund et al. (2011), conscientiousness also best predicts overall job performance, although it is a weaker predictor compared to the measures of intelligence. At the same time, the predictive power of intelligence decreases with job complexity, whereas conscientiousness continues to predict job performance across broader range of occupations, including managers (e.g., see meta-analysis in Barrick and Mount, 1991).

C. Studying personality through language

Our paper extends a stream of research that examines the relations between personality and language. In an early study, Pennebaker and King (1999) apply 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 find that these demonstrate internal consistency and out-of-sample classification power. They conclude "that linguistic style is an independent and meaningful way of exploring personality."

Subsequent research has explored the relations between personality and linguistic style in a variety of settings, such as recorded language (Mehl et al., 2006, Mairesse et al., 2007), corpus of e-mail messages (Oberlander and Gill, 2006), essays (Mairesse et al., 2007), self-narratives (Hirsh and Peterson, 2009), and text messages (Holtgraves, 2011). For instance, Mehl et al. (2006) follow 96 participants over two days using electronic recorders. They find evidence of Big Five traits manifesting in features of recorded language usage (e.g., extraverts talking more, but with shorter words). Mairesse et al. (2007) use two corpora, the first corpus contains 2,479 essays from psychology students (1.9 million words); the second is recorded speech from 96 students (97,468 words). They use word categories from LIWC, as well as features from the MRC Psycholinguistic database, utterance type (command, question, etc.), and voice features. They find that linguistic markers are helpful in classifying participants in terms of Big Five personality traits.

Some studies have also examined data from the social networks, such as Twitter and various blogs. Qiu et al. (2012) examine the tweets of 142 participants to study how Big Five personality

traits are associated with linguistic markets 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 the 576 personality survey respondents to derive mappings from LIWC categories and individual words to Big Five traits. Overall, a number of studies finds significant associations between certain LIWC categories and Big Five traits (see also Hirsh and Peterson, 2009, Holtgraves, 2011). Finally, 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.

II. Data

A. Conference calls

ThomsonReuters's StreetEvents provides conference call transcripts. We parse these data into individual utterances. For each utterance, we have data on its position relative to other utterances, the name of the speaker who made it, his or her employer and title (generally "analyst" for speakers not working for the subject firm), and whether the utterance was part of the corporate presentation or question-and-answer (Q&A) portion of the call.

StreetEvents provides us with linguistic data on 4,456 CEOs participating in 66,979 earnings conference calls. For each CEO-call observation, we require a minimum of 150 words in both presentation and Q&A portion of a call. We consider 34 linguistic features extracted from conference calls as described in Section III and Table VI.

B. CEO personality

Our data on personality for 111 CEOs come from two sources: O'Reilly et al. (2014) and Kaplan et al. (2012). Each of the data sources relies on observers' assessments, the accuracy of which has been shown to dominate that of self-assessments (e.g., Funder, 2012, Mount et al., 1994). We start with the personality data on 29 CEOs of U.S. high-tech firms from O'Reilly et al. (2014) and 82

CEOs of public firms from Kaplan et al. (2012) whom we are able to match to data in StreetEvents.

O'Reilly et al. (2014) collected these data from 246 current employees who completed the Ten-Item Personality Inventory (Gosling et al., 2003) for the CEOs at their respective firms. Each of the Big Five personality dimensions has two polar traits (e.g., extraversion v. introversion). The O'Reilly et al. (2014) data are coded on a Likert scale ranging from "disagree strongly" (1) to "agree strongly" (7) for each of the five traits corresponding to one end of the respective Big Five dimension. For each dimension, we code an indicator variable equal to one if the CEO's rating is closer to the trait that is less common in our sample (i.e., introversion, neuroticism, disagreeableness, unconscientiousness, and low openness to experience).

The data from Kaplan et al. (2012) is provided by the management assessment firm ghSMART. ghSMART conducts 4-hour interviews with candidates for CEO positions at firms involved in buyout and venture capital transactions. These interviews result in 20- to 40-page reports in which each CEO is assigned a letter grade for each of 30 characteristics. Although the Big Five traits are not assessed in these interviews, we map these characteristics into Big Five dimensions as described in Table I.[3] We average the letter grades of characteristics that correspond to the same Big Five dimension and code indicator variables for each CEO for each of the Big Five traits using a cutoff that yields a distribution that aligns with that for the O'Reilly et al. (2012) data an overall basis.

We require an executive to be a CEO at the time of a call and that he has at least 150 words in both presentation and Q&A portions of a call. After imposing these filters, we are left with 84 CEOs for whom we have personality data and data in StreetEvents. For each CEO, we have data on earnings conference calls for between one and 46 calls over the period from 2001 to early 2013 giving us a total of 1,220 earnings conference calls. Table II provides descriptive statistics for these CEOs. The proportion of the Big Five traits among individual CEOs and CEO-calls is almost identical. The most frequent trait is disagreeable and the least frequent trait is unconscientious. About 30% of CEOs are disagreeable, followed by about 20% of CEOs who are neurotic or open low, about 15% on introverts, and 5% of unconscientious.

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

III. Measuring personality

A. Feature selection

We use the sample of CEOs for which we have data on both Big Five personality traits and on conference calls to estimate personality models. We further use these models and conference call narratives to classify all CEOs in terms of the Big Five traits.

A.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 the Linguistic Inquiry and Word Count (LIWC) described in (Pennebaker and King, 1999). According 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 by adding word categories from Larcker and Zakolyukina (2012) and four categories constructed for this paper. These additional categories modify the existing LIWC categories by grouping them into smaller subcategories, such as extreme and non-extreme positive emotion words. They also add dimensions which were hypothesised to be related to the Big Five traits by prior research, but which are missing from LIWC, such as 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 more features (e.g., use 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 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." Given that, following prior research on personality, we have chosen a much smaller feature set, the issue of high-dimensionality is not as significant in our approach.

Models that use a much 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.[4] 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 considered 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.

Given the 34 linguistic features we identify, one approach to model-fitting would be to include

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

all features in a logistic regression of the form:

$$\mathbb{P}(y_i = 1|X_i) = \frac{1}{1 + e^{-\alpha - X_i'\beta}}, \tag{1}$$

where y_i is one of the Big Five trait indicators for executive i and X_i is a vector of linguistic features for executive i. This approach, which we label the *All Features* approach, can, based on a given CEO's linguistic features, be used to estimate a probability that a CEO has a particular Big Five trait. Accordingly, one can choose a probability cutoff to classify a CEO as having or not having the particular trait. For instance, for a model with the introversion indicator as the dependent variable, a CEO with an estimated probability above the cutoff would be classified as an introvert and a CEO with an estimated probability below the cutoff would be classified as an extravert.[5]

A.2. Feature selection: General approach

First, *All Features* approach is likely to result in overfitting and worsen its out-of-sample classification performance (Hastie et al., 2009). To narrow down our list of predictors, we use the *lasso* variable selection technique (Tibshirani, 1996).

Because we are primarily concerned with the out-of-sample classification ability of our models, we follow the statistics literature in using the area under the ROC curve (AUC) statistic as the primary criterion for selecting features for inclusion (Fawcett, 2006). The ROC curve plots true positive rates (e.g., the proportion of introverts that are correctly classified) and false positive rates (e.g., the proportion of extraverts that are incorrectly classified as introverts) for all possible values of the cutoffs from zero to one. The AUC statistic for the introversion indicator corresponds to the probability that a randomly chosen introvert would be assigned a higher likelihood of being an introvert than a randomly chosen extravert. A higher AUC of a classification model implies better performance. A perfect classifier has an AUC of 100% and a random classifier has an AUC of 50%.

To identify candidate feature sets for evaluation, we use the lasso approach, which for logistic

[5]Note that in none of analyses do we fix a cutoff; our measures of Big Five traits are expressed as the estimated probability.

regression, maximizes the penalized log-likelihood:

$$\max_{(\alpha,\beta)} \left[\frac{1}{N} \sum_{i=1}^{N} \left\{ y_i \ln F(\alpha + X_i'\beta) + (1 - y_i) \ln(1 - F(\alpha + X_i'\beta)) \right\} - \lambda \sum_{j=1}^{p} |\beta_j| \right], \tag{2}$$

where $F(\cdot)$ is the logistic function $F(z) = \frac{1}{1+e^{-z}}$; (α, β) is a $1 \times (p+1)$ vector of coefficients; and λ is the lasso penalty parameter (Friedman, Hastie, and Tibshirani, 2010).[6] In contrast to ridge regression, lasso not only shrinks coefficients as the penalty parameter increases, but also sets some coefficients to zero. In other words, the lasso approach will yield a subset of predictors for inclusion in the model. As λ increases, the lasso approach will generally select a smaller set of features for inclusion.

For each candidate value of λ, we estimate the AUC statistic using 5-fold cross-validation (Efron and Tibshirani, 1993, Witten and Frank, 2005, Hastie et al., 2009). Specifically, we split the data randomly into five equal samples (*folds*) in a way that preserves the fraction of a given personality trait in each fold as in the original sample. We consider each of the five folds in turn as a validation sample, using the data for the remaining four folds to estimate the model (i.e., as the training sample). We repeat this procedure 20 times to yield 100 (5×20) estimates of the AUC statistic for each Big Five trait and candidate value of λ.

One approach to feature selection, which we label *Highest AUC* approach, is to retain the model (i.e., the λ and set of features) that has the highest estimated AUC. However, because the AUC statistics are estimated with noise and the cross-validation provides us with the estimate of the standard error, we follow the approach of Friedman et al. (2010), by focusing on the model that has an AUC statistic within one standard error of the AUC of the *Highest AUC* model and, emphasizing parsimony, selecting the model with the smallest number of features from these models; we label this model the *Final Model*.

[6] We use the **glment** package by Friedman, Hastie, and Tibshirani (2010) to estimate lasso in R (R Core Team, 2015).

A.3. Results

Having chosen parsimonious sets of linguistic features for each of the Big Five dimensions, we estimate logistic regressions using these features and compare the AUCs from 5-fold cross-validation repeated 20 times for models which include all features (*All features*) and models derived from the *Highest AUC* and *Final Model* approaches described above.

Figure 1 plots the ROC curves for these models. For each trait, the *All Features* model has an ROC curve close to the diagonal line, which is the ROC curve of randomly guessing. In contrast, the ROC curves for the *Final Model* approach are noticeably better than those of the random classifier and generally better (albeit statistically indistinguishable) from those for the *Highest AUC* approach.[7]

Table V summarizes the classification performance of our models. The diagonal elements are the AUC measures for each model, while the t-statistics below relate to differences between the AUC of each model and that of a random guess (i.e., AUC = 50%). Each off-diagonal element equals the difference between the AUC measure of the model in the column and that of the model in the row, with the t-statistics for the difference reported below. Statistical significance is estimated based on corrected re-sampled t-tests (e.g., Nadeau and Bengio, 2003, Witten and Frank, 2005).[8]

The out-of-sample classification performance of the *Highest AUC* and *Final Model* specifications are similar and significantly better than that of a random classifier. The *Final Model* AUCs range from 79% for *Disagreeable* to 96% for *Unconscientious*, which is significantly better than the 50% corresponding to a random guess.

[7] Because the logistic regressions we estimate do not attenuate the coefficients in the way that the lasso approach does, the AUC estimates here may differ from those of the lasso estimates above.

[8] For cross-validation, the standard t-statistic is inappropriate because the training samples overlap in a single cross-validation run. The corrected re-sampled t-statistic is

$$t = \frac{\overline{d}}{\sqrt{\left(\frac{1}{k} + \frac{n_2}{n_1}\right)\hat{\sigma}_d^2}},$$

where d is the paired difference in a performance measure (in our case, the AUC), k is the total number of cross-validation runs (in our case, $k = 100$), n_1 is the number of observations used for training, and n_2 is the number of observations used for testing (in our case, $n_2/n_1 = 1/4$).

B. Relation between features and personality

We report the estimates of the logistic regressions for our final models in Table VI. The estimated models generally differ across the Big Five traits, consistent with their interpretation as personality *factors* (i.e., in principle, they are largely orthogonal to each other).

In the following discussion, we highlight some features of the fitted *Final Model* specifications and relate these to prior research on the relation between language features and personality. In discussing our results, we note that not all of the linguistic features selected by the lasso are statistically significant. As discussed in Shmueli (2010), the statistical significance of regression coefficients plays little or no role in assessing the out-of-sample predictive performance of a model. Specifically, a variable that is not significantly associated with an outcome in a regression 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. Second, the context that we study—corporate earnings conference calls—is arguably very different from those studied in prior research, which has examined 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), and text messages (Holtgraves, 2011). One advantage of our setting may be 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, hence less revealing of personality. Third, the goal of our study is to classify CEOs' personalities 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.

B.1. Introversion

Features that are selected for introversion include anger, which has a positive association in the presentation portion of the call. This is consistent with Holtgraves (2011), who also finds a positive association between anger and introversion. However, the estimated coefficient for the Q&A portion of the call is negative. In contrast to Holtgraves (2011) and Hirsh and Peterson (2009), which report positive associations between anxiety and introversion, we find that the association is negative (albeit insignificant). While Qiu et al. (2012) find that introverts assent more than extraverts, we find a negative association between assent and introversion. Oberlander and Gill (2006) argue that introverts use more personal pronouns than extraverts, which is consistent with the associations we document for both portions of the call. However, these findings are inconsistent with Holtgraves (2011) and Yarkoni (2010), who find negative associations.

Like Holtgraves (2011), we find no association between positive emotion words and introversion. Pennebaker and King (1999) and Mairesse et al. (2007) report a positive association between introversion and use of negations. This is consistent with our finding for the presentation portion of the call, but not with our finding for the Q&A portion. Similar to Oberlander and Gill (2004), we find a negative association between vague quantifiers and introversion in the presentation portion of the call.

Yarkoni (2010) also reports a positive association between inhibition and introversion. Pennebaker and King (1999), Mairesse et al. (2007), and Yarkoni (2010) report that introverts use less inclusive related words. In addition, Pennebaker and King (1999) find that introverts use more exclusive related words. Mairesse et al. (2007) and Qiu et al. (2012) report a positive association between hesitation and introversion. While prior research suggests that introverts are less talkative than extraverts (Mehl et al., 2006, Oberlander and Gill, 2004), we find that they talk more, and use more words, than extraverts in the presentation portion of the call, but speak less frequently in the Q&A portion of the call. This seems consistent with introverts preferring to convey more during the portion of the call where there is less interaction with others. While Oberlander and Gill (2006) find that introverts also use fewer conjunctions, we find a negative association in the presentation portion of the call, and a positive on in the Q&A portion.

B.2. Neuroticism

Like Pennebaker and King (1999), Mairesse et al. (2007), and Yarkoni (2010), we find a positive association between the use of first-person singular pronouns. Costa and McCrae (1980) suggest that neurotics' general emotionality, impulsivity, fear, and anger predisposes them towards extreme negative emotion. Pennebaker and King (1999), Holtgraves (2011), Hirsh and Peterson (2009), Mairesse et al. (2007), Costa and McCrae (1980), Yarkoni (2010) find a positive association between extreme negative emotion and neuroticism. Consistent with this, our *Final Model* uses this feature from the Q&A portion of the call. Hirsh and Peterson (2009), Mairesse et al. (2007), and Yarkoni (2010) find a positive correlation between anger, anxiety, and sadness with neurotics, consistent with our results for the anger, but inconsistent with our finding for anxiety. Mairesse et al. (2007) and Pennebaker and King (1999) report a negative correlation between positive emotion words and neurotics. Our results are mixed, with the feature being used, but with different signs, in both portions of the call.

While Yarkoni (2010) finds a positive association between neuroticism and both tentativeness and certainty, we find a strong negative relation between tentativeness and neuroticism. Neurotics use more filled pauses when talking because they are more apprehensive (Mairesse and Walker, 2010), consistent with our *Final Model*. Like Mairesse and Walker (2010), we find a positive association between hesitation and neuroticism.

Mehl et al. (2006) report a negative association between the number of words spoken and neuroticism, whereas Mairesse et al. (2007) report a positive association between the number of words spoken and neuroticism. Our model is more consistent with the latter paper. While Oberlander and Gill (2006) and Qiu et al. (2012) report a positive correlation between the use of conjunctions and neuroticism, we find a negative association.

B.3. Disagreeable

While prior research (Yarkoni, 2010, Mehl et al., 2006, Pennebaker and King, 1999, Mairesse et al., 2007) finds that disagreeable individuals use fewer first person pronouns, we find that they use more. But, we do confirm prior research (Hirsh and Peterson, 2009, Holtgraves, 2011, Mairesse

et al., 2007, Yarkoni, 2010) in finding that disagreeable individuals show more anger in their choice of words. Pennebaker and King (1999), Holtgraves (2011), Mairesse et al. (2007), and Yarkoni (2010) find a positive association between use of negative emotion words and disagreeableness individuals, consistent with our Final Model, although the relation we document is not statistically significant.

Hirsh and Peterson (2009) report a negative association between certainty and disagreeable, which we confirm most strongly in the presentation portion of the call. While Yarkoni (2010) finds a positive association between causation and disagreeable, we find a negative one that is statistically significant in both portions of the call. We observe that disagreeable individuals appear to speak more often, use longer sentences and more words than agreeable individuals.

B.4. Unconscientious

Unsurprisingly, there are very few unconscientious CEOs in our sample, with just 4 of the 84 CEOs being coded as unconscientious (representing 57 of 1,220 CEO-call-level observations). Our Final Model for unconscientiousness uses 19 features, noticeably fewer than the models of the other four traits, yet has a noticeably higher AUC (97.44%). We find that positive emotion words, words spoken, words $>$ 6 letters, assent, and insight have significant predictive power. While we confirm Mairesse et al. (2007) and Yarkoni (2010), who report a positive association between assent and unconscientious, most of the features with predictive power in our model either have not been examined or have no support in prior empirical research. Nonetheless, some the coefficients are intuitively plausible. For example, we find that unconscientious individuals used fewer, and shorter, words in the Q&A portion of the conference call. They also appear to use more first person plural pronouns, and fewer first person singular pronouns, in the presentation portion of the call, consistent with preparation of these remarks being more willingly shared by unconscientious individuals.

B.5. Open Low

Like Pennebaker and King (1999), Mairesse et al. (2007), Yarkoni (2010), we find a positive association between first-person singular pronouns and low openness to experience (open low). Consistent with Yarkoni (2010) and Qiu et al. (2012), we a find positive association between extreme positive emotion words and open low. While Yarkoni (2010) finds a negative association between inclusive and open low, we find a positive association, and a negative association between exclusive and open low. Similar to Pennebaker and King (1999) and Mairesse et al. (2007), we find a negative association between words greater than 6 letters and open low. Mairesse et al. (2007) and Yarkoni (2010) report a positive association between numbers and open low. Qiu et al. (2012), Pennebaker and King (1999), Mairesse et al. (2007), Yarkoni (2010) report negative associations between articles and open low. Our *Final Model* is consistent, though the effect is small and not statistically significant.

C. Calculating the personality measure

We use our fitted Big Five personality models and conference calls to estimate executive traits for the full sample of CEOs drawn from StreetEvents. We standardize all linguistic features from the presentation and Q&A portions of the call in the same way we standardize them for the CEOs with personality data. To construct a firm-year measure of CEO personality, we use the mean of estimates from the associated quarterly calls, which we take to be those falling into the window that starts three months after the end of the prior fiscal year and ends three months after the current fiscal year. For instance, for the fiscal year that ends on December 31, 2010, we consider the calls in the window that starts on April 1, 2010 and ends on March 31, 2011. This heuristic allows for the fourth-quarter conference calls to be held after the end of the fiscal year. Table VI reports descriptive statistics for the linguistic features for the samples of CEOs with and without personality data. There are 65,759 calls for CEOs without personality data. As discussed above, most of our word categories are from LIWC by Pennebaker et al. (2007), while other categories are from Larcker and Zakolyukina (2012), and four categories are constructed for this paper are in Table IV.

Descriptive statistics of linguistic features are very close in both samples of CEOs. The most frequently used word categories are inclusive words (e.g., *each*, *including*), first person plural pronouns (e.g., *we*, *us*, *our*), nonextreme 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*)—are the most rare in both portions of the call. The frequencies of some categories in the presentation and Q&A portions differ. For instance, frequency of the first person singular pronouns (e.g., *I*, *me, mine*), negations (e.g., *no, not, never*), asset words (e.g., *agree, OK, yes*), word categories in the certainty subcategory except for numbers, insight words (e.g., *admitting, analy**), discrepancy words (e.g., *besides, could*), exclusive words (e.g., *either, except, exclu**), hesitations and fillers, conjunctions (e.g., *although, and, as*), and adverbs (e.g., *about, absolutely*) are higher in the Q&A portion than in the presentation portion. This is consistent with an interactive nature of the Q&A portion.

On the other hand, frequencies of other word categories are lower in the Q&A portion than in the presentation portion. These are extreme positive emotion words (e.g., *fantastic, great*), numbers, causation words (e.g., *allow*, attribut*, based*), and words longer than six letters. This is, again, consistent with an interactive nature of the Q&A portion—fewer complex words—and the Q&A portion being less scripted compared to the presentation portion—fewer numbers and causal explanations. Less frequent use of extreme positive emotion words in the Q&A portion compared to the presentation portion is perhaps consistent with CEOs not being able to fully control the overall tone of the interactive portion.

D. CEO personality: Descriptive statistics

As we rely on statistical models to estimate CEOs' Big Five personality traits, these measures are unavoidably estimated with noise. While research in personality psychology shows that Big Five personality traits change over an individual's lifetime, they do so relatively slowly and changes are least in the middle adulthood (age 40-60) (e.g. Srivastava et al., 2003, Roberts and Mroczek, 2008). Therefore, we expect the true underlying personality to be relatively stable over our sample period because most CEOs fall into the late middle adulthood cohort, as the median

CEO is 55 years old with 5 years of tenure (Yim, 2013). For this reason, regardless of their out-of-sample predictive performance, these measures would capture CEO personality less credibly, if within-CEO variation exceeded between-CEO variability.

In Table VII, we compute the ratios of between-CEO mean-square error to within-CEO mean-square error for the raw 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 7.34 (4.74) for unconscientiousness and the highest ratio is 11.46 (6.85) for openness low for the quarterly (final) measures. These ratios are consistently lower for our final measures. Thus, after aggregation of our personality measure on an annual basis, variation in personality between CEOs is less pronounced than variation within CEOs.

Table VII also reports summary statistics for our final measures. For all Big Five traits, distributions are skewed to the right with the mean value being higher than the median value. The mean probability of a CEO to be introvert is 0.13, neurotic is 0.25, disagreeable is 0.33, unconscientious is 0.07, and open low is 0.18. We compare these results with the findings reported by Srivastava et al. (2003). The authors provide summary statistics for Big Five personality scores for the large sample of adults aged 21–60 collected from the Internet. Their sample includes $4,180$ individuals in the approximate age range for CEOs aged 50–60. After converting their raw scores to the fraction of maximum possible scores, their means of Big Five personality scores are 0.45 for introvert, 0.50 for neurotic, 0.26 for disagreeable, 0.28 for unconscientious, and 0.28 for openness low.[9] Compared to the Srivastava et al. (2003) sample, CEOs are on average less introverted, less neurotic, more disagreeable, less unconscientious, and are more open to experiences.

Table VIII reports means and standard deviations for our final personality measures by industry. We classify firms into 20 industries as in Moskowitz and Grinblatt (1999). The probability of a CEO being introverted is highest in apparel and the lowest in railroads industries. The probability of a CEO being neurotic is highest in petroleum and lowest in electrical equipment, chemical, and paper industries. The probability of a CEO being disagreeable is highest in petroleum and lowest in chemical industries. The probability of a CEO being unconscientious is highest in railroads and lowest in primary metals industries. Finally, the probability of a CEO having low openness to

[9]The Big Five metric has 1-to-5 scale. To convert it to 0-to-1 scale, we subtract 1 and divide by 4.

experience is highest in petroleum and lowest in primary metals industries.

The estimates of Big Five personality traits are correlated. Table IX presents these correlations. Pairwise correlations are positive across all traits. Consistent with the literature in personality psychology (e.g. Van der Linden et al., 2010), introversion is positively correlated with neuroticism, disagreeableness, unconscientiousness, openness low; neuroticism is positively correlated with disagreeableness, unconscientiousness, and openness low; disagreeableness is positively correlated with unconscientiousness and openness low; and unconscientiousness is positively correlated with openness low. Although, some of these pairwise correlations are insignificant in meta-analysis of prior research (Van der Linden et al., 2010). According to the multivariate regressions of each Big Five traits on others, there is no statistically significant association between introversion and neuroticism, whereas there is a statistically significant negative association between neuroticism and unconscientiousness.

IV. Firm policies

We examine the association between CEO personality and a number of firm policies and economic outcomes. The policies and outcomes we consider are generally modeled after Bertrand and Schoar (2003), who investigate the effect of managerial style on those. In our regressions, we include alternative permutations of controls and fixed effects: industry fixed effects only, industry and year fixed effects, and industry and year fixed effects with controls. We do not include firm fixed effects because our Big Five measures do not exhibit enough variation to survive in these specifications. Moreover, given the relative stability of personality in the middle adulthood, taking out firm fixed effects likely leaves us mostly with a measurement error in CEOs personality traits making these variables meaningless. In discussing our empirical results, we focus on the specification with industry and year fixed effects with controls for parsimony, but highlight differences in inferences, if any, that apply to the other specifications.

Similar to Bertrand and Schoar (2003), we include the following controls (Compustat data codes are included in parentheses). *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the natural logarithm of book-to-market. Book equity is computed as in Cohen

et al. (2003). *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) divided by lagged total assets (AT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). We winsorize all variables at the 1st and 99th percentiles and present their descriptive statistics in Table X. When estimating regressions, we standardize Big Five trait measures and control variables to have zero mean and unit variance. Because the Big Five measures are standardized, we can assess the economic magnitudes of their change directly from the regression coefficients. Note, though, that a one standard deviation change in a Big Five measure may not be a plausible change because the standard deviations of these measures exceed or very close to both their mean and median values (see Table VII).

An important qualification for our analyses is that CEOs are not randomly assigned to firms, making it difficult to tease out the causal explanations for the associations we document. It seems plausible that a CEO's personality affects the kind of firm that an executive chooses to work at, the interest of the firm in hiring the executive as a CEO, as well as the kinds of policies that the CEO pursues at the firm. Yet observational data make it difficult to convincingly distinguish these alternative explanations. However, it seems reasonable that these forces would tend to act in concert and that a reasonable interpretation of our results is that they are attributable to some combination of the three forces acting together. Specifically, if a CEO's personality makes leading a firm pursuing R&D investment more attractive to him or her, then it seems reasonable that such a CEO would also be more attractive to such a firm and, if appointed, such a CEO would also pursue R&D investment at a higher level than a CEO whose personality would disfavor R&D investment.

A. Organizational strategy

Table XI presents results for three firm policies: *Size*, *R&D intensity*, and *Fixed asset intensity*. With respect to firm size, some theoretical models predict that managers with higher ability will work for larger firms (e.g., Rosen, 1982, Gabaix and Landier, 2008). Consistent with this prediction, Adams et al. (2014) find that higher-caliber CEOs are assigned to larger firms and that

non-cognitive abilities are a better predictor of appointment as a CEO of a large firm than cognitive abilities. Given that the Big Five trait with the most robust link to non-cognitive ability is unconscientiousness, it is surprising that the association between this variable and firm size is weak. Only when firm and year fixed effects with controls are included, does *Unconscientious* have a statistically significant relation with size. A one standard deviation increase in *Unconscientious* is associated with a decrease in the firm's total assets by 5 percentage points ($t = -2.69$).[10] In contrast, *Neurotic* and *Disagreeable* are highly significant, albeit with opposite signs. A one standard deviation increase in *Neurotic* is associated with a 16 percentage -point decrease in the firm's total assets ($t = -5.28$) and a one standard deviation increase in *Disagreeable* is associated with a 22 percentage-point increase in the firm's total assets ($t = 7.33$).[11]

Prior research links low risk aversion to high disagreeableness and low neuroticism (e.g., Borghans et al., 2009, Anderson et al., 2011). Given our findings for disagreeableness and neuroticism, one explanation for their association with size is the underlying differences in risk aversion. In larger firms, incentives could be more important because CEO effort could be amplified by firm size in the same way as CEO talent is amplified by firm size in models by Rosen (1982) and Gabaix and Landier (2008). At the same time, agency theory suggests that lower risk aversion reduces the cost of incentivizing a CEO (e.g., Prendergast, 1999) and, thus, larger firms might prefer CEOs with lower risk aversion. Similarly, Kihlstrom and Laffont (1979) provide a model in which less risk-averse entrepreneurs run larger firms in equilibrium. The coefficients on *Neurotic* and *Disagreeable* are consistent with these explanations.

Coles et al. (2006) argue that increasing investment in R&D and decreasing investment in PP&E increases risk and, thus, should be negatively associated with CEO risk aversion. However, there is no statistically significant association between *Neurotic* and either policy variable, and *Disagreeable* is only associated with R&D intensity, but the negative coefficient is inconsistent with *Disagreeable* proxying for risk tolerance. A one standard deviation increase in *Disagreeable* is associated with a 1.1 percentage-point ($t = -2.80$) decrease in R&D intensity, which has a mean

[10] We estimate linear regressions where *Size* equals the natural logarithm of total assets, in 2013 dollars. In this specification, the coefficient on an independent variable β is associated with the percentage change in the dependent variable equal $\exp^{\beta} - 1$, i.e., $\exp^{-0.05} - 1 \approx -0.05$.

[11] These effects equal $\exp^{-0.174} - 1 \approx -0.160$ for *Neurotic* and $\exp^{0.196} - 1 \approx 0.217$ for *Disagreeable*.

of 10 percentage points. This association is about two times smaller than that of size with R&D intensity.

In the models of Giat et al. (2009) and Galasso and Simcoe (2011), optimistic or overconfident CEOs are more likely to pursue innovation and greater risky investment. Empirical results in Galasso and Simcoe (2011) are consistent these predictions. Prior research suggests that disagreeableness, introversion, and unconscientiousness are negatively related to optimism (Sharpe et al., 2011) and that introversion is also negatively related to overconfidence (Schaefer et al., 2004). Thus the predictions of Giat et al. (2009) and Galasso and Simcoe (2011) are consistent with the negative coefficients on *Disagreeable* and *Introvert* in the R&D intensity regressions and the positive coefficients on *Unconscientious* in the fixed asset intensity regressions. In the R&D intensity regression when firm and year fixed effects with controls are included, the coefficient on *Introvert* has similar magnitude to the coefficient on *Disagreeable* ($t = -4.03$). In the fixed asset intensity regression when firm and year fixed effects with controls are included, a one standard deviation increase in *Unconscientious* is associated with a 1.1 percentage-point increase in fixed asset intensity ($t = 4.11$), which has a mean of 22.4%.

B. Investment and financial policy

Table XII presents results for six firm policies related to investment and financing: *Investment*, *Leverage*, *Interest coverage*, *Cash holdings*, *Dividend payout*, and *Net stock issuance*. We exclude financial firms (SIC in 6000 - 6999) and utilities (SIC in 4900 - 4999) because of the difficulties of interpreting these variables for them.

Research in behavioral corporate finance on investment (e.g., Gervais, 2010) and financial policy (e.g., Gider and Hackbarth, 2010, Ben-David, 2010) has focused on the effects of overconfidence, risk aversion, and optimism. Overall, it suggests that the behavior of overconfident and optimistic CEOs is similar along several dimensions such as investment, debt financing, and, to the lesser extent, equity issuance. For instance, while overconfidence may counteract the effect of risk aversion by reducing investment inefficiencies, it may also trigger value-destroying overinvestment (Goel and Thakor, 2008). Similarly, optimistic CEOs may overinvest because they overvalue

their investment projects (Heaton, 2002). Empirical results support these arguments. There is a positive association between CEO overconfidence and the sensitivity of investment to cash flows (Malmendier and Tate, 2005). Likewise, there is a positive association between miscalibration—one manifestation of overconfidence—and the level of investment (Ben-David et al., 2013).

Furthermore, overconfident or optimistic CEOs may differ from rational CEOs with respect to financial policy. For instance, they may choose higher debt levels (e.g. Hackbarth, 2009, Ben-David et al., 2013). To the extent that cash is equivalent to negative debt, we would expect that optimistic or overconfident managers would have lower cash holdings. It may seem unclear whether payment of dividends reflects confidence in future cash-flow generating potential (Ben-David, 2010) or skepticism about returns expected from incremental investment. Nevertheless, the empirical results are consistent with overconfident CEOs lowering their dividend payout to build financial slack (e.g., Cordeiro, 2009, Deshmukh et al., 2013). With respect to equity financing, optimistic managers may believe that capital markets undervalue their firm's equity and, thus, they are reluctant to raise funds externally and, instead, repurchase shares (e.g., Heaton, 2002, Hackbarth, 2008). Yet, in contrast to Malmendier and Tate (2005), Hackbarth (2008) suggests that purely overconfident managers perceive their equity to be overvalued and, hence, prefer to issues shares rather than repurchase shares.

We find a negative coefficient on *Neurotic* in the investment, interest coverage, and cash holdings regressions, and a positive coefficient in the leverage regression. A one standard deviation increase in *Neurotic* is associated with a -1.1 percentage-point decrease in corporate investment ($t = -4.47$), which has a mean of 25.1 percentage points; a 0.86 decrease in interest coverage ($t = -1.75$), which has a mean of 40.96; and a 1.2 percentage-point decrease in cash holdings ($t = -4.53$), which has a mean of 17.9 percentage points. At the same time, a one standard deviation increase in *Neurotic* is associated with a 1.2 percentage-point increase in leverage ($t = 4.25$), which has a mean of 21.3 percentage points.

That *Neurotic* is associated with greater risk aversion and lower optimism might explain the negative association between *Neurotic* and corporate investment (e.g., Goel and Thakor, 2008, Heaton, 2002). However, these assumed relation between *Neurotic* and optimism is not consistent

with the positive association of *Neurotic* with leverage or the negative association with interest coverage and cash holdings (e.g., Hackbarth, 2009, Ben-David et al., 2013).

Beyond neuroticism, we find a negative coefficient on *Introvert* in the cash holdings and net stock issuance regressions. A one standard deviation increase in *Introvert* is associated with a 0.4 percentage-point decrease in cash holdings ($t = -2.07$), and a 0.5 percentage-point decrease in net stock issuance ($t = -1.76$), which has a mean of 11.2 percentage points. We find similar result for *Unconscientious*, i.e., a negative association with cash holdings of a similar magnitude. A negative association between *Introvert* and *Unconscientious* and cash holdings cannot be explained by either low optimism or low overconfidence. However, a negative association between *Introvert* and net stock issuance resonates with a prediction, based on Hackbarth (2008), that managers with less confidence perceive their equity to be undervalued and, hence, prefer to repurchase equity.

Looking beyond the predictions from behavioral corporate finance, we find a number of associations that are interesting, but which suggest that further work is needed to understand them. We note that strong associations between *Disagreeable* and all six firm policy variables become much weaker and statistically insignificant when controls are included. *Open low* is positively associated with both *Investment* and *Net stock issuance*, and negatively associated with *Dividend payout*.

C. Growth and volatility

Table XIII presents results of regressions with measures of growth and volatility as dependent variables. We measure growth using *Book-to-market*. A lower level of book-to-market, i.e., a higher stock price relative to book value, can be interpreted as higher future growth. We calculate two measures of volatility. We interpret *Volatility of return on assets* as a measure of fundamental volatility and *Volatility of stock returns* as a measure of market volatility.

Prior literature examines the associations between growth and volatility and the CEO characteristics of risk aversion and overconfidence. A standard agency model suggests that CEOs with higher risk aversion are less likely to be hired by, or to want to work for, firms with higher volatility, and are also less likely to seek to increase volatility of the firms for which they work (e.g.,

Prendergast, 1999). Risk-averse CEOs also tend to work for firms with lower growth rates (Graham et al., 2013). In contrast to risk averse CEOs, overconfident CEOs tend to work for growth firms and firms with greater return volatility (Hirshleifer et al., 2012).

We find that introversion is positively associated with growth. A one standard deviation increase in *Introvert* is associated with a decrease by 4 percentage points ($t = -4.16$) in book-to-market.[12] This finding is not consistent with the joint hypothesis that introversion is negatively associated with overconfidence (Schaefer et al., 2004) and that overconfidence is associated with growth (Hirshleifer et al., 2012). The Big Five trait that appears to be negatively associated with both measures of volatility is *Disagreeable*.

A one standard deviation increase in *Disagreeable* is associated with a 0.1 percentage-point decrease in volatility of return on assets ($t = -3.69$), which has a mean of 1.8 percentage points, and a 0.02 percentage-point decrease in volatility of stock returns ($t = -1.87$), which has a mean of 2.73 percentage points. Given that disagreeableness is negatively associated with risk aversion (Borghans et al., 2009), this finding is surprising. In fact, the only trait that appears to be associated with volatility in the direction predicted by prior research is neuroticism. In particular, *Neurotic* has a negative association with the volatility of stock returns, which is consistent with the joint hypothesis that neuroticism is positively associated with risk aversion (e.g., Borghans et al., 2009, Anderson et al., 2011) and that risk aversion is negatively associated with volatility. A one standard deviation increase in *Neurotic* is associated with a 0.04 percentage-point decrease in the volatility of stock returns ($t = -3.68$).

D. Operating performance

Table XIV contains results for regressions with contemporaneous measures of performance as the dependent variable and Table XV has subsequent changes in operating performance as the dependent variable. We measure performance as *Return on assets*, *Asset turnover*, and *Profit margin*. Because the literature in behavioral corporate finance does not have different predictions for the effect of CEO traits on current or future performance, we combine the discussion of these results.

[12] Because book-to-market is expressed as the natural logarithm, this effect equals $\exp^{-0.039} - 1 \approx -0.04$.

Prior literature has considered the effect of overconfidence and ability on firm performance, with overconfidence having an ambiguous effect. While Gervais and Goldstein (2007) argue that overconfidence increases firm value, a sufficiently high overconfidence can generate overinvestment and a decrease in firm value (Goel and Thakor, 2008). In a model of leadership by Bolton et al. (2008), the key attribute of a good leader is a form of overconfidence—resoluteness. More resolute CEOs tend to be better leaders than "good listeners" because resoluteness can help coordinate the followers' actions around a leader's strategy. Building on this insight and using data on 30 personality characteristics of CEO candidates in private equity and venture capital transactions, Kaplan et al. (2012) find that subsequent performance is positively associated with general ability and execution-resoluteness skills with interpersonal-team or "listening" skills generally negatively associated with performance. Similarly, various CEOs' credentials as measures of CEO ability are positively associated with firms' performance (Falato et al., 2014). Finally, Green et al. (2014, p.2) use the fitted model for extraversion from Mairesse et al. (2007) to estimate CEOs' extraversion from their conference call narratives, but find that their "linguistic extraversion measure is largely unrelated to firm performance."

The only two Big Five traits consistently associated with contemporaneous and future performance are introversion and disagreeableness. However, both of these traits are not the strongest predictors of general ability. A one standard deviation increase in *Introvert* is associated with a 0.3 percentage-point increase in return on assets ($t = 3.26$), which has a mean of 10.8 percentage points, and a 0.1 percentage-point increase in change in future return on assets ($t = 3.15$), which has a mean of -0.3 percentage points.

With respect to the mechanism, both asset turnover and profit margin are positively associated with *Introvert*. Although the literature seems to lack direct evidence on the association between introversion and performance, low overconfidence of introverted CEOs could potentially prevent decisions that negatively affect profitability along the lines of the overinvestment argument as in Goel and Thakor (2008). We find almost identical results for *Disagreeable*. While, again, the literature does not relate disagreeableness to general ability or overconfidence, *Disagreeable* is associated with lower risk aversion (e.g., Borghans et al., 2009) which may result in better incentives

and, thus, better performance.

Our findings with respect to the Big Five traits related to ability—unconscientiousness and openness low—are ambiguous. Conscientiousness and openness high are the strongest predictors of non-cognitive ability (e.g., Almlund et al., 2011). However, there is a positive association between *Unconscientious* and return on assets and a negative association between *Open low* and return on assets. A one standard deviation increase in *Unconscientious* is associated with a 0.2 percentage-point increase in return on assets ($t = 2.24$). The magnitude of the coefficient on *Open low* is the same but has a different sign. Although the finding for *Open low* resonates with *Open low* capturing lower ability and, thus, lower performance, the finding for *Unconscientious* is not consistent with an argument based on ability.

E. Discussion of results

While a number of our findings are consistent with prior research in economics and finance, others seem less so. In some cases, one explanation is that performance implications of executive traits such as overconfidence are unclear. Additionally, the mapping from the Big Five personality traits to traits studied by economists, such as risk aversion, ability, and optimism or overconfidence, is likely imperfect and incomplete. In summary, our results suggest that further work is necessary to understand whether our measures of personality are capturing executive traits beyond risk aversion, ability, and optimism or overconfidence that also have implications for firm policies.

V. Conclusion

We use linguistic features extracted from conferences calls and statistical learning techniques to develop a measure of CEO's personality in terms of Big Five traits: Extraversion (versus Intraversion), Emotional Stability (versus Neuroticism), Agreeableness, Conscientiousness, and Openness to Experience. We find that our linguistic measures have strong out-of-sample classification performance and are stable over time. We find that our measures of the Big Five personality factors are associated with a number of organizational strategy choices, investment and financial policy,

and firm performance. However, our results are preliminary and further work is necessary to understand whether our measures of personality are capturing executive traits beyond risk aversion, ability, and optimism or overconfidence that also have implications for firm policies.

REFERENCES

Adams, Renee B, Matti Keloharju, and Samuli Knüpfer, 2014, Match made at birth? What traits of a million Swedes tell us about CEOs .

Almlund, Mathilde, Angela Lee Duckworth, Heckman James J., and Tim Kautz, 2011, Personality psychology and economics, in Stephen Machin Eric A. Hanushek, and Ludger Woessmann, eds., *Handbook of The Economics of Education*, volume 4 of *Handbook of the Economics of Education*, 1 – 181 (Elsevier).

Anderson, Jon, Stephen Burks, Colin DeYoung, and Aldo Rustichini, 2011, Toward the integration of personality theory and decision theory in the explanation of economic behavior, in *Unpublished manuscript. Presented at the IZA workshop: Cognitive and Non-cognitive Skills*.

Antweiler, Werner, and Murray Z. Frank, 2004, Is all that talk just noise? The information content of internet stock message boards, *The Journal of Finance* 59, 1259–1294.

Balakrishnan, Ramji, Xin Ying Qiu, and Padmini Srinivasan, 2010, On the predictive ability of narrative disclosures in annual reports, *European Journal of Operational Research* 202, 789–801.

Barrick, Murray R., and Michael K. Mount, 1991, The Big Five personality dimensions and job performance: A meta-analysis, *Personnel Psychology* 44, 1–26.

Ben-David, Itzhak, 2010, *Dividend Policy Decisions*, 435–451 (John Wiley & Sons, Inc.).

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, 2013, Managerial miscalibration, *Quarterly Journal of Economics* forthcoming.

Bertrand, Marianne, and Antoinette Schoar, 2003, Managing with style: The effect of managers on firm policies, *Quarterly Journal of Economics* 118, 1169–1208.

Bolton, Patrick, Markus K Brunnermeier, and Laura Veldkamp, 2008, Leadership, coordination and mission-driven management, Technical report, National Bureau of Economic Research.

Borghans, Lex, James J. Heckman, Bart H. H. Golsteyn, and Huub Meijers, 2009, Gender differences in risk aversion and ambiguity aversion, *Journal of the European Economic Association* 7, 649–658.

Borghans, Lex, Huub Meijers, and Bas Ter Weel, 2008, The role of noncognitive skills in explaining cognitive test scores, *Economic Inquiry* 46, 2–12.

Budescu, David V., Thomas S. Wallsten, and Wing Tung Au, 1997, On the importance of random error in the study of probability judgment. part ii: Applying the stochastic judgment model to detect systematic trends, *Journal of Behavioral Decision Making* 10, 173–188.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *The Journal of Finance* 58, 609–642.

Coles, Jeffrey L., Naveen D. Daniel, and Lalitha Naveen, 2006, Managerial incentives and risk-taking, *Journal of Financial Economics* 79, 431–468.

Cordeiro, Leonardo, 2009, Managerial overconfidence and dividend policy, *Available at SSRN: http://ssrn.com/abstract=1343805* .

Costa, Paul T., and Robert R. McCrae, 1980, Influence of extraversion and neuroticism on subjective well-being: Happy and unhappy people, *Journal of Personality and Social Psychology* 38, 668.

Daly, Michael, Colm P Harmon, and Liam Delaney, 2009, Psychological and biological foundations of time preference, *Journal of the European Economic Association* 7, 659–669.

Deshmukh, Sanjay, Anand M. Goel, and Keith M. Howe, 2013, CEO overconfidence and dividend policy, *Journal of Financial Intermediation* 22, 440–463.

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde, 2010, Are risk aversion and impatience related to cognitive ability?, *The American Economic Review* 100, 1238–1260.

Efron, Bradley, and Robert Tibshirani, 1993, *An Introduction to the Bootstrap*, volume 57 (CRC press).

Falato, Antonio, Dan Li, and Todd Milbourn, 2014, Which skills matter in the market for CEOs? Evidence from pay for CEO credentials .

Fawcett, Tom, 2006, An introduction to ROC analysis, *Pattern Recognition Letters* 27, 861–874.

Friedman, Jerome, Trevor Hastie, and Robert Tibshirani, 2010, Regularization paths for generalized linear models via coordinate descent, *Journal of Statistical Software* 33, 1.

Funder, David C., 2012, Accurate personality judgment, *Current Directions in Psychological Science* 21, 177–182.

Gabaix, Xavier, and Augustin Landier, 2008, Why has CEO pay increased so much?, *Quarterly Journal of Economics* 123, 49–100.

Galasso, Alberto, and Timothy S. Simcoe, 2011, CEO overconfidence and innovation, *Management Science* 57, 1469–1484.

Gervais, Simon, 2010, *Capital Budgeting and Other Investment Decisions*, 413–434 (John Wiley & Sons, Inc.).

Gervais, Simon, and Itay Goldstein, 2007, The positive effects of biased self-perceptions in firms, *Review of Finance* 11, 453–496.

Giat, Yahel, Steven T. Hackman, and Ajay Subramanian, 2009, Investment under uncertainty, heterogeneous beliefs, and agency conflicts, *Review of Financial Studies* 23, 1360–1404.

Gider, Jasmin, and Dirk Hackbarth, 2010, *Financing Decisions*, 393–412 (John Wiley & Sons, Inc.).

Gill, Alastair J., and Jon Oberlander, 2003, Perception of e-mail personality at zero-acquaintance: Extraversion takes care of itself; neuroticism is a worry, in *Proceedings of the 25th Annual Conference of the Cognitive Science Society*, 456–461, Citeseer.

Goel, Anand M, and Anjan V Thakor, 2008, Overconfidence, ceo selection, and corporate governance, *The Journal of Finance* 63, 2737–2784.

Goldberg, Lewis R., 1992, The development of markers for the Big-Five factor structure, *Psychological Assessment* 4, 26.

Goldberg, Lewis R., 1993, The structure of phenotypic personality traits, *American Psychologist* 48, 26–34.

Gosling, Samuel D., Peter J. Rentfrow, and William B. Swann, 2003, A very brief measure of the Big-Five personality domains, *Journal of Research in Personality* 37, 504–528.

Graham, John R., Campbell R. Harvey, and Manju Puri, 2013, Managerial attitudes and corporate actions, *Journal of Financial Economics* 109, 103–121.

Green, T. Clifton, Russell E. Jame, and Brandon Lock, 2014, Executive extraversion: Career and firm outcomes, *Available at SSRN: http://ssrn.com/abstract=2503663* .

Hackbarth, Dirk, 2008, Managerial traits and capital structure decisions, *Journal of Financial and Quantitative Analysis* 43, 843–881.

Hackbarth, Dirk, 2009, Determinants of corporate borrowing: A behavioral perspective, *Journal of Corporate Finance* 15, 389–411.

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman, 2009, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (New York, NY: Springer-Verlag New York).

Heaton, James B, 2002, Managerial optimism and corporate finance, *Financial management* 33–45.

Hirsh, Jacob B., and Jordan B. Peterson, 2009, Personality and language use in self-narratives, *Journal of Research in Personality* 43, 524–527.

Hirshleifer, David, Angie Low, and Siew Hong Teoh, 2012, Are overconfident ceos better innovators?, *The Journal of Finance* 67, 1457–1498.

Holtgraves, Thomas, 2011, Text messaging, personality, and the social context, *Journal of Research in Personality* 45, 92–99.

Iacobelli, Francisco, Alastair J. Gill, Scott Nowson, and Jon Oberlander, 2011, Large scale personality classification of bloggers, in *Affective Computing and Intelligent Interaction*, 568–577 (Springer).

John, Oliver P., and Sanjay Srivastava, 1999, The Big Five trait taxonomy: History, measurement, and theoretical perspectives, *Handbook of Personality: Theory and Research* 2, 102–138.

Kaplan, Steven N., Mark M. Klebanov, and Morten Sorensen, 2012, Which CEO characteristics and abilities matter?, *The Journal of Finance* 67, 973–1007.

Kaplan, Steven N, and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *Quarterly Journal of Economics* 169–215.

Kihlstrom, Richard E, and Jean-Jacques Laffont, 1979, A general equilibrium entrepreneurial theory of firm formation based on risk aversion, *The Journal of Political Economy* 719–748.

Larcker, David F., and Anastasia A. Zakolyukina, 2012, Detecting deceptive discussions in conference calls, *Journal of Accounting Research* 50, 495–540.

Li, Feng, 2008, Annual report readability, current earnings, and earnings persistence, *Journal of Accounting and Economics* 45, 221–247.

Li, Feng, 2010, The information content of forward-looking statements in corporate filings: A Naïve Bayesian machine learning approach, *Journal of Accounting Research* 48, 1049–1102.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *The Journal of Finance* 66, 35–65.

Mairesse, François, and Marilyn A. Walker, 2010, Towards personality-based user adaptation: Psychologically informed stylistic language generation, *User Modeling and User-Adapted Interaction* 20, 227–278.

Mairesse, François, Marilyn A. Walker, Matthias R. Mehl, and Roger K. Moore, 2007, Using linguistic cues for the automatic recognition of personality in conversation and text, *Journal of Artificial Intelligence Research* 30, 457–500.

Malmendier, Ulrike, and Geoffrey Tate, 2005, CEO overconfidence and corporate investment, *The Journal of Finance* 60, 2661–2700.

Malmendier, Ulrike, and Geoffrey Tate, 2008, Who makes acquisitions? CEO overconfidence and the market's reaction, *Journal of Financial Economics* 89, 20–43.

Malmendier, Ulrike, Geoffrey Tate, and Geoffrey Tate, 2005, CEO overconfidence and corporate investment, *The Journal of Finance* 60, 2661–2700.

Mehl, Matthias R., Samuel D. Gosling, and James W. Pennebaker, 2006, Personality in its natural habitat: Manifestations and implicit folk theories of personality in daily life, *Journal of Personality and Social Psychology* 90, 862.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *The Journal of Finance* 54, 1249–1290.

Mount, Michael K., Murray R. Barrick, and J. Perkins Strauss, 1994, Validity of observer ratings of the Big Five personality factors., *Journal of Applied Psychology* 79, 272.

Nadeau, Claude, and Yoshua Bengio, 2003, Inference for the generalization error, *Machine Learning* 52, 239–281.

Oberlander, Jon, and Alastair Gill, 2004, Language generation and personality: Two dimensions, two stages, two hemispheres, in *Proceedings from the AAAI Spring Symposium on Architectures for Modeling Emotion: Cross-Disciplinary Foundations*, 104–111.

Oberlander, Jon, and Alastair J. Gill, 2006, Language with character: A stratified corpus comparison of individual differences in e-mail communication, *Discourse Processes* 42, 239–270.

O'Reilly, Charles A., David F. Caldwell, Jennifer A. Chatman, and Bernadette Doerr, 2012, The promise and problems of organizational culture: CEO personality, culture, and firm performance, *Working Paper* .

O'Reilly, Charles A., Bernadette Doerr, David F. Caldwell, and Jennifer A. Chatman, 2014, Narcissistic CEOs and executive compensation, *The Leadership Quarterly* 25, 218–231.

Pennebaker, James W., Cindy K. Chung, Molly Ireland, Amy Gonzales, and Roger J. Booth, 2007, The development and psychometric properties of LIWC2007.

Pennebaker, James W., and Laura A. King, 1999, Linguistic styles: Language use as an individual difference., *Journal of Personality and Social Psychology* 77, 1296.

Prendergast, Canice, 1999, The provision of incentives in firms, *Journal of Economic Literature* 7–63.

Qiu, Lin, Han Lin, Jonathan Ramsay, and Fang Yang, 2012, You are what you tweet: Personality expression and perception on Twitter, *Journal of Research in Personality* 46, 710–718.

R Core Team, 2015, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria.

Roberts, Brent W., 2009, Back to the future: Personality and assessment and personality development, *Journal of Research in Personality* 43, 137–145.

Roberts, Brent W., and Daniel Mroczek, 2008, Personality trait change in adulthood, *Current Directions in Psychological Science* 17, 31–35.

Rosen, Sherwin, 1982, Authority, control, and the distribution of earnings, *The Bell Journal of Economics* 311–323.

Schaefer, Peter S., Cristina C. Williams, Adam S. Goodie, and W. Keith Campbell, 2004, Overconfidence and the Big Five, *Journal of Research in Personality* 38, 473–480.

Sharpe, J. Patrick, Nicholas R. Martin, and Kelly A. Roth, 2011, Optimism and the Big Five factors of personality: Beyond neuroticism and extraversion, *Personality and Individual Differences* 51, 946–951.

Shmueli, Galit, 2010, To explain or to predict?, *Statistical Science* 289–310.

Srivastava, Sanjay, Oliver P. John, Samuel D. Gosling, and Jeff Potter, 2003, Development of personality in early and middle adulthood: Set like plaster or persistent change?, *Journal of Personality and Social Psychology* 84, 1041–1053.

Thurstone, L. L., 1934, The vectors of mind, *Psychological Review* 41, 1–32.

Tibshirani, Robert, 1996, Regression shrinkage and selection via the lasso, *Journal of the Royal Statistical Society. Series B* 58, 267–288.

Van der Linden, Dimitri, Jan te Nijenhuis, and Arnold B. Bakker, 2010, The general factor of personality: A meta-analysis of Big Five intercorrelations and a criterion-related validity study, *Journal of Research in Personality* 44, 315–327.

Vedel, Anna, 2014, The Big Five and tertiary academic performance: A systematic review and meta-analysis, *Personality and Individual Differences* 71, 66–76.

Witten, Ian H., and Eibe Frank, 2005, *Data Mining: Practical Machine Learning Tools and Techniques* (Morgan Kaufmann).

Yarkoni, Tal, 2010, Personality in 100,000 words: A large-scale analysis of personality and word use among bloggers, *Journal of Research in Personality* 44, 363–373.

Yim, Soojin, 2013, The acquisitiveness of youth: CEO age and acquisition behavior, *Journal of Financial Economics* 108, 250–273.

Figure 1. ROC Curves for the Big Five Personality Traits.

This figure depicts the out-of-sample ROC curves for the Big Five personality traits. The false positive rate (FPR)—the cost of increasing the probability cutoff—is on the x-axis and the true positive rate (TPR)—the gain from increasing the probability cutoff—is on the y-axis. For instance, for introverts, TPR equals the proportion of introverts that are correctly classified; and FPR equals the proportion of extraverts incorrectly classified as introverts. The ROC curves are obtained by 5-fold cross-validation repeated 20 times for the models with the highest AUC (*Highest AUC*), including all features (*All features*), and the five-to-ten variables models selected using the criteria discussed in Section III (*Final model*). The diagonal line corresponds to the ROC curve of a random classifier.

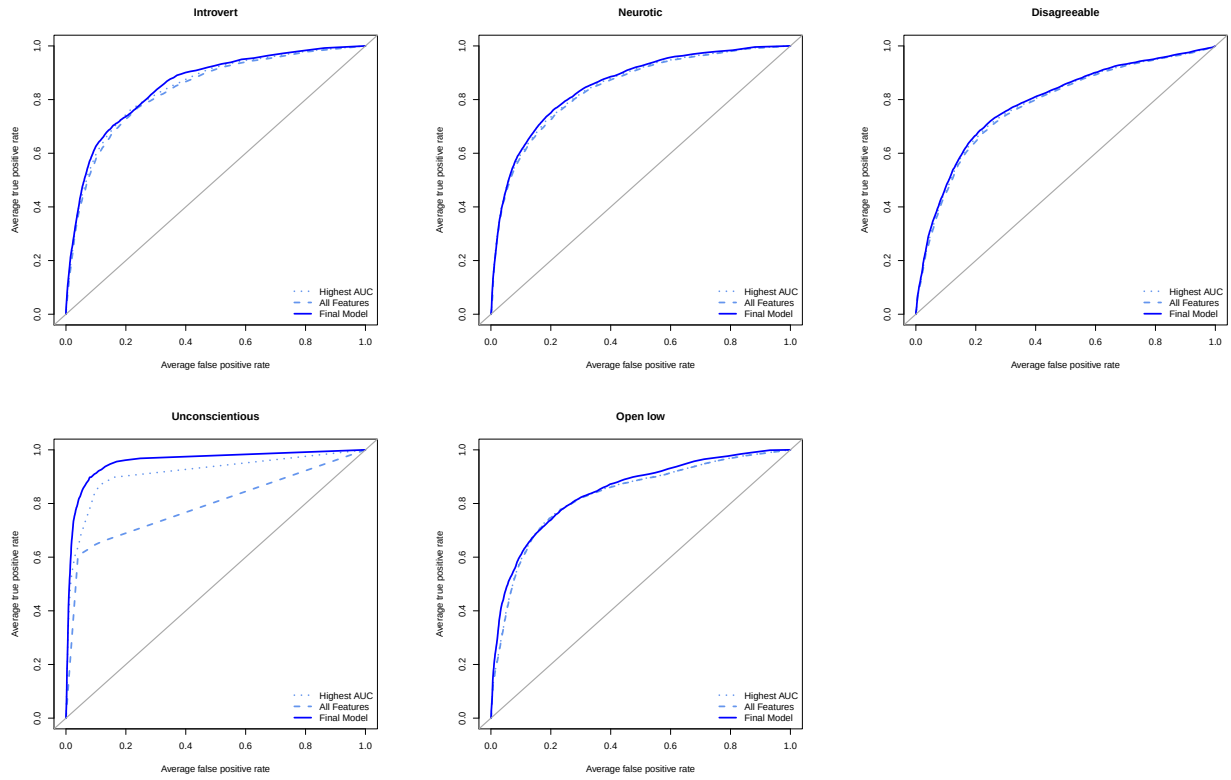

Table I
Big Five Personality Data

This table contains details on the Big Five classification for the ghSmart data. The ghSMART characteristics are described in Table 1 of Kaplan, Klebanov, and Sorensen (2012, pp. 976–978). When interpreting ghSMART characteristics, we reference Big-Five personality taxonomy from Tables 4.1 and 4.2 of John and Srivastava (1999). The adjectives lists describing each Big Five trait is from Table 3 (Goldberg, 1992, pp. 34–35) and John and Srivastava (1999).

	ghSMART characteristics	Adjectives
Introvert	Low score on: Network, Aggressive, Fast, Enthusiasm, Proactive, Persuasion.	**Introvert:** bashful, inhibited, introverted, quiet, reserved, retiring, shy, silent, sober, timid, unadventurous, unaggressive, withdrawn; **Extravert:** active, adventurous, affectionate, aggressive, assertive, bold, bossy, confident, daring, dominant, energetic, enthusiastic, extraverted, extroverted, forceful, fun-loving, noisy, outgoing, outspoken, show-off, sociable, social, spunky, talkative, unrestrained, verbal, vigorous.
Neurotic	Low score on: Respect, Calm.	**Neurotic:** anxious, despondent, easily upset, emotional, envious, fearful, fretful, high-strung, insecure, irritable, jealous, moody, nervous, self-pitying, self-punishing, temperamental, temperamental, tense, touchy, unstable, worrying; **Emotionally stable:** calm, contented, emotionally stable, imperturbable, masculine, optimistic, patient, relaxed, stable, uncritical, undemanding, unemotional, unenvious, unexcitable, unselfconscious, secure, self-satisfied.
Disagreeable	Low score on: Listening Skills, Open to Criticism, Teamwork.	**Disagreeable:** cold, critical, cruel, demanding, distrustful, fault-finding, hard, hard-hearted, harsh, inconsiderate, insensitive, insincere, quarrelsome, rude, ruthless, selfish, stern, stingy, suspicious, thankless, uncharitable, uncooperative, unfriendly, unkind, unsympathetic; **Agreeable:** affectionate, agreeable, appreciative, considerate, cooperative, forgiving, friendly, generous, gentle, good-natured, helpful, kind, pleasant, praising, sensitive, soft-hearted, sympathetic, trustful, trusting, understanding, unselfish, warm.
Unconscientious	Low score on: Develops People, Removes Underperformers, Efficiency, Organization, Commitments, Attention to Detail, Persistence, Work Ethic, High Standards, Holds People Accountable.	**Unconscientious:** careless, disorderly, disorganized, forgetful, frivolous, haphazard, impractical, impulsive, inconsistent, inefficient, irresponsible, negligent, slipshod, sloppy, indefensible, undependable, unsystematic; **Conscientious:** careful, cautious, conscientious, deliberate, dependable, disciplined, efficient, neat, orderly, organized, painstaking, planning, practical, precise, prompt, reliable, responsible, self-disciplined, steady, systematic, thorough.
Open low	Low score on: Flexible, Brainpower, Analytical Skills, Strategic Vision, Creative.	**Open low:** commonplace, conforming, conventional, imperceptive, narrow interests, practical, preference for routine, shallow, simple, uncreative, unimaginative, uninquisitive, unintellectual, unintelligent, unreflective, unsophisticated; **Open high:** artistic, bright, civilized, clever, complex, creative, curious, deep, dignified, foresighted, imaginative, independent, ingenious, innovative, insightful, intellectual, dignified, introspective, inventive, logical, original, philosophical, polished, preference for variety, resourceful, sharp-witted, sophisticated, wide interests, wise, witty.

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

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

	Number of CEOs						Number of conference calls					
	O'Reilly		ghSMART		Total		O'Reilly		ghSMART		Total	
	Num.	%	Num.	%	Num.	%	Num.	%	Num.	%	Num.	%
Introvert	4	16.67	8	13.33	12	14.29	91	15.85	95	14.71	186	15.25
Neurotic	6	25.00	11	18.33	17	20.24	107	18.64	133	20.59	240	19.67
Disagreeable	7	29.17	21	35.00	28	33.33	133	23.17	240	37.15	373	30.57
Unconscientious	0	0.00	4	6.67	4	4.76	0	0.00	57	8.82	57	4.67
Open low	5	20.83	11	18.33	16	19.05	110	19.16	120	18.58	230	18.85
CEO obs.	24		60		84		574		646		1,220	

Table III
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 of 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 IV. We standardize all features across conference calls. For word categories, we divide the raw word count by the words spoken by the CEO in the corresponding section and multiply by 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 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 the median word count of all speakers on a call. For each CEO-call observation, we require a minimum of 150 words in both Presentation and Question and Answer sections of a call.

Feature	Description	**Panel A:** CEOs with data on Big Five				**Panel B:** CEOs without data on Big Five			
		Presentation section		Question and answer		Presentation section		Question and answer	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
				Self-reference					
First per. singular	LIWC "I": I, me, mine, etc.	12.19	9.59	30.21	12.16	12.08	9.14	29.74	13.56
First per. plural	LIWC "we": we, us, our, etc.	101.26	26.30	91.60	22.35	98.78	27.13	93.80	22.92
				Negative emotion					
Sadness	LIWC "sad": devastat*, disadvantage*, etc.	3.17	3.72	2.28	2.32	3.72	4.06	2.56	2.77
Anxiety	LIWC "anx": worried, fearful, nervous, etc.	1.42	2.16	1.41	1.69	1.89	2.77	1.69	2.25
Anger	LIWC "anger": hate, kill, annoyed, etc.	1.64	2.19	1.54	2.04	1.56	2.51	1.40	2.02
Extreme negative	LZ based on LIWC "negemo": absurd, adverse, awful, etc.	3.22	3.39	3.80	3.06	3.23	3.45	3.65	3.25
				Positive emotion					
Extreme positive	LZ based on LIWC "posemo": fantastic, great, definitely, etc.	18.99	8.93	11.05	5.61	14.63	8.28	9.12	5.83
Nonextreme positive	LZ based on LIWC "posemo": love, nice, accept, etc.	55.11	14.51	52.20	13.45	55.37	16.17	53.17	15.77
				Agreement					
Negations	LIWC "negate": no, not, never, etc.	4.49	4.07	18.70	7.53	5.52	4.74	21.07	9.15
Assent	LIWC "assent": agree, OK, yes, etc.	0.27	0.83	4.59	4.11	0.28	1.05	5.10	4.43
Thanks	Self-constructed: thank you, thanks, you're welcome, etc.	3.01	2.20	2.84	3.49	3.18	2.79	3.94	4.91

Table III—*Continued*

Feature	Description	**Panel A:** CEOs with data on Big Five traits				**Panel B:** CEOs without data on Big Five traits			
		Presentation section		Question and answer		Presentation section		Question and answer	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
				Certainty					
Certainty	LIWC "certain": always, never, etc.	15.98	7.50	24.24	8.66	16.10	7.40	23.02	8.56
Numbers	Number of numbers	19.38	13.58	7.94	6.44	23.91	17.99	10.38	8.97
Quantifiers	LIWC "quant": all, a lot, bit, etc.	51.60	14.23	60.32	13.35	51.98	14.18	58.72	13.54
Tentative	LIWC "tentat": maybe, perhaps, guess, etc.	18.92	10.08	47.40	14.23	23.08	11.36	50.29	14.90
Vague quantifiers	Self-constructed: a load of, a lot of, etc.	27.14	10.83	34.30	9.59	26.85	10.15	35.18	10.63
Qualifiers	Self-constructed: arguably, as a whole, etc.	22.10	9.90	44.79	13.56	25.20	11.49	45.78	14.38
Generalizations	Self-constructed: all that stuff, almost, etc.	12.47	6.61	30.05	9.24	13.68	7.24	28.95	9.57
				Cognitive processes					
Insight	LIWC "insight": admitting, analy*, etc.	26.33	10.95	43.18	12.79	25.30	10.65	41.31	13.55
Causation	LIWC "cause": allow*, attribut*, based, etc.	40.57	13.23	31.93	9.95	36.88	13.64	29.31	10.69
Discrepancy	LIWC "discrep": besides, could, etc.	11.55	6.43	22.38	8.74	13.75	7.16	24.36	9.76
Inhibition	LIWC "inhib": abandon*, abstain*, etc.	7.08	6.21	5.31	3.55	7.06	5.54	5.66	4.26
Inclusive	LIWC "incl": each, inclu*, inside, etc.	138.66	23.99	143.97	22.72	134.17	24.38	143.25	24.22
Exclusive	LIWC "excl": either, except, exclu* , etc.	12.42	8.59	43.26	11.81	14.90	9.66	44.58	12.82
				Hesitation and fillers					
Hesitations	LZ based on LIWC "filler": ah, um, etc.	0.02	0.24	0.12	0.53	0.02	0.34	0.21	1.36
Gen. knowledge references	LZ: you know, investors well know, etc.	0.40	1.08	1.80	3.36	0.50	1.19	2.56	4.78
				Linguistic processes					
Times spoken	Number of times spoken	4.42	1.44	3.58	1.29	5.12	1.60	4.01	1.54
Words spoken	Number of words spoken ignoring articles	2293.79	850.45	2293.75	889.16	2669.29	1113.07	2398.50	1009.39
Words per sent.	Words per sentence	23.22	3.20	22.75	4.79	23.89	3.47	21.44	4.44
Words > 6 letters	Words longer than 6 letters	648.33	75.45	430.50	42.13	629.04	83.87	420.77	50.59
Articles	LIWC "article": a, an, the	113.37	19.31	122.25	17.55	120.44	20.75	121.19	18.74
Conjunctions	LIWC "conj": although, and, as, etc.	97.04	16.44	121.24	18.00	94.70	17.57	117.18	18.26
Adverbs	LIWC "adverb": about, absolutely, etc.	43.64	20.08	101.02	18.35	44.02	19.70	95.85	18.70
Calls obs.		1,220				65,759			

Table IV
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 V
Out-of-sample Classification Performance

This table compares the out-of-sample classification performance of three approaches to model selection: Highest AUC (choosing the model that maximizes the area under the ROC curve), All Features (using all linguistic features), and our Final Model (choosing the model using the "one-standard-error" rule discussed in Section III). These models are trained and evaluated using data on personalities from the O'Reilly and ghSMART samples and using linguistic features extracted from utterances by CEOs on earnings conference calls. Reported values are the average AUCs obtained using 5-fold cross-validation repeated 20 times. Diagonal elements correspond to the AUC for each model; the t-statistics below compare the AUC of the model to a random classifier (AUC = 50%). The off-diagonal elements correspond to a difference in the AUC between the model in the column and the model in the row, with t-statistics for the differences reported below. The statistical significance is estimated using a corrected re-sampled t-test (Nadeau and Bengio (2003)). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Highest AUC	All Features	Final Model
	Introvert		
Highest AUC	84.11	−0.78	0.81
	$(22.82)^{***}$	$(-2.64)^{***}$	(1.52)
All-categories		83.33	1.59
		$(21.05)^{***}$	$(2.58)^{***}$
Final model			84.92
			$(23.26)^{***}$
	Disagreeable		
Highest AUC	78.57	−0.49	0.39
	$(17.65)^{***}$	$(-2.94)^{***}$	(1.50)
All-categories		78.07	0.88
		$(17.37)^{***}$	$(2.77)^{***}$
Final model			78.95
			$(18.52)^{***}$
	Open low		
Highest AUC	82.21	−0.08	1.43
	$(17.96)^{***}$	(−1.19)	$(1.74)^{*}$
All-categories		82.13	1.52
		$(17.71)^{***}$	$(1.83)^{*}$
Final model			83.65
			$(21.08)^{***}$

	Highest AUC	All Features	Final Model
	Neurotic		
Highest AUC	84.79	−0.86	0.45
	$(28.38)^{***}$	$(-2.39)^{**}$	(0.89)
All-categories		83.93	1.30
		$(27.60)^{***}$	$(2.48)^{**}$
Final model			85.23
			$(30.26)^{***}$
	Unconscientious		
Highest AUC	95.16	−12.92	0.92
	$(16.82)^{***}$	$(-3.08)^{***}$	(0.43)
All-categories		82.25	13.83
		$(8.94)^{***}$	$(3.75)^{***}$
Final model			96.08
			$(39.87)^{***}$

Table VI
In-sample Logistic Regressions Predicting Big Five Personality Traits

This table presents estimated coefficients from logistic regressions of Big Five on linguistic features selected using the Final Model approach described in Section III. All variables are defined in Table . AUC is the area under the ROC curve. *t*-statistics clustered by CEO are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Linguistic features are standardized to have mean zero and unit standard deviation.

	Presentation section					Question and answer section				
	Introvert	Neurotic	Disagreeable	Unconscientious	Open low	Introvert	Neurotic	Disagreeable	Unconscientious	Open low
First person singular				-0.769^{*}	0.316^{*}	0.343	0.411^{*}	0.438^{**}	-0.171	0.348^{**}
				(-1.92)	(1.78)	(1.46)	(1.79)	(2.04)	(-0.44)	(2.08)
First person plural	0.694^{**}	-0.430		0.562^{**}	-0.085		0.481^{**}	0.591^{**}		
	(2.47)	(-1.53)		(2.53)	(-0.28)		(2.35)	(2.26)		
Sadness		-0.287^{**}	-0.368^{**}	-1.130^{**}			0.139	-0.131		-0.201
		(-2.16)	(-2.06)	(-1.99)			(1.11)	(-1.05)		(-1.60)
Anxiety	-0.269	-0.180	-0.173		-0.161		-0.233^{**}	-0.060		
	(-1.59)	(-1.41)	(-1.03)		(-1.10)		(-2.26)	(-0.66)		
Anger	0.280^{*}	0.437^{***}	0.301^{***}		0.185	-0.207^{**}	0.036	0.385^{**}		
	(1.66)	(3.27)	(2.77)		(1.33)	(-2.09)	(0.25)	(2.17)		
Extreme negative			0.001				0.360^{**}	0.127		
			(0.01)				(2.31)	(0.83)		
Extreme positive	0.235		-0.139				0.228	0.087	0.585^{***}	0.471^{***}
	(1.50)		(-0.93)				(1.48)	(0.67)	(2.79)	(3.03)
Nonextreme positive	-0.330^{*}	0.365^{**}	0.100	0.868^{***}			-0.246^{*}	-0.245^{*}		
	(-1.69)	(2.04)	(0.71)	(3.33)			(-1.72)	(-1.65)		
Negations	0.224	0.207	0.073			-0.127	0.358^{**}			
	(1.60)	(1.27)	(0.55)			(-0.57)	(2.01)			
Assent	-0.241		0.055		-0.255^{**}	-0.537^{**}	-0.281	-0.159	-1.618^{***}	
	(-1.34)		(0.41)		(-2.20)	(-2.23)	(-1.09)	(-0.81)	(-4.42)	
Thanks	0.393^{*}	0.195	0.016			0.166	-0.606^{**}	-0.192		
	(1.79)	(0.96)	(0.09)			(0.78)	(-2.16)	(-0.92)		
Certainty	0.323^{*}	-0.301^{*}	-0.351^{***}			0.247	0.221	-0.026		
	(1.85)	(-1.73)	(-3.22)			(1.10)	(1.12)	(-0.15)		
Numbers		0.245	0.254		0.809^{***}			-0.185		
		(1.26)	(1.57)		(3.93)			(-1.30)		
Quantifiers	0.611^{***}	0.209	0.101			0.157	0.172	-0.077	0.231	
	(3.37)	(1.41)	(0.68)			(0.79)	(1.09)	(-0.51)	(1.14)	
Tentative			-0.176		-0.314	-0.923^{***}	-0.044	-0.181		
			(-0.96)		(-1.37)	(-3.41)	(-0.18)	(-0.86)		
Vague quantifiers	-0.356^{*}		-0.255		-0.133		0.317^{**}	0.355^{**}	0.318	0.199
	(-1.70)		(-1.34)		(-0.68)		(2.03)	(2.10)	(0.86)	(1.34)

Table VI—*Continued*

	Presentation section—*Continued*					Question and answer section—*Continued*				
	Introvert	Neurotic	Disagreeable	Unconscientious	Open low	Introvert	Neurotic	Disagreeable	Unconscientious	Open low
Qualifiers		−0.586***	−0.083		−0.142	0.522*	−0.496*	−0.130		
		(−3.37)	(−0.42)		(−0.55)	(1.83)	(−1.79)	(−0.59)		
Generalizations		0.155	0.303*			0.163		−0.103		
		(0.65)	(1.91)			(0.68)		(−0.65)		
Insight		−0.177				−0.342*	−0.243	−0.344*	−0.847***	−0.303
		(−1.25)				(−1.80)	(−1.21)	(−1.93)	(−2.58)	(−1.40)
Causation	0.163	−0.468***	−0.325**			−0.161	−0.191	−0.262**		−0.131
	(0.81)	(−2.97)	(−2.00)			(−1.01)	(−1.35)	(−2.43)		(−0.84)
Discrepancy	−0.237	−0.278	−0.227		−0.149	0.164			−0.216	−0.209
	(−1.25)	(−1.48)	(−1.62)		(−0.81)	(1.15)			(−0.90)	(−1.02)
Inhibition	−0.514**	−0.555*	−0.600***		0.307	−0.526***		0.117	−0.055	
	(−2.38)	(−1.78)	(−3.35)		(1.46)	(−3.72)		(0.95)	(−0.35)	
Inclusive	−0.624**	0.005	−0.115		−0.159			−0.317*		0.263
	(−2.35)	(0.02)	(−0.65)		(−0.49)			(−1.80)		(1.53)
Exclusive		0.544**	0.627***				−0.254	−0.022		−0.539**
		(2.03)	(3.07)				(−1.22)	(−0.12)		(−2.52)
Hesitations			−0.485***				0.114*	0.158*		
			(−2.74)				(1.70)	(1.71)		
General knowledge	−0.070	0.203**				−0.072	−0.182	−0.107		−0.229
	(−0.41)	(2.51)				(−0.45)	(−1.11)	(−0.76)		(−1.39)
Times spoke	0.623**	0.383	0.195	1.534***		−0.284		0.477*	−0.398	−0.142
	(2.20)	(1.34)	(0.82)	(2.82)		(−1.02)		(1.92)	(−1.29)	(−0.64)
Words spoke	0.354*		−0.175				0.260	−0.715**	−0.945**	
	(1.87)		(−0.80)				(0.96)	(−2.15)	(−2.33)	
Words per sentence				1.372***	0.338	0.151	−0.072	0.279**		
				(4.74)	(1.46)	(0.98)	(−0.37)	(2.40)		
Words> 6 letters	0.508				0.388	0.074		0.131	−1.282***	−0.646**
	(1.24)				(1.05)	(0.28)		(0.68)	(−5.59)	(−2.53)
Articles	−0.225	0.200	−0.176					0.116		−0.184
	(−1.09)	(1.09)	(−1.14)					(0.49)		(−0.95)
Conjunctions	−0.384	−0.403**	−0.080	−0.564**		0.481***	−0.281		−0.281	
	(−1.54)	(−1.99)	(−0.43)	(−2.45)		(2.92)	(−1.40)		(−1.50)	
Adverbs	0.369						−0.295	−0.148		
	(1.60)						(−1.59)	(−0.81)		
						(−6.62)	(−6.72)	(−3.98)	(−8.01)	(−5.48)
Obs.						1220	1220	1220	1220	1220
Obs. with Big 5 trait						186	240	373	57	230
In-sample AUC						88.66	89.20	84.14	97.44	86.09
Pseudo-R^2						0.357	0.379	0.276	0.603	0.315

Table VII
Descriptive Statistics: Big Five Traits

This table provides descriptive statistics for measures of Big Five traits for our full sample of CEOs without personality data. We compute the probability for each CEO being a specific personality type using the CEO's utterances from quarterly earnings conference calls and classification models presented in Table VI. We futher aggregate these probabilities and define our final measures as the average probabilities based on conference calls within a fiscal year. B/W denotes the ratio of between-CEO mean-square error to within-CEO mean-square error. Quarterly B/W are for the Big Five traits probabilities estimated using quarterly conference calls. Annual B/W are for our final measures, i.e., the average probabilities based on conference calls within a fiscal year.

	Quarterly B/W	Annual B/W	Annual				
			Mean	Std.Dev.	25th	50th	75th
Introvert	7.58	4.90	0.13	0.16	0.02	0.07	0.19
Neurotic	10.27	6.36	0.25	0.23	0.07	0.19	0.38
Disagreeable	8.37	5.31	0.33	0.21	0.16	0.30	0.47
Unconscientious	7.34	4.74	0.07	0.14	0.00	0.01	0.06
Open low	11.46	6.85	0.18	0.19	0.04	0.11	0.25
Obs.	65,759		20,415				

Table VIII
Descriptive Statistics: Big Five Traits by Industry

This table provides descriptive statistics for our Big Five trait measures for CEO-years by industry. We classify firms into 20 industries as in Moskowitz and Grinblatt (1999).

	Obs.	Introvert		Neurotic		Disagreeable		Unconscientious		Open low	
		Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.	Mean	S.Dev.
Mining	995	0.08	0.12	0.24	0.20	0.29	0.18	0.12	0.21	0.25	0.23
Food	343	0.19	0.19	0.25	0.21	0.37	0.19	0.07	0.14	0.14	0.13
Apparel	211	0.21	0.18	0.27	0.22	0.37	0.18	0.11	0.16	0.18	0.17
Paper	214	0.13	0.15	0.19	0.18	0.30	0.18	0.06	0.12	0.14	0.16
Chemical	1,458	0.11	0.15	0.19	0.20	0.26	0.20	0.04	0.11	0.13	0.15
Petroleum	133	0.12	0.14	0.38	0.28	0.49	0.27	0.04	0.10	0.32	0.25
Construction	99	0.19	0.19	0.34	0.25	0.32	0.19	0.05	0.15	0.13	0.12
Prim. Metals	278	0.16	0.15	0.25	0.20	0.31	0.18	0.03	0.06	0.11	0.12
Fab. Metals	237	0.10	0.13	0.32	0.24	0.39	0.22	0.06	0.11	0.16	0.18
Machinery	1,101	0.14	0.15	0.23	0.21	0.31	0.20	0.05	0.12	0.19	0.17
Electrical Eq.	1,669	0.13	0.16	0.19	0.22	0.28	0.20	0.04	0.11	0.17	0.17
Transport Eq.	468	0.11	0.13	0.29	0.25	0.36	0.21	0.07	0.13	0.27	0.25
Manufacturing	1,409	0.13	0.15	0.22	0.22	0.28	0.20	0.05	0.12	0.18	0.18
Railroads	53	0.06	0.08	0.28	0.22	0.48	0.22	0.19	0.21	0.19	0.17
Other Transport	427	0.12	0.14	0.28	0.23	0.37	0.20	0.07	0.13	0.14	0.15
Utilities	826	0.08	0.12	0.22	0.19	0.32	0.19	0.07	0.14	0.18	0.19
Dept. Stores	109	0.16	0.16	0.32	0.24	0.41	0.19	0.12	0.18	0.18	0.20
Retail	1,966	0.18	0.18	0.29	0.24	0.39	0.20	0.12	0.19	0.20	0.19
Financial	3,570	0.10	0.14	0.26	0.24	0.33	0.21	0.07	0.14	0.19	0.20
Other	4,849	0.15	0.16	0.28	0.23	0.36	0.21	0.07	0.14	0.17	0.18

Table IX
Correlations: Big Five Traits

This table reports correlations between our Big Five trait measures. Big Five trait measures are standardized. Panel A reports pairwise Pearson correlations between traits. Panel B reports estimates of multivariate regressions of a personality trait on other traits. t-statistics based on robust standard errors clustered by CEO are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Pairwise correlations				
	Introvert	Neurotic	Disagreeable	Unconscientious	Open low
Introvert	1.000				
Neurotic	0.135^{***}	1.000			
Disagreeable	0.177^{***}	0.632^{***}	1.000		
Unconscientious	0.234^{***}	0.092^{***}	0.136^{***}	1.000	
Open low	0.157^{***}	0.277^{***}	0.238^{***}	0.247^{***}	1.000

	Panel B: Multivariate regressions				
	Introvert	Neurotic	Disagreeable	Unconscientious	Open low
Introvert		0.014	0.076^{***}	0.193^{***}	0.070^{***}
		(1.40)	(8.57)	(13.61)	(5.94)
Neurotic	0.022		0.604^{***}	-0.042^{***}	0.206^{***}
	(1.40)		(65.54)	(-3.13)	(12.22)
Disagreeable	0.119^{***}	0.600^{***}		0.078^{***}	0.068^{***}
	(8.52)	(63.96)		(5.93)	(4.81)
Unconscientious	0.198^{***}	-0.027^{***}	0.051^{***}		0.203^{***}
	(14.04)	(-3.09)	(5.75)		(14.61)
Open low	0.074^{***}	0.139^{***}	0.046^{***}	0.210^{***}	
	(5.84)	(13.08)	(4.82)	(13.58)	
Adj. R^2	0.082	0.416	0.413	0.104	0.134
Obs.	20,415	20,415	20,415	20,415	20,415

Table X
Descriptive Statistics: Firm Policies

This table reports descriptive statistics for firm policies. *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *R&D intensity* R&D expense (XRD) divided by sales (SALE). *Fixed asset intensity* equals net PP&E (PPENT) divided by assets total (AT). *Investment* equals capital expenditures (CAPX) divided by net property, plant, and equipment (PPENT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). *Interest coverage* equals EBITDA (OIBPD) divided by net interest expense (XINT − IDIT). As in Kaplan and Zingales (1997), we set interest coverage to 100 if coverage exceeds 100, to 0 if EBITDA is negative, and to 100 if net interest expense is negative. *Cash holdings* equals cash and cash equivalents (CHE) divided by total assets (AT). *Dividend payout* equals total dividends (DVT) divided by EBITDA (OIBPD). We set dividend payout to 0 if EBITDA is negative. *Net stock issuance* is net stock issuance over prior 36 months computed as the natural logarithm of growth in shares outstanding adjusted for splits from CRSP. *Book-to-market* is the natural logarithm of book-to-market. Book equity is computed as in Cohen et al. (2003). *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT). *Asset turnover* equals sales (SALE) divided by lagged total assets (AT). *Profit margin* equals EBITDA (OIBDP) divided by sales (SALE). *Cash flow* equals cash from operations (OANCF or, if missing, computed using balance sheet method) divided by lagged total assets (AT). *Volatility of return on assets* is the standard deviation of return on assets over the prior twelve quarters. *Volatility of stock returns* is the average of standard deviations of daily stock returns computed monthly over prior 12 months from CRSP expressed in percentage points. *Change in future return on assets*, *change in future asset turnover*, and *change in future profit margin* are the corresponding changes in return on assets, asset turnover, and profit margin from year t to year $t+1$. All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses.

	Obs.	Mean	Std.Dev.	25th	50th	75th
Size	20,415	7.184	1.855	5.864	7.152	8.399
R&D intensity	20,378	0.101	0.424	0.000	0.000	0.040
Fixed asset intensity	20,415	0.224	0.238	0.039	0.136	0.332
Investment	19,270	0.251	0.184	0.118	0.201	0.337
Leverage	20,415	0.213	0.198	0.029	0.178	0.337
Interest coverage	20,123	40.957	42.967	4.652	14.548	100.000
Cash holdings	20,415	0.179	0.207	0.030	0.094	0.254
Dividend payout	20,121	0.123	0.253	0.000	0.000	0.137
Net stock issuance	18,577	0.112	0.248	-0.014	0.038	0.165
Book-to-market	20,415	-0.734	0.829	-1.213	-0.666	-0.188
Volatility of return on assets	19,758	0.018	0.024	0.005	0.010	0.021
Volatility of stock returns	20,415	2.728	1.333	1.792	2.438	3.325
Return on assets	20,415	0.108	0.154	0.048	0.111	0.181
Asset turnover	20,415	1.014	0.848	0.388	0.830	1.379
Profit margin	20,378	0.071	0.696	0.070	0.141	0.249
Cash flow	20,415	0.085	0.132	0.035	0.085	0.145
Change in future return on assets	17,313	-0.003	0.090	-0.025	0.000	0.023
Change in future asset turnover	17,313	-0.021	0.318	-0.081	0.000	0.076
Change in future profit margin	17,281	0.007	0.379	-0.019	0.001	0.022

Table XI
Organizational Strategy

This table reports results of regressions of firm outcome variables on Big Five trait measures and controls. Big Five trait measures correspond to the probabilities of a CEO being a specific personality type. These probabilities are estimated as average probabilities based on earnings conference calls within a year. *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *R&D intensity* R&D expense (XRD) divided by sales (SALE). *Fixed asset intensity* equals net PP&E (PPENT) divided by assets total (AT). *Book-to-market* is the natural logarithm of book-to-market. Book equity is computed as in Cohen et al. (2003). *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) divided by lagged total assets (AT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses. Big Five trait measures and control variables are standardized. t-statistics based on robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Size			R&D intensity			Fixed asset intensity		
Introvert	-0.017	-0.016	-0.013	-0.018^{***}	-0.018^{***}	-0.011^{***}	-0.004^{*}	-0.004^{*}	-0.003
	(-0.63)	(-0.61)	(-0.55)	(-5.15)	(-5.06)	(-4.03)	(-1.87)	(-1.73)	(-1.39)
Neurotic	-0.144^{***}	-0.156^{***}	-0.174^{***}	-0.002	-0.004	-0.005	0.002	0.002	0.001
	(-4.05)	(-4.51)	(-5.28)	(-0.43)	(-0.96)	(-1.22)	(0.84)	(0.68)	(0.33)
Disagreeable	0.246^{***}	0.247^{***}	0.196^{***}	-0.038^{***}	-0.037^{***}	-0.011^{***}	0.003	0.003	-0.002
	(8.45)	(8.50)	(7.33)	(-6.28)	(-6.28)	(-2.80)	(1.00)	(1.03)	(-0.75)
Unconscientious	-0.026	-0.025	-0.050^{***}	-0.007^{***}	-0.007^{***}	0.002	0.013^{***}	0.013^{***}	0.011^{***}
	(-1.32)	(-1.32)	(-2.69)	(-2.60)	(-2.58)	(0.99)	(4.68)	(4.69)	(4.11)
Open low	0.012	0.016	0.022	0.006	0.007	0.004	-0.002	-0.002	-0.002
	(0.45)	(0.66)	(0.91)	(1.39)	(1.60)	(1.03)	(-0.89)	(-0.75)	(-0.71)
Size						-0.025^{***}			0.004
						(-4.74)			(1.27)
Book-to-market			0.225^{***}			-0.088^{***}			0.023^{***}
			(6.68)			(-14.79)			(7.57)
Return on assets			0.312^{***}			-0.189^{***}			0.010^{***}
			(9.85)			(-13.97)			(2.99)
Cash flow			0.091^{***}			-0.042^{***}			0.019^{***}
			(3.08)			(-5.05)			(4.99)
Leverage			0.441^{***}			-0.034^{***}			0.042^{***}
			(15.70)			(-8.67)			(11.98)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.013	0.015	0.128	0.014	0.015	0.343	0.006	0.007	0.097
Obs.	20,415	20,415	20,415	20,378	20,378	20,378	20,415	20,415	20,415

Table XII
Investment and Financial Policy

This table reports results of regressions of firm outcome variables on Big Five trait measures and controls. Big Five trait measures correspond to the probabilities of a CEO being a specific personality type. These probabilities are estimated as average probabilities based on earnings conference calls within a year. *Investment* equals capital expenditures (CAPX) divided by net property, plant, and equipment (PPENT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). *Interest coverage* equals EBITDA (OIBPD) divided by net interest expense (XINT − IDIT). As in Kaplan and Zingales (1997), we set interest coverage to 100 if coverage exceeds 100, to 0 if EBITDA is negative, and to 100 if net interest expense is negative. *Cash holdings* equals cash and cash equivalents (CHE) divided by total assets (AT). *Dividend payout* equals total dividends (DVT) divided by EBITDA (OIBPD). We set dividend payout to 0 if EBITDA is negative. *Net stock issuance* is net stock issuance over prior 36 months computed as the natural logarithm of growth in shares outstanding adjusted for splits from CRSP. *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the natural logarithm of book-to-market. Book equity is computed as in Cohen et al. (2003). *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) divided by lagged total assets (AT). All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses. Big Five trait measures and control variables are standardized. We exclude financial firms (SIC in 6000 - 6999) and utilities (SIC in 4900 - 4999) from this analysis. t-statistics based on robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Investment			Leverage			Interest coverage		
Introvert	0.004	0.002	−0.000	−0.001	−0.001	0.000	−0.040	−0.133	−0.826*
	(1.49)	(1.01)	(−0.07)	(−0.55)	(−0.39)	(0.05)	(−0.07)	(−0.23)	(−1.91)
Neurotic	−0.010***	−0.011***	−0.011***	0.007**	0.008**	0.012***	−1.311*	−1.743**	−0.864*
	(−3.38)	(−3.86)	(−4.47)	(2.22)	(2.37)	(4.25)	(−1.71)	(−2.36)	(−1.75)
Disagreeable	−0.008***	−0.008***	−0.000	0.008***	0.008***	−0.001	−1.640**	−1.608**	−0.071
	(−3.24)	(−3.25)	(−0.05)	(2.77)	(2.75)	(−0.39)	(−2.37)	(−2.35)	(−0.16)
Unconscientious	0.000	0.000	0.001	0.002	0.002	0.003	−0.447	−0.417	−0.411
	(0.09)	(0.17)	(0.29)	(0.71)	(0.71)	(1.39)	(−0.76)	(−0.72)	(−1.12)
Open low	0.005**	0.005*	0.004*	−0.005*	−0.005*	−0.004*	0.427	0.515	−0.081
	(2.25)	(1.89)	(1.73)	(−1.75)	(−1.69)	(−1.69)	(0.67)	(0.82)	(−0.22)
Size			−0.034***			0.070***			−4.838***
			(−11.96)			(22.17)			(−8.90)
Book-to-market			−0.038***			−0.003			−5.945***
			(−11.32)			(−0.73)			(−9.82)
Return on assets			−0.017**			0.017***			1.115
			(−2.18)			(2.65)			(0.92)
Cash flow			0.016**			−0.043***			3.417***
			(2.56)			(−6.63)			(4.73)
Leverage			−0.035***						−26.014***
			(−12.25)						(−48.49)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.008	0.028	0.176	0.005	0.009	0.153	0.004	0.012	0.477
Obs.	15,894	15,894	15,894	15,897	15,897	15,897	15,615	15,615	15,615

Table XII—*Continued*

	Cash holdings			Dividend payout			Net stock issuance		
Introvert	-0.003	-0.003	-0.004^{**}	0.002	0.002	0.001	-0.007^{***}	-0.007^{**}	-0.005^{*}
	(-1.09)	(-1.19)	(-2.07)	(0.82)	(0.65)	(0.27)	(-2.62)	(-2.51)	(-1.76)
Neurotic	-0.012^{***}	-0.013^{***}	-0.012^{***}	0.002	0.004	0.005^{*}	0.002	-0.002	-0.007^{*}
	(-3.82)	(-3.82)	(-4.53)	(0.71)	(1.26)	(1.81)	(0.39)	(-0.59)	(-1.70)
Disagreeable	-0.023^{***}	-0.022^{***}	-0.004	0.005^{**}	0.005^{*}	0.001	-0.014^{***}	-0.013^{***}	-0.001
	(-6.57)	(-6.53)	(-1.64)	(1.99)	(1.94)	(0.25)	(-3.91)	(-3.74)	(-0.30)
Unconscientious	-0.009^{***}	-0.009^{***}	-0.006^{***}	-0.002	-0.002	-0.003	-0.003	-0.003	-0.001
	(-3.98)	(-3.98)	(-3.65)	(-0.81)	(-0.83)	(-0.91)	(-1.15)	(-1.11)	(-0.21)
Open low	0.004	0.004	0.002	-0.005^{**}	-0.005^{**}	-0.005^{**}	0.009^{***}	0.010^{***}	0.010^{***}
	(1.58)	(1.56)	(0.70)	(-1.96)	(-2.27)	(-2.23)	(2.68)	(2.94)	(3.12)
Size			-0.039^{***}			0.019^{***}			-0.028^{***}
			(-9.51)			(5.63)			(-6.55)
Book-to-market			-0.058^{***}			-0.008^{***}			-0.021^{***}
			(-16.87)			(-3.25)			(-3.66)
Return on assets			-0.089^{***}			0.003			-0.023^{***}
			(-13.35)			(0.96)			(-4.10)
Cash flow			0.032^{***}			0.004			-0.042^{***}
			(5.25)			(1.06)			(-8.21)
Leverage			-0.065^{***}			0.002			0.018^{***}
			(-23.96)			(0.66)			(5.74)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.028	0.030	0.404	0.001	0.004	0.021	0.005	0.014	0.110
Obs.	15,897	15,897	15,897	15,613	15,613	15,613	14,457	14,457	14,457

Table XIII
Growth and Volatility

This table reports results of regressions of firm outcome variables on Big Five trait measures and controls. Big Five trait measures correspond to the probabilities of a CEO being a specific personality type. These probabilities are estimated as average probabilities based on earnings conference calls within a year. *Book-to-market* is the natural logarithm of book-to-market. Book equity is computed as in Cohen et al. (2003). *Volatility of return on assets* is the standard deviation of return on assets over the prior twelve quarters. *Volatility of stock returns* is the average of standard deviations of daily stock returns computed monthly over prior 12 months from CRSP expressed 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) divided by lagged total assets (AT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses. Big Five trait measures and control variables are standardized. t-statistics based on robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Book-to-market			Volatility of return on assets			Volatility of stock returns		
Introvert	-0.061^{***}	-0.050^{***}	-0.039^{***}	-0.000	-0.000	-0.000	-0.049^{*}	-0.008	0.013
	(-5.28)	(-4.92)	(-4.16)	(-0.49)	(-0.28)	(-0.70)	(-1.94)	(-0.53)	(1.04)
Neurotic	-0.020	-0.002	0.008	0.001^{*}	0.001^{*}	0.000	-0.026	0.005	-0.040^{***}
	(-1.55)	(-0.13)	(0.72)	(1.83)	(1.95)	(0.53)	(-1.03)	(0.28)	(-3.68)
Disagreeable	0.008	0.004	0.009	-0.002^{***}	-0.002^{***}	-0.001^{***}	-0.101^{***}	-0.107^{***}	-0.020^{*}
	(0.75)	(0.44)	(0.95)	(-7.67)	(-7.75)	(-3.69)	(-6.78)	(-7.14)	(-1.87)
Unconscientious	0.002	0.002	0.012	0.000	0.000	0.000	-0.013	-0.009	-0.010
	(0.19)	(0.25)	(1.30)	(0.36)	(0.32)	(0.70)	(-1.05)	(-0.89)	(-1.15)
Open low	0.011	0.011	0.007	-0.000	-0.000	-0.000	-0.023^{*}	-0.011	-0.012
	(0.99)	(1.07)	(0.75)	(-0.84)	(-0.70)	(-0.81)	(-1.88)	(-0.98)	(-1.44)
Size			0.115^{***}			-0.007^{***}			-0.499^{***}
			(7.67)			(-18.38)			(-18.49)
Book-to-market						-0.003^{***}			0.146^{**}
						(-7.96)			(2.16)
Return on assets			-0.106^{***}			-0.004^{***}			-0.219^{***}
			(-5.04)			(-4.04)			(-6.36)
Cash flow			-0.102^{***}			0.001			-0.019
			(-5.81)			(0.64)			(-0.69)
Leverage			-0.042^{**}			-0.002^{***}			0.084^{*}
			(-2.28)			(-6.52)			(1.74)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.006	0.082	0.140	0.008	0.010	0.150	0.012	0.310	0.486
Obs.	20,415	20,415	20,415	19,758	19,758	19,758	20,415	20,415	20,415

Table XIV
Performance

This table reports results of regressions of firm outcome variables on Big Five trait measures and controls. Big Five trait measures correspond to the probabilities of a CEO being a specific personality type. These probabilities are estimated as average probabilities based on earnings conference calls within a year. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT). *Asset turnover* equals sales (SALE) divided by lagged total assets (AT). *Profit margin* equals EBITDA (OIBDP) divided by sales (SALE). *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the natural logarithm of 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) divided by lagged total assets (AT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses. Big Five trait measures and control variables are standardized. t-statistics based on robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Return on assets			Asset turnover			Profit margin		
Introvert	0.010^{***}	0.009^{***}	0.003^{***}	0.049^{***}	0.047^{***}	0.025^{***}	0.023^{***}	0.022^{***}	0.005
	(5.52)	(5.45)	(3.26)	(5.66)	(5.58)	(3.47)	(5.00)	(4.62)	(1.23)
Neurotic	0.002	0.001	0.004^{***}	0.025^{**}	0.021^{**}	0.011	-0.009	-0.008	-0.007
	(1.00)	(0.34)	(4.44)	(2.53)	(2.12)	(1.27)	(-1.28)	(-1.11)	(-1.13)
Disagreeable	0.015^{***}	0.015^{***}	0.003^{**}	0.031^{***}	0.032^{***}	0.027^{***}	0.062^{***}	0.062^{***}	0.011^{*}
	(6.68)	(6.75)	(2.57)	(3.09)	(3.13)	(3.08)	(6.42)	(6.41)	(1.75)
Unconscientious	0.005^{***}	0.005^{***}	0.002^{**}	-0.007	-0.007	-0.015^{*}	0.010^{**}	0.010^{**}	-0.006
	(3.83)	(3.81)	(2.24)	(-0.72)	(-0.70)	(-1.66)	(2.03)	(1.96)	(-1.34)
Open low	-0.003^{*}	-0.003^{*}	-0.002^{**}	-0.020^{**}	-0.020^{**}	-0.013	0.006	0.005	0.012^{**}
	(-1.81)	(-1.77)	(-2.42)	(-2.13)	(-2.18)	(-1.56)	(0.87)	(0.72)	(2.01)
Size			0.011^{***}			-0.131^{***}			0.056^{***}
			(7.89)			(-10.64)			(7.03)
Book-to-market			-0.007^{***}			-0.055^{***}			0.105^{***}
			(-4.84)			(-5.37)			(10.90)
Return on assets						0.305^{***}			0.386^{***}
						(12.30)			(22.86)
Cash flow			0.120^{***}			-0.061^{***}			0.051^{***}
			(66.89)			(-2.70)			(3.44)
Leverage			0.006^{***}			-0.091^{***}			0.058^{***}
			(4.19)			(-8.94)			(9.05)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.020	0.025	0.662	0.011	0.016	0.203	0.011	0.011	0.412
Obs.	20,415	20,415	20,415	20,415	20,415	20,415	20,378	20,378	20,378

Table XV
Future Performance

This table reports results of regressions of firm outcome variables on Big Five trait measures and controls. Big Five trait measures correspond to the probabilities of a CEO being a specific personality type. These probabilities are estimated as average probabilities based on earnings conference calls within a year. Dependent variables are changes in return on assets, asset turnover, and profit margin from year t to year $t+1$. *Return on assets* equals EBITDA (OIBPD) divided by lagged total assets (AT). *Asset turnover* equals sales (SALE) divided by lagged total assets (AT). *Profit margin* equals EBITDA (OIBDP) divided by sales (SALE). *Size* is the natural logarithm of total assets (AT), in 2013 dollars. *Book-to-market* is the natural logarithm of 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) divided by lagged total assets (AT). *Leverage* equals total debt (DLTT + DLC) divided by total assets (AT). All variables are winsorized at the 1st and 99th percentiles. Compustat data codes are included in parentheses. Big Five trait measures and control variables, except for return on assets, asset turnover, and profit margin, are standardized. t-statistics based on robust standard errors clustered by firm and year are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Change in future return on assets			Change in future asset turnover			Change in future profit margin		
Introvert	0.002^{***}	0.002^{***}	0.001^{***}	0.003	0.004	0.004^{*}	0.006^{***}	0.006^{***}	0.005^{***}
	(2.92)	(4.65)	(3.15)	(1.08)	(1.49)	(1.85)	(2.91)	(3.37)	(2.82)
Neurotic	-0.000	-0.001	0.000	0.005	0.004	0.004	-0.002	-0.002	0.000
	(-0.40)	(-0.86)	(0.94)	(1.23)	(1.33)	(0.93)	(-0.59)	(-0.53)	(0.03)
Disagreeable	0.003^{***}	0.003^{***}	0.002^{***}	-0.002	-0.001	0.004^{*}	0.008^{**}	0.009^{**}	0.004
	(2.96)	(3.23)	(3.23)	(-0.87)	(-0.59)	(1.66)	(2.16)	(2.28)	(1.25)
Unconscientious	0.000	0.000	0.000	-0.001	-0.001	0.001	0.001	0.001	-0.000
	(0.55)	(0.52)	(0.63)	(-0.16)	(-0.21)	(0.31)	(0.68)	(0.65)	(-0.16)
Open low	-0.000	0.000	0.000	-0.003	-0.002	-0.002	0.001	0.002	0.002
	(-0.12)	(0.28)	(0.03)	(-1.31)	(-1.09)	(-1.12)	(0.35)	(0.44)	(0.60)
Return on assets	-0.228^{***}	-0.225^{***}	-0.363^{***}						
	(-12.08)	(-13.50)	(-9.76)						
Asset turnover				-0.157^{***}	-0.154^{***}	-0.148^{***}			
				(-9.74)	(-9.25)	(-8.28)			
Profit margin							-0.217^{***}	-0.216^{***}	-0.256^{***}
							(-7.91)	(-7.96)	(-7.76)
Size			0.006^{***}			-0.008			0.021^{***}
			(6.42)			(-1.60)			(5.10)
Book-to-market			-0.013^{***}			-0.017^{**}			-0.007
			(-5.72)			(-1.97)			(-1.05)
Cash flow			0.021^{***}			-0.040^{***}			0.044^{***}
			(4.19)			(-6.37)			(3.52)
Leverage			0.001^{*}			-0.017^{***}			0.012^{***}
			(1.94)			(-3.90)			(3.16)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R^2	0.132	0.154	0.193	0.105	0.131	0.148	0.130	0.133	0.146
Obs.	17,313	17,313	17,313	17,313	17,313	17,313	17,281	17,281	17,281